THE VALUE AND RISK OF PROBABILISTIC THERMAL UPRATING SCENARIOS ON POWER SYSTEM RELIABILITY

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ABSTRACT

BY CHOMBA TUMELO-CHAKONTA

THE VALUE AND RISK OF PROBABILISTIC THERMAL RATING SCENARIOS ON POWER SYSTEM RELIABILITY. OCTOBER 2014.

According to the European Network of Transmission System Operators for Electricity (ENTSO-E) there is a need to invest 104 billion Euros to either refurbish or construct overhead lines (OHLs). This massive enterprise is mainly driven by the need to accommodate the proliferation of renewable energy generation projects across Europe in response to the European Commission’s directive to supply 20% of its energy from renewables by the year 2020. However, 30% of transmission projects experience delays; and moreover, it has been found that if the existing grid capacity is to be increased by about 1.3% it would facilitate about 3% of renewables. Therefore, attention towards the thermal uprating of existing networks has attracted research interest. In this thesis, the main contribution to this research is a probabilistic and holistically integrated system and OHL plant reliability centred thermal uprating evaluation methodology. This methodology is designed to aid the facilitation of the thermal uprating’s of existing lines, through a variety of multistage and multifaceted risk based decisions. These multifaceted aspects are subject to the conflicting views to thermal uprating which stem from various utility personnel; which further stem from their constricted views on system reliability. For example, plant maintainers may resist thermal uprating because it may require the need to increase maintenance works on right-of-ways, or because they may need to prevent conductors from ageing sooner than initially projected. However, restricting thermal uprating for these reasons will limit the capability of the system to facilitate renewables, and this will negatively affect overall system reliability. Therefore, the presented methodology aids to facilitate highly efficient interdependent decision making amongst plant designers and maintainers, and system planners and operators, to effectively manage thermal uprating risks in consideration to the overall utility’s goals. This thesis implements a variety of studies to enlighten utility personnel of the possible economic benefits and risk mitigation practices that could be realised through thermal uprating. To present robustly conclusive and compelling results, these studies research the value of thermal uprating from three possible time scales: long-, medium- and short-term time domains. Consequently, planners (through this methodology) will for the first time ascertain the true value of (1) uprating existing conductors by accepting the subsequent acceleration of their ageing, (2) selecting the optimal reconductoring technology from a suite of candidate (conventional and novel) conductor technologies, (3) the retensioning policy to implement (at a particular stage of a project) in order to maintain reliability, and (4) novel real-time OHL ageing management tools for power system operators to use reliably.
DECLARATION

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning

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<table>
<thead>
<tr>
<th>Acronym</th>
<th>Meaning</th>
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<tbody>
<tr>
<td>AAAC</td>
<td>All Aluminium Alloy Conductor</td>
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<tr>
<td>AAC</td>
<td>All Aluminium Conductor</td>
</tr>
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<td>AACSR</td>
<td>Aluminium Alloy Conductor Steel Reinforced</td>
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<tr>
<td>ACAR</td>
<td>Aluminium Conductor Alloy Reinforced</td>
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<td>Aluminium Conductor Steel Reinforced</td>
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<td>ACSS</td>
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<td>ADLC</td>
<td>Average Duration of Load Curtailment</td>
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<td>AEDV</td>
<td>Average Emergency Duration Value</td>
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<td>AEOV</td>
<td>Average Emergency Overload Value</td>
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<td>BC Hydro</td>
<td>British Colombia Power Utility</td>
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<td>BES</td>
<td>Bulk Electric System</td>
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<td>BPACI</td>
<td>Bulk Power-System Average MW Curtailment Index</td>
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<td>DISCOS</td>
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<td>Everyday Conductor Tension</td>
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<td>E-1</td>
<td>Generation Expansion 1</td>
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<td>Abbreviation</td>
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<td>EDC</td>
<td>Expected Damage Cost</td>
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<td>EDNS</td>
<td>Expected Demand Not Supplied</td>
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<td>ELC</td>
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<td>Expected Number of Load Curtailment</td>
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<td>EPSRA</td>
<td>Electric Power System Reliability Assessment</td>
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<td>FACTS</td>
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<td>( F(X_i) )</td>
<td>Reliability Index Function over a Given Assessment Period</td>
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<td>f/year</td>
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<td>Failure Prob.</td>
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<td>( f_i )</td>
<td>Frequency of Departing System State i</td>
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<td>( j_i )</td>
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<td>FL</td>
<td>Forecast Load</td>
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<td>FOR</td>
<td>Forced Outage Rate</td>
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<td>FPL</td>
<td>Forecast Peak Load</td>
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<td>Generating Companies</td>
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<td>HLI</td>
<td>Hierarchical Level 1</td>
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<td>HLII</td>
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<td>HLIII</td>
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<td>Hrs</td>
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<td>Acronym</td>
<td>Description</td>
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<tr>
<td>HTLS</td>
<td>High-Temperature Low Sag</td>
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<td>i</td>
<td>System State</td>
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<tr>
<td>IEAR</td>
<td>Interrupted Energy Assessment Rate</td>
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<tr>
<td>IEEE</td>
<td>Institute of Electrical and Electronic Engineers</td>
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<tr>
<td>IEEE-RTS</td>
<td>IEEE Reliability Test System</td>
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<tr>
<td>ISO</td>
<td>Independent System Operator</td>
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<td>k</td>
<td>Load Bus Number</td>
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<td>L</td>
<td>Annual System Peak Load</td>
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<td>LDC</td>
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<td>MBPCI</td>
<td>Modified Bulk Power Curtailment Index</td>
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<td>MCS</td>
<td>Monte Carlo Simulation</td>
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<td>MCT</td>
<td>Maximum Conductor Tension</td>
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<td>MVA</td>
<td>Mega Volt-Amperes</td>
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<td>MW</td>
<td>Mega Watts</td>
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<td>N</td>
<td>Set of all possible departure rates</td>
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<tr>
<td>NB</td>
<td>Total number of load buses</td>
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<tr>
<td>NESC</td>
<td>National Electric Safety Code</td>
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<tr>
<td>Occ/d</td>
<td>Occurrences per duration</td>
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<tr>
<td>OHL</td>
<td>Overhead Line</td>
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<tr>
<td>OPF</td>
<td>Optimal Power Flow</td>
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<tr>
<td>PAR</td>
<td>Phase Angle Regulator</td>
</tr>
<tr>
<td>PEO</td>
<td>Probability of Emergency Overloads</td>
</tr>
<tr>
<td>PST</td>
<td>Phase Shifting Transformer</td>
</tr>
<tr>
<td>p.u.</td>
<td>Per Unit</td>
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</tbody>
</table>
\[ P_i \] Probability of System State \( i \)

PLC Probability of Load Curtailment

QB Quadrature Booster

RBS Rated Breaking Strength

RC-TRAAP Reliability Centred Thermal Rating for Asset Planning

RES Renewable Energy Systems

ShMSC Shunt Mechanically Switched Capacitors

STATCOM Synchronous Static Compensators

SVC Static Var Compensator

TRANSCOS Transmission Companies

VLMWT Vibration Limited Maximum Working Tension
 DEFINITIONS

**Ampacity:** Is the maximum current that a conductor can safely carry at a given maximum conductor temperature and specified weather conditions

**Annealing:** A metallurgical process where high temperatures allow internal stress relaxation, which results in a softening and strength loss of the metal

**Conductor:** An overhead bare metal cable used to transmit electrical energy

**Conductor Temperature:** The temperature of a conductor is assumed to be isothermal (no axial or radial variation) for all steady-state calculations and for all transient calculations where the time period of interest exceeds 1 min or the conductor consists of a single material. With transient calculations less than 1 min with non-homogeneous aluminium conductor steel reinforced (ACSR) conductors, the aluminium strands are isothermal, but the heat capacity of the steel core is assumed to be zero.

**Creep, Accelerated Rate:** An increase in a conductor’s creep rate over general creep rate, usually associated with elevated temperature operation

**Creep, General:** The accumulative non-elastic elongation of a conductor under tension over an extended period of time at modest temperatures usually not in excess of approximately 75°C

**Creep, High Temperature:** The creep a conductor experiences over a period of time operating at conductor temperatures in excess of approximately 75°C

**Dynamic Thermal Rating:** The steady state electrical load that produces the maximum conductor operating temperature, calculated on an instantaneous basis for actual electrical loading and weather conditions

**Everyday Tension:** The design stress in an electrical unloaded conductor that is applied to minimise the Aeolian vibrations of the conductor

**Heat Capacity (Material):** When the conductor temperature is increased by \(dT\), as a result of adding a quantity of heat \(dQ\), the ratio \(dQ / dT\), is the heat capacity of the conductor

**High-Temperature Operation:** Operating conductors and connectors at temperatures where thermal effects can impact the safety, reliability and life of the transmission line.
Installation Sag: The initial conductor sag developed moments after the installation, at the installation temperature and with zero electrical loading.

Loss of Strength: The partial loss of a conductor’s mechanical strength through annealing

Maximum Conductor Operating Temperature: The constant electrical current that would yield the maximum allowable conductor temperature for specified weather conditions under the assumption that the conductor is in thermal equilibrium state.

Maximum Conductor Tension: The designed maximum working tension of the conductor on a particular OHL system at the minimum electrical unloaded conductor temperature with any additional wind and ice loading as specified by National Normative Aspects

Normal Conductor Operating Temperature: The temperature developed on the conductor under everyday electrical loading conditions

Operating Sag: The conductor sag developed at the instantaneous steady state load and weather conditions

Rated Breaking Stress: The maximum tensile load which a conductor is capable of withstanding under gradually and uniformly applied loading

Reynolds Number: A non-dimensional number equal to air velocity \((V_a)\) times conductor diameter \((D)\) divided by kinematic viscosity \((\mu / \rho)\)

Ruling Span: The dead-end span that gives the same change in tension from changes in loading, creep, and/or temperature as that in a series of suspension spans between tow dead-end structures

Specific Heat: The specific heat of a conductor material is its heat capacity divided by its mass

Static Thermal Rating: The current carried by a given transmission line conductor which results in the maximum conductor operating temperature for a particular set of conservative weather assumptions

Steady-state Thermal Rating: The constant electrical current that would yield the maximum allowable conductor temperature for specified weather conditions and conductor characteristics under the assumption that the conductor is in thermal equilibrium state

Steel Core: The inner strength member of a composite conductor composed of steel strands
**Thermal Time Constant:** The time required for the conductor temperature to accomplish 63.2% of a change in initial temperature to the final temperature when the electrical current going through a conductor undergoes a step change.

**Transient Thermal Rating:** The transient thermal rating is that final current ($I_f$) that yields the maximum allowable conductor current ($I_c$) in a specified time after a step change in electrical current from some initial current, $I_i$.

**Vibration Limited Maximum Working Tension:** The unloaded conductor tension used to limit Aeolian vibrations at the design load case which is defined by the minimum electrical unloaded conductor temperature and any additional wind and ice loading as specified by National Normative Standards.

**Wind Direction:** The direction of the movement of air relative to the conductor axis. The wind direction and the conductor axis are assumed to be in a plane parallel to the earth. When the wind is blowing parallel to the conductor axis it is termed “parallel wind”. When the wind is blowing perpendicularly to the conductor axis it is termed “perpendicular wind”.
ABOUT THE AUTHOR

The author of this thesis was born in Lusaka, Zambia in 1988. He received the B.Eng (Hons) First Class degree in Electrical and Electronic Engineering at the University of Manchester in 2008. In the Following year, he was awarded the MSc degree (with Merit honours—distinction in exams and merit in dissertation) in Electrical Power Engineering at the same institution. From 2010 to 2014, Mr Chomba Tumelo-Chakonta pursued research work at the University of Manchester in order to obtain the PhD degree in Electrical Power System Engineering.

To date the author’s research work has published six conference papers in peer-reviewed internationally renowned conferences (four as first author and two as third author). Furthermore, a journal paper, at present, stemming as a direct output of the research from this thesis is under review.

The author’s main research interests circumscribe reliability and security assessments; more precisely, the application of power system reliability concepts, algorithms and tools to aid the design and modelling of smart grid technologies to holistically solve techno-economic power systems asset management problems.
PUBLICATIONS

PUBLISHED/ACCEPTED CONFERENCE PROCEEDINGS


JOURNAL PUBLICATIONS UNDER REVIEW

To my dear beloved mother and in memory of my late father

To my immediate family
To the numerous people who by the abundant grace of God have graciously supported me throughout my life
So I set out to learn everything from wisdom to madness and folly. But I learned first-hand that pursuing all this is like chasing the wind. The greater my wisdom, the greater my grief. To increase knowledge only increases sorrow (Ecclesiastes 1:17-18)
CHAPTER 1
INTRODUCTION

Public objection and political directives are hampering utilities in procuring permits to build new lines [1, 2]. Thus, transmission and distribution (T&D) utilities, and researchers alike, are ubiquitously expressing research interest toward increasing the exploitation of existing T&D network capacity which has been latent for decades [3-8]. This research is demanded in order to establish whether existing power lines can be more frequently operated at and sometimes above their rudimentary design limits as well as for longer durations.

This research endeavour must account for the reality that much of the grid has aged beyond its design [9-11]. This is in order to ensure that as utilities tap more capacity from their existing networks, this pursuit will be engaged by ensuring that the concerns related to the increments in system operational risk (which may lead to increased numbers of congestions, blackouts and reliability threats) is maintained at acceptably minimum levels [12-14]. To aid in ensuring that these concerns are truly enforced, reliability councils such as the North American Electric Reliability Corporation (NERC) have thus recently mandated regulatory requirements on the establishment of transmission circuit ratings [15-22]. This mandate has subsequently imposed increased impetus and obligation on the need for electric utilities to possess tools that aid in the establishment of line ratings in a scientifically rigorous manner to ensure the supply of electrical power—reliably.

This thesis aims to undertake research in order to develop various tools and methodologies which enable power system utility planners to quantify the value and risk of increasing existing overhead line (OHL) system-wide thermal ratings (i.e., thermal uprating) on power system asset management engineering practices, capital investment, and reliability and operation.

1.1 FUNDAMENTALS OF POWER SYSTEM RELIABILITY AND OPERATION

Power system reliability is defined as the measurable [23-27] ability of a system to satisfy the consumer’s demand for electrical energy over a given period—usually a year. Clearly, this measurement must encompass the establishment of the magnitude, the frequency as well as the duration with which the power system will fail to supply its load [28, 29]. To establish these
measurements the reliability engineer must account for the likelihood of a system’s subjection to a variety of unpredictable operating conditions stemming from a combination of plant failures, load forecast uncertainty and energy generation uncertainty [30-34]. Furthermore, the measurement of reliability must be designed to also include the study of both the dynamic and static power system modes of operation [35]. Objectively, however, it must be emphasised that power system reliability is characterised by two concepts: adequacy and security [28, 29, 36].

1.1.1 Adequacy

From the outset, it must be stressed that adequacy is a reliability aspect solely characterised by the power system’s static operating conditions [26, 37-39]. Thus, adequacy must relate to the measured sufficiency of existing network generation, transmission and distribution plants to collectively satisfy electrical demand at an acceptable level. This must be ensured whilst respecting the operational constraints of these aforementioned plants [29]. Furthermore, this sufficiency implies on the need to account for the modes of failure [40-42] (as well as the failure rates [43]) of these system plants amid the objective of attempting to supply the electrical load. This is in order to more accurately predict the probability, frequency, duration and magnitude of experiencing curtailed load delivery states (within the overall system). In this regard, therefore, the reliability engineer must always be concerned with developing a robust understanding of these intimated plants— to model and predict their operational behaviours accurately [44-54].

1.1.2 Security

Security is a risk measurement of the ability of the power system to withstand disturbances arising within the system [29, 36]. Security assessment is not only limited to dynamic assessment but also incorporates static overloads and voltage assessments—as shown in Figure 1-1. A power system engineer engages dynamic analyses in order to study the system’s response to a disturbance within a time frame that spans from merely a few seconds up to a few minutes, and is mainly focussed on the need to ascertain whether (and how) system-wide (and/or generator specific) angular oscillations are to be effectively damped following an outage or a fault [36].

Figure 1-1 Power system security classifications [36]

More importantly, however, because the effects of loss of synchronism are dire and are capable
of compounding the propagation of cascading failures leading to blackouts, dynamic studies are required to ensure that the entire system will maintain synchronism between its healthy generators. For example, a blackout due to generator asynchronism was witnessed in the Western Systems Coordinating Council (WSCC) in 1996 (Western USA) which affected 7.5 million customers and subsequently resulted in a total curtailment of 30 Giga Watts (GWs) of electrical demand [55]. Conversely, static security analysis aims to study an arbitrary system’s ability to circumvent thermal overloading and over- or under-voltage security scenarios within time frames that span a few minutes up to a few hours, or to as well as years.

Therefore, by confirming the ability of a system to circumvent the aforesaid dynamic and/or static security concerns, the engineer can confidently ensure that an arbitrary system will have sufficient capability to meet its demand [56].

1.1.3 THERMAL RATING

Thermal ratings of an arbitrary power system plant circumscribe both adequacy and static-security properties, as shown in Figure 1-1. That is, the higher the thermal rating of a power system plant such as an overhead line (OHL), the higher will be a power system’s adequacy. Conversely, the higher the adequacy the higher the risk of overloading an OHL, and, subsequently, the higher the risk of infringing its statutory sag limits (i.e., due to an OHLs drooping in consequence to both its weight and operating temperature). The effect of this sag could resultantly increase the risk of flashover related OHL failures, and thereby spur cascading failures, which consequently affect the entire system’s capability to supply its electrical demand. Therefore, in order to engage in the proper engineering of the thermal uprating’s of OHLs (which address and mitigate these aforementioned risks whilst at the same time increasing power system adequacy) fundamental thermal rating concepts must be grasped.

1.1.3.1 THERMAL RATING CONCEPTS

The thermal rating (i.e., ampacity) is defined as the constant electrical current that would yield the maximum allowable conductor temperature \( T_{\text{max}} \) for specified weather conditions (i.e., wind, ambient temperature etc.) and conductor characteristics (i.e., resistance, heat capacity, material type etc.) under the assumption that the conductor is at thermal equilibrium [57].

Naturally, because the parameters on which the normal rating depends on vary with time, the rating over an arbitrary duration will vary as depicted in Figure 1-2 (blue line). This is termed as the dynamic thermal rating (DTR) —or the real-time thermal rating (RTTR) —and requires the installation of instrumentation on the line in order to capture all the parameters which influence conductor thermal rating [58-62]. With regards to \( T_{\text{max}} \) (Figure 1-2), the maximum conductor
thermal ratings have been traditionally limited to low maximum operating temperature values such that if the OHL conductor was operated continuously below or equal to these values, then the detrimental effects related to the loss of conductor strength (i.e., ageing) and the increase in its sag would be completely minimised [57, 63].

![Figure 1-2 The dynamic characteristics of a conductor’s thermal ratings](image)

The figure further shows that the maximum as well as the minimum possible ratings occur infrequently. Thus, rating and utilising the line at the maximum possible value over the time period indicated in the figure will result in constant thermal overloading over the stated duration. Antithetically adopting the lowest possible value over the stipulated duration will lower the risk of overloading to zero. The reduction of overloading risk is desirable according to Figure 1-1, because it enhances the security of the power system.

Traditionally, the maximum thermal rating that has been designed to be carried by a given transmission line conductor which results in the maximum conductor operating temperature has been historically evaluated on the basis of pre-determined worst case infrequent weather assumptions [1]. This tradition has been maintained for decades because the then planning tools, which largely remained unchanged until recent times, established that there was no need to install RTTR instrumentation [64-70]. Moreover, this decision was also compounded by the reality that the available technologies, control algorithms and research knowledge (at the time) were in infancy [60, 71, 72]. Subsequently, this conservative thermal rating—universally termed as the static thermal rating (STR)—has resulted in the almost ubiquitous utility practice of constantly scheduling the lowest possible rating [62, 73] as shown in Figure 1-2.

It must be mentioned that the electrical characteristics of OHLs pose the risk of limiting the increased amount of active power (i.e., thermal rating) that can flow through an OHL through dynamic thermal rating. This is because the increased transfer of active power across an OHL of a specified length will force its voltage at its receiving end to drop, potentially resulting in voltage instability. The relationship between voltage stability and active power depends on the length of an OHL. That is, the shorter an OHLs length the more stable will be its voltage profile and in turn...
this will allow the supply of the maximum possible active power which follows the exact profile shown in Figure 1-2. On the other hand, if an OHL is too long, then the active power flow across an OHL must be reduced in order to maintain voltage stability; in this case the maximum dynamic thermal rating will be applied as quasi-dynamic thermal rating by capping its maximum output and hence limiting the full potential of active power flow.

![Quasi-Dynamic Thermal Rating](image)

**Figure 1-3 Quasi-Dynamic Thermal Rating**

### 1.1.3.2 PROBABILISTIC THERMAL RATING CONCEPTS

In the bid to increase STRs, probabilistic thermal rating (PTR) methods have been proposed based on the probabilistic modelling of Equation 1-1 [74]. This equation implies that over a period of time \( t \), the probability \( P(T_c(t)) \) of attaining a particular conductor temperature will depend on the joint probability of attaining a particular wind speed \( V_w(t) \), ambient temperature \( T_a(t) \), a selected power-current flow \( I_{selected} \) and the solar radiation \( S(t) \) parameters.

\[
P(T_c(t)) = P(V_w(t), T_a(t), I_{selected}, S(t))
\]

Equation 1-1

Therefore \( P(T_c(t)) \) can be effectively used to estimate the probability of operating at elevated temperatures (i.e., above \( T_{max} \) Figure 1-2)), and this probability value can be converted to estimate the duration within a year wherein a conductor will be operated at elevated temperatures. This duration is commonly converted to a fraction of a year, and is termed as the exceedance [1]. To more fully exemplify this argument, consider Figure 1-4 which is an enhancement of Figure 1-2. In Figure 1-4, a horizontal black line is drawn to illustrate an elected adequacy rating \( I_{selected} \); which could be characteristic of an arbitrary thermal uprating scenario (TUS) candidate value. Clearly, the figure shows that at certain instances there is an expectation of a TUS exceeding an arbitrary conductor’s initially designed \( T_{max} \). Consequently, the risk pertaining to this TUSs exceedence is the manifestation of conductor ageing as shown in the figure. However, it is also shown in the figure that the probability of this ageing period will not be 1, because for the same rating there will be instances whereby the ambient conditions will cool
down the operating temperature of the line, as captured in Equation 1-1.

![Figure 1-4](image.png)

*Figure 1-4 The effect of ageing due to an increased selected adequacy thermal rate*

Therefore, utilities can justifiably accept invoking optimal TUSs in this manner, as long as $P(T_i(t))$ is acceptably low enough. The acceptability of $P(T_i(t))$ demands measuring and then costing the risks associated with implementing a particular TUS.

### 1.2 THERMAL UPGRATING SCENARIOS: ISSUES AND NEEDS

TUSs, as an outcome to the earlier discussion(s), inevitably and significantly increase either blackout or early reconductoring risks. Blackout and early reconductoring risks are mutually exclusive risks; increasing the other risk mutually reduces the other risk and vice versa. These risks are further explained in the following paragraphs.

Blackout risk constitutes the oversagging security risk to power system operation. Mitigating this risk demands the enterprise which is concerned with the selection of the optimal asset management activity solutions (AMASs). Examples of typical AMASs include (1) increasing the frequency of OHL right-of-way trimming and/or (2) increasing the frequency of OHL retensioning and/or (3) implementing OHL reconductoring. More explicitly, retensioning is an AMAS which involves the increased stretching (tensioning) of an existing conductor, so as to increase its clearance to ground [1, 2]. This in order to enable the existing conductor to operate at a higher temperature without infringing statutory clearance limits when the conductor experiences its maximum sag at the increased operating temperature. Reconductoring, on the other hand, as an AMAS involves the option of either replacing existing conductors on existing OHL structures with larger conductors of the same conductor technology, or with different technologically advanced conductor types in order to increase an OHLs thermal rating whilst improving its oversagging risk performance. Examples include replacing conventional aluminium conductor steel reinforced (ACSR) with ACSR conductors of larger diameters; or with different technology types such as all aluminium alloy conductors (AAAC); or the more advanced family of conductor types termed as
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high temperature low sag (HTLS) conductors [1, 5, 75].

Furthermore, once the blackout risk is mitigated, a utility must contend with another risk, namely, that of early conductor replacement due to ageing. In this regard utilities must establish whether they will financially profit (due to adequacy increase) by ageing an OHL over and against preserving its ageing. This is in order to, by the value gained due to ageing, pay for the cost of early reconductoring with a conductor technology characterised by better ageing risk performance. Therefore, whether it is to ameliorate blackout (due to OHL oversagging) or early reconductoring (due to increased ageing) risk, a number of AMAS processes and cost considerations have to be holistically modelled within a reliability evaluation tool and framework, for the first time in open literature, in order to elect the optimal TUS by addressing the gaps in [9, 10, 13, 14, 75-78].

1.3 Overview of the Proposed Electro-thermal Reliability Evaluation Tool

Realising the optimal TUS and AMAS must be engaged through a holistic power system reliability assessment framework. Toward this pursuit, as a starting point, this thesis argues that the current probabilistic-based system level modelling framework must be modified to incorporate detailed modelling of conductor (electro-thermal) operational characteristics. Thus, through this novelty, the holistic decision making process which must incorporate all relevant AMASs (to facilitate optimal TUS selection by mitigating relevant TUS risks) as shown in Figure 1-5 is made possible. This decision process begins at a utility corporate level’s decision to establish the best TUS as shown in Figure 1-5 step 1 on the left. These TUSs must accurately model OHL behaviours coherently and correctly at the system-wide level modelling in order to establish either a TUS’s adequacy and ageing or a TUS’s blackout risk.

![Figure 1-5 A holistic electro-thermal decision making process framework](image)

The computed values resulting from step 2 can be used at the OHL plant level (step 3) to evaluate the various AMAS costs, namely, retensioning, reconductorin, right-of-way and inspection maintenance on ameliorating a TUS’s risks. Once this step is completed, results are appended to a
project ledger, and this project ledger is transferred to the risk management team at the corporate level for further comparative assessments (step 4). At the risk management level, the knowledge of all the possible risks peculiar to a TUS (as well as its corresponding reliability credit) will aptly inform corporate level planners in determining the optimal TUS which can be economically and reliably justified. This economic justification is, of course, made after having ensured for the provision of technically acceptable risk circumventing AMASs, as realised through iterative dialogues between the corporate, system and plant personnel as depicted in Figure 1-5, i.e., through the feedback loop to step 2.

Once this process has been completed and a TUS and its corresponding AMAS decisions have been made, that TUS can be engineered into the power system (step 5). Once engineered in the power system, guidelines and novel operational tools must then be developed to enable power system operators with monitoring and managing (on-line) the utilisation of conductors at justified high temperatures in a manner which adheres to the pre-planned utility corporate directives.

1.4 Thesis Aim and Objectives

The main aim of this thesis is to complete research into a holistic mathematical OHL plant and network electro-thermal power system reliability model (as described in 1.3). This is in order to measure and, consequently, explore the potential for TUS adequacy benefits against TUS risk amelioration AMAS costs as a credible solution for the modern power system reliability design problem. Achieving this aim relies on achieving particular objectives:

- To review the current probabilistic power system reliability evaluation framework, namely, the state of the art sequential Monte Carlo simulation (SMCS) tool and technique used to evaluate system-wide reliability and to critically assess its OHL plant behavioural model
- To review the OHL plant level electrical, mechanical and thermal modelling related to OHL behaviour and to subsequently integrate an appropriate OHL electro-thermal model into the SMCS based power system reliability evaluation framework
- To further improve the electro-thermal SMCS by developing a more holistic and accurate simulation process of power system-and-OHL-plant behaviour in order to capture both early reconductoring and blackout risks, and to develop new OHL plant visibility and performance indices to measure and quantify these aforementioned risks
- To test and validate the novel electro-thermal power system reliability tool by the traditional coefficient of variation (cov) method in order to validate the ability of the tool to acceptably measure both early reconductoring and blackout risks
To appropriately model a techno-economic framework by which to select the optimal AMASs needed to mitigate OHL early reconductoring and blackout risks

To model uncertainties related to both the AMAS and electro-thermal SMCS power system reliability evaluation frameworks

To model a framework based on decision trees by which to extract the knowledge necessary to develop strategies which help to mitigate risks due to both AMAS and electro-thermal modelling uncertainties

To integrate (1) the holistic power system-and-OHL-plant SMCS electro-thermal reliability evaluation tool framework and its uncertainty model, (2) the AMAS framework and its uncertainty model and (3) the decision tree framework into a multifaceted holistic asset management framework; incorporating regulatory constraints, life-cycle considerations, multistage decision making strategies, and PESTRE (political, economic, social, technological, regulatory and environmental) concerns

To integrate the novel holistic multifaceted asset management framework into a multistage optimisation algorithm in order to strategize ways to optimise OHL life-cycle AMAS implementations in a manner which maximises (amidst uncertainties) both long term power system reliability and OHL life-cycle utilisation.

To develop real-time monitoring and evaluation tools to aid the real-time management of OHL thermal ageing (amid uncertainties) and to thus provide the means by which the decision to age an OHL can be effectively made by the operator in real-time in a manner which adheres to the optimised holistic long term asset management based ageing strategy

1.5 Thesis Contributions

The work in this thesis has realised a holistic OHL asset management power system electro-thermal reliability assessment based framework wherein the optimal TUS and AMAS over an OHL’s life-cycle can be realised in a manner which optimally satisfies PESTRE constraints. In completing the set objectives, this work contributed to the broader areas of long term strategic asset management, power systems reliability and risk assessment, and power systems security analysis. Succinctly, however, the contributions of this thesis are categorised into two areas of knowledge: (1) power system methodological and modelling, and (2) power network planning assessment.

1.5.1 Electro-Thermal AND AMAS Methodological and Modelling Improvements

The development of a holistic multifaceted and multistage OHL life-cycle asset management
framework has been completed using the Dynamic Programming (DP) algorithm. The DP has been developed to account for multiple criteria which must be considered within this holistic framework. This novel framework improves on the electric power research institute’s (EPRI) framework [1] which does, amongst other things, not optimise the utilisation of an OHL over its life-cycle through robustly mathematical means, rather this optimisation within the EPRI framework is made mainly through engineering judgement techniques. As a result, utilities cannot evaluate the optimal number as well as stages within an OHL in which to implement AMASs for a given TUS—this makes it difficult to identify the optimal TUS to schedule.

Therefore, to realise the improvements, over the EPRI model, the DP tool utilised both a novel electro-thermal SMCS power system reliability evaluation tool and an uncertainty based techno-economic AMAS evaluation tool, as described next.

1.5.1.1 **NOVEL ELECTRO-THERMAL SMCS POWER SYSTEM RELIABILITY EVALUATION TOOL**

A variety of modelling improvements have been made to the existing reliability evaluation framework (discussed in chapter 2) in order to propose the novel electro-thermal reliability methodological tool to evaluate different TUSs within a wider network performance. This novel tool provides reliability engineers with the ability to compute ageing visibility indices of OHLs.

Ascertaining ageing visibility indices requires the development of a four OHL operational state model (an improvement from the two state operational model currently employed in existing literature). The ageing visibility methodology models four possible OHL electrical loading operating states: the normal operating state, the pre-contingency high operating state, the post-contingency high loading state and the failure state.

This detailed modelling aids to realise high visibility of OHL performance due to either its normal ($\lambda_n$) or its emergency failure rate ($\lambda_e$). The $\lambda_e$ models the blackout risk due to cascading failures, whereas $\lambda_n$ models the risk first failure. In order to capture the effect of all failures on the OHL performance a creep modelling function (specific to a conductor type) is used to capture the ageing of network’s OHL due to expected failures and operating conditions.

These aforementioned models are augmented to the traditional reliability evaluation methodology to produce novel reliability indices in order to capture the expected ageing occurred in the network due to the expected operating decisions and increase network status visibility. The expected magnitude of extra loading (EMEL), the expected frequency of extra loading EFEL, the expected duration of extra loading EDEL, and the expected equivalent ageing index EEAI are the proposed indices.
This novel electro-thermal reliability evaluation tool improves on the electric power research institute’s (EPRI) TUS evaluation model [1]. More explicitly, the EAI index and the emergency loading failure rate formulations within this electro-thermal tool (in comparison to those developed within the EPRI model) have been shown to compute more accurately (and thus facilitate) the indices required to assess both the early reconductoring and blackout risks, respectively, for a given TUS.

1.5.1.2 **NOVEL LONG AND SHORT TERM UNCERTAINTY BASED TECHNO-ECONOMIC AMAS EVALUATION TOOL**

The techno-economic modelling improvements augment the AMAS processes for a TUS to the proposed electro-thermal reliability evaluation tool in order to identify an optimal ageing utilisation strategy for a TUS. The ageing utilisation flexibility tool of a TUS models both long term and short term characteristics of conductor ageing.

The long-term techno-economic modelling considers the long term ageing utilisation flexibility tool and is used in order to optimise the frequency and stage based implementation of AMASs and to make strategic planning decisions. This tool considers only the OHL’s steady state thermal model in order to simplify the analysis and speed up the simulation. In this methodology, thermal uprating AMASs (TU-AMASs), blackout risk AMAS (BR-AMASs) and early reconductoring risk AMAS (ER-AMASs) are modelled. To further model scenarios which capture the decision on whether to engage in a live-line or an offline TU-AMAS, a line outage scenario based on a proposed parallel sampling technique is implemented. Furthermore, in order to decide on whether to engage in a retensioning/ROW maintenance or a do nothing BR-AMAS, the $\lambda_e$ function is modelled to capture the blackout risk cost. Lastly, the ER-AMAS is modelled to capture benefits from using conventional and novel conductors.

To capture the revenue from ageing utilisation flexibility of a TUS, the regulated market price of electricity model and the performance based regulatory framework for the reliability model are implemented. The inherent uncertainties in AMAS investment costs are taken into account and assessed through decision trees. A dynamic programming computational algorithm is implemented to account for the highly stochastic aspect of this multi-year problem. The stochastic attribute of this long-term techno-economic modelling is mainly due to the PESTRE (political, economic, social, technological, regulatory and environmental) factors. Finally, the key contribution of this methodological enhancement is that it, for the first time, facilitates the computation of the optimal AMAS implementation frequency indices for an arbitrary OHL’s TUS over the course of its life-cycle.

The short-term techno-economic modelling is developed to increase power system operator
flexibility during real-time emergency operating modes, by providing to the operator more options to realise an improved thermal operating state strategy (TOSS) which optimises network performance and costs. In this regard, a transient OHL thermal model is employed along with an increased resolution (up to 1 minute) of power system plant modelling to capture small time-step changes. The short-term techno-economic model evaluates the power system’s performance within the emergency state only by employing two additional novel indices. The expected resiliency duration (ERD) and the traversal risk (TR) indices.

1.5.2 **STRATEGIC AND RISK-BASED NETWORK ASSESSMENTS**

The developed methodological improvements facilitate a variety of novel analyses both within the network planning and operating domains, which could not have been effectively made through the existing modelling tools in a quantitative assessment. These novel analyses, because they also include uncertainty models, thus help utilities more accurately realise, for a given TUS, the conditions in which they will require to implement different long term strategies (such as to defer, or to wait, or to engage in long term maintenance contracts and so on) for particular AMAS implementations in order to maintain both the profitability of the OHL and the reliability (i.e., blackout risk minimisation) of the power system.

1.5.2.1 **LONG TERM STRATEGIC OHL ASSET MANAGEMENT ACTIVITY SCENARIO ASSESSMENTS**

Long term strategizing is facilitated by the novel indices developed increase network visibility; as they facilitate a more thorough assessment of OHL as well as network states, because the visibility indices are able to capture the true reliability performance of an OHL as a function of the variability of its thermal loading and therefore its operating state. Moreover, visibility indices can compare the effect on the network performance as well as the individual lines on an objective basis various TUSs (namely STR, DTR and PTR) for the first time. Consequently, the visibility indices are jointly used with traditional power system reliability evaluation indices to assess the adequacy improvement and risk of early reconductoring and blackout of various TUSs.

One of the key outputs from these novel indices was to facilitate the development of an OHL ageing spectrum. This spectrum, by realising both the critical and non-critical OHLs, was used as a guide to help allocate the type of maintenance policy to implement on an OHL based on its criticality to the system. It was found that the critical lines (which comprised less than 10% of the studied network’s circuits) generally required rigorous online condition monitoring techniques, whereas the less critical lines required little maintenance as their reliability was not critical to the system. The criticality of lines to system reliability was realised from the application of a performance based regulation (PBR) framework, also from which the incentivised payment for
reliability could be calculated in order to fund a particular maintenance scheme. Thus, the remunerated income could then be used to fund AMASs for the critical lines over their life-cycle for a selected TUS.

The ER AMAS assessments showed that a TUS is conductor technology (i.e., ACSR, AAAC, ACCC, ACCR etc.,) specific and thus particular technologies with resilience in ageing (ageing immune) are more beneficial when compared with technologies that are prone to ageing (ageing encumbered). Historically, the comparison between novel (e.g., ACCR, ACCC) and conventional conductors (e.g., ACSR, AAAC) has been accounted for by solely considering their technical merits and their first time investment (and not their recurring AMAS) cost. In this regard, although technically supreme, novel conductors have been unable to economically compete on a first time investment basis. However, in addition to accounting for the first time investment cost, by accounting for the recurring AMAS investment cost associated with a conventional conductor’s ageing, it has been possible to show that novel conductors (which have zero recurring ageing related AMAS costs) can now compete economically with conventional conductors (which are encumbered with recurring AMAS costs).

1.5.2.2 Network Operating Corrective Control Sequence Improvement Assessment

Once the optimal long term strategic OHL asset management activity scenario has been realised, further optimisation due to more certainty amid real-time monitoring (in comparison to long term assessments) of an OHL TOSS can be achieved. Moreover, during real-time network operating situations, power system operators are charged with making decisions in complicity to dynamic or static overload constraints. Therefore, the less constrained an operator’s decision space is, the more economical and reliable the TOSS is. This result has been clearly shown through the computation of a short-term techno-economic modelling served to expand the operator’s TOSS space and provide more power flow capacity, thereby increasing the ability for operators to employ corrective control techniques whilst ensuring that their actions are in complicity with the long term OHL ageing strategy. It has been further shown that by utilising less reliable and less responsive generating plants with increased risk of ageing an OHL more resiliencies against blackouts could be built into a power system, assuming an appropriate AMAS is in place.

1.6 Thesis Structure

Chapter 2 reviews the state-of-the-art tools and techniques extant in aiding engineers to accurately model, compute and hence measure the reliability of an arbitrary power system. Upon critical analysis of the gaps within these tools and techniques, the conceptual ground work for the novel electro-thermal tool presented in this thesis and fully exemplified in chapter three is first
presented in this chapter.

Chapter 3 introduces the computational methodology undergirding the tool that holistically integrates OHL plant electro-thermal properties within the state-of-the-art power system reliability evaluation model. To facilitate this holistic computational perspective, the requirement for novel OHL ageing indices that capture the true operation of arbitrary OHLs are discussed and subsequently developed and integrated into the proposed computational methodology.

Chapter 4 validates the developed electro-thermal computational tool; and in order to narrate convincing results of the methodology’s accuracy and precision in capturing both the true operation of an arbitrary power system and its inherent OHLs plants, the widely assented IEEE Reliability Test System (RTS) is employed in this chapter, on both which novel OHL ageing indices and traditional system indices are computed.

Chapter 5 presents an electro-thermal based techno-economic methodology which showcases how the optimal AMAS can be selected for a given TUS at minimum cost, and maximum provision of reliability. To aid this analysis, three risk criteria are proposed: thermal uprating, oversagging blackout and reconductoring risk thresholds. The ageing which is computed from the holistic electro-thermal methodology is weighed against these three risk criteria in order to guide the selection of the optimal AMAS.

Chapter 6 expands the electro-thermal based techno-economic methodology proposed in chapter 5 to a multi-year TUS problem. This is in order to compute the optimal \textit{AMAS implementation frequency indices} for an arbitrary OHL’s TUS over the course of its life-cycle. The computation of optimal \textit{AMAS implementation frequency indices} (which in turn aids in the realisation of the truly holistic solution to the problem discussed in section 1.3) is realised through the implementation of the dynamic programming technique.

Chapter 7 addresses the gap inherent in the tool presented in chapter 6, namely, the inability to account for TUS transient behaviour. Whereas the TUS problem in chapter 6 focusses on the long term life-cycle challenge inherent in selecting the optimal TUS (and its corresponding \textit{AMAS implementation indices}), the TUS transient behaviour can only be accounted for by focussing the TUS problem to the short-term real-time domain. Hence, by accounting for the transient behaviour of a TUS, it is possible to further increase the value of a TUS without violating \textit{AMAS implementation frequency indices}. Therefore, chapter 7 presents a novel real-time electro-thermal based TUS transient behaviour operational methodological tool in order to aid the proposition of novel TUS utilisation guidelines which allow for the increased and more flexible
TUS operation of OHLs during real time operation whilst adhering to AMAS implementation frequency indices constraints.

Chapter 8 concludes the key outcomes of this thesis by acutely stressing the contributions made to knowledge. Subsequently, the directions for future research are exemplified.
Chapter 2
Appraising the Power System Reliability Assessment Framework

Power system reliability assessment has been studied for over half a century. Consequently, researchers within the field of reliability evaluation have conceptualised a generic framework toward the pursuit of reliability assessment (Figure 2-1). The blocks in the figure represent the particular tenets that any reliability engineer must consider prior to engaging in any reliability evaluation exercise. Depending on the nature of the exercise, however, certain aspects within these tenets can be modified [80]. The driving force underpinning this modification will invariably rely on the required level of system modelling complexity and the required simulation speed (i.e., time frame) by which to realise solutions, and both are influenced by the system model developed. Moreover, these two pre-requisites are influenced by particular problem contexts.

These contexts can be broadly classed into either system expansion planning or operations planning problems [81], further discussed in section 2.1. Within these broadly defined universal problem contexts exist particular problem sub-contexts which are wide ranging and varied. Subsequently solving any reliability problem with respect to any of these particular sub-contexts will require the tailored modification and/or advancement in the utilisation of certain reliability simulation techniques, theories and system models [64-70, 80].

Figure 2-1 An integrated approach to power system reliability assessment [80]

Re-examining Figure 2-1, one can observe that objectives and data inputs will always guide the modelling process of the problem. Although it is discussed further in section 2.2, data input briefly refers to the particular numerical values rendered through their inherent mathematical functions which describe system operational parameters and constraints. Within the modelling block, which is discussed more in section 2.3, all system plant properties and their failure rates are integrated.
to form a complete system topology—suitable to compute system power flow operations amid randomly failing plants. Furthermore, it must be reiterated that the level of detail *modelling* will be limited by the computational resources available. Thus, painstaking skill must be exercised in order to achieve a desired model with sufficiently realistic accuracy whilst significantly relieving computational burdens. Subsequent to the *modelling* process, the system *simulations* are performed by invoking appropriate system failure state sampling techniques (discussed further in 2.4). Once all possible failed states have been sampled, various load-flow network solutions (based on the reliability engineer’s desire and/or purpose) can be computed in order to establish the states which lead to system violations (e.g. overloads, voltage and/or transient security limits exceedances) discussed in chapter 1.

Once these states have been isolated, optimisation algorithms must be utilised in order to ascertain the optimum manner through which to curtail load demand—in order to restore system operation to within its security limits. The magnitude, frequency and duration of load curtailments formulate the unreliability risk indices, as further discussed in this chapter. These computations take place within the *analysis* block, further discussed in section 2.5. The results of the *analysis* are then compared against one of three, namely, comparison-based, co-operative-based or penalty-reward-based, *reliability criterions*, which are further discussed in 2.6. These criteria are necessary in order to effectively benchmark system performance and invoke managerial decisions. Thus, to this end, for at least the past six decades a plethora of *reliability-performance* and *reliability-cost* risk indices have been formulated [23].

In this chapter, the foundational principles and mathematical theories which govern the particular tenets of the contemporary reliability evaluation framework (Figure 2-1) will be discussed. This will include reviews of the Monte Carlo (MC) technique and its competing variants, as well as a wide variety of failure state selection techniques employable within the reliability evaluation probabilistic framework [64-70]. It will be impossible to fully review the myriads of publications over these past six decades. This chapter will instead present a broad and sufficiently comprehensive review of the fundamental principles (inherent within each of the six tenets) which have been discovered (and unanimously consented) as seminal to aid the reliability evaluation process [28, 29, 80-83]. Techniques which have been applied solely within the static domain are reviewed—hence neglecting those realised within the dynamic domain [35, 84]. Finally, the specific applications to which this framework has been tailored to are narrated within the annals of reliability evaluation bibliographical volumes [64-70].
2.1 Reliability Assessment: Objectives

The main objective in reliability evaluation of power systems can be broadly subjected to either the operation or the planning contexts. The planning context describes the means of selecting the best solution from a suite of candidate alternatives. In the past this selection was made solely on a benefit approach; which established the best candidate on the sole basis of measuring the improvement it offered toward overall system reliability [85]. Contemporarily, the selection of the best candidate is made on the basis of a cost-benefit approach; centred on ascertaining the candidate that best balances the improvement in reliability against the cost of its investment [86]. Conversely, the operation reliability problem attempts to select the best approach to operating the power system within the constraints of the already existing plants and infrastructure. In parallel to the planning context, selection of the best operating plan dependson evaluating all possible candidate operation plans and marking out the plan which is most robust against all possible system failure states. The cost-benefit approach has also been adopted within the operation framework [87, 88].

2.1.1 Addressing the Tripartite Reliability Evaluation Complexity

In addition to the planning context in question, the selection of the ideal candidate depends on a tripartite consideration base of (1) the required speed with which this selection process must be completed, (2) the selection criteria to be employed and (3) the selection model. The selection model relates to the required minimum level of system modelling complexity upon which the best candidate can be selected with acceptable accuracy. The selection criteria could be either a benefit or cost-benefit requirement. The speed (be it in minutes, days, weeks or months) relates to the time frame wherein a selected solution must be realised—through one of many simulation techniques. The complexities inherent in unifying this tripartite approach (so as to realise acceptably optimised solutions within their inherent constraints) are relayed through the model in Figure 2-2—which at the base is founded by two of the three tripartite members. The levels A to D are characteristic of the different classes (as defined in Table 2-1) of the simulation tools required to be invoked, based on the combinatorial nature of these two tripartite members.

![Figure 2-2 The relationship between selection process speed and the system model complexity](image-url)
Thus, by analysing Figure 2-2, reliability engineers can be able to clearly understand the influence of each tripartite member on the outcome of the simulation tool required to select the best candidate. For example, as Figure 2-2 shows, if the engineer were to model the system with high complexity and if the solution were required to be realised in an expeditious time frame, then a simulation technique within class B would need to be employed. This is not a trivial decision process because it requires the engineer to possess the ability to ascertain the most ideal technique from a suite of competing alternatives (Table 2-1) by weighing their merits (accuracy) and demerits (computation time) with respect to the problem at hand. The merits and demerits of these candidates in Table 2-1 are fully discussed in section 2.4. Thus, it must, however, be borne in mind that as a result of this non-triviality, the engineer is also required to tactfully approximate the system model (with minimal loss of complexity). This is so as to guide the adoption of the best simulation tool able to realise acceptable solutions within set constraints. Subsequently, when constrained by computation time, the reliability engineer’s pursuit toward accurate reliability evaluation is realised by initially establishing the particular hierarchical level upon which to model the system and the reliability evaluation criteria upon which to evaluate the reliability of the system (Figure 2-3).

![Figure 2-3 Sub-objectives within the universal objective block](image-url)
2.1.2 ADDRESSING RELIABILITY EVALUATION COMPLEXITIES WITH HIERARCHICAL SYSTEM LEVEL MODELLING

In the attempt to evaluate the reliability of a given power system, the engineer must model (1) the transportation (i.e., the deliverability) model of the system and (2) all the necessary adequacy and security considerations (as narrated in chapter 1), based on the sampling of random system states which originate from a variety of facility outage combinations. Modelling the transportation, adequacy and security aspects of system operation characterises a large scale problem which subsequently superimposes heavy computation burdens when all these segments are modelled under a single detailed framework. Thus, reliability engineers have deemed it prudent to develop a hierarchical approach to reliability assessment modelling as shown in Figure 2-4.

![Figure 2-4 Hierarchical Reliability Assessment Structure [89-92]](image)

HL-1 studies engage reliability evaluation by modelling only generating and demand resources and their inherent failure modes. Thus, in addition to the up-down failure modes of the plants, the inability to serve load through amputated generation capacities is evaluated [89-92]. HL-2 studies engage reliability evaluation by modelling generating, transmission and demand resources and their correspondingly more detailed failure modes [89-92]. These system failure modes include voltage instability, transient instability and plant thermal overloads. It is not possible to capture these failure modes at HL-1; and thus if capturing these modes of failure is not the concern of the reliability engineer, huge computational burden relief can be realised by invoking the HL-1 model [89-92]. HL-3 studies engage reliability evaluation by modelling the complete generating, transmission, distribution and demand resources. However, at present it is impossible to conduct HL-3 in its entirety; as such, HL-3 analysis has been limited to distribution level analysis, consequent to developed system equivalents that are sufficiently representative of both the generation and transmission plants [89-92].

If entire HL-3 analysis was invoked with full modelling and analysis at each level, the reliability engineer, due to the sheer wealth of data, would be overwhelmed with ascertaining ways to analyse this data; and would be mostly limited to investigating power system reliability from a global view. This global analysis will essentially limit the full intent of a full HL-3 study; as the
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Localisation of reliability to the delivery point level within distribution systems is also indispensable. This is because it allows the assessment of the impacts of voltage sags on induction motor performance connected to a particular bus—for example—to be made [93]. Furthermore, while it may be reasonable enough to assume only the modelling of three phase faults at the HL-2 level, it may not be so at HL-3 level; as line-to-ground (L-G), phase-to-phase (P-P) etc., faults must be accounted for as well [93]. Expectedly, it would be impossible to incorporate all these modelling needs into one framework.

Conversely, there is much benefit to be derived from this hierarchical approach to reliability assessment—apart from the relief of computational and data analytical concerns. This is because the reliability engineer can solely focus on accounting for the failure modes as seen from each hierarchical level. For example, HL-2 evaluation enables the reliability engineer to consider the behaviours relating to generator abilities to supply loads through existing electrical paths within an arbitrary system. In so doing, the engineer is able to establish the failures caused by transmission overloads and voltage constraints when the system in question is subjugated to random failures. Conversely, when evaluating HL-1 reliability, the engineer only considers generator capability to supply load and the only mode of failure in this case is the inability of generators to supply load. In a deregulated market environment, this delineated hierarchical framework aids the independent system operator to establish which market entity (i.e., generation, transmission or distribution) and also how much this market entity may need to invest into the overall system in order to appraise that the overall system will be acceptably reliable.

2.1.3 Addressing Reliability Evaluation Complexities through Security State Classifications and Modelling

The complex, large and non-linear characteristics of power systems requires engineers to conceptualise (and thus appraise) the reliability performance of power systems through classified security operational states [94-97]. Thus, by measuring the probability and duration values characteristic of a security state in which the system is likely to reside, reliability planners are better able to design the optimal system action (i.e., whether it be at HL-1, HL-2 or HL-3 levels) capable of either maintaining the system within an acceptable operating and economical security state or steering the system to a new acceptable operating and economical security state with the highest probability and residence duration time [96].

In this regard, when modelling security requirements, engineers must conceptualise security by not only explicitly defining and categorising the subjective forms of failure that a power system can sustain (i.e., thermal overloads, switchgear rating overloads, voltage outside limits, steady
state, transient and dynamic stability and voltage instability [36]), but also by the objective security states within which a system might reside. These objective states and their possible transitional arrows are shown in Figure 2-5, and are explained next.

The Normal State is deemed as such if a system’s equipment and operating constraints such as voltage, transient stability, thermal loadings are within their limits, and also continue to operate within their limits if the credible loss, typically specified by some criteria (e.g. N-1), of an arbitrary equipment was to occur [29, 36]. In this regard, there is no requirement for algorithms to further optimise this security state.

The Alert State is a state which arises when some system plants are loaded at their limits or when the system is operating at its voltage or stability limits as a result of the loss of an arbitrary set of system plants. This means that in this state, the system no longer has sufficient margin to withstand any subsequent loss of system elements. Therefore, when in this state, models and algorithms must be developed to optimally enforce some form of preventive action such as generation re-dispatch or line switching in order to restore the system to a new normal state, and to, at the same time, prevent it from traversing to a more detrimental security state [29, 36]. Moreover, these algorithms must find a solution which is implementable in the shortest possible time in order to lower the probability of another failure occurring whilst the system is still residing within the alert state.

Emergency State: A system is judged to be in the emergency state when both/either its equipment ratings and/or system operating constraints (i.e., voltage and/or transient stability) are violated; i.e., exceed acceptable limits. Usually, however, there is no load curtailment during this state. Furthermore, if control measures are not computed in time to return the system to either the alert or normal state, the system will be expected to degrade into an extreme emergency state due to generation, load change or even another plant failure [29, 36]. Consequently and in similitude to the alert state, algorithms must be developed to optimally correct this emergency state to either the normal or alert states.
In the extreme-emergency state, plant and system constraints are violated, and a significant amount of load is curtailed, and the system subsequently experiences large and/or system wide blackouts. Depending on the system’s adequacy to return to the normal or alert states, the system operator must enforce restorative actions such as the black starting of generators, and then slowly reconnect the load (i.e., the restorative state,) until the entire system is restored and returned to its secure state [29, 36]. Inevitably appropriate models and algorithms must be designed to correct this undesirable extreme-emergency state.

These security states are probabilistic in nature and have been historically computationally cumbersome to complete in sufficiently acceptable time frames. Therefore, deterministic computations of reliability have been widely adopted within industry and pervasively used as the epitomical criteria by which to appraise the reliability of a system.

2.1.4 Addressing Reliability Evaluation Criteria Complexities

Deterministic criteria appraise an arbitrary system as reliable if it can supply its load whilst withstanding any combination of $m$ failures compliant to the N-$m$ criteria [16, 17]. Thus if a system comprises N plants, $m$ could represent any value between 1...N. Normally $m$ is limited to 2, but can be extended beyond 2 if desired [16, 17]. However, deterministic criterions are characterised by a weakness: they segregate failures characterised by low probabilities of occurrence, in spite of the fact that they may impose large load curtailments when they do occur.

Moreover, they are incapable of simulating the deep-rooted stochastic behaviours of power systems. More explicitly, it was shown in the post mortem reports of major blackouts—in the US (2003, 2011)[98, 99], India (2012)[100], Italy (2003)[101]—that system failure’s deemed improbable played significant roles in compounding the propagation of these blackouts. Moreover, it has been exemplified in [102] that the propagation of events leading to a blackout is based on the level of stress within the system. Since deterministic criteria only provide a binary indicator of security (i.e., secure or non-secure), these criteria are unable to account for the level of stress within the system [102]. Studies on blackouts [102-106] have narrated a process similar to that depicted in Figure 2-6 with S indicating the secure normal state, A the alert security state, E the emergency and EE the extreme emergency security states.

When deterministic criteria are applied, the operator is only aware that the system is secure (green code) and consequently, the operator is unaware of the level of stress (grey dotted line).

This level of stress depends on many factors, including (but not limited to) the rotor angle (and damping controller) statuses of generating units [36, 107], the probabilities of generating, transmission and distribution plants failing at that point in time [29], the probability of insufficient operator awareness of the present and anticipated operating conditions [108], the probabilities of
high order failures such as circuit breakers [109] and so on. Thus the system stress level at a given point in time must be conceived as a probabilistic description of the system’s security state. One characteristic of this probabilistic description is that it can describe the most likely propagation path to the extreme emergency state. Moreover, it can inform how much load curtailment a system is likely to encounter on the basis of the present level of stress; even though the deterministic criteria deems the system as secure [102].

Figure 2-6 Timeline depiction of the development of a system or a single delivery point blackout

Thus, re-examining Figure 2-6, it is observable that as time elapses, even though the system is still secure, it traverses to a new stress level as the plants status and electrical demand change. Consequently, the probability of a plant failure increases as time elapses further shifting the system to a new and higher stress level. Thus, in this manner the stress level will continue to increase and consequently transition the system into the extreme emergency state. Once in the emergency state, the system is heavily stressed and cascading failures of various plants are triggered. The triggering of these failures leads to a time series of load curtailments which continue up to a limit. This is the system’s maximum resiliency point, beyond which cascading failures and load curtailments can no longer propagate. This could be at a point where either a total or a partial system blackout has occurred; and this limit has been conclusively shown to be correlated to the initial level of stress during the secure state [102].

Additionally, it has been cited that different stress levels of different secure states exist; because the states of the factors upon which the stress level of the system depends, are constantly under flux [102]. Therefore, through the measurement of the level of stress inherent within a system, operators are more likely to identify high risk operating levels even though the system is deemed secure: through deterministic criteria. Thus, the level of risk adds an extra dimension and consequently does not subvert the necessity for applying deterministic criteria [102].

However, although research work has documented the synergistic benefit of jointly utilising deterministic and probabilistic criteria, this comes at a heavy computational cost [110]. Consequently, it is only prudent to invoke joint probability-deterministic computations if the
problem to be solved necessitates it. Therefore, when challenged to make a choice between invoking either deterministic or probabilistic assessment criteria, it is clear that the reliability engineer must adopt probabilistic evaluation criteria. This adoption is still computationally expensive, but the inaccuracy endemic to deterministic models provides ample reason to neglect their utility, as their solutions will eventually lead to costly blackouts.

2.1.5 Addressing Reliability-Based System Expansion Planning Evaluation Complexities

It was earlier discussed that within the system expansion planning objective framework are various sub-objectives and within these sub-objectives are further sub-objectives and so on. In this section two contemporary sub-objectives are reviewed in order to provide an appreciation of the challenges faced by reliability engineers to realise solutions to these problems.

2.1.5.1 Addressing Reinforcement Planning Complexities

Within the reinforcement planning paradigm, the reliability engineer will be engrossed with studying the inherent mathematical behaviours of candidate reinforcement options in order to understand how to best espouse their behaviours into the existing network’s behaviour most accurately; and without imposing heavy requirements for computational resources.

The generating sector has witnessed the proliferation of a variety of renewable technologies of which the most prominent are defined by the wind and solar technologies [111]. Within transmission and distribution realms, the contemporary solutions being presented as reinforcement candidates include flexible alternating current transmission system (FACTS) devices [112, 113], high voltage direct current (HVDC)[114, 115], wide area measurement systems (WAMS)[116, 117], system integrity protection schemes (SIPS)[118] and Energy Storage (ES)[111] etc. As a result of these technological revolutions, a number of erudite ideas illustrating the numerous ways in which these plants could be modelled within a power system have been widely narrated in the citations provided.

In addition to ensuring a robust technical model of each of these plants, reinforcement planning also hinges upon defining an optimal selection process framework. This stage of the objective is vitally important as it greatly influences the outcome of the optimal candidate. For example it was shown that implementing a FACTS solution rendered the optimal techno-economic solution in the short run, whereas its competing line reinforcement solution was most ideal in the long run [110]. Therefore, the decision process must aim to define whether a solution can be optimally selected with consideration to short, long or medium term planning time frames.

These considerations further bring up other considerations: such as how to accurately model load growth (and its inherent uncertainties) within the simulation model, i.e., whether it should be a
sequential or a step model or incorporate demand response and so on. These considerations are further exacerbated by the need to consider if any of the competing solutions will result in the scheduling of existing facility outages. In this case, the reliability engineer must establish the maximum risk [81] that may be accepted due to the need to schedule outages in order to facilitate reinforcement within a given season of a given operational year [119].

Clearly, modelling all these intimated concerns in a single framework renders an intractable computational and analytical challenge [80]; and in cases whereby the engineer is constrained by time to render a solution, further simplifications to the problem can be made by restricting the exercise to one of the applicatory areas recorded in Table 2-2.

Table 2-2 Topical areas for reliability evaluation [64-70]

<table>
<thead>
<tr>
<th>Application Area</th>
<th>Required Model Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation Capacity Reliability Evaluation</td>
<td>HL–1</td>
</tr>
<tr>
<td>Operating Reserve Reliability Evaluation</td>
<td>HL–1</td>
</tr>
<tr>
<td>Composite Generation-Transmission Reliability Evaluation</td>
<td>HL–2</td>
</tr>
<tr>
<td>Multi-Area Reliability Evaluation</td>
<td>HL–2</td>
</tr>
<tr>
<td>Transmission and Distribution Reliability Evaluation</td>
<td>HL–3</td>
</tr>
<tr>
<td>Reliability Worth Evaluation</td>
<td>Any Level</td>
</tr>
</tbody>
</table>

Furthermore, amid any of these applicatory areas, reliability engineers always presuppose the system plants to be repairable and thus ageless. Contemporarily, however, the ageing of system assets is a growing challenge in the realm of reliability engineering [9]. To more accurately account for non-repairable or aged plants, in order to plan their retirement, the objective must be modified as discussed in the next sub-section.

2.1.5.2 ADDRESSING RETIREMENT AND MAINTENANCE PLANNING COMPLEXITIES

The main concern amid this paradigm requires modelling the retirement decision process as well as modelling the mathematics of ageing into the simulation framework so as to accurately manage the retirement processes [81]. Initially, reliability engineers must establish the proportion of aged assets comprising the system, as illustratively shown by an arbitrary distribution (red line) in Figure 2-7 (the aged assets are those residing within stage C, which is bounded by the vertical black intermittent line in the figure). After this the appropriate ageing model for only those aged
of assets must be established [82]. This is achieved by modelling the failure rates of these aged assets according to that behaviour which is bounded by stage C (intermittent vertical line), as illustrated by the blue line in the figure. In this figure this blue line is mimicking a bathtub, sectioned into three A, B and C stages [81].

According to reliability theory, stage A is the infant mortality stage of a newly installed facility. The failure rate (y-axis) is initially high and falls to a constant level as it enters stage B. The reason for this infant mortality stems from complications that arise as this new facility is integrated to an existing system. However, as experience with this new system develops, asset managers are able to lower this failure rate, through effective maintenance strategies. This can be achieved up to a point upon which no further drop in the failure rate can be realised (i.e. at the commencement of stage B). However, once the plant ages beyond a point (i.e. at the commencement of state C) irrespective of the excellence of the available maintenance strategies, the failure rate will rise and continue to do so until eventual death.

There are various stages of a plant’s life cycle, such as A for infant mortality, B for steady state, and C for wear and tear.

Therefore, if a large proportion of assets are ageing, and if their mathematical ageing model is developed, the next consideration will be to engage in comparative assessment exercises of various maintenance schemes. The retirement planning problem is further complicated by the need to realise probabilistic assessments that answer challenging questions: such as when is the optimal time (or stage) within stage C wherein to retire a plant, i.e., should it be at the beginning, middle or end of stage C? This problem requires an accurate simulation and system model in order to evaluate the exact cost inherent in each consideration [81, 82].

An optimal retirement plan will ideally possess solutions to all the stated problems. However, achieving this ideal position is impeded by the contemporary enormity of the retirement planning problem; largely exacerbated by the data uncertainties and unavailability’s required to accurately model the retirement planning problem [82]. Consequently, effort is expended toward attempting to develop robust yet fast techniques to first overcome data uncertainty [81, 82]. At present these
robust techniques are computationally and analytically demanding. Therefore, the retirement planning (with data uncertainty modelling) is restricted to the areas in Table 2-3.

Table 2-3 Topical areas for retirement planning [81, 82]

<table>
<thead>
<tr>
<th>Application Area</th>
<th>Required Model Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowest-risk scheduling based on either predictive or corrective maintenance</td>
<td>Any Level</td>
</tr>
<tr>
<td>The ranking of the most important of components upon which to schedule outages</td>
<td></td>
</tr>
<tr>
<td>Optimal retirement planning policies</td>
<td></td>
</tr>
</tbody>
</table>

2.1.6 ADDRESSING RELIABILITY-BASED SYSTEM OPERATIONAL PLANNING EVALUATION COMPLEXITIES

As earlier stated a power system’s security state is always dynamic and is thus probabilistic. Therefore, the objective within probabilistic operations planning aims to establish how to secure an operator’s action plans at a particular operating point [81]. To exemplify this point, one must consider what is shown in Figure 2-8. This figure narrates that when an operating point enters an alert from a normal state, the operator may implement one of the actions illustrated in Figure 2-8 in order to return the system to a new normal state. However, it has been earlier discussed that this new normal state will have a probabilistic path to a blackout.

![Figure 2-8 An illustration of some of the preventive actions which the operator could employ in order to realise a new secure normal state](image)

Therefore, it is not at all obvious which of these preventive actions will be able to return the power system to a normal state which is characterised by the least likelihood of traversing to a blackout. The main aim in employing probabilistic modelling to operations planning is to aid in objectively ranking the risks of various actions [120-122] and to convey these results to operators to ensure that they are aware of the risk associated with employing a particular action. With this knowledge the operator would prudently judge whether changing certain generation patterns; or operating at certain load levels; or temporarily reconfiguring network topologies; would realise in a new normal power system state that is operated with the least risk of load curtailment both at that time and in the next time series [120-122]. Considering this problem requires modelling the
solution to this problem in a manner that can guarantee solutions in the most expedient of times, i.e., as close as possible to real-time operation. However at present all solutions are produced offline [81, 88].

2.2 RELIABILITY ASSESSMENT: DATA

Recited, power systems are characterised by abundant engineered complexities and for this reason, a thorough and highly detailed model is illogical to conceive—as has been communicated through the various earlier discussions. Thus, if the reliability engineer understands the objective of the study then it would be justifiable to simplify the modelling of the system. The first step in modelling commences with collecting data models of system plants such as generators, lines, load points, transformers and substations. This data is then utilised to realise the model that governs the overall power system operational behaviour; which in its most basic formulation is an integrated transportation model of the plant models that comprise it. The data which characterises these plant models are briefly narrated next.

2.2.1 PLANT PHYSICAL AND OPERATIONAL DATA

Plant data is required to represent models characteristic of either the dynamic or steady state operational behaviours of power systems [83]. The review in this section is focussed on the steady state data representation of power system plants. Moreover, only the basic foundational plants (which can be ubiquitously found globally in any contemporary power system) are reviewed. Thus, non-electrical plants such as WAMS and/or advanced electrical plants such as FACTS, for example, are omitted from this review.

2.2.1.1 GENERATOR PLANT DATA

Delivery of power through a network originates from generators that supply converted raw energy such as oil, coal, gas, wind etc., into electrical power. Within a transportation model, a generator connected to any network node is represented as a complex power injection. A generator is usually connected to a node commonly referred to as a bus and this bus is connected to the rest of the network through existing paths. The injected power at the bus must obey Kirchhoff’s Current Law (KCL); therefore, the apparent power injected into the bus must equal the sum of powers leaving the bus. Mathematically, the injected apparent power is represented by its reactive and active power plants as shown below [83, 123]:

\[ S_k^{\text{injected}} = P_k^{\text{injected}} + jQ_k^{\text{injected}} \]  

**Equation 2-1**

Where \( S_k^{\text{injected}} \) is the apparent power injected into an arbitrary bus \( k \) with \( P_k^{\text{injected}} \) representing the active injected power and \( Q_k^{\text{injected}} \) the injected reactive power. In a system replete with
large number of generation injections, the representation of all power injections at busses $[1 \ldots N]$ is given by the matrix formulation $S_{3p}$ [83, 123]:

$$S_{3p} = [S_1 \ldots S_N] \quad \text{Equation 2-2}$$

However, it must be noted that limits on the maximum as well as minimum amount of power that could be injected by any given generator within a system must be imposed to avoid overheating of the mechanical plants of the generating units and their connecting cables. Thus the upper limits $S_{\text{upper lim}}$ for all existing units within a system $[1 \ldots N]$ must be defined within an array as shown in Equation 2-3. Likewise the matrix of lower limits $S_{\text{lower lim}}$ is represented in Equation 2-4 [83, 123].

$$S_{\text{upper lim}} = [S_{\text{upper lim}}^1 \ldots S_{\text{upper lim}}^N] \quad \text{Equation 2-3}$$

$$S_{\text{lower lim}} = [S_{\text{lower lim}}^1 \ldots S_{\text{lower lim}}^N] \quad \text{Equation 2-4}$$

When the demand profile within the system changes, generating units are depended upon to increase or decrease their outputs in order for the system to match the change in demand. The rate at which a unit can change its output is defined as the ramp rate of the unit. In this accord, the ramp rate matrix representative of all existing system units (as is given in Equation 2-5) is rendered as $S_{\text{MW/min}}$; where $\text{MW}$ is the power in mega Watts and $\text{min}$ is the time in minutes denoting the unit of the ramp rate. Finally, the cost matrix $C$ as a function of their output power $P$ in MWs for all units $[1 \ldots N]$ is given in Equation 2-6 [83, 123]:

$$S_{\text{MW/min}} = [S_{\text{ramp rate}}^1 \ldots S_{\text{ramp rate}}^N] \quad \text{Equation 2-5}$$

$$C = [C(P_1) \ldots C(P_N)] \quad \text{Equation 2-6}$$

These data models are generic, but incisions can be made into them so as to further model the intricacies related to how operational characteristics peculiar to wind, solar and/or various generating technologies give value into these generic models [124-126]. Moreover, it must be emphasised that these values must low in either epistemic or stochastic uncertainty or both in order to guarantee robust solutions.

### 2.2.1.2 Line Plant Data

Lines (or branches) within a power network provide connective paths for power (or current) to flow. To enable this behaviour, lines are characterised by their impedance $Z$, capacitive susceptance $Y$, reactance $X$ and resistance $R$ as shown in Equation 2-7 [83, 123]. Within the transportation model, lines are generally represented by a conceptual $\pi$ model – which thus
models a line’s total capacitive susceptance to be observed solely at either ends of the line. Thus, according to Equation 2-8, it can be noted that the shunt model susceptance \( B \) at either end of the line is mathematically represented by half of the total line’s capacitive susceptance \([83, 123]\); where \( Y = 1/X_c \) and \( X_c \) is the total capacitive reactance of a given line.

\[
Z = R + jX \quad \text{Equation 2-7}
\]

\[
B = \frac{Y}{2} \quad \text{Equation 2-8}
\]

To foster safe power flow through lines, the thermal limits for all lines \([1 \ldots N]\) in a system would be given in a vector as illustrated in Equation 2-9. When utilising emergency ratings, \( T_{\text{MAX}} \) is raised to an emergency temperature \( T_{c,\text{EM}} \) for a limited duration \( t \). Thus the thermal limit matrix is noted as in Equation 2-10 \([83, 123]\)

\[
\begin{align*}
L_{\text{LIMIT}} &= S((T_c = T_{\text{MAX}}), T_c, V_a, S) \\
L_{\text{LIMIT}}^{\text{EM}} &= S^{\text{EM}}((T_c = T_{c,\text{EM}}), T_c(t), V_a(t), S(t))
\end{align*}
\]

As mentioned in 2.2.2.1, also these data models in this section are generic, but incisions can be made into them to illustrate how operational characteristics peculiar to wind speed \( V_w \), ambient temperature \( T_a \), solar radiation \( S \) etc., give value into these generic models \([6, 60, 127]\). As well, it must be emphasised that these values must low in either epistemic or stochastic uncertainty or both.

2.2.1.3 LOAD PLANT DATA

Load demand values are assumed to follow annual chronological patterns, aggregated at the various load points within the system. Therefore according to Equation 2-11 \([83, 123]\) \( L_1(t) \) is the load at the first load bus within the system at time \( t \) and \( L_N(t) \) is the last load bus within the system at time \( t \). \( L_{\text{Load}} \) is thus the vector matrix of all existing load points and their chronological values. As expected, incisions too can be made to give these to model the effect of demand response \([128]\) or clustered demand \([129]\) or demand uncertainty \([31]\) representations.

\[
L_{\text{Load}} = \begin{bmatrix} L_1(t) & \cdots & L_N(t) \end{bmatrix} \quad \text{Equation 2-11}
\]

2.2.2 PLANT RELIABILITY DATA

Network reliability modelling entails collecting the associated times-to-fail (TTF) and times-to-repair (TTR) for each system plant. These values are recorded from historical statistical analysis of
past plant failures [43, 130], or derived from mathematical predictive formulations that are able to evaluate the failure rate of a plant based on its age or condition (or both) [80-82]. Within the transportation model, these values are arrayed within a matrix formulation represented in [80-82] and shown below:

$$\text{TTF}_{\text{sys}} = \begin{bmatrix} \text{TTF}_1 & \cdots & \text{TTF}_n \end{bmatrix}$$ \hspace{1cm} \text{Equation 2-12}$$

$$\text{TTR}_{\text{sys}} = \begin{bmatrix} \text{TTR}_1 & \cdots & \text{TTR}_n \end{bmatrix}$$ \hspace{1cm} \text{Equation 2-13}$$

Due diligence must be exercised to ensure that these recorded results are accurate and consistent with the data collection process [81]. This is in order to ensure that the computed failure rates as shown in 2.3.2 are low in epistemic uncertainty.

### 2.3 RELIABILITY ASSESSMENT: MODELLING

A basic network of generators and loads interconnected via transmission paths is illustrated in Figure 2-9. In order to establish the optimal pattern of flows through the network from generators to the loads (depicted by the arrows in the diagram), the dispatch of the generators must be optimised. This entails dispatching the cheapest units available to serve the load at the busses.

![Figure 2-9 Representation of a network of generators and loads interconnected via transmission paths](image)

To realise this goal, models of the individual plants must be linked holistically to formulate a complete system behavioural model. This linkage is achieved by establishing relationships between the generation injections and the nominated voltages at the busses through transmission paths in accordance with Kirchoff’s Voltage Law (KVL). Furthermore, the ontological state transitional behaviours inherent to these plants must be modelled, as well, in order to more accurately simulate their behaviours.
2.3.1 Auxiliary Plant Modelling

As earlier stated, incisions can be made into the earlier presented equations (i.e., Equation 2-1, 2-9, 2-10 and 2-11) in order to capture the ontological operational characteristics peculiar to a given plant (i.e., generator or line) or to the load. Some (selected yet commonly employed) auxiliary mathematical modelling methods to help complete these incisions are discussed, especially related to thermal rating of overhead lines (OHLs) —as this is the focus of this thesis. However, similar techniques can be also applied to generating systems [33, 131] and the demand points [132] as well. This is because they acquiesce to the same principles which stem from the branches of pure mathematics and statistics.

2.3.1.1 Weather Modelling for Thermal Ratings

Weather distributions are designed to be used offline for designing and planning thermal ratings of conductors [6, 59-61, 133, 134]; as well as online for the validation, management and ascertainment of the viability of exploiting more thermal capacity during real-time operating conditions [60, 135-137]. Thus, in order to formulate a weather distribution profile, relevant weather data must be collected. This collection can be realised through either widely spaced geographical weather monitoring stations or through locally measured data gleaned from conductor thermal rating instrumentation [1, 61, 138]. Collection of data through local measurements is more accurate and reliable toward enabling effective thermal rates; nevertheless, this approach is more costly than the alternative [1]. Either way, two methods of developing weather distributions have been developed: the uncorrelated and the correlated weather distribution formulation methods [1, 134]. The uncorrelated distribution model does not consider the inherent correlation between the weather variables implemented to calculate the thermal rating. The correlated weather models, conversely, takes into account this inherent weather and time correlation. Figure 2-10 illustrates the flowcharts that are used to derive the uncorrelated weather distribution (left) as well as the correlated weather distribution (right).

The uncorrelated weather distribution modelling process initiates with the gathering of raw historical data for the wind speed, wind direction, ambient temperature and solar radiation [6, 61, 134]. Proceeding with the wind data processes, it can be observed from the figure (left) that it is necessary to compute the effective wind speed (EWS) [57] in order to minimise the computation efforts of separately computing wind speed and wind direction distributions. Generally, the effective wind speed is computed by ascertaining the wind speed at an incidence angle of 90°C to the conductor that produces the same temperature as that which is established through the wind speed and wind angles of the actual measured data.
Following this computation, the EWS Weibull distribution is formulated through its evaluated histogram [134]. Focussing on the raw data from the ambient temperature and the solar radiation in Figure 2-10 (left), it can be asserted that the process of formulating their weather distributions is similar to the aforementioned [134]. Thus, once probability distributions pertaining to the ambient temperature and solar radiation data have been realised, a final tabulation of the combinations of the probabilities of occurrence for all the weather variables is computed. From this, the state space of conductor temperatures and their corresponding probabilities is evaluated for an input distribution of historically recorded or anticipated ampacity values.

Figure 2-10 A flow chart pertaining to the evaluation of uncorrelated (left) and correlated (right) weather distributions

However, it is worth noting that there exists correlation between the weather variables [1]. Therefore, the approach toward the formulation of the correlated weather distribution is similar to that used to formulate the uncorrelated weather distribution. The difference between the two, however, rests on the fact that correlation factors have to be computed for the raw weather data series—see in Figure 2-10 (right and highlighted)—in order to account for a more accurate weather distribution formulation. Higher ampacity designs have been reported through the correlated method [1, 134, 139] when compared to the uncorrelated method; because when correlation is taken into account the conjoint probability of experiencing high temperatures, high solar radiation and low wind speeds simultaneously is lowered.

2.3.1.2 Time Series Modelling

Whereas the weather distribution model is best suited to the state based Monte Carlo sampling method (later discussed in this chapter), the state duration (another sampling technique later discussed in this chapter) is best suited to the sampling of thermal ratings generated through time series prediction or simulation models [140, 141]. The generation of time series based thermal ratings is possible because, naturalistically, the thermal rating weather variables vary with time.
Time series models are designated by the acronym ‘ARMA’. Time series models are characterised by two properties: the AR (auto regressive) and the MA (moving average) [141]. Thus, more completely, the ARMA is designated as ARMA \((n, m)\); where \(n\) denotes the number of auto regressive parameters and \(m\) the number of moving average parameters required to describe a time varying data signal. More explicitly, a designation such as ARMA \((2, 3)\) indicates that the particular time series at any given moment can be defined by two AR parameters and 3 MA parameters. Mathematically, an ARMA model is defined in Equation 3-10 [141]. Accordingly, \(y_t\) is the time series value at time \(t\) based on \(\phi_i (i = 1, 2...n)\), \(\theta_j (j = 1, 2...m)\) (i.e., the previous time series values); \(y_t\) is limited by the AR value; and the previous (randomly uncorrelated) white noise parameter value \(\alpha_{tj}\) is limited by the MA parameters.

\[
y_t = \sum_{i=1}^{n} \phi_i y_{t-i} + \alpha - \sum_{j=1}^{m} \theta_j \alpha_{tj}
\]

Equation 2-14

Moreover \(\alpha\) is defined as a white noise variable that is described by a normal distribution with zero mean and a variance \(\sigma^2\), more elegantly noted as \(\alpha_t \sim NID(0,\sigma^2)\); \(NID\) is an acronym for Normally Independent Distribution. Therefore, the main efforts towards the development of a time series model are pointed toward the establishment of the AR, MA and data noise models [141]. Following this, the simulated actual weather parameter \(SWA_t\) (Equation 3-11) value at time \(t\) is computed by accounting for the mean speed \(\mu\) and standard deviation \(\sigma\) of the data and its associated time series \(y_t\) [125]

\[
SWA_t = \mu + \sigma y_t
\]

Equation 2-15

To finalise this section it must be mentioned that both the distribution (uncorrelated and correlated) and ARMA modelling techniques have been applied (albeit slightly tailored) to the modelling of wind generating studies [142], load point forecast uncertainty studies [31] and a number of other studies [143].

Nevertheless, once the ontological behaviours of every system plant have been more accurately modelled (through either distributional or time series modelling), the overall power system’s admittance matrix must be modelled. Both the system admittance matrix and the plant behaviour must be modelled in order to sample their ontological states during a reliability evaluation simulation. More explicitly, the system admittance matrix is simulated in order to stochastically fail some system plants, and of those plants not failed, their ontological behavioural states, namely, their operational (i.e., adequacy) limits are simulated through sampling either their time series or distribution models.
2.3.2 System Admittance Matrix Modelling

According to Figure 2-9 the lines are represented by their admittances. For instance, the connection between bus 1 and bus 2 is the line admittance $Y_{12}$. Thus a mathematical representation of a system injection model states that the vector of ampacity injections from the generating sources must equate to the matrix multiplication of the system’s admittances (interconnected between busses) by the voltages nominated at those busses. This statement is represented in Equation 2-16 [83, 123].

$$
\begin{pmatrix}
I_1 \\
\vdots \\
I_n
\end{pmatrix} =
\begin{pmatrix}
Y_{11} & \cdots & Y_{1n} \\
\vdots & \ddots & \vdots \\
Y_{n1} & \cdots & Y_{nn}
\end{pmatrix}
\begin{pmatrix}
V_1 \\
\vdots \\
V_n
\end{pmatrix}
$$

Equation 2-16

Where $I$ represents a given generator injection modelled as a current source injection, $Y_{ij}$ the line admittance connecting an existing path between two busses ($i$ and $j$) and $V_i$ the nominal voltage at a given bus $i$ terminal. Moreover, line lengths influence the value of the admittance between two lines and subsequently this consideration must be accounted for when calculating the individual admittances within the admittance matrix. These values, however, are also a function of failure, because the plants comprising an arbitrary system will not be available 100% of the time—as it has been established (through Equations 2-12 and 2-13). Therefore an injection matrix can be represented as Equation 2-17; where $\lambda_{ij}$ represents the failure rate associated with a particular interconnection ($i$ and $j$) and $\lambda_n$ represents the failure rate associated with a particular generator.

$$
\begin{pmatrix}
I_1(\lambda_1) \\
\vdots \\
I_n(\lambda_n)
\end{pmatrix} =
\begin{pmatrix}
Y_{11}(\lambda_{11}) & \cdots & Y_{1n}(\lambda_{1n}) \\
\vdots & \ddots & \vdots \\
Y_{n1}(\lambda_{n1}) & \cdots & Y_{nn}(\lambda_{nn})
\end{pmatrix}
\begin{pmatrix}
V_1 \\
\vdots \\
V_n
\end{pmatrix}
$$

Equation 2-17

2.3.3 System Admittance Matrix Alteration

The existence of failure rates serve to alter the admittance and injection matrix of a system. Therefore, a mathematical value for an arbitrary failure rate $\lambda$ (which will need to be randomly sampled when system operation is simulated) must be realised. This is so that the admittance matrix of a given system can be randomly altered in time—as this form of modelling captures the most realistic system operational behaviour. Thus, stemming from basic principles, a plant reliability model can be mathematically defined through its availability $A$ as shown below [81]:

$$
A
$$
Equation 2-18 defines $\lambda$ as the failure rate of an arbitrary plant and $\mu$ as the corresponding repair rate. The reciprocals of $\lambda$ and $\mu$ are defined as the mean time to failure (MTTF) and mean time to repair (MTTR) respectively. These values (i.e., MTTF and MTTR) are the computed statistical averages from the data in Equations 2-12 and 2-13 respectively [81].

Equation 2-18, however, only gives a constant value for the availability of a given plant. This constancy impedes the true time-based alteration of the admittance matrix from being captured. Therefore, further computations to the data values given in Equations 2-12 and 2-13 must be performed in order to extract values replicative of $\lambda$ and $\mu$—as these values are most able to realise the time-based operation of power systems. The initial step, then, is to transform the data in Equations 2-12 and 2-13 into their failure density distribution functions $f(t)$ —where $f(t)$ is a generic expression of a probability distribution [144]. It is, however, important to capture the particular expression of a plant’s failure density distribution in order to account for the stage in the bathtub curve in which a given plant resides. Thus, particular probability distribution functions must be fitted to the data given in Equations 2-12 and 2-13 in order to realise the true function.

Based on the derivative process fully engaged in [144], Table 2-4 has been produced to illustrate the relationships between a given distribution, its failure density function $f(t)$, survivor function, failure rate $\lambda$ and mean time (expected) values. As can be seen in the table, since the exponential distribution has a constant failure rate $\lambda$, its failure density function $f(t)$ is adjudged to be characteristic of the plants which reside in the second (or repairable) stage of the bathtub curve. Conversely, the Weibull failure model is judged to be characteristic of the plants residing within the third (or the non-repairable) stage of the bathtub curve.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Failure Density</th>
<th>Survivor Function</th>
<th>Hazard (Failure) Rate</th>
<th>Expected Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential</td>
<td>$\lambda e^{-\lambda t}$</td>
<td>$e^{-\lambda t}$</td>
<td>$\lambda$</td>
<td>$\frac{1}{\lambda}$</td>
</tr>
<tr>
<td>Weibull</td>
<td>$\frac{\beta t^{\beta-1}}{\alpha^\beta} e^{-\left(\frac{t}{\alpha}\right)^\beta}$</td>
<td>$e^{-\left(\frac{t}{\alpha}\right)^\beta}$</td>
<td>$\frac{\beta t^{\beta-1}}{\alpha^\beta}$</td>
<td>$\alpha e^{-\beta + 1}$</td>
</tr>
</tbody>
</table>

Subsequently, a system reliability description can be instead represented as a vector of natural failure rates $\lambda_n$ and repair rates $\mu_n$ for plants $\{1 \cdots N\}$ as in Equations 2-19 and 2-20 [83].
Therefore, if the failure rates of the plants within a system can be deduced and if the aged statuses of the plants are known, the appropriate failure or repair function can be manipulated in order to simulate the appropriate times to fail or repair, which is illustrated in the next section.

### 2.4 Reliability Assessment: Simulation Techniques

A power system state is an arbitrary configuration of a system by virtue of the failed or operational state of each plant making up the system as well as the demand for energy at the particular point in time. The simulation process is the art of realistically mimicking the behaviour of a power system as it encounters one of its myriad possible states through its admittance matrix alteration. The end goal of reliability assessment simulation is to realise indices that measure how reliable a given system design is over the myriad of simulated power system states.

#### 2.4.1 Power System Operation States

The state description of a power system is complex that it must be conceived as a conglomerate of four dimensions as illustrated in Figure 2-11. The dimension texts are labelled in the aqua-blue texts in the figure, and each dimension consists of a two-dimension planar space. For example in the up state 1st dimension, one can witness an hourly chronological time space in the x-axis and a random operation duration – TTF in the y-axis direction. In a similar manner the x-y plants of the other three dimensions can be noticed. The narrative that this figure exposes can be understood by beginning at the 1st dimension at the black oval shape.

This shape represents a randomly sampled system TTF state from the 1st dimension state space, at a particular demand level. Subsequently, at this point the system state will traverse to a new state within the first dimension. However, this will only happen after it traverses through the other three dimensions, and depending on the traversal path it might end up in one of the three green oval state shapes. As can be further witnessed in this 1st dimension space, depending on which green state the system transitions to, it will transition to a particular blue oval state and this random behavioural process will repeat itself in order to sample a sufficient number of the myriad possible system TTF states in order to measure the reliability of an arbitrary system.

Returning to the 1st dimension black oval shape, it can be seen that once a failure occurs, the system will transition to a particular state within the 2nd dimension. The possibility of occupying a particular state (within the 2nd dimension space) will depend on the degree of the derated x-axis space (i.e., the system adequacy) and the degree of security (i.e., voltage or overload) violations y-
axis space rendered by that failure. Consequently, depending on the where in the 2nd dimension space the system transitions to, it will traverse to a particular state within the 3rd dimension space. Thus, within this 3rd dimension space (influenced by its initial position within the 2nd dimension space) the system will exhibit a particular magnitude of load curtailment (x-axis) and duration of curtailment (y-axis) behaviour which is based on the severity of curtailment. Additionally, this particular occupied state within the 3rd dimension will also be dependent on, and subsequently compounded by, both the present and prospective electrical demand levels.

Therefore, it is possible that zero load curtailment can occur if failures occur when the demand is low. Hence, this state space is characterised by both failed (curtailed) and success (non-curtailed) states. These factors will further compound and influence (within the 4th dimension) the degree of restoration and repair duration times available to restore the system to its new up state (in the 1st dimension). This is shown through the green arrows protruding from the 4th dimension through the 3rd and 2nd right up to the 1st dimension. Thus, if there was no load curtailment (within the 3rd dimension) there would be no need for restoration (within the 4th dimension) and vice versa. Conversely, it is also possible to experience a colossal disconnection of power supply across large portions of the system. Consequently, this disconnection may last for a few minutes to hours up to a few days—depending on the on the ability of an arbitrary system to safely reconnect its generating resources to its customers. Therefore, through this discussion, it can be appreciated that the intricacies and scope of the 3rd and 4th dimension states is broad. However, once the system is restored back to its up state in the first dimension, this multi-dimension traversal process repeats itself as shown through the blue oval shapes in the figure, through the earlier
discussed mechanisms. The aim of reliability evaluation is to mathematically capture, compute and tabulate as many as possible of these behaviours in the bid to evaluate system reliability indices.

This section, however, focuses on discussing the state selection techniques developed to simulate the 1st (i.e., the TTF) and 4th dimension (i.e., the TTR) values of the simulation process. Section 2.5 will focus on discussing techniques developed to simulate the 2nd (i.e., load flow and security analysis) and 3rd (i.e., optimal power flow and adequacy analysis) dimension computational algorithms.

Past research annals have demonstrated that a wide variety of failure state selection techniques have been employed within the probabilistic reliability evaluation framework. These major techniques can be summarised into six classes: the cut-set, fault tree, Markov, Monte Carlo, analytical and hybrid methods [64-70]. Nowadays, as they are unable to deal with large systems, virtually no disseminated research work utilises the cut-set, fault-tree or Markov state selection techniques to invoke a full reliability evaluation exercise. Therefore the focus of the next section is consolidated to the Monte Carlo, analytical and hybrid methods.

2.4.2 Monte Carlo Simulation (MCS) Techniques

The MCS was fundamentally developed upon the notion of probabilistic system state sampling through the random number generation of plant (and subsequently system) up (TTF) and down (TTR) states. When it was proposed to the reliability framework amid the 1970s, its advantage over the cut-set, fault-tree or Markov techniques lay principally on the fact that the sampling of system states, through the MC, was independent of system size and thus applicable to large systems; whereas the earlier techniques were limited to application on small systems. Since then, the MC technique has been developed to be broadly classified into two variants: (1) the state based MC and (2) the state duration MC—discussed further later in the section. Foundationally, however, the MC is based upon invoking a probability-based axiomatic principle: the law of large numbers [29]. Through this approach the MC can be confidently depended upon to reach a point of convergence. Once convergence is realised, it can be assured that all relevant system states have been sampled, and the resultant value of the estimated expected reliability index of a particular system is obtained.

2.4.2.1 Rate of Convergence

According to probability sampling theory, if a system state (symbolised by \( \psi \)) can be described as a vector comprising the joint states \( \psi \) of its ‘m’ plants, such that \( \psi = [\psi_1 \ldots \psi_m] \), then the expected reliability value \( E(L) \) of its index \( L(\psi) \) will be[29]:
\[ E(L) = \sum_{\psi \in S} L(\psi) p(\psi) \]  \hspace{1cm} \text{Equation 2-21}

Where \( S \) is the set of all possible system states and \( p(\psi) \) is the probability of attaining an arbitrary system state. Thus, in a MC Simulation, this expected value \( E(L) \) can be estimated through the formulation shown below [29]:

\[ E(L) = \frac{1}{n} \sum_{\psi \in S} n_p(\psi) \]  \hspace{1cm} \text{Equation 2-22}

Where \( n_p(\psi) \) is the number of times that an arbitrary state \( \psi \) occurs and \( n \) is the number of MC samples needed to estimate the expected reliability value of an arbitrary system.

The rate of convergence defines the total number of samples required to achieve a desired degree of confidence in the calculation of an expected reliability index value. Thus, according to statistical principles, the variance of a distribution is the average dispersion of a random value within a distribution from the random value’s distribution mean value. Therefore, with a mean value i.e., \( E(L) \) calculated from Equation 2-22, the sample variance \( V(X) \) (assuming the sample size is large) is given as in Equation 2-23 [29], where \( N \) is the total number of MC samples and \( X_i \) is the recorded index in a sampled state \( i \)

\[ V(X) = \frac{1}{N} \sum_{i=1}^{N} (X_i - E(L))^2 \]  \hspace{1cm} \text{Equation 2-23}

By expansion, Equation 2-23 becomes [29],

\[ V(X) = \frac{1}{N} \sum_{i=1}^{N} X_i^2 - \frac{1}{N} \sum_{i=1}^{N} 2X_i E(L) + \frac{1}{N} \sum_{i=1}^{N} E(L)^2 \]  \hspace{1cm} \text{Equation 2-24}

Substituting Equation 2-22 into 2-24, yields [29]

\[ V(X) = E(L) - E(L)^2 \]  \hspace{1cm} \text{Equation 2-25}

It should be noted however that \( E(L) \) gives only an estimate of system unreliability. Therefore, the aleatory (stochastic) uncertainty around this estimate is evaluated by the variance \( V(E(L)) \) of the expectation estimate [29]:

\[ V(E(L)) = \frac{1}{N} V(X) = \frac{1}{N} E(L) - E(L)^2 \]  \hspace{1cm} \text{Equation 2-26}

The accuracy level of the MC is normally expressed by the coefficient of variation \( \alpha \) (i.e., the normalised measure of dispersion of a probability distribution), mathematically given as[29]:

\[ \alpha = \sqrt{\frac{V(E(L))}{E(L)}} \]  \hspace{1cm} \text{Equation 2-27}
Therefore, by substituting and re-arranging, the final equation can be re-written as [29]

\[
N = \frac{1 - E(L)}{\alpha^2 E(L)} \tag{2-28}
\]

Subsequently, for a desired accuracy level, the number of required samples \( N \) depends on the unreliability \( E(L) \) of the system and it is independent of the system size. Moreover, the resulting Equation 2-28 is proof that MC Methods are therefore well suited to large-scale system reliability evaluation as earlier discussed.

### 2.4.2.2 The State Sampling Technique

The state sampling technique is a most simplified approach to system state selection sampling [29]. The inherent simplicity of this method is narrated by the fact that it neglects the chronological operation of a power system; usually by sampling system states at a static demand and/or system operation level. As a result, this method yields the benefit of requiring much less computational resources (in comparison to the other MC variants). In a state based sampling approach, two simulations are executed: (1) a random probability value between \([0 \cdots 1]\) is sampled from a uniform distribution function for each plant, and (2) the probability of failure for the plant. Assuming it is repairable and not aged, the plant’s probability of failure \( R(t) \) is calculated using equation 2-31 which is derived from Equations 2-29 and 30 [29, 144]. Approaches to compute the failure functions of aged plants are provided in [29, 144] as well. The notations in Equations 2-29 to 2-31 are synonymous with those in [29, 144] and have been earlier defined in this chapter as well.

\[
R(t) = 1 - \int_{0}^{t} f(t) dt \tag{2-29}
\]

\[
R(t) = 1 - \int_{0}^{t} \lambda e^{\lambda t} dt \tag{2-30}
\]

\[
R(t) = 1 - e^{\lambda t} \tag{2-31}
\]

Thus, if the value from the simulated uniform distribution is greater than the given plant’s failure probability \( R(t) \), then the plant will be ascertained to have failed. This check is undertaken for all plants in order to determine a system state; and is repeated for all possible system states as the MC seeks to attain an acceptable rate of convergence. Consequently, once a sufficient number of system states have been sampled, the final overall reliability index is evaluated and used to invoke managerial decisions [29].
However, the critique of the state based sampling technique may be made through the exemplification of the process depicted in Figure 2-12. In this figure the true operation of a power system is shown to follow a chronological order of the maximum system adequacy (dotted blue line) and electrical demand (continuous black line). The black shades indicate those states when load curtailment occurs. The boxes in the figure (through their arrowed directions) illustrate that a system amid either a curtailed or non-curtailed state will change state, as it traverses to either a lower (state 3) or a higher curtailed state (state 4); or to either a higher secure state (state 2) or a further higher secure state (state 1). The red intermittent line is the threshold demarcating a system secure (adequate) against an adequacy curtailed state.

![Figure 2-12 Pictorial comparison between state based and sequential MC](image)

Thus, when the state based algorithm is simulated it can be pictured to work as illustrated by the blue vertical lines. Considering the 1st curtailment scenario, it can be seen that the frequency of load curtailment sample is counted more than once even though there is no transition from the load curtailment to non-load curtailment state. This no transition state change is shown by the shaded boxes lying within the curtailed state (Figure 2-12). Therefore, the true frequency of load curtailment over this assumed four hour period is one; but the state sampling simulation counts four, one for each hour—as Δt within the figure is set to one hour (practically, however, Δt can be set to represent any desired time interval).

Re-considering Figure 2-12, it is evident that the same mistake is made whilst sampling the 2nd curtailment scenario, as the figure shows. Thus, clearly, if a large number of load curtailment scenarios were to manifest, it would be plain to cognise that a true estimate of the magnitude of load curtailment would be computed through the state based method; as it would be able to sample the entire state space through this method. However, the frequency of load curtailment would be overestimated [29, 110] as there would be no way for the state sampling method to recognise whether a system transitions from adequacy to inadequacy state (and vice versa) had transpired throughout the course of time. Furthermore, as a natural corollary to the earlier
discussion, it can be clearly envisioned that as $\Delta t$ becomes smaller than one hour, this estimation error will significantly increase.

### 2.4.2.3 The State Duration Sequence Sampling Technique

The state duration sequence sampling technique—also known as either the sequential MC simulation (SMCS) or the chronological MC simulation (CMCS)—aims to address the inability to capture the chronology of the system’s operation characterised with the state sampling technique [29]. This inability hampers the correct evaluation of the frequency and duration of a system failure state. The calculation of frequency and duration values are required to calculate the cost of unreliability. The unreliability cost is used by reliability engineers to determine the optimum required investment in order to reinforce a power system. Therefore, if the frequency and duration values are incorrectly evaluated reliability engineers would be led to enforce costly reinforcement solutions; a result which regulators would clearly not encourage [29].

The state duration sequence sampling technique samples the exponential probability density function $f(t) = \lambda e^{-\lambda t}$ by assuming the system is composed of non-aged plants. If the system is, however, composed of aged plants then the Weibull distribution (as earlier discussed) would have to be assumed. However to keep simplicity in this narrative, the exponential distribution is assumed. Therefore a summary rendering of the SMCS methodological technique is discussed as follows [29]:

1. All plants are assumed to be initially up (i.e. healthy)
2. Then the duration of each plant staying up is sampled from its reliability distribution function $f(t) = \lambda e^{-\lambda t}$. As a result of transforming $f(t) = \lambda e^{-\lambda t}$ to its inverse transform rendering, the time-to-failure (TTF) is sampled by using Equation 2-32; where $U$ is a randomly generated number from a uniform distribution lying between $[0 \cdots 1]$ and $\lambda$ is the failure rate of the plant.

$$TTF = -\frac{1}{\lambda} \ln(1 - U)$$ \hspace{1cm} \text{Equation 2-32}

3. Similarly if a plant is down, it’s time to repair (TTR) is sampled in the same way as in Equation 2-32. However, in this context, the repair rate of the plant, $\mu$, will replace $\lambda$.
4. Steps 2 and 3 are repeated over the duration of the system’s mission time to create an array of system states in a chronological fashion.
This way, descriptions of the system state for the whole time span are obtained allowing for the desired adequacy or security index to be calculated. Thus, as can be seen in Figure 2-13, the SMCS samples horizontally and thereby is able to capture all relevant system information to compute more accurately required reliability indices.

Consequently, the main advantage of the SMCS technique is that it can be used to evaluate frequency and duration indices accurately and it is mathematically simple to implement [145]. Its disadvantage is the increase in computation time due to the need to model all chronological behaviours of a power system.

2.4.2.4 THE PSEUDO-CHRONOLOGICAL SAMPLING TECHNIQUE

The pseudo-chronological technique aims to establish a compromise between the state based and the state duration based system sampling techniques [146]. This method attempts to ascertain the entire possible number of state transitions from the load curtailment to the no load curtailment without the need to employ a chronological system operation history and thus saving vast computational resources. To evaluate the entire possible number of the transitions, a Markov Chain algorithm is formulated within the state-based MC sampling framework [147].

This method was introduced and widely used during the 1990s [147]. Its main advantage is that the accurate frequency and duration evaluations of events can be achieved in much faster execution times when compared to the state duration or the SMCS approaches. Its disadvantage is that it is mathematically difficult to conceive in comparison to the either the state-based or the SMCS sampling techniques. This is especially true as the number of models characterised by chronological operation (e.g. annual hourly demand or wind generation profiles or sequences of line overloads etc.) within the system increases. This complexity escalates because the combinations of state transitions from a single state exponentially increase with each added plant that is characterised by a chronological behaviour. In contemporary times, fewer publications utilising this method have been proposed as opposed to increased publications utilising the state duration method. This is principally due to the fact that the state duration is mathematically easier to conceive as well as the computational power has significantly advanced since the 1990s.
In addition other reduction techniques have been developed to enhance the state duration method [148, 149].

2.4.3 Statistical Variance MCS Reduction Techniques

Simpler and more mathematically friendly versions able to evaluate power system reliability via either the MCS or SMCS state sampling can be implemented by tuning the MCS reliability index estimation technique. Inherently, the MCS is fluctuating process; as a result it will exhibit large variations as it crudely attempts to estimate a power system’s reliability index.

However, by utilising prior known information about the power system simulation model, it is possible to minimise these fluctuations and thereby help steer the MCS toward a more expeditious solution. This technique is known as variance reduction as it reduces the variations inherent in the MCS sampling and subsequently expedites the reliability index estimation process [29]. Figure 2-14 shows a comparative plot between the crude MC (in green) and a variance reduction-based MC (in black). The areas under the curves illustrate the number of computations invoked to estimate the true reliability value (illustrated by the red intermittent line). Clearly, a variance reduction-based approach will estimate the true index with lesser samples, thereby resulting in faster evaluations [29].

![Figure 2-14 Illustration of the variation of a crude and variance-based MC trial](image)

The more information a reliability engineer possesses in regard to the behaviour of a particular system and its operating conditions, the more significant will be the variance reduction that could be realised [29]. A number of variance reduction techniques have been developed and are broadly summarised in table 2-5 [29]. In this section a brief discussion of the two most common techniques are engaged. These techniques are boldly highlighted in Table 2-5. The notion that governs antithetic sampling is based upon the fact that a system could be described by a random variable (RV) and its antithetic pair. The relationship between an RV and its pair must be one of negative correlation [29]. Consequently, the attainable amount of variance reduction will depend
on the amount of negative correlation between the antithetic variables i.e., the higher the negativity, the higher the variance reduction.

Table 2-5 A broad list of variance reduction techniques [29, 150]

<table>
<thead>
<tr>
<th>Variance reduction methods</th>
<th>Antithetic random variables</th>
<th>Control variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Importance sampling</td>
<td></td>
<td>Stratified sampling</td>
</tr>
<tr>
<td>Conditional Monte Carlo</td>
<td></td>
<td>Latin Hypercube Sampling</td>
</tr>
<tr>
<td>Dagger Sampling</td>
<td></td>
<td>Correlated Sampling</td>
</tr>
</tbody>
</table>

Therefore, studious selection of these variables is of crucial importance. Subsequently, the success of this method is subject to a system that is characterised by RV’s that exhibit high levels of negative correlation; and this may not be the case for all systems. Consequently, a number of RV’s have been tested and applied to enhance the antithetic method of power system reliability evaluation: the expected energy not served (EENS), expected cost (ECOST), loss of load probability (LOLP) etc., indices. These RV indices are further discussed in section 2.5.2.

If an RV is the output of a performed simulation and another RV is obtained from the same simulation run, then one of these RVs will be termed as a control variable [29]. It is the duty of the reliability engineer to ascertain the manner in which these RVs are correlated (i.e., whether either negatively or positively) prior to the selection of the control variable. Once the control variable has been realised consequent to an initial running of a crude MCS, further trial runs can be reduced by using the control variable to reduce the estimated variance. Thus, the running of an initial crude MCS prior to the selection of the control variable is the fundamental difference between the antithetical and the control variable methods. Studies have shown that the merits between these two techniques are case specific and expert engineer judgement is requisite to the selection of the most appropriate method [120].

2.4.4 ALTERNATIVE SAMPLING TECHNIQUES TO THE MCS METHODS

2.4.4.1 BACKGROUND

A power system’s behaviour can be described by the two energy delivery states, the success and fail, as it has been exemplified by the 3rd dimensional space described in Figure 2-11. These states can be collated to formulate a power system’s universal energy delivery state space which is demonstrated by the success (white circle) and the failure (black circle) states with the use of Figure 2-15. Moreover, the four different universal energy delivery state spaces in Figure 2-15 serve to demonstrate the seminal attributes of a power system’s energy delivery state behaviour. The first attribute to note is the state space size, which is denoted by using the physical
dimensions of the states, where b consists of a larger state space than a. Subsequently, a system characterised by a larger state space will also exhibit a larger mix of success and failed states, inevitably increasing the complexity of the sampling process. The second attribute to note is the reliability level inherent within a universal space. Therefore, systems that are characterised by the same sample spaces can be differentiated by the proportion of failed states inherent within them. Thus, a system with low failed states is obviously more reliable, which in this case d is more reliable than b; and c is more reliable than a. These two attributes which differentiate system energy deliverability states pose intricate problems in regard to the MC simulation process.

Figure 2-15 Illustrations of the two seminal attributes of power system states: state size and reliability space

MC (with or without variance reduction techniques) samples without partiality both the success and failure states of this universal state space. Thus, MC methods are inherently memory-less and unintelligent simulation methods. This means that MC treats the reliability evaluation process as a series of numerous trial runs of random experiments—which repeatedly sample previously sampled states on many occasions—in order to ascertain an expected reliability index value. Subsequently, their inefficient demand for huge trial runs increases computational burdens for certain applications—such as real time operational planning—in spite of the existing generally advanced computational ability. In such circumstances it is impetuous to investigate the validity of employing alternative methods that are equally suited and/or superlatively faster than the MC approach.

However, it is not all that straightforward in deciding to employ an alternate approach to the MC. This is because the salient benefit of the MC to any of its competing algorithms resides in the MC’s ability to most proficiently handle problems characterised with large uncertainties most accurately. Thus, as uncertainties in contemporary and future systems rise, the MC promises to be a continued supreme method of choice within reliability evaluation studies, in spite of its other
weakness(es). Progenitorial researchers have conceptualised a model (Figure 2-16) to aid reliability engineers to discern the appropriate occasions to invoke either the MC or one of its alternative methods. As Figure 2-16 shows, it must be first established whether a system is described by a high or low model complexity.

Admittedly, there is no consensus on what constitutes a high or low model complexity of a system. However, it could be suggested that an HL-1 system could comprise a low model complexity system, whereas the HL-2 or HL-3 could comprise a high complexity system. Conversely, a system which is fast and easy to evaluate compared to one that is not, can be considered as a low model complex system. Thus, as can be noted, model complexity is a subjective connotation to be defined by the engineers themselves [80].

Either way, after establishing the system complexity order, the next step requires ascertaining the system’s sample space size and reliability level as shown in the figure. Thus, if prior experience has shown the reliability engineer that a given system is low in reliability and that this reliability index is only attainable through a large amount of samples, then the MC is the method of choice for a high model system. Conversely, if experience has shown the engineer that the reliability of the studied system is high and the sample size is large, then it would be prudent to invoke hybrid techniques in future studies. The same analysis could be done for the other options depicted in the figure. More importantly, however, these alternative sampling techniques are discussed next.
2.4.4.2  **STATE ENUMERATION ANALYTICAL METHOD**

The state enumeration is an analytical method that aims to speed up the evaluation of system reliability by limiting the universal energy delivery state search through one of two methods: a particular *contingency level* or *probability* of failure threshold [81]. In the former, *contingency* levels may be limited to up to a maximum of *n* plant outages where \( n = 1, 2, 3, \ldots N \). In the latter, the *probabilities* of combinatorial failures above a given threshold are assessed within the reliability evaluation process and those exogenous to this probability level are omitted from study. Thus, the state enumeration is a state pruning technique, where the number of states to be evaluated is reduced, hence leading to faster computation execution time. The drawback of this technique is that highly detrimental system states that occur with extremely low probabilities may be omitted from the study. This is shown in Figure 2-17, where load curtailment states in level 6 (L6) may be missed if the maximum contingency level was set to 5, for example.

![State space illustration of particle swarm and genetic algorithmic state selection behaviours](image)

To address this deficiency to some extent, contingency selection methods such as the performance index method (PIM) [151, 152], hybrid or more intelligent state space search techniques have been conceived.

2.4.4.3  **INTELLIGENT HYBRID TECHNIQUES**

Newer breeds of state selection algorithms that promise faster and more efficient system state sampling, such as particle swarm optimisation [153], genetic algorithms [154] and support machine vector learning algorithms [155]—to mention the prominent few—have been proposed.

Particle swarm algorithms work on the principle modelled after the behaviour of a population of swarms as they move in packs led by a swarm leader in search of food sources [153]. The particle swarm algorithm employed to the energy delivery state space populates a group of *swarms* in search of those elusive (to the state enumeration method of identifying) system failed states—especially in highly reliable systems. In order to capture these states, colonies of swarms must be defined by the engineer [153]. For example consider Figure 2-18(a) in which six failure states reside. In order to capture these states, six colonies of swarm populations (of four swarms per colony) have been defined in order to find these states. As can be noted in the figure once they
find a failed state, the lagging swarms are used to prune the non-failed states so that when this population of swarms’ returns to search for the new failure space, the search time is lowered by the omission of these pruned states.

Another alternative method is the genetic algorithm (GA) state sampling mechanism which has been designed to lower the likelihood of repeatedly sampling the same state as well as to simultaneously identify the likely failed state to sample [154]. The difference with the particle swarm approach resides in their different approaches toward searching for failed states. In GA this is achieved through the definition of the fitness function which is modelled in similitude to the genetic function within biology used to predict the fitness of the offspring of a sampled population of species.

Each offspring which is created by its parents is termed as a generation; and only the fittest within that population of offspring survive to act as progenitors to the next generation. Thus, in the context of reliability evaluation, this survival translates to the realisation of a failed system state. Once again six generations of populations are defined in Figure 2-18(b) in order to capture all the six failed system states. The first generation of red species result in one survivor. This survivor populates a new generation of yellow species from which another survivor is realised. In this manner further coloured populations of species serving as the posterity to their progenitors are realised. Subsequently, this realises in the identification of all failed system states. For the GA to work, the system behaviours of mutation and chromosome crossover must properly modelled [154].

These two discussed examples are some of the many developed intelligent algorithms classified under the broader title of population based simulation techniques [153, 156-159]. This is because they populate entire state spaces in order to simultaneously prune the success states from future sampling, and to as well capture elusive failed states. Conversely, the support vector machine learning algorithm is the flagship algorithm which falls under the broader title of state classification intelligent search algorithms [155]. This, and its competing algorithms under their common classes, work by learning from past system state samples in order to ascertain the
factors which lead to a failed state; they subsequently use this knowledge to predict future failure states.

The key differences between any of these methods (under their respective classes) are truly nuanced; mainly influenced by the differently applied approaches they use to identify failed states. Furthermore, although literary works have cited the massive computational gains and the more accurate reliability evaluation efficiency levels exhibited by these population-based or classification-based methods, they are not stand alone algorithms. Just like variance reduction techniques, they too need espousal to the MC algorithm. Adopting these algorithms into the MC requires a high level of ingenuity and mathematical proficiency. For this reason, acceptance of these methods within the research community is not wide reaching yet. This slowness to majority adoption is further exacerbated by the need to always engage the laborious exercise of tuning the many parameters upon which these algorithms hinge; as well as the heuristic guessing of the stopping criterion for maximum system samples, every time a new reliability assessment exercise is requisitioned [153, 155]. Therefore, the endeavour to realise the promised computational efficiency rendered through these families of algorithms must be traded off against their discussed impediments.

2.4.4.4 Multi-Level Hybrid State Selection Models

Hybrid state selection models have been contrived to model power system uncertainties characterised by different modes or behaviours. Common examples include the reliability evaluation under weather states or non-chronological load durations [146, 160]. Recent examples include the joint evaluation of the electrical and non-electrical failure aspects on system reliability [161]. Work that has focussed on reliability evaluation whilst considering the influence of weather considers a Markovian process denoted by state transitions between fair, moderate and adverse weather conditions. Within a given weather state, the appropriate MC sampling technique has been applied to establish system states. This four weather state Markov model is shown in Figure 2-19.

The transitions out of a weather state are represented by $\lambda$ and the transitions into a weather state are represented by $\mu$. Clearly by observing the black dot numbers, it can be seen that a different weather state can influence reliability; and thus in this manner the reliability of power systems has been evaluated accounting for the effects of weather. Other alternatives have included the cut-set method in combination with either the Markov-Chain MC [160] or exclusively with the MC method [162]. The cut-set method has been employed to truncate large Markov weather states and thus realise faster computations [160]. However, similar techniques to Figure 2-19 have been applied to reliability evaluation of systems characterised by non-chronological
load (or clustered) models as well as modelling the impact of non-electrical failures (Markov) on electrical failures (MC) on system reliability [161].

![State space illustration of particle swarm and genetic algorithmic state selection behaviours](image)

**Figure 2-19** State space illustration of particle swarm and genetic algorithmic state selection behaviours

### 2.5 RELIABILITY ASSESSMENT: ANALYSIS TECHNIQUES

Irrespective of the state selection technique used, a system within a contingent state will require a mathematical analysis in order to ascertain the extent to which system violations may have manifested (as it has been illustrated with the 2\textsuperscript{nd} dimension in Figure 2-10). This section reviews techniques applicable solely at HL-2. HL-1 and HL-3 techniques are omitted but are discussed in [28, 29].

#### 2.5.1 CONTINGENCY STATE ANALYSIS TECHNIQUES

Solutions to the load flow algorithms are important within reliability evaluation because reliability engineers are able to determine weak areas in the systems that require corrective actions (including load curtailment) to stabilise the system and preserve its health as much as possible, in a computationally efficient manner. The load flow could be realised through a DC or an AC fast decoupled formulation.

#### 2.5.1.1 DC LOAD FLOW

The power system is modelled as a transportation model that transfers power from its generation to the load by injections into the grid. Thus the statement $\mathbf{P} = \mathbf{B} \circ \mathbf{\delta}$ represents a matrix of generation injections $\mathbf{P}$ from various points in the system. The flows consequent to these injections are dependent on the resistance of the network paths traversed and this consideration is formulated by a vector of OHL system susceptance values $\mathbf{B}^\prime$. 

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The matrix of angular differences, denoted by $\delta$ between electrical paths necessitates the potential for power to flow through these paths. Thus, the flow of power through a line (based on angular differences between the line’s connecting nodes) is mathematically represented by equation 2-33 [163]; where $i$ represents the node at one end of the line and $j$ the node at the other end; and $x_{ij}$ represents the reactance of that path.

$$\rho = \frac{\delta_i - \delta_j}{x_{ij}}$$  

Equation 2-33

Thus, the DC load flow (DCLF) can be employed to determine overloading conditions subsequent to arising system contingencies. However, the short-coming of the DC power flow method is characterised by its inability to evaluate voltage and/or reactive constraints as well as transmission losses. In spite of this short-coming, it is widely employed due to its computational speed and its ability to always converge.

2.5.1.2 AC FAST DECOPLED LOAD FLOW

To address the short-comings of the DCLF whilst still maintaining adequate computation speed, the fast decoupled load flow (FDLF) has been developed; aimed at attaining sufficient compromise between the faster DCLF technique and the more accurate (yet slower) AC load flow technique. Within the FDLF framework, mismatches of active and reactive power injections are formulated through equations 2-34 and 2-35 respectively [163]. The itemised plants of the equations, i.e., $\Delta P$ describe the vector of active power mismatches and $\Delta Q$ the vector of reactive power mismatches across the network nodes. The vector of angular differences necessitating power throughput potential between connecting lines is modelled by the angular matrix $\Delta \delta$. The FDLF utilises the Jacobian sub-matrix of partial derivatives of the mismatches with respect to the angles at all network nodes $J_\delta$ and another Jacobian sub-matrix of partial derivatives of the mismatches with respect to the voltages at all network nodes $J_v$, as shown in equations 2-34 and 2-35 respectively [163].

$$\Delta P = J_\delta \Delta \delta$$  

Equation 2-34

$$\Delta Q = J_v \times \Delta V / V$$  

Equation 2-35

The solution to the FDLF is reliant upon the assumption that for any two nodes $ij$, $\cos(\delta_i - \delta_j) \approx 1$, $g_{ij} \sin(\delta_i - \delta_j) \ll b_{ij}$ (where $g_i$ is the OHLs conductance and $b_i$ its susceptance) and that $Q \ll Q^2$. Following these assumptions, the final problem formulation is simplified to equations 2-36 and 2-37 [163]:

---

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\[ \Delta P / V = B \Delta \delta \]  
Equation 2-36

\[ \Delta Q / V = B \Delta V \]  
Equation 2-37

These formulations are characterised by the real and sparse matrices \( B \) and \( B' \) that only contain network admittances (due to the simplifications). The benefit of the aforementioned matrices is that since they represent constant values, they only need a single matrix inversion computation; usually made at the initialisation stage. Thus only, the voltage magnitudes and phase angles require modification through an iterative process. These formulations are shown in equations 2-38 and 2-39 [163].

\[ \delta_{\text{new}} = \delta_{\text{old}} + \Delta \delta \]  
Equation 2-38

\[ V_{\text{new}} = V_{\text{old}} + \Delta V \]  
Equation 2-39

In this manner, the solution to the FDLF formulation enables voltage and reactive violations to be ascertained by reliability engineers during a given system state. Once these violations are identified, they must be corrected in the most economical manner. The list of system violations is presented through the equations below; where Equation 2-40 refers to the vector of voltage violations, Equation 2-41 to the vector of generator real power violations, Equation 2-42 to the vector of generator reactive power violations and Equation 2-43 to the vector of transmission line thermal limit violations [163].

\[ V_{\text{min}} < V < V_{\text{max}} \]  
Equation 2-40

\[ P_{\text{min}} < P < P_{\text{max}} \]  
Equation 2-41

\[ Q_{\text{min}} < Q < Q_{\text{max}} \]  
Equation 2-42

\[ |T| < T_{\text{max}} \]  
Equation 2-43

### 2.5.2 Contingency Adequacy and Security State Analysis and Optimisation

Once violations to any of Equations 2-40 to 2-43 have manifested, optimisation algorithms must be computed in order to establish whether untapped adequacy states exist wherein violations could be eradicated in order to ensure that Equations 2-40 to 2-43 are observed. Optimisation algorithms are designed to primarily search for a solution that proposes the optimal economic manner by which generation could be re-dispatched. Secondarily, optimisation algorithms search for the optimal manner by which to enforce load curtailment, if the rescheduling of generation cannot alleviate any of the aforementioned violations.
If the primary and secondary searches return infeasible solutions, optimisation algorithms may be designed to then recommend both the re-dispatching of generation and the curtailment of selected loads as the optimal solution. The optimal power flow is the commonly employed optimisation algorithm, and it is modelled as a linear quadratic programming algorithm whose objective function is to minimise generator dispatch cost $\mathcal{C}$ for generator $i$ in a system composed of $n$ generating systems as in Equation 2-44 [81]. This formulation must be subjugated to the inequality constraints defined in Equations 2-40 to 2-43 as well as those equality constraints in Equations 2-45 and 2-46.

$$\min \sum_{i=1}^{n} C_i$$

Equation 2-44

In equation 2-45, $\mathbf{P}$ is vector of the total real power produced, $\mathbf{D}_c$ is the total demand curtailed and $\mathbf{D}$ is the vector of the total demand in the system.

$$\mathbf{P} + \mathbf{D}_c = \mathbf{D}$$

Equation 2-45

In Equation 2-46 $\mathbf{Q}$ is the vector of the total reactive power produced and $\mathbf{D}_q$ is the vector of the total reactive power demand in the system.

$$\mathbf{Q} = \mathbf{D}_q$$

Equation 2-46

Following this formulation a variety of optimisation solvers such as interior point programming and others can be utilised to solve the problem, as demonstrated in [163].

2.5.2.1 ENERGY DELIVERY RELIABILITY INDICES

Energy delivery indices are designed to capture the magnitude, duration and frequency with which load curtailment will manifest over the entire set of network sampled states (i.e., the failure states). Initially the $\mathbf{D}_c$ vector matrix is queried amid each sampled state to ascertain if any busses have undergone load curtailment, and if they have, the probability of that state is computed and the particular magnitude, duration and frequency values are evaluated as well.

Table 2-6 presents a summary of the commonest utilised magnitude, duration and frequency reliability indices as applied to each hierarchical level. As can be noted the mathematical formulations of these indices are similar (e.g. LOLP with PLC and LOEE with EENS). However, they convey different physical meanings. The LOEE records the loss of load at every state only when generation fails to meet the load—as its model complexity is only HL-1. Conversely, the EENS records the loss of load when the generation fails to meet its load or when system voltage,
overload or reactive violations manifest within the system—as its model complexity is at the HL-2 level.

Table 2-6 Examples of commonly employed probabilistic indices [29]

<table>
<thead>
<tr>
<th>Title</th>
<th>Acronym</th>
<th>Mathematical description</th>
<th>Model Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss of Load Probability</td>
<td>LOLP</td>
<td>$\sum_{k=1}^{n} p_k$</td>
<td>HL–1</td>
</tr>
<tr>
<td>Loss of Load Expectation</td>
<td>LOLE</td>
<td>$\sum_{k=1}^{n} p_k \times t_k$</td>
<td>HL–1</td>
</tr>
<tr>
<td>Loss of Energy Expectation</td>
<td>LOEE</td>
<td>$\sum_{k=1}^{n} p_k \times E_k$</td>
<td>HL–1</td>
</tr>
<tr>
<td>Probability of Load Curtailment</td>
<td>PLC</td>
<td>$\sum_{k=1}^{n} p_k$</td>
<td>HL–2</td>
</tr>
<tr>
<td>Expected Energy not Served</td>
<td>EENS</td>
<td>$\sum_{k=1}^{n} p_k \times E_k$</td>
<td>HL–2</td>
</tr>
<tr>
<td>Expected Frequency of Load Curtailment</td>
<td>EFLC</td>
<td>$p_k \sum_{j=1}^{m} \lambda_j$</td>
<td>HL–2</td>
</tr>
<tr>
<td>System Average Interruption Frequency Index</td>
<td>SAIFI</td>
<td>$p_k \sum_{j=1}^{m} \lambda_j$</td>
<td>HL–3</td>
</tr>
<tr>
<td>System Average Interruption Duration Index</td>
<td>SAIDI</td>
<td>$\sum_{k=1}^{n} p_k \times t_k$</td>
<td>HL–3</td>
</tr>
</tbody>
</table>

$n = number of outage states; p_k =$ probability of outage state $k$
$t_k = duration of lost load in state $k$
$E_k = energy not served in state $k$
$\lambda_j = transition rate into state $j$
$m = number of load curtailment transitional states$

2.5.2.2 Composite Static Security Health Indices

It must be emphasised that the aforementioned energy delivery indices (Table 2-6) only measure the reliability of a system amid the extreme emergency security state—i.e., S4, from the security state model summarised in Table 2-7. However, Table 2-7 further shows that a system can reside in any one of four security states (earlier described in this chapter). Therefore, by converting this knowledge to a state space purview such as that shown in Figure 2-20 (left), it can be derived that if the reliability evaluation algorithm solely focusses on capturing the S4 states, only a fraction of the entire system space will be assessed.

By converting the information from Table 2-7, however, into the state space view as shown in Figure 2-20 (right), this will result into the conception of an energy delivery state space which has been further classified into one of the other three aforementioned states (Table 2-7). Thus, by evaluating these states, it is possible to thoroughly convey a comprehensive reliability health description of any given system. Nevertheless, to describe a system’s full security health diagnosis, static reliability-security indices are necessitated.
Table 2-7 Concise descriptions of the four system security states

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Normal State</td>
</tr>
<tr>
<td>S2</td>
<td>Alert State</td>
</tr>
<tr>
<td>S3</td>
<td>Emergency State</td>
</tr>
<tr>
<td>S4</td>
<td>Extreme Emergency State</td>
</tr>
</tbody>
</table>

Figure 2-20 Comparison between a partially (left) and a fully (right) classified state space

These risk indices must be able to describe the expected probability, frequency and/or duration with which a system is expected to transition to as well as reside within these intimated security states. Furthermore, it may be relatively challenging (in the cases of systems characterised by high reliability state spaces) to use intelligent search population based hybrid sampling methods to evaluate these holistic indices; since these hybrid methods always attempt to truncate the system space. Subsequently, full MC simulations may with relative ease evaluate these system state indices across the entire space in order to holistically estimate a system’s health. Billinton and his co-researchers [164-166] have proposed a simplified security state framework titled the system well-being mainly to lower computation time. In the system well-being framework, the normal state is designated as the healthy state, the alert and the emergency states as the joint marginal state and extreme emergency state is designated as the at risk state. The restorative state is omitted from the framework. The transformation of the conventional security state model (left) to the well-being model (right) is shown in Figure 2-21.

Figure 2-21 A comparison between the conventional security state model (left) and the well-being model (right)
Furthermore, the resulting system health measurement indices are summarised in Table 2-8, and the detailed methodologies to calculate these indices are rendered in [166].

Table 2-8 List of static security indices. [164-166]

<table>
<thead>
<tr>
<th>Title</th>
<th>Acronym</th>
<th>Title</th>
<th>Acronym</th>
<th>Title</th>
<th>Acronym</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of Healthy</td>
<td>P(H)</td>
<td>Frequency of Healthy</td>
<td>F(H)</td>
<td>Duration of Healthy</td>
<td>D(H)</td>
</tr>
<tr>
<td>Probability of Marginal</td>
<td>P(M)</td>
<td>Frequency of Marginal</td>
<td>F(M)</td>
<td>Duration of Marginal</td>
<td>D(M)</td>
</tr>
<tr>
<td>Probability of at Risk</td>
<td>P(R)</td>
<td>Frequency of at Risk</td>
<td>F(R)</td>
<td>Duration of at Risk</td>
<td>D(R)</td>
</tr>
</tbody>
</table>

Furthermore, it has been narrated that computing these security metrics is a more computationally exhausting procedure in comparison to just computing the energy delivery reliability indices [110]. The advantage of comprehensively capturing the true value of a system’s health leads to improved decision making and a better understanding of a system’s operation. This thereby enhances investment and risk-based operational planning strategies [110].

2.6 RELIABILITY ASSESSMENT: DECISION MAKING CRITERIA

The reliability analysis techniques discussed earlier in this chapter have shown and subsequently accounted for the numerous ways through which a reliability engineer would be equipped to more accurately measure a vast array of unreliability indices. However, these indices must be converted into monetary metrics; able facilitate economical decisions with respect to network planning/investment or to short/long term power system operation. Thus, economical decision making can be realised through utilising one of three criterions: comparison, co-operative and penalty-reward criterions.

2.6.1 COMPARISON BASED DECISION MAKING CRITERIA

The comparison decision making criterion requires that a utility be affronted with the decision to select the optimal solution from a suite of candidates (e.g. a FACTS device, a SIPS scheme, a transmission line upgrade or combinations of these options). If maintenance is the objective, the set could comprise a corrective maintenance and a preventive maintenance strategy. If operation is the objective, this set could presuppose a variety of operator actions. Either way, the comparison decision making criteria will identify the candidate solution which exhibits the least risk through a set of reliability evaluations for each candidate and their comparisons [29]. The problem with this approach is that utilities may be forced to heavily invest in a solution irrespective of whether the society will truly value this solution—by paying extra for the
improvement it would render. Thus, the utility and the society must co-operate in order to reach an acceptable compromise.

**2.6.2 Co-operative Based Decision Making Criteria**

Co-operative decision criteria are also known as value-based or reliability-worth criteria [29]. Thus, reliability-worth assessments evaluate utility decisions to invest in a particular candidate from a set of candidates based on the cost of societal inconvenience inherent in the candidate. Mathematically it is represented by Equations 2-47 and 2-48 [81]. \( \text{ECOST} \) represents the societal inconvenience expected cost—and it is a function of \( \text{ENS} \) and \( C(d_{ijkl}) \)—which is the cost to society as a function of the duration and magnitude for which the demand for electricity is unmet. The suffixes \( i,j,k \) respectively represent the simulation year, the simulation hour within the year and the system bus within the simulation hour. Once \( \text{ECOST} \) is computed, the total cost of a candidate is computed through Equation 2-48; where the \( \text{System Operation Cost} \) characterises the cost of generating electrical energy.

\[
\text{ECOST} = \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{Z} C(d_{ijkl}) \times \text{ENS}_{ijkl} \quad \text{Equation 2-47}
\]

\[
\text{Total Cost} = \text{Utility Investment Cost} + \text{ECOST} + \text{System Operation Cost} \quad \text{Equation 2-48}
\]

Therefore, in this manner a utility can only implement those investments which realise the optimal compromise between the society and the utility, and this is illustrated in Figure 2-22.

![Figure 2-22 Theoretical relationship between the level of utility investment to improve reliability and the reduction of customer inconvenience costs](image)

Figure 2-22 illustrates the relationship between a utility’s investment costs in order to improve reliability (red line) and the resulting reduction in customer inconvenience societal costs (green line). The figure further illustrates that the aim of reliability assessment is to deduce the optimal total cost (black line) of providing reliable energy. This total cost is the summed value of the utility (red line) and customer costs (dark green line). Technically, the black line is termed as the reliability-worth curve and its lowest value is taken as the best established solution.
2.6.3 **REWARD-PENALTY REGULATORY BASED DECISION MAKING CRITERIA**

For a co-operative mechanism to succeed, a vast amount of highly accurate data regarding customer valuations of unsupplied energy must be collected—and this is a mammoth task. A complimentary approach to the reliability worth is offered through the performance-based regulatory (PBR) scheme [79]. The PBR is a framework developed with the aim to provide utilities with incentives for economic gain through a reward-penalty mechanism. Figure 2-23 defines the PBR scheme by three zones [167-170]. It is further defined by a regulatory mandated target reliability value. Therefore, if a utility meets this target zone, it will receive no monetary reward because the target value resides in the dead zone. However, if a utility’s investment solution results in a reliability metric which resides in the reward zone, a utility can expect to earn revenue capped by the maximum reward value.

![Figure 2-23 Performance Based Regulation – Pictorial Illustration of application to the thermal uprating problem](image)

The reward zone comprises two areas: one in which the maximum regulatory payment can be received and one in which only a fraction of the maximum payment can be received. The actual fraction depends on where on the slanted line the reliability metric resides. Conversely a utility can be penalised if it proposes an investment solution which results in a reliability metric residing within the penalty zone. In similitude to the reward zone, the penalty zone is comprised of two areas.

To exemplify this concept of penalty and reward zones Figure 2-24 is implemented with a distribution curve (dotted line), which represents the measured unreliability index random variable—which could be ENS, FLC or DLC (Table 2-6) observations, for example. The a, b, c, and d points in the figure allow for the development of both the reward and penalty zones as shown and therefore the calculation of the expected reward payment (ERP) value according to Equation 2-49 [110]. In Equation 2-49, the suffix $i$ in the equation represents an observed value—from the distribution inherent to the reliability index random variable. $RPS$ stands for the reward payment scheme and $P$ for the probability distribution represented by the reliability index random variable—as shown in Equation 2-50.
Therefore, Equation 2-49 shows how the \( ERP \) formulation is able to account for the probability of a selected reliability index random variable to lie within both the reward and penalty zones. Subsequently, by using the standard deviation zones (a to d letters) within the figure, the \( RPS \) can be calculated as in Equation 2-51 and 2-52 [110]. Therefore, through such a scheme a utility can be easily incentivised to invest in a solution that realises the highest level of reliability—as it will also realise the highest \( ERP \) reward value.

**2.7 CONCLUDING REMARKS**

This chapter has reviewed the various methods used to simulate the true stochastic behaviours of power systems. The most common utilised method is the crude Monte Carlo (MC) technique. However, when stochastic models are used to measure energy deliverability indices (e.g., EENS, FLC, DLC, PLC) crude MC technique is not efficient and fast. For this reason, MC variants such as the sequential Monte Carlo simulation (SMCS), as well as variance reduction techniques have been employed. Reiterated, these techniques mainly target at measuring the probability, magnitude, duration and frequency of load curtailment, for a particular power system design or
operating philosophy. Subsequently, these techniques are well suited to measure the reliability of a given power system characterised by a design or operating philosophy which employs conservative thermal rating limits on its plants. By employing conservative thermal rating limits, what is resultantly missing from these techniques is the inherent ability to model and thereby account for the dynamic characteristics of the plants amid stochastic thermal loading modes. The need to account for the aforementioned dynamic and stochastic behaviour of plants is of particular importance contemporarily, because power systems are increasingly expected to operate and/or be planned with a philosophy that legitimises a less conservative operation of its system plants—more explicitly, higher thermal loading of its plants [1].

Therefore, one gap that this thesis will endeavour to fill will involve the dynamic modelling of the parameters of overhead lines (OHLs)—i.e., resistance, reactance, capacitance and thermal age—in order to investigate the safe extent to which less conservative high temperature operational modes could be reliably accepted—as discussed in chapter 1. These OHL parameters (i.e., resistance, reactance, capacitance and thermal age), although dynamic by nature, have traditionally been modelled as static parameters throughout the reliability evaluation simulations, until recently [171]. The neglect to model these parameters accurately (i.e., to also include high temperature ageing) results in a loss of accurate data about these plants’ behaviours—data which is vital to the OHL plant asset management process. Therefore, a methodology capable of filling this gap (which is unable to perform the reliability evaluation of power systems considering the thermal health and condition of OHLs) is presented in the next chapter.
This chapter presents an electro-thermal power system reliability methodological tool which adds properties of OHL electro-thermal behaviour of OHL systems as an augmentation to the reliability framework reviewed in chapter 2. The pervasively growing interest amongst power system planners to realise a tool able to justify the increased power flow (through proper quantification of ageing visibility and utilisation flexibility) from OHLs in an efficient, economical, technically-robust and reliable manner [1, 63, 76, 172] is the main driver for the development presented in this chapter.

However, increasing power flow results in high temperature operation. High temperature operation in turn results in accelerated OHL ageing. This ageing in turn accelerates the OHL from the second stage (i.e., useful life) of the bathtub curve to its third and final stage and thus forces utilities to engage in early reconductoring activities. This phenomenon is briefly illustrated in Figure 3-1 (left), where ‘rating A’ is an OHL’s failure rate and corresponding loss of strength (ageing) performance at high temperature; and ‘rating B’ is the comparative performance of the same OHL, albeit, at a conservative low operating temperature. Subsequently, as the orange and black intermittent lines close to point C show that, ‘rating A’ will reduce an OHL’s duration within the useful life stage (i.e., B in Figure 3-1 left) in comparison to ‘rating B’.

![Figure 3-1 Simple illustration between loss of strength and failure rate for temperatures A and B](image-url)
Another concern related to high temperature flows is the conditional increase of its failure rate (Figure 3-1 right) which could lead to cascading failure related blackouts. It is, therefore, necessary to possess knowledge of how the pursuit to increase power flows is bound to affect the health of OHLs, through the accurate quantification of early reconductoring and blackout risks. Through this knowledge planners will undoubtedly facilitate prompt weighing of conductor ageing cost against the reliability monetary benefit rendered through increased power flows in order to assess the economic viability of implementing risk mitigating asset management activity solutions (AMASs) as discussed in chapter 1 (i.e., right-of-way (ROW) maintenance, OHL retensioning and/or reconductoring).

Although OHLs are sub-system plants of power systems, they are also a complex stand-alone entity [2, 173]. Thus it would not be prudent to integrate all the characteristic aspects of the OHLs into the traditional power system reliability framework as this would overwhelmingly complicate the analysis and computational time. Thus, this methodology proposes to focus on only integrating the ageing and elevated temperature reliability aspects and properties of OHLs [63]. This simplified approach provides reliability planners the benefit of still being able to evaluate and address the above concerns without overwhelmingly increasing the required analysis and/or computation time and resources. To do so will require augmenting only the relevant (1) thermal, (2) electrical and (3) mechanical properties of OHL plants into the reliability evaluation system model. This holistically conjoined OHL plant and system model is termed as the electro-thermal reliability evaluation tool.

3.1 Computational Outline

3.1.1 Computational Electro-thermal Steps

The first steps which a reliability engineer must complete within reliability evaluation studies is to collect system and plant raw data, and then formulate this raw data into their mathematical equivalents (discussed more in section 3.2) which are able to most accurately facilitate the system simulations which efficiently lead to the computation of reliability indices. The first step related to data collection is illustrated in Figure 3-2 (Figure 3-2 also illustrates the overview of the electro-thermal reliability evaluation methodology).

One benefit in formulating mathematical data models is that it aids in the selection of the minimum system state transition time-step $\Delta t$ that ought to be used within the simulation process. This $\Delta t$ value is realised by comparing the smallest time change resolution between the OHL weather and the power demand data (Figure 3-2). After all requisite mathematical data formulations have been realised, these mathematical data models are then convolved to form a
holistic system topological model; and its (system) status is initialised in order to initiate subsequent simulations and analyses. As shown in Figure 3-2, the incumbent system simulation and analyses are performed within two distinct iterative computational loops. The first one is implemented within a time-step $\Delta t$, which randomly simulates changes to both plant and system statuses. The second iteration loop analyses a system state so as to eventually determine annual reliability metrics. These two distinct iterative loops subsume (1) the network constraint mapping, (2) the network optimization and (3) network & OHL state reliability mapping blocks (Figure 3-2).

The network constraint mapping computations evaluate the adequacy of each OHL component of the network by considering reliability, operational, weather and OHL system data; so as to map the system topology and identify the operation state of each element during their operation and restoration histories. A sequential Monte Carlo simulation (SMCS) algorithm is implemented for the component state selection. SMCS has been selected for this electro-thermal model as it most accurately considers, in addition to demand changes, the weather changes in every time-step, $\Delta t$, and consequently, the time dependence on thermal constrains of OHLs.

As a result of capturing the time dependence on thermal constrains of OHLs, it is then possible, through the additional small computational feedback (Figure 3-2), to capture the potential for cascading failures occurring during a given $\Delta t$ period. Moreover, this feedback loop is used to further perform the role of updating a system’s topology; after realising all possible cascading events which may have occurred within a $\Delta t$ period. Once the final network topology at $\Delta t$ is...
realised, the network constraint mapping output feeds into the network optimisation calculations, in which AC power flow (ACPF) computations are initially performed to identify any static network constraints (i.e., voltage or thermal). When at least either a voltage or a thermal constraint is identified, an AC optimal power flow (ACOPF) is performed considering corrective re-dispatching and load shedding actions; aiming to minimise the total operation cost. Within the network optimisation block, the network and OHL state reliability mapping is performed (Figure 3-2) by utilising results from the network optimisation to update the calculated indices required to capture the cost of network operation. These indices are grouped into two categories: (1) those which describe the performance of the complete network, namely, the expected energy not served (EENS), the expected frequency of load curtailment (EFLC), the expected duration of load curtailment (EDLC), and the probability of load curtailment (PLC); and (2) those which describe the performance of each OHL separately, namely, the expected equivalent ageing index (EEAI), the expected frequency of extra loading (EFEL), the expected duration of extra loading (EDEL), the probability of extra loading (PEL) and the expected magnitude of extra loading (EMEL). The mathematical formulations of these indices are further discussed in 3.4. It must be reiterated, however, that the OHL performance indices are visibility indices.

As it can be seen in Figure 3-2, all the calculations are performed iteratively until the analysis within a simulated year is completed, upon which a new simulation year is computed (from the beginning) by creating new operation and restoration histories of the network elements. The simulation is then terminated when the covariance (cov) of the measured EENS index has reached a tolerance of 5%; according to standard reliability evaluation practice (as discussed in chapter 2).

3.1.2 Electro-thermal Data Requirements

It is clear that the electro-thermal methodology requires four types of input data, namely, (1) Reliability (2) Operational (3) Weather and (4) OHL system data. It is, therefore, necessary to expound upon these data types.

3.1.2.1 Reliability Data and Reliability Functions

Reliability data are needed, based on their standard annual historical performances (as discussed in chapter 2), to describe the failure $\lambda_x$ and repair $\mu_x$ rates of a power system comprising a total of $x$ components. Moreover, an additional reliability parameter, $\lambda_y$, is introduced in this electro-thermal methodology to determine the failure rates of $y$ components, $\forall y \in x$, during any given $\Delta t$ whilst operating at a critical operating temperature due to a failure of any $x$ components within the system and/or due to an unfavorable severe change in weather and loading. Finally, the reliability engineer must also ascertain that the $\lambda_y$ and $\lambda_x$ parameters are converted to the
Chapter 3: Reliability Modelling Framework Incorporating OHL Electro-Thermal Design Properties

The smallest \( \Delta t \) defined in the system status initialization. Therefore, whereas the former failure rate parameter describes only cascading events during \( \Delta t \), the latter describes the failures at the beginning of \( \Delta t \).

3.1.2.2 Operational Data

The operational data demand the specification of a variety of power system operating limits (as discussed in chapter 2). These are defined by the generator maximum power output; generator operating costs and cost functions; generator technology types; transformer maximum power ratings and impedances; transformer tap changing positions and synchronous condenser operating limits; circuit maximum ratings and impedances; capacitor bank operating limits; circuit breaker data; bus data, zones and names; as well as the annual load point chronological demand.

3.1.2.3 Weather Data

In this methodology, this set of data specifies the values of the key weather parameters required in order to evaluate the conductor temperatures of a given line at a given time. Weather data include annual historical wind speeds and incidence angles, ambient temperatures, as well as solar radiations.

3.1.2.4 The OHL System Data

The OHL system data are used in the methodology developed are those which describe the size, weight, stranding pattern, maximum strength, operating temperature and the corresponding resistance of the conductor technology that is installed on a given system. Further definitions include the tower type (e.g. lattice, suspension or wood pole) on which it is installed, the conductor span length i.e., the distance between two towers, its total geo-spatial circuit length, the initial stringing tension of the conductor and the system conductor configuration (i.e., single or bundle) [5, 174-176].

Figure 3-3 illustrates the importance of data in aiding the SMCS process. As figure 3-3 shows, at \( t=0 \), in order to simulate a system failure state, the reliability data of the system is needed and resultantly at \( t=\Delta t \) a system plant is failed (the intermittent black line in the figure). Subsequently, to ascertain the adequacy of the system amid the \( \Delta t \) period, the system is checked for violations (for example the red line shown in the figure). To enable this check, operational data is necessary. Traditionally, for OHL’s, violations are checked on the basis of their power ratings which are an approximation of an OHL’s true thermal rating and hence thermal state. Therefore, in this electro-thermal model an extra step is added to improve how OHL violations are ascertained. In order to so it is necessary to convert the raw data OHL system and weather data into mathematical models.
suitable to be synchronised with the SMCS. These models must be able to capture the modes illustrated in Figure 3-4, which shows that during $\Delta t$ when the power rating is violated an OHL’s thermal state can reside in one of two states: the reliable thermal and the unreliable thermal state. Ascertaining any of these states will require weather data which is accurately sampled during the $\Delta t$ period in order to compute the thermal state and subsequently an OHL’s sag.

**Figure 3-3 Illustration of an outage scenario**

**Figure 3-4 An OHL four state quadrant**
As can be shown if the OHL’s sag is within limits then its thermal state is reliable and only its ageing will need to be calculated. However, if this sag is infringed then the OHL will be deemed to be in its unreliable thermal state and to compute its probability of failure, its \( \lambda_e \) function will have to be firstly formulated, and, secondly, from this function the OHL’s time-to-failure will have to sampled. Computing the OHL’s sag depends on computing its mechanical state at \( t=0 \) as shown in Figure 3-4 (quadrant three). Moreover, computing the thermal state of an OHL is not only dependent on an OHL’s mechanical sag properties and its ambient weather conditions but also on its electrical properties as shown in Figure 3-4 in the fourth quadrant.

### 3.2 DATA PROCESSING AND MODELLING

In developing this electro-thermal methodology it was found that only the following data had to be processed/mathematically modelled in order to integrate them into the SMCS tool: \( \lambda_{e-y} \), weather and OHL system data. \( \lambda_{e-y} \) data was required to be modelled in order to predict the modes and \( \Delta t \) time period in which OHLs would fail during high temperature flows. Weather data was processed and modelled in a form which facilitated the easy and accurate computation of the appropriate adequacy-temperature value of an OHL amidst \( \Delta t \) a period. Finally, the OHL system data was needed to describe the electrical, thermal and mechanical attributes of any type of OHL.

Therefore, by establishing the electrical, thermal and mechanical models, it is possible to model any OHL technology into this electro-thermal reliability evaluation tool. These models are discussed in this section. Finally, there was no need to pre-process or model the rest of the data as it was judged that these data, in their raw formats as earlier discussed, were sufficiently accurate to be employed into this electro-thermal reliability evaluation tool.

#### 3.2.1 MODELLING OHL SYSTEM DATA

The OHL system data to be used in the electro-thermal reliably evaluation tool must be those which most accurately describe the mechanical, electrical and thermal attributes of an OHL. The mechanical aspects include size, weight, stranding pattern and maximum strength of the conductor. Further mechanical data required to define the OHL system include the tower type (e.g. lattice, suspension or wood pole) on which the conductor is installed, the conductor span length i.e., the distance between two towers, its total geo-spatial circuit length, the initial stringing tension of the conductor and the system conductor configuration (i.e., single or bundle).

These mechanical aspects are required to compute an OHLs initial sag and this sag is required to evaluate an OHLs ageing after the thermal and electrical states have been ascertained during SMCSs (as will be discussed later in this chapter). Nevertheless, briefly stated, the thermal
attributes relate to a conductor’s maximum operating temperature, while the complete electrical performance model of a conductor erected on an OHL is defined by its electrical resistance inductance, reactance, capacitance and admittance of the conductor technology that is installed on a given OHL system [5, 174-176].

3.2.1.1 Electrical Modelling of an OHL

Calculating the OHL Resistance

The electrical resistance of an OHL is a heavy influencer in the design of OHLs. This is because power and energy losses are an explicit function of the phase conductor resistance. Thus accurate quantification of resistance is vital. A uniform cylindrical conductor of diameter \( d \) has a total resistance per unit length, in \( \text{m} \), to direct current expressed by [2, 173]

\[
R_{\text{DC}} = \frac{\rho}{A} = \rho \times \left( \frac{4}{\pi d^2} \right)
\]

Equation 3-1

\( R_{\text{DC}} \) denotes the resistance in \( \Omega/\text{m} \), \( \rho \) the conductor’s resistivity in \( \Omega \cdot \text{mm}^2/\text{m} \), \( A \) the conductor cross section in \( \text{mm}^2 \) and \( d \) the diameter in \( \text{mm} \). It must be emphasised that is \( R_{\text{DC}} \) a function of temperature, expressed through the relationship

\[
R_{\text{DC}}' = R_{20, \text{DC}} \left[ 1 + \alpha (T - 20) \right]
\]

Equation 3-2

Where \( R_{\text{DC}}' \) is the dc value of resistance at an operating temperature \( T \). Moreover, it can be noted that the evaluation of \( R_{\text{DC}}' \) is dependent on establishing the 20°C dc resistance (and this value is usually provided from manufacturer data sheets) by as well considering the conductor’s coefficient of thermal expansion \( \alpha \) (\( \Omega/\text{m} \cdot \text{C} \)). The value of 20 in the above equation is the temperature value in degree Celsius corresponding to \( R_{\text{DC}}' \). When conductor bundles are considered, the total resistance of the phase conductor may be evaluated through \( R_{\text{tot}} = R_{\text{DC}}'/n \); where \( n \) is the number of conductor bundles [173].

Since OHLs generally transmit AC (unless they configured as HVDC lines), to account for the skin effect due to the AC current flow, the DC resistance formulation is transformed to its effective AC resistance value using appropriate techniques and formulations through the use of the empirically evaluated curves such as the one shown in Figure 3-5 [2]. The ratio between \( R_{\text{AC}} \) and \( R_{\text{DC}} \) may be obtained by firstly establishing the ratio of the inner core radius \( r_o \) to the outer core radius \( r_r \) of a conductor technology. For homogenous conductors this value will always be 0, since the conductor is made up of the same material throughout. However, in the case of non-homogenous conductors this ratio will vary depending on the ratios of \( r_o \) to \( r_r \). For this reason a family of
curves has been plotted in the figure to illustrate the influence of different $r_o$ to $r_n$ ratios on the evaluation of the $R_{ac}/R_{dc}$ ratios. Initially, however, a conductor's dc resistance must be converted to the equivalent dc resistance in ohms-per-mile as shown on the x-axis label of the figure. Consequently the corresponding $R_{ac}/R_{dc}$ ratios can then be ascertained from the appropriate curve.

Figure 3-5 Curves depicting the relationship between $r_o$ and $r_n$ [2]
CALCULATING THE OHL REACTANCE

When evaluating the reactance of an OHL, one must consider the design of the OHL i.e., whether it is a single or a bundled configuration and also whether this configuration is a single or double circuit. This is because these considerations greatly influence an OHLs steady state reactance as will be discussed in the following. Therefore, the steady state reactance which is commonly known as the positive sequence inductive reactance (PSIR) of a three-phase fully transposed OHL is given by Equation 3-3 [2, 173]

\[ X = \omega L = \left( \frac{\omega \mu_o a}{2\pi} \right) \left( \ln \frac{D_m}{r_b} + \frac{1}{4n_2^2} \right) \quad \text{Equation 3-3} \]

Where \( \omega \) is the angular frequency \( (2\pi f) \), \( L \) the positive sequence inductance in \( H/m \), \( a \) the conductor length in \( m \). \( D_m \) is the geometric mean distance separation in \( m \) between the phase conductors; whereas \( \mu_o \) is the constant of magnetic field i.e., \( 4\pi \times 10^{-7} \) \( H/m \). Finally the bundle equivalent conductor radius is given by \( r_b \), where \( r_b \) is further defined mathematically in Equation 3-4 [2, 173]

\[ r_b = \frac{n^2}{2} x r_0 x r_0^{n-1} = r_0^2 \left( (k_x s/r) \right)^{n-1} \quad \text{Equation 3-4} \]

Where \( n_2 \) is the number of conductors comprising the bundle, \( s \) is denoted as the sub conductor distance within the bundle, \( r_0 \) is the radius of the bundle circle, \( r \) is the individual conductor radius within the bundle and \( k_x \) is a conductor bundle constant as shown in Table 3-1 (in the fourth column). The table further illustrates how different values for \( r_b \) could be calculated based on the number of conductors and their corresponding \( k_x \) factors.

<table>
<thead>
<tr>
<th>No. of Conductors</th>
<th>Bundle Radius</th>
<th>Conductor bundle equivalent Radius ( r_b )</th>
<th>( k_x )</th>
<th>Example ( r_b ), ( r_s = 16mm ), ( s = 400mm )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-</td>
<td>( r )</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>2</td>
<td>( s / \sqrt{3} )</td>
<td>( \sqrt{s^2} )</td>
<td>1</td>
<td>80</td>
</tr>
<tr>
<td>3</td>
<td>( s / \sqrt{3} )</td>
<td>( \sqrt{s^2} )</td>
<td>1</td>
<td>137</td>
</tr>
<tr>
<td>4</td>
<td>( s / \sqrt{2} )</td>
<td>( \sqrt{s^2 x \sqrt{2}} )</td>
<td>1,12</td>
<td>195</td>
</tr>
<tr>
<td>5</td>
<td>0.851s</td>
<td>( \sqrt{2.618s^2} )</td>
<td>1,272</td>
<td>255</td>
</tr>
<tr>
<td>6</td>
<td>( s )</td>
<td>( \sqrt{6s^2} )</td>
<td>1,43</td>
<td>315</td>
</tr>
<tr>
<td>8</td>
<td>1.307s</td>
<td>( \sqrt{52.12s^2} )</td>
<td>1,76</td>
<td>438</td>
</tr>
</tbody>
</table>

The geometric mean distance earlier alluded to is mathematically defined as [2, 173]

\[ D_m = \frac{\sqrt{D_{ab} \cdot D_{ac} \cdot D_{bc}}}{3} \quad \text{Equation 3-5} \]
Where $D_{ab}$ is the mean distance between phase A and B of a single circuit line, $D_{ac}$ is the mean distance between phase A and C and $D_{bc}$ is the mean distance between phase B and C. Considering double circuit lines, the positive sequence inductive reactance is modified to:

$$X = \omega L = \left(\omega \mu_0 a/2\pi\right) \ln\left(\frac{D_{M2}}{r_p D_{M1}} + \frac{1}{4n_z}\right)$$  \hspace{1cm} \text{Equation 3-6}

$$D_{M1} = \sqrt[4]{D_{ab} \cdot D_{bc} \cdot D_{cc}}$$  \hspace{1cm} \text{Equation 3-7}

$$D_{M2} = \sqrt[4]{D_{ab} \cdot D_{ac} \cdot D_{bc}}$$  \hspace{1cm} \text{Equation 3-8}

Where $D_{ab}$ is the mean distance between the circuit phase A and the second circuits phase a. The same logic is applicable to the rest of the parameters in Equations 3-7 and 3-8.

**Calculating the OHL Capacitance**

The capacitance of an OHL is a property of OHLs through which the storage of electrically separated charges manifests consequential to the existence of a potential difference between its conductors, shield wires and the ground; and these are influenced by an OHL’s geometric design. Capacitance is measured in Farads and its mathematical expression is granted as in Equation 3-9; where $X_C$ is the capacitive reactance denoted in $\Omega$. The inverse of $X_C$ is termed as the susceptance i.e., $B_C = 2\pi f C$ [2, 173]

$$X_C = \frac{1}{2\pi f C}$$  \hspace{1cm} \text{Equation 3-9}

For single circuit lines the positive sequence capacitance is granted as [2, 173]

$$C_{io} = \frac{2\pi \varepsilon_o}{\ln\left(\frac{D_M}{r_g \sqrt{1 + (D_M/2h_M)^2}}\right)} \approx \frac{2\pi \varepsilon_o}{\ln\left(D_M/r_g\right)}$$  \hspace{1cm} \text{Equation 3-10}

Moreover, to consider the effect of earth (shield) wires the above equation (Equation 3-10) can be used, as the effect of earth wires in such a geometric design is negligible. Equally, in an OHL geometric design which includes double circuit wires without earth (shield) wires, the positive sequence capacitance per unit length is derived as [2, 173]

$$C'_{io} = \frac{2\pi \varepsilon_o}{\ln\left(\frac{D_{M2}}{r_p D_{M1}} \cdot \frac{D_{M1}}{r_g D_{M2}} \cdot \frac{1}{\sqrt{1 + (D_{M1}/2h_{M1})^2}}\right)} \approx \frac{2\pi \varepsilon_o}{\ln\left(D_M D_{M2} / r_p D_{M1}\right)}$$  \hspace{1cm} \text{Equation 3-11}

To aid OHL designers in undertaking electric circuit OHL calculations, as the power system level, it is consensually mandated to use the shunt *admittance* to ground rather than the impedance to
ground mathematical formulation. Therefore, in applying the vector representation, the positive unit shunt admittance $Y$ is given by [2, 173]

$$Y = G + jB$$ \hspace{2cm} \text{Equation 3-12}

Where $G$ is the real part of the admittance otherwise termed as the conductance and $B$ the imaginary part, termed as the susceptance. The conductance is usually characterised by a value very close to zero and can be neglected from Equation 3-13. This negation leads to the relationship between the shunt admittance and the OHL capacitance (i.e., from Equation 3-12) to be defined as [2, 173]

$$Y = \frac{1}{X_c} \text{ in S/km}$$ \hspace{2cm} \text{Equation 3-13}

**CALCULATING THE OHL IMPEDANCE**

For an OHL model to be used in power flow computations, it must have both its impedance and admittance attributes defined. It’s impedance attributes constitute the ohmic resistance and the inductive reactance. Therefore once the ohmic resistance and inductive reactance have been formulated, the final impedance formula (per km) discussed in Equation 2-7 and recapitulated in Equation 3-14 can be realised to describe any given line and its conductor parameters [2, 173].

$$Z_{km} = R_{km} + jX_{km}$$ \hspace{2cm} \text{Equation 3-14}

Furthermore, for the admittance attribute, the capacitive susceptance expressed in Equation 3-13 must be used. Therefore, by following the steps discussed and by using Equations 3-1 to 3-14, the reliability engineer would be able to produce impedance and admittance values for any OHL and conductor technology in order to more accurately evaluate the OHL’s performance within the electro-thermal reliability evaluation tool.

**3.2.1.2 THERMAL MODELLING OF AN OHL**

Once the electrical model of the OHL has been completed, the next step in data processing and modelling requires the selection of a thermal rating model which is able to capture the thermal behaviour of the developed OHL.

At this stage, the reliability engineer will have to make a choice regarding which thermal model to implement during the SMCSs. There are essentially three industry standard thermal rating methods available at present: the IEC TR 61597; CIGRE WG 22.12 ELECTRA No. 144; and the IEEE-738 [4, 8, 57]. All these methods essentially rely on the heat balance theory in order to estimate the thermal state (i.e., temperature of an OHL). Heat balance theory states that an observed conductor temperature must equate to the electrical current flowing through and must be
balanced, through some tangible relationship, by specified prevailing weather conditions. This means, for example, that if the conductor losses more heat than it produces, it can allow more power to flow at low internal thermal state (i.e., temperature) and vice versa. This is possible because the convection and radiation cooling abilities of the OHL tend toward increasing the current that can flow, whereas the amount of solar radiation, maximum conductor operating temperature and its resistance tend toward limiting the current that can flow.

Although the three aforementioned thermal rating methods essentially rely on the heat balance principle to ascertain an OHL’s thermal state, the methods and models by which they compute an OHL’s thermal state are different (consequent to their input data requirements). Nevertheless, in the final analysis the results of their outputs are markedly close (with the errors between these methods truly miniscule) [4, 8, 57]. Therefore, selection, to the reliability engineer, of the thermal rating method to employ in the SMCS tool will be made based on data availability or based on which is the most assented industry standard thermal rating model or both of the aforementioned reasons. For these reasons, the IEEE-738 model was employed in this electro-thermal reliability evaluation tool. Therefore, through this model can the reliability engineer then evaluate any electrical current for a desired maximum temperature, by following the logical steps as follows:

1. The reliability engineer must initially understand that an OHL’s operating temperature $T_c$ is directly related to $S_{3o}$ i.e., the three phase power and electrical current $I$ flowing through it and the system line-to-line voltage $V_{il}$ connected to it, through the relationship shown in Equation 3-15.

$$I(T_c) = S_{3o} / \left( \sqrt{3} \times V_{il} \right)$$  \hspace{1cm} \text{Equation 3-15}

2. Since Equation 3-15 shows that the thermal rating $I$ is a function of OHL temperature $T_c$ [57], the direct relationship between $I$ and $T_c$ is defined through Equation 3-16.

$$I = \sqrt{Q_c(T_c, V_w, T_a) + Q_r(T_c, T_a)} / R(T_c)$$  \hspace{1cm} \text{Equation 3-16}

Where $Q_c$ represents the convection cooling capabilities of the OHL conductor temperature $T_c$ and this cooling is dependent on the wind speed $V_w$ and the ambient temperature $T_a$. Moreover, the radiated conductor heat $Q_r$ to the immediate surroundings is dependent upon the conductor temperature operation $T_c$ at that moment and the ambient temperature $T_a$. Additionally, $R(T_c)$ is the conductor temperature...
based resistance and $Q_s$ is the solar heating effect on the conductor [57]. These parameters and their sub-parameters are fully exemplified in the IEEE-738 standard [57].

This equation (Equation 3-16) therefore defines the thermal rating model that the reliability engineer must implement in the SMCS electro-thermal reliability evaluation tool to capture those conditions which lead to elevated temperature operation. Once elevated temperature operation (ETO) has been captured, the SMCS electro-thermal tool will need to utilise a mechanical behavioural model of the OHL in order to evaluate either its ageing (in the case that the OHL does not fail during ETO) or its failure (in the case that the OHL does fail during ETO).

### 3.2.1.3 MECHANICAL MODELLING OF AN OHL

ETO relates to operating conductors and connectors at temperatures where thermal effects can impact the safety, reliability and life of the transmission line [13, 63, 133, 172, 177]. The main effect of ETO is the reduction of the mechanical strength (leading to accelerated permanent conductor creep) [6, 178, 179].

According to the IEEE 1283 standard [63], the definitions for OHL conductor creep (as applied to aluminium type conductors) as given as follows: “accelerated (elevated) creep (ETC) rate is an increase in the conductor’s creep rate over general creep rate usually associated with ETO.” And general creep rate is defined as: “the accumulative non-elastic elongation of a conductor under tension over an extended period of time at modest temperatures usually not in excess of approximately 75°C”. Consequently, it can be clearly understood from these two definitions that their difference lies in the magnitude of the temperature with which the OHL is being operated.

ETO-based ETC performance is conductor technology type, size, weight, diameter and elongation behaviour specific; and all these parameters have been considered in the creep predictor equations (for both general and accelerated creep) that have been developed for most common conductor technology [63] types as shown in Table 3-2. As it can be seen in Table 3-2 the equations are affected by the constants K, M, G, and C that are affected from the conductor structure and methodology of manufacturing. The exact values for the most common stranding patterns and conductor types are shown in Table 3-3.

Thus, overtime as shown in Figure 3-6, if a conductor is being operated at even a low temperature, the effect will be such that the resulting sag will be much higher due to creep. Therefore, in this electro-thermal reliability evaluation tool, it is vital to calculate OHL sag in order to evaluate the mechanical creep effects related to high temperature creep (ageing) performance.
Table 3-2 Creep Predictor Equations for Different Conductor Types [63]

<table>
<thead>
<tr>
<th>Cond. Type</th>
<th>Normal Temperature</th>
<th>Elevated Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAC</td>
<td>$e_c = K \sigma t^{1.36}$</td>
<td>$e_c = M T^{1.4} \sigma t^{1.36}$</td>
</tr>
<tr>
<td>AAAC</td>
<td>$e_c = G \sigma t^{1.36}$</td>
<td>$e_c = 0.077 T^{1.3} \sigma t^{1.36}$</td>
</tr>
<tr>
<td>ACAR</td>
<td>$e_c = (0.19 + 1.36 \frac{A_{Al}}{A_{St}}) \sigma t^{1.36}$</td>
<td>$e_c = (0.0019 + 0.012 \frac{A_{Al}}{A_{St}}) T^{1.4} \sigma t^{1.36}$</td>
</tr>
<tr>
<td>ACSR</td>
<td>$e_c = C (%RBS)^{1.2} t^{0.16}$</td>
<td>$e_c = 0.24 (%RBS)^{1.2} T^{0.16}$</td>
</tr>
</tbody>
</table>

$e_c$: creep strain ($\varepsilon$) (mm/km)  
$\sigma$: stress in Tension/area (N/mm$^2$)  
$T$: conductor temperature (°C)  
$A_{Al}$: aluminum cross-section area (mm$^2$)  
$A_{St}$: steel cross-section area (mm$^2$)  
$t$: elapsed time (hours)

Table 3-3 Conductor stranding pattern based creep predictor formula constants [63]

<table>
<thead>
<tr>
<th>Constant</th>
<th>7 Strands</th>
<th>19 Strands</th>
<th>37 Strands</th>
<th>61 Strands</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_1$</td>
<td>1.3600</td>
<td>1.2900</td>
<td>1.2300</td>
<td>1.1600</td>
</tr>
<tr>
<td>$K_2$</td>
<td>0.8400</td>
<td>0.7700</td>
<td>0.7700</td>
<td>0.7100</td>
</tr>
<tr>
<td>$M_1$</td>
<td>0.0148</td>
<td>0.0142</td>
<td>0.0136</td>
<td>0.0129</td>
</tr>
<tr>
<td>$M_2$</td>
<td>0.0090</td>
<td>0.0090</td>
<td>0.8400</td>
<td>0.6177</td>
</tr>
<tr>
<td>$G$</td>
<td>0.7100</td>
<td>0.6500</td>
<td>0.7700</td>
<td>0.6100</td>
</tr>
<tr>
<td>$C_1$</td>
<td>2.400</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C_2$</td>
<td>1.400</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Subscript “1” denotes 1350-H19 strands drawn from hot-rolled rod  
Subscript “2” denotes 1350-H19 strands drawn from continuous-cast rod

Figure 3-6 Effect of Thermal Rating on OHLC Sag on a flat terrain

Consequently, the mathematical expressions for conductor sag evaluations must be selected so as to reflect the relevant terrain conditions of an OHL. The equation describing the sag relationship for a conductor installed on a flat terrain is narrated in Equation 3-17 [173]; where $W$ is the conductor weight (kg/m), $D$ is the span length (m) and $T$ (kN) is the conductor’s tension on the erected structure. To consider the evaluation of sag on an incline, Equation 3-18 may be employed [5] pertaining to the Cartesian coordinate envisioning of an OHL on an incline as
depicted in Figure 3-7 from which Equation 3-18 can be employed. The full derivation of this formula is fully rendered in [5]. In the final rendition, Equations 3-17 and/or 3-18 must be employed by the reliability engineer to set an OHL’s initial creep conditions which will then be modified in order to calculate OHL ageing as the SMCS performs its calculations. This is discussed in more detail in section 3.4.

\[ S = \frac{T}{W} \left[ \cosh \left( \frac{WD^2}{2T} \right) - 1 \right] \]

Equation 3-17

\[ S_{\text{INCLINED}} = D_b - \left( \frac{h}{2} \right) - y_b \]

Equation 3-18

\[ \text{Figure 3-7 Planar depiction of conductor sag erected on an incline [5]} \]

3.2.2 WEATHER DATA PROCESSING AND MODELLING

It is impossible to evaluate ageing without evaluating an OHLs temperature and it is impossible to evaluate an OHLs temperature without a weather model. As discussed in chapter 2, deciding how to model plant or system or both (plant and system) behaviours in a reliability evaluation exercise is not an easy task. When processing or modelling weather data so as to synchronise it with the SMCS, certain challenges must be overcome and the final model selected must acquiesce to sufficient compromise between computational practicality and accuracy.

Figure 3-8 illustrates a system being sampled though SMCS, as the up (TTF) and down (TTR) histories show. During a down system state, the computation of a reliability index (black shade) can be completed in one of two ways: (1) considering a deterministic model of adequacy (i.e., blue intermittent line in the figure), or (2) considering the true stochastic nature of adequacy described by a probability distribution (pd) at every time step (\( \Delta t \)). Considering the stochastic nature of adequacy is clearly more accurate as it captures all possible adequacy states; but this comes at a heavy computational cost, because for every \( \Delta t \) period an adequacy probability distribution is sampled and for every sample an adequacy computation is completed. This process is repeated for all \( \Delta t \) periods.
A practical approach is to assume a deterministic model of adequacy (as shown in Figure 3-8), but this simulation approach is less accurate; something which will work to hamper the benefit of completing electro-thermal based reliability evaluations.

A more effective approach is to employ a time-series adequacy model (blue dynamic line in Figure 3-9). This is because, mathematically, by employing a time-series adequacy model (in comparison to employing the pd adequacy model, Figure 3-8) the number of plant adequacy states per demand level $\Delta t$ to be sampled reduces drastically. Moreover, it is possible to further increase the computational speed by decreasing the $\Delta t$ resolution; the optimal level of $\Delta t$ resolution decrement that is decided upon will be up to the engineer. Furthermore, computational speed can be realised by converting the time-series data to equivalent step values calculated from the dynamic line plot shown in Figure 3-9.

The following steps are needed to convert the weather data into a time-series adequacy model through the IEEE-738 model:

1. Select the recorded weather data (i.e., wind speed, wind angle, ambient temperature, solar radiation, etc.) and calculate (through the equations discussed in chapter 2) the moving average (MA) and auto-regressive (AR) model parameters which most accurately represent these intimated raw weather data.
2. Following the ascertainment of the AR and MA model parameter, the reliability engineer must then calculate the mean and standard deviation values of the stated weather data.

3. Once the MA, AR, mean and standard deviations of these data have been produced they can be further used with the IEEE-738 thermal rating model to produce a thermal rating time-series model as illustrated in Figure 3-10.

4. From this created time-series adequacy rating signal (Figure 3-10), the AR and MA and mean and standard deviation of this model can be extracted in order to be simulated during SMCSs in a manner similar to that shown in Figure 3-10. Furthermore, as shown in the figure, by capturing solely the ARMA, mean and standard deviation parameters, it can be established that any simulated rating value will lie within the boundaries shown by the orange lines.

![Figure 3-10 Thermal rating time-series signal](image)

However, in order to generate a time-series adequacy rating in the manner discussed assumes that the raw data used to generate it is pure enough to guarantee that a time-series model can be generated from it; and this may not always be the case. Subsequently, in these cases, when it is impractical to generate time-series adequacy ratings, it is necessary to select a deterministic adequacy rating more intelligently.

![Figure 3-11 Illustration of an intelligent deterministic adequacy rating concept to capture ageing](image)

In Figure 3-11, the orange shadowed area indicates an event at which the deterministic adequacy rating (black intermittent line) provides inaccurately more capacity on the network compared to the more accurate and realistic time-series adequacy rating (blue dynamic line). In this instance of
using a deterministic adequacy rating, the electro-thermal reliability modelling does not capture the actual ageing risk (shown in the orange shade) unless an improved algorithm is employed to capture the ageing without significantly increasing the computational complexity of the electro-thermal reliability modelling. A solution to this (once the adequacy indices are calculated during a Δt period) is to produce weather distributions which can be used to calculate the OHL indices during a Δt period. This point is aided through Figure 3-12, during a Δt period,

The IEEE-RTS thermal rating model is used to generate the conditions for which a weather variable could be exceeded for the Δt period. Figure 3-12 illustrates the wind speed and ambient temperature distributions and the red areas indicate the probability of exceeding the values. As it can be seen there is no exceedance of ambient temperature for the data set used. It is then from this region that the expected ageing of an OHL is computed. A more detailed example of this approach is given in chapter 4 where the electro-thermal modelling is thoroughly validated. The process to capture the ageing as described here requires the following two data processing steps:

1. Narrow down the recorded weather data to effective wind speed (EWS) and effective ambient temperature (EAT) as discussed in chapter 2.
2. From the generated EWS and EAT datasets ascertain and then extract the parameters describing the ascertained probability distribution which best describes the EWS and EAT datasets. These extracted parameters are used to sample the weather states necessary for estimating an OHLs adequacy and subsequent ageing state (by sampling of the red area as, for example, shown in Figure 3-12) during the Monte Carlo reliability simulation process.

![Figure 3-12 Wind and ambient temperature distributions during a Δt period](image)

The weather correlated modelling approach is a more accurate for calculating OHL ageing as it accounts for the correlation between the EAT and the EWS as shown through the contour plot in
Figure 3-13 below. To generate a correlated distribution, the solution to the mathematical relationship, namely, \( \sigma(EWS,EAT) = E[EWSEAT] - E[EWS]E[EAT] \); where \( \sigma(EWS,EAT) \) is the covariance (i.e., the measure of how the EWS and EAT variables change simultaneously), \( E[EWSEAT] \) is the joint statistical expectation of the EAT and EWS random variables, and \( E[EWS] \) and \( E[EAT] \) are the univariate intrinsic statistical expectations of the EWS and EAT random variables respectively. Resultantly, from these computed values, a multivariate distribution can then be produced as shown in Figure 3-13 which can be further used to invoke the proper sampling of the multivariate EAT and EWS distribution points in order to evaluate an OHLs adequacy within the Monte Carlo simulations during a \( \Delta t \) period.

![Correlated wind and ambient temperature distributions during a \( \Delta t \) period](image)

**Figure 3-13 Correlated wind and ambient temperature distributions during a \( \Delta t \) period**

### 3.2.3 MATHEMATICAL FORMULATION OF \( \lambda_c \)

It is only possible to evaluate the ageing of an OHL if that OHL is operationally reliable to facilitate high temperature operation. The operational reliability of an OHL will depend on the effect of conductor sagging due to elevated temperature operation (ETO) coupled with the reduction in clearances to vegetation and other moving objects, such as vehicles [5] etc. Thus, this reduction will increase the probability of flashover—and hence line failure and public risk [14]. Furthermore, the operational reliability formulation is compounded by the design of the line and the health of its other plants e.g., joints, insulators, tower structures and so on.

However, the decision to uprate an existing line will include a thorough joints replacement analysis and activity [13, 14, 63]; therefore, the main cause for concern relating to uprating will be solely based on the formerly narrated sag effects [63]. Furthermore, OHL conductor operational reliability models are lacking within literature, because data on OHL designs and historical emergency loading failures are non-existent. Thus in this chapter, a reliability model will be conceived from theoretically rudimentary principles according to [144].
An OHL conductor’s reliability performance within a given environment will begin to degrade once its temperature $T_c$ crosses a temperature reliability threshold value $T_{thresh}$. Furthermore, because of the seasonal variability of tree growth as well as the objects passing and/or growing beneath the OHL, $T_{thresh}$ will fluctuate. However, due to lack of data and also to the need for simplicity, $T_{thresh}$ was assumed constant within this work. Therefore, once $T_{thresh}$ is crossed, according to reliability theory a failure relationship must be established—this is achieved through a failure density function $f(t)$ [144]. Also, it can be envisioned that $f(t)$ could take many forms. Thus, in this thesis, concentration was centred on developing a flexible function and consequentially, the Weibull failure function was utilised.

The Weibull formulation, in Equation 3-19, is flexible enough to recognise failure modes that can be represented by various distributions—including normal and exponential types through the alteration of its parameter $\beta$ (Equation 3-19). When $\beta = 1$ is used the time-to-failure will be represented by an exponential distribution, while for $\beta = 3.5$ the failures follow a normal distribution [144]. In Equation 3-19, $\alpha$ is the scale factor. Once $T_{thresh}$ is eclipsed, the probability of survival is computed through Equation 3-20 where $R(t)$ is characteristic of the reliability survivor function [144].

$$f(t) = \frac{\beta t^{\beta-1}}{\alpha^\beta} e^{-\left(\frac{t}{\alpha}\right)^\beta}$$  \hspace{1cm} \text{Equation 3-19}$$

$$R(t) = \int_{t}^{\infty} f(t) = e^{-\left(\frac{t}{\alpha}\right)^\beta}$$  \hspace{1cm} \text{Equation 3-20}$$

A failure density function can characterise both tangible and intangible factors which contribute to reliability. In this study it is assumed that intangible OHL failure factors are intrinsic to the conductor: i.e., the mechanical, electrical and thermal integrities which define particular OHL behaviours such as electrical treeing, loss of strength, partial discharges, time-based cracking, corrosion, oxidation, Maxwell stress, and abrasion and so on [180, 181].

These behaviours are so inherently stochastic [181] that they can be only collectively described by a distribution—as described by Equation 3-19. Figure 3-14 illustrates the varied distributions which can be computed based on different shape factors ($\beta$). As it can be seen, the exponential distribution is the one which solely characterises a failure survival probability which is reduced with the passage of time.
Therefore, the $\beta = 1$ Weibull distribution is selected against other values. Equation 3-19 is used to calculate the general distribution of the failure rate. Equation 3-21 is applied for the $\beta = 1$ case, where $\alpha$ represents the tangible factors which influence the distribution.

$$\lambda = \frac{\beta t^{\beta-1}}{\alpha^\beta}$$  \hspace{1cm} \text{Equation 3-21}

In this study it is assumed that the tangible factors influence the scale (stretch) of the exponential distribution; as shown in the Figure 3-15 with the different $\alpha$ values—stretching the distribution as their values drop.

Tangible factors account for (1) the compounding impact of the environment on the high temperature operational reliability and (2) the number of critical spans at risk of failure on any given line. Thus in this study $\alpha_n$ is weighted through Equation 3-22 in order to capture the relative reliability credit of the natural failure rate $\lambda_{n,i}$ of an arbitrary OHL on reliability; as $\lambda_{n,i}$ is assumed to be descriptive of the environment within which an OHL resides

$$\alpha_n = \frac{\text{max}(\lambda_{n,i})}{\lambda_{n,i}}$$  \hspace{1cm} \text{Equation 3-22}
\[
\lambda_c = \frac{1}{\alpha} = \text{SpanFailures}\% \times \alpha_n \times k_{\text{loading factor}}
\]

Equation 3-23

\[
k_{\text{loading factor}} = \begin{cases} 
T_c^{\text{actual}}(t) & \text{if } T_c^{\text{actual}}(t) \geq T_{\text{thresh}} \\
T_{\text{thresh}} & \text{if } T_c^{\text{actual}}(t) < T_{\text{thresh}} \\
0 & \text{if } T_c^{\text{actual}}(t) < T_{\text{thresh}}
\end{cases}
\]

Equation 3-24

whereas \( \max(\lambda_n) \) is representative of the highest natural failure rate of the OHL within the system. Thus accounting for \( \alpha_n \) and the \( \text{SpanFailures}\% \); \( \lambda_c \) with \( \theta = 1 \) is reformulated with its tangible factors as in Equation 3-23, with the \( k_{\text{loading factor}} \) defined in Equation 3-24. When a time-series model is utilised it is relatively easy to ascertain the condition \( T_c^{\text{actual}}(t) \geq T_{\text{thresh}} \). However, when utilising either a correlated or uncorrelated weather model, \( T_c^{\text{actual}} \) for a given \( \Delta t \) period becomes probabilistic and in this case the reliability engineer must produce these probability plots and establish at what probability value of \( T_c^{\text{actual}}(t) \geq T_{\text{thresh}} \) the OHL will be ascertained to have eclipsed \( T_{\text{thresh}} \).

### 3.3 Simulation of System States

Once the data has been modelled as earlier discussed, the next step must model the algorithm required to guide the electro-thermal reliability evaluation simulations towards capturing both system and OHL adequacy state and indices. In this regard, four OHL thermal operational states were identified for capturing in order to capture all possible electro-thermal and power system states: normal operation, pre-contingency high-loading, post-contingency high-loading, and failure states. These are shown with their distinct grey paths in Figure 3-16. In Figure 3-16, the Present Network Status is the initial system state at \( t=0 \), prior to simulation initialisation and the system state at \( t=t \) after the simulation has been initialised.

The rest of the flows shown in the figure illustrate the logical manner in which to identify each OHL plant’s high-loading state in order to decide which amongst \( \lambda_n \) or \( \lambda_e \) to be used so as to sample each plant x’s reliability state. Therefore, at a given time an OHL’s \( T_c^{\text{actual}}(t) \) is calculated by employing Equation 3-16 based on its computed power flow during the current transition time. Following this, for an OHL x, the comparison \( T_c^{\text{actual}}(t) < T_{\text{thresh}} \) is made and if this result is true then \( \lambda_n \) is selected for component x. Conversely if \( T_c^{\text{actual}}(t) \geq T_{\text{thresh}} \) is true then \( \lambda_e \) is selected. This calculation is performed within the thermal constraint of \( y \) components block in Figure 3-16 where \( y \) indicates the number of components x that are thermally constrained.
3.3.1 NORMAL OPERATION STATE

The normal operation state is defined as one in which at time \( t \) there is no OHL plant failure and in which the weather change does not force any OHL to experience thermal rating constraints. In this case, \( T_{c,\text{act}}(t) < T_{\text{thresh}} \) is true, and, inevitably, the sampling of the time to fail (TTF) for every OHL plant \( x \), \( TTF_{n-x} \), for the next \( t+\Delta t \) period, is computed by using Equation 3-25 and pictorially this logical flow is illustrated by the grey normal operation state arrow in Figure 3-16. Moreover, the \( TTF_{n-x} \) in Equation 3-25 considers that \( \lambda_{n-x} \) follows an exponential failure distribution [29] with \( U_n \) randomly generated between 0 and 1.

\[
TTF_{n-x} = -\frac{1}{\lambda_{n-x}}\ln(U_n)
\]  
Equation 3-25

3.3.2 PRE-CONTINGENCY HIGH-LOADING STATE

The pre-contingency high-loading state shown in the grey arrow in Figure 3-16 is the state at time \( t \) which materialises when the weather transition leads to one or more OHLs being operated within their pre-contingency high-loading state (i.e., no system plant failures) to force the condition \( T_{c,\text{act}}(t) \geq T_{\text{thresh}} \) to manifest. Resultantly, within the algorithm, \( \lambda_{e-y} \) is implemented from which the \( TTF_{e-y} \) is computed according to Equation 3-26, which is then stored within the network mapping which then formulates the next the network status for the adequacy calculations during the \( t+\Delta t \) period. The symbols in the Equations are similar to those earlier defined through Equations 3-22 to 3-24.
Moreover, this pre-contingency high-loading state also scans further events to OHL plants which result in the high-loading operating mode of a OHL plant \( y \), \( \forall y \in x \), due to unfavourable weather conditions or demand increase or both. In this case, the \( \lambda_{e_y} \) is queried to estimate the \( TTF_{e_y} \) for plant \( y \). Furthermore, if there is plant \( y \) failure, the next step in the algorithm is to execute a more realistic modelling of OHL behaviour which leads to the identification of occasions when plant \( y \) failures failure can lead to further cascading failures within the power system (see Figure 3-16 left hand).

In briefly digressing, however, it must be mentioned that overloading conditions either increase or decrease in intensity as the hours progress due to weather variability. This hence affects the \( k_{\text{loading_factor}} \) and subsequently its effect on \( TTF_{e_y} \) is amended every \( \Delta t \) period. Thus, it is possible that an overloading failure could be subverted or even accelerated due these complex behavioural mechanisms, and sometimes cascading failures can be avoided if the weather conditions improve.

Nevertheless, in regressing, if ascertained, then the cascading failure will be deemed to have occurred at the same time-step (i.e., during the present \( \Delta t \) period) as highlighted by the plant cascading failure grey block in Figure 3-16. In this case the \( TTR_{n,a} \) is stored in the updated present network mapping which in turn is used (as the output to this calculation step) to feed into a new network optimization computation, performed at the current time-step (Figure 3-2). This considers that the cascading plant failure \( z \) contributes an additional OHL plant \( x \) in failure mode at the current \( \Delta t \), and that the failures at the present network status have increased by \( z \) ( \( \forall z \in y \) ). The process in Figure 3-16 commences by scanning for all network \( x \) OHL plants; with the new failed OHL plants being increased by the previous identified cascading failure \( z \). In the event that another cascading failure takes place, the process is repeated until all the \( y \) OHL plants that are experiencing the high-loading state (during the present \( \Delta t \) period) are simulated and all possible cascading failures have been identified.

### 3.3.3 Post-Contingent High-Loading State

The post-contingent high-loading state models the impact of high-temperature loadings on cascading failures. It is in fact quite similar to the OHL plant state selection process of the pre-contingency high-loading state. However, the high-loading of a plant \( y \) is due to the failure of
another plant \( x \) of the network (and not due to unfavourable weather conditions or demand increase or both). This state identifies plant failures that have resultantly influenced selected healthy lines to operate in high-loading state; and therefore increased their probability of failure. Consequently, this state models the likelihood of failure as a consequence of the decision to operate healthy lines at high temperatures in the quest to improve system adequacy during post-contingent states. In this operating state Equation 3-26 is once again invoked to compute \( TTF_{e,y} \) following the traversal path shown in Figure 3-16.

### 3.3.4 Component Failure State

Once a component \( x \) has been identified to be in a failed state during a current \( \Delta t \), then the network mapping should be updated for the next computational time-step (see Figure 3-16 bottom right). Therefore, the new \( TTR_{n,x} \) for the failed component \( x \) is appropriately considered within the updated network mapping, and is computed according to Equation 3-27. When \( TTF_{n,x} \) predicts a component \( x \)'s failure to occur within a present \( \Delta t \), then Equation 3-27 is used to compute the time to repair (TTR) of component \( x; TTR_{n,x} \). This value is then stored within the network mapping for the next \( \Delta t \) calculations (Figure 3-16, bottom right). In similitude to the aforementioned, based on the resulting \( TTF_{e,y} \) value the \( TTR_{n,x} \) is computed, when required, by also using Equation 3-27 and it is used to update network mapping of the same step-time, \( \Delta t \) (Figure 3-16, bottom right).

\[
TTR_{n,x/e,y} = -\frac{1}{\mu_{n,x/e,y}} \ln U_n
\]

Equation 3-27

### 3.4 System State Optimisation and Reliability Evaluation

Network optimisation computations are initiated by considering the present network status as shown in Figure 3-17 which is fed by the output of Figure 3-16. This state, therefore, contains the new present network status (including \( z \) cascading failures) data produced from the network constraint mapping computations as well as the initial raw operational data. Subsequently with this data, an initial ACPF of the new present network status is performed, and when no thermal and/or voltage constraints are identified by the ACPF, no optimisation of the network is performed as shown in Figure 3-17. In this situation, no update of the network and OHL indices takes place, and therefore the reliability and OHL state mapping remains the same at this time-step.

Conversely, when violations of the constraints are identified, the optimisation of the network is performed; driven by three different objective functions that can be used in combination or
individually. These include the conventional minimisation of generation and load curtailment objective cost function $C_{ij} \cdot G_{ij}$, as well as the proposed minimisations of OHL power losses objective cost function $C_{ij} \cdot P_{ij}$, and OHL’s ageing cost function $C_{ij} \cdot EEAI_{ij}$ (Figure 3-17). The inclusion of electro-thermal modeling helps to capture the power losses and ageing of each OHL, and, consequently, the optimisation of OHL losses and ageing costs can be implemented to specific OHLs, or to the complete network. Furthermore, the electro-thermal modeling computes, with increased accuracy, OHL power losses, as it accounts for the effect of conductor temperature on its resistance. In any situation, the objective functions must be minimised subject to voltage (KVL), current flow (KCL), generation apparent power at a particular time $G_{\text{MAX}}(t)$ and OHL maximum continuous apparent power at a particular time $S_{\text{MAX}}(t)$ constraints (assuming that a time series model has been implemented). If it is not possible to implement a time series weather model then a time invariant $S_{\text{MAX}}$ is used instead; as it the conventional case.

Minimisation of the objective function is achieved through an iteration loop within the network & OHL state reliability mapping block that calculates the network and OHL performance indices as shown in Figure 3-1. This iterative process is necessary for the $C_{ij} \cdot P_{ij}$ and $C_{ij} \cdot EEAI_{ij}$ costs due to their optimisation being solvable only through the iterative benders decomposition method [182]. The $C_{ij} \cdot G_{ij}$ cost is solvable through simpler quadratic programming techniques. Once the minimisation iteration is completed for the current $\Delta t$ time-step, the updated system and OHL indices are stored within the updated present network status (in Figure 3-17) and they are updated in every $\Delta t$ loop until the completion of the year.

![Figure 3-17 Flowchart of the network optimisation procedure.](image-url)
3.4.1 Network Performance Indices

System optimisation is used to compute network performance indices as earlier stated. Therefore, the EDLC, PLC, EFLC and EENS system performance indices earlier defined are evaluated based on computing (during each optimisation process) Equations 3-28 to 3-31; Where, \( d_{ij} \) in Equation 3-28 is the duration of load curtailment of the \( j^{th} \) system interruption in simulation year \( i \); \( N_i \) in Equation 3-30 is the number of load curtailment occurrences; and \( SysENS_{ij} \) in Equation 3-31 is the system energy not supplied (in MWh) for the \( j^{th} \) system interruption in simulation year \( i \).

\[
EDLC = \sum_{i=1}^{N} \left( \sum_{j=1}^{M} d_{ij} \right) / T_s \tag{Equation 3-28}
\]

\[
PLC = EDLC / 8760 \tag{Equation 3-29}
\]

\[
EFLC = \sum_{i=1}^{N} N_i / T_s \tag{Equation 3-30}
\]

\[
EENS = \sum_{i=1}^{N} \left( \sum_{j=1}^{M} SysENS_{ij} \right) / T_s \tag{Equation 3-31}
\]

3.4.2 OHL Performance Indices

Alongside the time when power system indices are computed, OHL performance indices are computed too during the optimisation process. Therefore, the EDEL, PEL, EFEL and EMEL OHL performance visibility indices earlier defined are evaluated based on computing Equations 3-32 to 3-35, for the \( \Delta t \) period of the simulation.

\[
EDEL = \sum_{i=1}^{N} \left( \sum_{j=1}^{M} d_{emeij} \right) / T_s \tag{Equation 3-32}
\]

\[
PEL = EDEL / 8760 \tag{Equation 3-33}
\]

\[
EFEL = \sum_{i=1}^{N} N_{eme} / T_s \tag{Equation 3-34}
\]

\[
EMEL = \sum_{i=1}^{N} \left( \sum_{j=1}^{M} LineOverload_{ij} \right) / T_s \tag{Equation 3-35}
\]

Where, \( d_{emeij} \) in Equation 3-32 is the duration of emergency line loading of the components of the \( j^{th} \) system interruption in simulation year \( i \); \( N_{eme} \) in Equation 3-34 is the number of emergency loading occurrences; \( LineOverload_{ij} \) in Equation 3-35 is defined as the magnitude of emergency loading (in MWs or MVAs) for the \( j^{th} \) system interruption in simulation year \( i \).
Once these OHL indices are computed, they are further used in the second stage, during a $\Delta t$ period. Therefore, the resultant EMEL from the first stage of the OHL performance indices calculations is used as an input along with the modelled OHL plant data and the present network status thermal rating model introduced through Equation 3-16 to compute the conductor temperature, $T_c(t)$, conductor stress, $\sigma_x$, and non-ageing thermal rating, $T_{c,\text{max}}(t)$, of each OHL at $\Delta t$ (according to the process illustrated in Figure 3-18). These parameters are required in order to compute the $\text{EEAI}_x$ of each OHL of the network at $\Delta t$—i.e., to compute OHL ageing. Therefore, for a component $x$ operating at temperature $T_c$ that results in an elevated conductor ageing $\varepsilon_{x,T_c}$ the general equation (i.e., Equation 3-36) can be used that indicates the dependence of $\varepsilon_{x,T_c}$ on the conductor type $K_x$, temperature $T_c$, stress $\sigma_{x,T_c}$, and duration of operation $t_{x,T_c}$ [183].

\[
\varepsilon_{x,T_c} = f(K_x, T_c(t), \sigma_{x,T_c}, t_{x,T_c}^{0.16}) \quad \text{Equation 3-36}
\]

From Equation 3-36 it is obvious that the ageing is segmented based on OHL conductor temperature mapping, which varies for each year. Resultantly, in order to generate a more measurable quantity the $\varepsilon_{x,100}$ is introduced that can be used to evaluate the annualized ageing on different conductor types and lines within the system. This $\varepsilon_{x,100}$ is the total ageing occurred at 100°C operation and $t_{x,100}$ duration that is equivalent to the $\varepsilon_{x,T_c}$ of any conductor operating temperature $T_c(t)$ and duration $t_{x,T_c}$. This equality criterion is described by Equation 3-37.

\[
f(K_x, T_c(t), \sigma_{x,T_c}, t_{x,T_c}^{0.16}) = f(K_x, 100^\circ C, \sigma_{x,100}, t_{x,100}^{0.16}) \quad \text{Equation 3-37}
\]

Consequently, Equation 3-38 is produced to calculate the $\text{EEAI}_x$ produced at 100°C, in hours, for an OHL $x$ that has experienced a number of elevated temperature events at various elevated temperatures $T_c(t)$ and durations $t_{x,T_c}$.
The value and risk of probabilistic thermal uprating scenarios on power system reliability

\[ EEAI_x = \sum_{i=1}^{LTE} T_{x,100} = \sum_{i=1}^{LTE} \left( \frac{e_{x,T_c}}{e_{x,100}} x t_{0.16} \times t_{e}^{6.25} \right) \]

Equation 3-38

3.5 CONCLUDING REMARKS

The main tenets comprising the proposed electro-thermal reliability evaluation tool have been narrated. In its most compact description this computational tool can be defined in three parts: (1) the network constraint mapping block, (2) the network optimisation block and (3) the network reliability indices block. The first block is designed to ascertain, in addition to the failure statuses of its plants, the appropriate sampling technique based upon an OHL’s loading status. This was achieved through a high temperature reliability model developed from reliability theoretical first principles. From this formulation the \( \lambda_e \) sampling function was developed in order to simulate the times-to-fail for lines loaded above a set \( T_{thresh} \) level. This improvement resulted in the modification of a sampling algorithm sensitive to first failure conditions, pre- and post-contingent emergency loading failures.

The optimisation block is developed to compute a more accurate behaviour of network operation while the final block computes the network reliability indices as well as novel OHL performance indices—including their ageing indices. Moreover, a variety of input data which more ably (and accurately) model the workings of OHLs have been thoroughly discussed and illustrated; as to how they correctly integrate into the reliability methodical framework. More explicitly, it was shown how any conductor of any type could be modelled solely through the appropriate calculation of the resistance, reactance and capacitance values. Following this, the procedure upon which to calculate both traditional system and novel plant indices was then exemplified.

Thus, in its completeness, the key strength of this methodology is that it is a tool that can be utilised to aid reliability engineers in answering adequacy and economic related questions pertaining to increasing the capacities of existing lines.
When it is necessary to facilitate system reinforcement through thermal uprating, utilities are usually challenged with the massive exercise of realising the best solution—from a suite of thermal uprating scenarios (TUSs)—amid technical [75] and budgetary [184] constraints. Moreover, the use of appropriate tools able to model these TUSs is requisitioned in order to robustly assess them. Presently, there is an increasing interest to evaluate the adequacy credits of various TUSs in order to select the best TUS in a manner that is robustly justifiable. This mandates the utilisation of a tool that is able to model both the technical and economic aspects of a TUS. Consequently, in this chapter a standard reliability test network is used with the methodology discussed in chapter 3 in order to engage in selected TUS studies with the aim of establishing their various adequacy credits to system reliability performance (figure 4.1). According to Figure 4-1, the output indices relate to both the traditional reliability and the novel OHL performance visibility indices.

4.1 SOFTWARE ENVIRONMENT IMPLEMENTATION

The methodology within this thesis has been implemented within the Matlab programming environment. The load flow and optimisation algorithms have utilised the MatPower [185] suite of algorithms albeit tailored to the methodology presented. The optimisation solver utilised is based on interior point programming and is invoked within the Modified MatPower algorithm. The input and output data are handled through Matlab struct variable and data types for prior and post analysis of this methodology’s computed results. The time-series modelling algorithms.
were used to fit and simulate chronological thermal rating parameter behaviours [186]. Moreover, extensive use of various Random Number Generation algorithms and a variety of data analysis and statistical analytical tools [187] within Matlab was engaged throughout this thesis’ work. Alongside Matlab, Ms Excel was used as a conductor database to house a variety of conductor data, obtained from [188].

4.2 Test System Description

The proposed sequential Monte Carlo methodology and TUSs are tested and validated on the IEEE 24 bus reliability test system (IEEE-RTS [83]) considering more plant properties for the OHL network components as well as weather data that are required for the implementation of the proposed methodology.

4.2.1 Reliability Test System Base Case

The IEEE-RTS is composed of thirty-eight line circuits and nine generating areas connected to the busses as shown in the figure. The generating areas are comprised of generating units of varying types i.e., nuclear, hydro, coal/steam, gas and oil. Thus the total number of generating units within this system spread over the nine generation areas is thirty-two. A synchronous condenser for voltage support at bus 14 is inherent to this system. This power system is typified by twenty-four load delivery points through the busses shown in the figure. Further details pertaining to this system are given in [83] and for convenience, the main system and reliability data for this network and its plants are given within appendix A.

The delivery point compositions are classified into industrial, residential, government, commercial, agricultural, large users and office customer sectors in accordance with [128]. The actual mix of sectors at each of the narrated load points is described in appendix B. Moreover, classification of these sectors allows the value of the customer damage cost (CDC) to be estimated according to the value that each customer sector places on energy not served to it. The methodologies given in [29] are employed in this study to establish the delivery point customer sectors and CDCs respectively. The customer sector damage cost in $/KW per sector for a given outage duration in minutes utilised within this thesis are given in the Table 4-1. Also it must be emphasised that Interpolation techniques are employed to evaluate the CDC pertaining to any sector for any duration, based on the data provided above.

It is assumed that the plants comprising this system are all repairable and thus reside within the second stage of the bathtub curve. Moreover, it is further assumed that there is no uncertainty about the data relating to the failure rates of these plants and any of those used to describe the IEEE-RTS.
Within this study, certain modifications to the base values of the IEEE-RTS system are employed. The demand level at all busses is multiplied to 1.5 times of their nominal values and also the maximum generator capacity outputs are doubled with the aim to stress the transmission system in order to depict the contemporary conditions faced by utilities. Additionally, only line and...
transformer failures are considered in this study, hence the generation is assumed to be 100% reliable. Since transmission planning aims to design systems so that they are still able to facilitate lower cost generation of power amid all possible system security states, assuming that generation is 100% reliable is reasonable [82].

Furthermore, the demand at the delivery points is assumed to be 100% correlated with other delivery points within the same system. However, it is appreciated that in reality this may not be the case [148]—albeit this assumption had to be made due to lack of real uncorrelated demand data. Virtual generators are inserted at the delivery points albeit price marked with a high cost in accordance with [189] and are thus only scheduled as a measure of last resort. These generators are thus employed to model load shedding within the system. Virtual reactive injections at all the busses are modelled to facilitate voltage compensation in order to ensure that the AC OPF model developed within the thesis converges when the system is islanded due to the manifestation of certain system splitting failures.

4.2.2 OHL Design Properties

Aluminium Conductor Steel Reinforced (ACSR) technologies are the most commonly employed technologies. According to a 1998 CIGRE survey on OHLs over 100kV [77], 82% were established to be ACSR, 6% established as All Aluminium Alloy Conductors (AAAC), 4% as Aluminium Alloy Conductors (AAC) and the remaining 6% was credited to other technologies combined. Plover ACSR is one of the most preferable conductor technologies employed on the 230 kV and Drake ACSR on the 138 kV networks [7]. Therefore, Plover is assumed to compose the power lines of the studied 230kV and Drake for the 138 kV network on the IEEE-RTS. Other technologies may be considered by modelling into the algorithm their properties (discussed in chapter 3). A description of conductor technology types is given [1, 5].

Typical 230 and 138 kV tower and span configurations are given in [190] and detailed in Figure 4-3. Therefore, it is assumed that this configuration is representative of the spans within the 138 and 230 kV sections of IEEE RTS. The OHL system configurations further assume that the span lengths are 400m for the 230 kV and 300m for the 138 kV with their conductors strung at 20% of their rated breaking strength at everyday tension (EDT). These assumptions are required in order to evaluate elevated temperature creep (ETC-Sag) calculations according to [63]. Furthermore, the bundle configuration for these lines is single as is the circuit configuration. Based on the description provided and the utilisation of Equations 3-12 to 3-27, the positive sequence reactance, resistance and capacitive values for the IEEE-RTS system are computed according to the discussion in chapter 3.
CHAPTER 4: VALIDATING THE OHL ELECTRO-THERMAL PROPERTIES WITHIN THE RELIABILITY FRAMEWORK

4.2.3 OHL WEATHER AND THERMAL RATING MODELS

4.2.3.1 ENVIRONMENTAL WEATHER SCENARIO

The weather zones within which a system resides hugely affects the ageing of conductors. Moreover, it must be stressed that thermal ageing is only one aspect of conductor ageing. Broadly stated, conductor ageing can be delineated into either environmental or operational ageing [9, 77]. Operational ageing results from high temperature operation whereas environmental ageing is the ageing influenced by the environment wherein a conductor operates. These two ageing modes compete, and thus compound the overall rate of ageing of a conductor [181]. Therefore, to secure thermal ageing, environmental ageing must be mitigated as much as possible. Examples of the consequences of the environmental ageing aspects that compound a conductor’s age include corrosion and/or metal oxidation, vibrations, air pressure variability and so on [9, 11, 13].

Hence, through many different mechanisms, these modes of ageing increase the conductor’s resistance (and hence its operating temperature at low ampacity flows). Also these forms of ageing aid to diminish the diameter of the conductor and thus cause it to lose strength [13]; further resulting in increased thermal ageing at lower than specified values during operation [13]. However, it must be emphasised that well engineered methods have been devised to circumvent environmental ageing. Examples of solutions include the greasing and surface treatment of conductors to improve resistance to corrosion, the application of Stockbridge dampers to minimise conductor vibrations or reconductoring with conductors more adept to handle vibrational and corrosion risks [180].

In this study it is assumed that the complete network lies in the same weather zone due to lack of actual data. Moreover, in this study it is considered that the 138kV network section is poorly maintained and consequently the environmental ageing factors compound and stress the system conductors such that ageing occurs when the Drake conductors are operated at and above 75°C.
However, if these environmental factors were to be circumvented, thermal ageing would start at 100°C [63]. Drake is classified as a hard ACSR type of conductor because its steel to aluminium ratio content is about 7% to 93% [5]. Moreover, soft ACSRs are those whose steel to aluminium ratio content are at least 13% to 87%; and together with the all-aluminium type conductors (AAAC, ACAR, AAC) experience thermal ageing at temperatures of 75°C and above when other ageing mechanisms are alleviated [63]. Although Plover conductor is a hard ACSR, in order to evaluate ageing an appropriate weather model must be conceived. Therefore, it is assumed that the 230kV section of the IEEE-RTS experiences ageing at temperatures 95°C and above.

4.2.3.2 Static Thermal Rating (STR) Weather Scenario

The IEEE 738 standard [57] proposes ambient weather profiles for line ratings by assuming worst case values for ambient temperatures and wind speeds i.e., \( T_{\text{Ambient}} = 40°C \), \( \text{Wind Speed} = 0.61 \text{ m/s} \); as well as for the other thermal rating parameters. Table 4-2 presents the relationship between \( T_{\text{MAX}} \) and the selected power capacity at each voltage level of the examined network. These are based on these stipulated weather conditions and on the provided selected capacities for the lines comprising the IEEE-RTS.

<table>
<thead>
<tr>
<th></th>
<th>138 kV ( T_{\text{MAX}} ) and MVA Rate</th>
<th>230 kV ( T_{\text{MAX}} ) and MVA Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal Rate</td>
<td>75°C</td>
<td>175</td>
</tr>
<tr>
<td>LTE Rate</td>
<td>90°C</td>
<td>200</td>
</tr>
<tr>
<td>STE Rate</td>
<td>95°C</td>
<td>220</td>
</tr>
</tbody>
</table>

It has already been discussed that weather models are inherently probabilistic. Therefore, to more accurately rate the lines, actual weather data must be collected. In order to be able to do so weather data employed from National Grid-UKs Canterbury CAT-1 real-time weather measurement system to facilitate the studies within this thesis. The data provided included errors due to failures and erroneous measurements of the instrumentation. The data, however, was utilised in its original form in order to model the impact of instrumentation failures on ageing and rating calculations.

4.2.3.3 Probabilistic Thermal Rating (PTR) Weather Scenario

One advantage of collecting and relying on real data to rate lines is that it provides an inexpensive method of uprating OHLs. This is achieved by employing probabilistic techniques to study the weather in order to ascertain the limits to which the redefinition of weather assumptions coupled with reconsidered \( T_{\text{MAX}} \) values could be stretched—in order to realise a desired MVA adequacy rate for a given line. In order to aid the realisation of the acceptability of a desired rate, the
probability (and hence the duration) with which the candidate rate will exceed the maximum operating temperature is calculated by employing the given relationship [1, 74]:

\[ P\left( T_{\text{max}}^{\text{ex}} | I_{\text{adq}}^{\text{nominated}} \right) = P\left( V_{w}^{\text{ex}}, T_{a}^{\text{ex}}, S^{\text{ex}} \right) \]  

Equation 4-1

Thus, the probability of exceeding a particular \( T_{\text{MAX}} \) for any arbitrarily nominated adequacy (static thermal) rate \( I_{\text{adq}}^{\text{nominated}} \) is realised by accounting for the joint probabilities of exceeding the weather variables in Equation 4-1 [1]. For example the probability of exceeding the \( T_{\text{MAX}} \) rates typified in Table 4-2 is zero because the stipulated weather conditions are assumed to be at their worst case values. Supposing it was required to attain an adequacy of 700 MVA for Plover, the many ways through which this adequacy could be achieved are summarised in Table 4-3; which shows (through the shaded cells) the combinations by which different thermal rating parameters could be probabilistically modified.

Table 4-3 Possible parameters to vary in order to obtain the exceedence for a desired adequacy to maintain reliability

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>2</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Considering combination 1 (in which only the wind speed is probabilistically altered), the wind speed value will be raised to a value that realises the 700 MVA rate (in this case this value changes from 0.61 m/s to 1 m/s). Following this, the weather distribution model representative of the wind speed random variable will be generated. Based on this, the probability of the wind speed being less than 1 m/s will be evaluated and established as the exceedence for the new adequacy rating. Consequently, if this probability is below pre-specified limits this solution will be accepted.

Although, exceeding the operating temperature increases conductor sag as well as ageing, justification for uprating in this manner is accepted when a low probability of switching surge voltages and electromagnetic emissions with worse weather conditions and high current loading is maintained [1, 191, 192]. The data from CAT-1 are used to indicate the probabilistic nature of this rating method (Figure 4-4). The red shade illustrates the probability of experiencing wind speeds of less than 1 m/s while there is negligible probability of exceeding the 40°C ambient temperature as it is the highest measured value.
The resulting temperature distribution to depict the possible temperatures that this Plover conductor could experience (at the selected 700 MVA rate when the wind speed is less than 1 m/s) is shown in Figure 4-5. Operating at 700 MVA will result in a probability of eclipsing the 95°C temperature threshold beyond the red vertical line. This probability value has been computed to be approximately 1.5%. This approach to thermal rating has over past decades gained increased interest. It is termed as the probabilistic thermal rate (PTR) and it is implemented as a static thermal rate (STR) with a calculated and justified % of exceeding its thermal design limits for a given operational period e.g. a year [1].

When using this approach to thermal rating, calculating the ageing of a line is treated as a secondary concern, whereas the earlier risks are treated with preeminent care. Therefore, if the primary risks are deemed acceptable, planners choose to not perform further calculations—including ageing [192].

Table 4-4 is illustrating an example of PTR with the Max.Op.Temp indicting the maximum design temperature; Exc, (in %) being the allowable percentage of exceeding the Max. Op. Temp. value. The four exceedence cases are calculated within the table based on the seasonal weather. In the table Det is the deterministically selected thermal rating value which is used as STR with an
accepted exceedence value of 0.2 %, whereas Prob indicates the PTR value corresponding to its equivalent Exc. Value (see Table 4-4). Planners usually invoke seasonal thermal ratings in order to realise larger thermal capacities during specific periods of the year. In this example it can be seen, however, that STR (i.e., deterministic ratings) are not always risk free and in some cases may be more risky (exceedence-wise and potentially sag-wise) than certain PTR candidates shown in the table. Therefore, STRs must always be evaluated for their inherent risk.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>75°C</td>
<td>0.1</td>
<td>912</td>
<td>1000</td>
<td>1090</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>905</td>
<td>1071</td>
<td>1118</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>989</td>
<td>1105</td>
<td>1153</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>1020</td>
<td>1135</td>
<td>1165</td>
</tr>
</tbody>
</table>

The next section considers the application of the various weather models discussed in chapter 3 to this study. As a side note it must be emphasised that it is possible to increase the details of OHL line construction model to include detailed spatial characteristics of OHLs across their lengths and geospatial regions [59, 133]. However this would overwhelmingly complicate the data acquisition process. Moreover, the consequential analysis and computation times would be escalated. Therefore, this thesis does not engage in the aforementioned modelling. However it must be borne in mind that ageing is spatial; meaning it is not possible to age the entire line circuit at exactly the same rate and magnitude—certain portions will age quicker whereas others will age less and others will not age at all. Research on these spatial aspects has received relatively little attention; however the following resources present interesting pioneering findings on the subject [133]. Combination four from Table 4-3 is employed within this study because the ambient temperature has been generated as an equivalent value at a constant solar radiation value of 14 Watts/m. This constant solar radiation value was arbitrarily set and did not alter the validity of the results.

### 4.2.4 PTR Evaluation Scenarios

As discussed in chapter 3 there are essentially three weather models that could be utilised to perform PTR analysis: the uncorrelated, the correlated and the time-series models. A comparative analysis of these models is necessary in order to select which model to implement into the holistic electro-thermal reliability evaluation tool in order to accurately compute OHL ageing. This section performs this comparative assessment.
4.2.4.1 Uncorrelated Weather Modelling Scenario

Figure 4-6 illustrates the uncorrelated distributions of the effective wind speeds and ambient temperatures spanning the UK’s summer, winter, spring and autumn seasons from data that are obtained from National Grid’s CAT-1 weather instrumentation. The wind distributions in the figure illustrate that the effect of weather instrumentation failures invariably results in altering the naturalistically characterised Weibull wind random variable to either the exponential (during winter and autumn seasons) or the logistic distribution (during summer and spring seasons). Turning attention to the ambient temperature distribution plots, it is noticeable that these follow their expected normal distribution plots, as described by their relevant statistical data. The wind speed and ambient temperature distributions are utilised to evaluate the seasonal exceedence rating probabilities when PTR is implemented for the proposed IEEE RTS adequacy capacity rates in Table 4-2.

This approach is engaged in two stages. The initial stage assumes 0% exceedence based on the seasonal distributions in Figure 4-6 and then evaluates whether the resulting conductor’s $T_{\text{MAX}}$ value is already exceeding its ageing threshold. If it is already exceeding its ageing threshold then the 0% weather exceedence values are ascertained to constitute the assumed weather thermal rating variables. In the second stage, if the aforementioned is not the case, the weather variables will be appropriately manipulated (in accordance with the earlier discussed example in 4.2.3.2) in order to establish an exceedence rate. Therefore, the results in Table 4-5 and 4-6 are illustrative of the manipulated weather exceedence evaluations.

Thus, the subsequent $T_{\text{MAX}}$ exceedence duration values in hours (and their equivalent values in terms of % of exceedence) are recorded in the intimated tables (i.e., the red highlights for the duration and the black text for the % of exceedence). It is clear from both tables that the winter season experiences more $T_{\text{MAX}}$ exceedence durations, and this result is, in part, due to the higher number of instrumentation failures in the winter season than any other season. This is because during these instrumentation-based failure events, the wind speed is recorded as 0 m/s and/or the ambient temperature is recorded at the maximum expected seasonal value, for each season.
The total annual exceedence for the 230kV section at 600 MVA is 60 hours and at 625 MVA is 66 hours. This difference is evident because a higher wind speed rate had to be assumed in order to attain the 625 MVA rate, according to the earlier given example in 4.2.3.2. The total exceedence values for the 138kV section Drake at 208 MVA is 50 hours whereas at 220 MVA, this value is 56 hours.

<table>
<thead>
<tr>
<th>Adequacy Rate MVA</th>
<th>$T_{\text{MAX}}$</th>
<th>Exc. Hrs Summer</th>
<th>Exc. Hrs Autumn</th>
<th>Exc. Hrs Winter</th>
<th>Exc. Hrs Spring</th>
<th>Exc. Hrs Annual Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hrs</td>
<td>%</td>
<td>Hrs</td>
<td>%</td>
<td>Hrs</td>
</tr>
<tr>
<td>500 95°C</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>600 15 0.68</td>
<td></td>
<td>15</td>
<td>0.68</td>
<td>5</td>
<td>0.23</td>
<td>37</td>
</tr>
<tr>
<td>625 18 0.82</td>
<td></td>
<td>18</td>
<td>0.82</td>
<td>7</td>
<td>0.32</td>
<td>37</td>
</tr>
</tbody>
</table>

Table 4-6 Uncorrelated weather exceedence thermal rates for the 138 kV Drake IEEE RTS conductor

<table>
<thead>
<tr>
<th>Adequacy Rate MVA</th>
<th>$T_{\text{MAX}}$</th>
<th>Exc. Hrs Summer</th>
<th>Exc. Hrs Autumn</th>
<th>Exc. Hrs Winter</th>
<th>Exc. Hrs Spring</th>
<th>Exc. Hrs Annual Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hrs</td>
<td>%</td>
<td>Hrs</td>
<td>%</td>
<td>Hrs</td>
</tr>
<tr>
<td>175 75°C</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>208 11 0.50</td>
<td></td>
<td>11</td>
<td>0.50</td>
<td>3</td>
<td>0.14</td>
<td>35</td>
</tr>
<tr>
<td>220 14 0.64</td>
<td></td>
<td>14</td>
<td>0.64</td>
<td>5</td>
<td>0.23</td>
<td>35</td>
</tr>
</tbody>
</table>

### 4.2.4.2 CORRELATED WEATHER MODELLING SCENARIO

Chapter 2 discussed that non-correlated distributions are less accurate because they omit to account for the inherent correlation between the wind and temperature distribution. To investigate this effect, the correlation weather model is employed in this section. The generation of the correlated distributions for the effective wind and ambient temperature variables was realised through the computation of multi-variate analysis of the CAT-1 data within Matlab. Consequently, the output data is represented as contour plots in Figure 4-7; with the four plots representing the four seasons. The resulting exceedence values are tabulated in Table 4-7 and Table 4-8.

The correlations between the effective wind and ambient temperature observations are realised by computing the covariance matrix for these two observed signals. The covariance matrix is analogous to the variance of a univariate distribution. Therefore, the covariance matrix is a useful indicator of how much a multivariate distribution will vary based on the combined observances of
these two signals (i.e., wind and ambient temperature). Consequently, when tables 4-7 and 4-8 are compared with tables 4-5 and 4-6, it is clear that accounting for the correlation between variables will lower the total expected exceedence duration.

Figure 4-7 Multi-variate probability distribution contour plots of the seasonal relationship between wind speed and ambient temperature having accounted for instrumentation failures

Table 4-7 Correlated weather exceedence thermal rates for the 230kV Plover IEEE RTS conductor

<table>
<thead>
<tr>
<th>Adequacy Rate MVA</th>
<th>$T_{\text{MAX}}$</th>
<th>Exc. Hrs Summer</th>
<th>Exc. Hrs Autumn</th>
<th>Exc. Hrs Winter</th>
<th>Exc. Hrs Spring</th>
<th>Exc. Hrs Annual Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hrs</td>
<td>%</td>
<td>Hrs</td>
<td>%</td>
<td>Hrs</td>
</tr>
<tr>
<td>500</td>
<td>95°C</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>600</td>
<td></td>
<td>9</td>
<td>0.41</td>
<td>0</td>
<td>0.00</td>
<td>28</td>
</tr>
<tr>
<td>625</td>
<td></td>
<td>9</td>
<td>0.41</td>
<td>0</td>
<td>0.00</td>
<td>28</td>
</tr>
</tbody>
</table>

Table 4-8 Correlated weather exceedence thermal rates for the 138 kV Drake IEEE RTS conductor

<table>
<thead>
<tr>
<th>Adequacy Rate MVA</th>
<th>$T_{\text{MAX}}$</th>
<th>Exc. Hrs Summer</th>
<th>Exc. Hrs Autumn</th>
<th>Exc. Hrs Winter</th>
<th>Exc. Hrs Spring</th>
<th>Exc. Hrs Annual Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Hrs</td>
<td>%</td>
<td>Hrs</td>
<td>%</td>
<td>Hrs</td>
</tr>
<tr>
<td>175</td>
<td>75°C</td>
<td>0</td>
<td>0.00</td>
<td>0</td>
<td>0.00</td>
<td>0</td>
</tr>
<tr>
<td>208</td>
<td></td>
<td>7</td>
<td>0.32</td>
<td>0</td>
<td>0.00</td>
<td>20</td>
</tr>
<tr>
<td>220</td>
<td></td>
<td>7</td>
<td>0.32</td>
<td>0</td>
<td>0.00</td>
<td>20</td>
</tr>
</tbody>
</table>

Moreover, it is observable that there is no recorded exceedence during the spring season for tables 4-7 and 4-8 because there is no possibility of jointly experiencing ambient temperatures.
above 12°C and wind speeds below 0.5 m/s. As a result, these aforementioned conditions constitute the worst case weather variables for the spring season, and, subsequently, the conductor temperatures remain below 95°C for Plover and below 75°C for Drake. Therefore, by invoking similar analysis as that of tables 4-5 and 4-6, the final exceedences recorded through tables 4-7 and 4-8 is realised—including their total annual exceedence hours.

### 4.2.4.3 TIME SERIES WEATHER MODELLING SCENARIO

The ARMASA is a suite of programs [186] specifically designed to optimally compute ARMA models. It is most fully representative of an input signal was utilised to develop the ARMA models for both the effective wind speed and ambient temperature data series. ARMASA is designed to utilise various Matlab statistical tool boxes [187] coupled with additional algorithms to enhance the ARMA computations. Consequently, the (optimally) evaluated ARMA model fitting errors are provided in Table 4-9 and Table 4-10. Clearly, it is evident by studying the recorded fitting error percentage values of the aforementioned tables that the ARMA model is not performing well on fitting the data provided to it. The reason for this may be due to the inherent high noise within the weather signals due to instrumentation failures coupled with erroneously recorded measurements.

The ARMA model thrives on ascertaining seasonal and cyclic trends within a dataset [141]. It is then possible that the CAT-1 ambient weather data recording failures (due to their random nature) distort these trends and hence turn the model fitting process for the ARMA algorithm into a severe conundrum. Moreover, when tested against data from the *Environment Canada* website [193], the ARMA model was able to reproduce a model with 8.9% fitting error. This comparative result therefore emphatically suggests that the CAT-1 data provided was of low quality. However, the fitting errors from the previous uncorrelated and correlated weather distribution studies fell within the range of less than 10%.

<table>
<thead>
<tr>
<th>Temperature Measurement Season</th>
<th>Summer</th>
<th>Autumn</th>
<th>Winter</th>
<th>Spring</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMA Model Fitting Error, %</td>
<td>88.52</td>
<td>19.93</td>
<td>66.5</td>
<td>51.02</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Wind Speed Measurement Season</th>
<th>Summer</th>
<th>Autumn</th>
<th>Winter</th>
<th>Spring</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMA Model Fitting Error, %</td>
<td>47.64</td>
<td>47.62</td>
<td>26.79</td>
<td>42.05</td>
</tr>
</tbody>
</table>
The reason for this higher accuracy stems from the fact that mathematically, distribution functions are designed to solely observe the occurrences of events in a signal; and hence are insensitive to the noise intrinsic to the signal— as the noise too, is part of the observation. Thus, it was judged that the level of error from the earlier computed distributions was acceptable to declare their models worthy of most accurately describing the weather data.

4.3 Electro-thermal Reliability Evaluation Model Validation and Enhancement

Having made the necessary assumptions pertaining to the system conditions to be studied and then having further prepared relevant weather models to aid in calculating thermal ratings during the electro-thermal evaluation process, the next step engages in the testing of the sequential Monte Carlo simulation (SMCS) algorithm tool’s ability to perform electro-thermal reliability evaluation studies. To facilitate this engagement two thermal ratings are considered: thermal rating at 1 pu of the IEEE-RTSs normal rating and a TUS at 1.2 pu of the IEEE-RTSs normal rating.

4.3.1 Case Study-I: Optimising the Monte Carlo’s Electro-thermal Algorithm’s Convergence

Since SMCS algorithms aim to estimate the expected value of a given reliability measurement random variable, it is possible to test the accuracy of the SMCS by checking whether the variance of the reliability measurement random variable lies within specified tolerances [29]. In this study convergence is deemed when the variance of the measured reliability index lies within 5% of the estimated variable [29]. Since the EENS is the epitomical probabilistic index, its variance is measured in this study in order to test the efficacy of the methodology. Results to the performance assessment of the sequential Monte Carlo algorithm are presented in Figure 4-8. The y-axis records the EENS values for two thermal rating values of 1 pu (i.e., the Normal rating provided in Table 4-2) and of 1.2 pu TUS (i.e., the LTE rate provided in the same table) with the light blue and dark blue curves respectively. The x-axis records the number of simulation years.

By observing the figure, it is evident that 2500 crude simulations are computed to in order to notice a flattened line indicating the EENS variance is within acceptable tolerances. Further careful observation will show that there are moments of premature convergences prior to the 2500 mark; and these are shown by the red vertical intermittent lines in the plot. Therefore, this observation attests to the fact that it is not necessary to run 2500 simulation years since this comes at a high computation cost; as it should be noted that running a single full adequacy evaluation (on a standard desktop computer) at a single thermal rating method through the employment of the crude sampling technique resulted in computation times that lasted on average for about twelve hours with parallel computations, and over a day with singular computation techniques.
This was mainly due to the high computational burden of running both AC power flow and AC OPF algorithms. However, reliability planners usually perform multiple evaluations in order to ascertain reliability trends or to compare various candidate solutions. In this regard, it becomes necessary to realise faster techniques that realise solutions in much less than the quoted times.

To achieve faster convergence, the correlated sampling technique [149, 194] was employed in order to take advantage of the pre-mature convergence points and to thus realise faster execution times—through variance reduction computations. The mathematical formulation and proof for this method is fully presented in Appendix C. Results to this correlated sampling technique against the crude sampling is shown in Figure 4-9, in dictating that the orange line flattens much sooner than the blue one (for 1.2 pu TUS case) over the simulated 850 years shown in the figure.

The observed accelerated convergence was realised due to two factors. Firstly, the evaluated correlation (between the 1 pu and 1.2 pu case in the previous figure) of 0.98 according to the mathematical theory (discussed in Appendix C) guaranteed a fast convergence. Secondly, this convergence (again according to the mathematics) could be further boosted through the application of a variable control variate parameter (discussed in appendix C).

Therefore, the result shown in Figure 4-9 engenders the conclusion that if an initial crude SMCS run is invoked at a given thermal rate, the subsequent (trial run) rates can be computed using this correlated sampling technique; on the basis of the knowledge of the high correlation that exists between different rates. Consequently, through this approach, convergence was arrived at between 400 and 500 simulation years; this is 5 times faster (between 4 and 6 hours) than the subsequent computation times through the employment of the singular computation method.
Figure 4-9 Monte Carlo simulation results using correlated (orange) and crude (blue) sampling technique

Furthermore, in this study, an analysis into the chronological state performance of the system (after the correlated simulation was invoked) was undertaken and results are displayed in Figure 4-10.

Figure 4-10 A state space probabilistic density representation of the occurrences of failure within a given year

The y-axis denotes the probability density of the plots and the x-axis the corresponding hours. This figure illustrates the distribution of the system failures statistically compiled pertaining to the 400 simulation years; and shows that between approximately [0 – 4300] and [4300 – 9000] hours (demarcated by the vertical intermittent line) the contribution to the final adequacy metric of the system was approximately 50:50 on either side—calculated through numerical integration techniques in Matlab.

Therefore, based on these findings, it was appropriate to only sample from either half of the aforesaid hours over the course of the 400-500 simulation years in order to estimate the same adequacy value as that which would have manifested in consequence to a full crude simulation approach—subsequent to the full sampling of the failed states over 8760 hours. Consequently, through the utilisation of the singular computation method, the simulation time was reduced to between 2 and 3 hours. This thereby resulted in the two fold benefit of significantly increasing
computation time whilst at the same time greatly relieving computational resources as the need for parallel computing capability was avoided.

Figure 4-11 illustrates the error recorded due to this sampling approach. Clearly, beyond the 400 simulation year mark, the residual error lies within a 1% band for the approximately 90% of the simulation years indicating that the optimisation algorithm is sampling the state space well enough to fully estimate the system reliability to within the quoted error value. This 1% estimated fluctuation value is due to the inherent imperfection of the Monte Carlo sampling technique itself [29]. It should be unsurprising that the full system reliability index can be represented by this chronologically splitting sampling technique because it can be seen from Figure 4-12 that the chronological load demand repeats twice in a given year. Therefore, an engineer observant to these behaviours can fully justify adopting the speeding up technique presented.

![Figure 4-11 expected index estimation error plot for the chronological splitting technique](image)

**Figure 4-11** expected index estimation error plot for the chronological splitting technique

![Figure 4-12 Chronological representation of the IEEE RTS demand data](image)

**Figure 4-12** Chronological representation of the IEEE RTS demand data

### 4.3.2 Case Study-II: Evaluating the Efficacy of Weather Data Models on Electro-thermal Ageing Indices

In the previous section various weather models were developed and the exceedence durations were calculated. However, these exceedences merely represent the duration of exceeding $T_{\text{MAX}}$
and consequently the resultant ageing amid this duration must be established. Additionally, the weather model that is employed to evaluate ageing must also be accurate—the accuracies of various weather models on the data provided have been engaged in previous sections.

Consequently, in this section, the resultant ageing of the lines when a TUS of 1.2 pu is used has been evaluated and their expected EAI (EEAI) visibility values (in hours) are shown in Table 4-11 (there was no ageing recorded at 1 pu) for the selected lines. The bold values indicate the most critically overloaded lines with the most recorded ageing within the system under the simulated scenario for both correlated and uncorrelated weather variable modelling. Consequently, the table allows for a comparative analysis between the accuracies of employing the uncorrelated and the correlated weather models used to calculate OHL thermal ratings and estimate the expected ageing.

<table>
<thead>
<tr>
<th>Line No.</th>
<th>6</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>23</th>
<th>28</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncorrelated</td>
<td>0.067037</td>
<td>0.024557</td>
<td>0.305008</td>
<td><strong>6.418109</strong></td>
<td>0.451561</td>
<td><strong>19.5684</strong></td>
<td><strong>23.43543</strong></td>
</tr>
<tr>
<td>Correlated</td>
<td>0.057606</td>
<td>0.021102</td>
<td>0.262096</td>
<td><strong>4.655831</strong></td>
<td>0.216169</td>
<td><strong>14.70195</strong></td>
<td><strong>16.64075</strong></td>
</tr>
</tbody>
</table>

It has to be noted that no ageing is recorded when the simulation performed using 1 pu line rating. Therefore, by focussing on results based on the simulations when the lines were rated at 1.2 pu, from the table it is clear that the 230kV section of the test network ages more than the 138kV section because of the increased ageing on lines 23 and 28. The rest of the lines recorded in the table reside within the 138kV. It is further evident from the table that the correlated weather model results to an average 37% reduced ageing when compared to the uncorrelated case. This indicates the significance of considering the weather correlation within the Monte Carlo algorithm in order to efficaciously predict the conductor ageing by considering more realistic weather conditions.

### 4.4 ELECTRO-THERMAL MODELLING FOR THERMAL UPRATING SCENARIOS (TUSs)

Having validated the initial performance of the electro-thermal reliability evaluation tool and discussed recommendations for further computational enhancements, it is then justifiably possible to perform a full range of TUS studies (through their visibility indices). This section exemplifies how a variety of TUS studies can be performed and analysed in order to draw practical applications for power systems. These studies include assessing the benefits (case study-I) and risks (case study-II) as well as risk mitigating solutions (case study-III) for a number of TUSs.
4.4.1 CASE STUDY-I: BENEFITS OF TUSs THROUGH ELECTRO- THERMAL RELIABILITY MODEL

4.4.1.1 STUDY BACKGROUND

In the attempt to employ thermal uprating activities, utilities are afforded with a number of TUSs [1]. In the previous sections, a discussion pertaining to the evaluation of the exceedence rating method as a TUS has been engaged. In addition to this, utilities can choose to employ dynamic thermal rating (DTR) TUS at 0% exceedence or with limited exceedence. Figure 4-13 illustrates the STR (red line), PTR (black line) with a specific risk of exceedance and the DTR (blue line). The black shaded regions indicate the risk of ageing when PTR is considered. The larger the exceedence the larger the risk and therefore the black areas should be evaluated in order to measure an OHLs ageing and determine whether the selected PTR exceedance is acceptable.

![Figure 4-13 Pictorial representation of thermal uprating scenarios](image)

Furthermore by observing the intermittent red line in Figure 4-13, it is immediately obvious that there is a (static) limit to the thermal rating which a system can reliably handle; because the increased levels of thermal rating to support large power transfers largely affect the voltage stability within the system. For this reason it is necessary to cap the maximum power flow or to alter system impedances in order to tap more capacity provided from the different thermal rating methods.

![Figure 4-14 Relationship between dynamic and static thermal limits](image)

Figure 4-14 illustrates this constraint by conveying that there are two limits to consider when transferring power: the static and the dynamic [5]. These are a function of line’s length and consequently, the capping point is that point at which the two trend lines cross as shown in the figure.
From the figure, the static limit relates to the thermal limit of an OHL (as discussed in Chapter 3), whereas the dynamic limit relates to the electrical (more specifically the inductive reactance) characteristic of an OHL as expressed by equation 4-2; where $P$ is the transferable capacity in MWs, $V_s$ is the sending end nominal voltage, $V_r$ is the receiving end nominal voltage of the OHL and $\delta_{sr}$ is the phase angle difference between the sending and receiving ends of the line and $X_{OHL}$ is the inductive reactance of the line which is a function of the OHLs length (as discussed in Chapter 3).

$$P = \frac{V_s V_r \sin(\delta_{sr})}{X_{OHL}}$$

Equation 4-2

### 4.4.1.2 TUSs

In order to better understand the influence of TUS and on network reliability different TUSs case studies shown in Table 4-12 are modelled. Four TUS scenarios are considered with a fifth, case e, being a base case thermal rating characteristic of a non-TUS in order to compare benefits of network performance resulting from the proposed TUSs.

<table>
<thead>
<tr>
<th>Case</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>Thermal uprating via unconstrained DTR at 0% $T_{MAX}$ exceedence</td>
</tr>
<tr>
<td>b</td>
<td>Thermal uprating via constrained DTR (capped at 1.25 pu) with the correlated model based $T_{MAX}$ exceedence</td>
</tr>
<tr>
<td>c</td>
<td>Thermal uprating via unconstrained DTR with the correlated model based $T_{MAX}$ exceedence</td>
</tr>
<tr>
<td>d</td>
<td>Thermal uprating via constrained STR (capped at 1.2 pu) with the correlated model based $T_{MAX}$ exceedence</td>
</tr>
<tr>
<td>e</td>
<td>Thermal uprating via constrained STR (capped at 1 pu) with no $T_{MAX}$ exceedence</td>
</tr>
</tbody>
</table>

### 4.4.1.3 STUDY RESULTS

Tables 4-13 to 4-16 show results pertaining to the network analysis for the stated case studies. The EENS, EFLC, EDLC, PLC and ECOST indices employed to guide the system analysis while the EDEL and EAI visibility operational indices describe the OHL performance. It is interesting to observe from Table 4-13 that although TUS case-c offers the most uprating capacity credit, it does not result in the most adequate operation of the system within the extreme emergency state.

This indicates that attempting to increase adequacy of the lines at 1.25pu results in system voltage constraints that lead to increased load curtailments. TUS case-b, on the other hand, results in the most robust system adequacy operation when compared against the other
competing TUS and non-TUS cases as is shown by both the ECOST and EENS % values. This result further alludes to the notion that it may be beneficial to age the line amid the manifestation of unfavourable weather conditions, because it will improve system adequacy. Therefore, this result justifies the need to invest more in asset management activity solutions (AMASs) that will improve the right-of-way performance of an OHL so as not to experience failures (leading to blackouts due to OHL oversagging) amid the stated operating conditions.

Having compared the system perspective reliability performance of the TUSs and the non-TUS, their ageing performance is compared next. The correlated model was established as most apt to evaluate ageing and thus the results are based on the stated model. From Table 4-14 it can be seen (as expected) that TUS case-b results in the most ageing of the lines.

### Table 4-13 Traditional Reliability Indices

<table>
<thead>
<tr>
<th>Case</th>
<th>EENS MWh/yr</th>
<th>EFLC Occ/yr</th>
<th>EDLC Hrs/yr</th>
<th>PLC</th>
<th>ECOST M$/yr</th>
<th>EENS % improvement</th>
<th>ECAST % improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>2498.45</td>
<td>2.6542</td>
<td>6.8667</td>
<td>0.0007883</td>
<td>2.7405</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>b</td>
<td>2467.45</td>
<td>2.4253</td>
<td>6.4338</td>
<td>0.0007365</td>
<td>2.6943</td>
<td>+1.24</td>
<td>+1.68</td>
</tr>
<tr>
<td>c</td>
<td>3376.65</td>
<td>3.4514</td>
<td>7.4436</td>
<td>0.0008521</td>
<td>3.8659</td>
<td>-26.01</td>
<td>-41.07</td>
</tr>
<tr>
<td>d</td>
<td>2934.65</td>
<td>2.9212</td>
<td>7.1848</td>
<td>0.0008224</td>
<td>3.0375</td>
<td>-17.45</td>
<td>-10.93</td>
</tr>
<tr>
<td>e</td>
<td>8526.86</td>
<td>6.5325</td>
<td>14.2612</td>
<td>0.0016324</td>
<td>5.7669</td>
<td>-235.34</td>
<td>-110.43</td>
</tr>
</tbody>
</table>

TUS case-b and TUS case-d record the same ageing, in spite of the differently evaluated system indices. This is the result of implementation of the minimum thermal rating using the PTR therefore the exceedence (and therefore the ageing) in TUS case-b and TUS case-d is identical. However, the TUS case-b is more reliable than TUS case-d. TUS case-a and TUS case-e do not manifest any ageing because they operate below the ageing temperature threshold.

### Table 4-14 Selected EEAI (Hrs) Visibility Indices

<table>
<thead>
<tr>
<th>Line No.</th>
<th>6</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>23</th>
<th>28</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>b</td>
<td>0.22257</td>
<td>0.21102</td>
<td>0.262096</td>
<td>4.655831</td>
<td>0.216169</td>
<td>14.70195</td>
<td>16.64075</td>
</tr>
<tr>
<td>c</td>
<td>0.07867</td>
<td>0.056437</td>
<td>0.0589778</td>
<td>1.235043</td>
<td>0.0543520</td>
<td>8.95433</td>
<td>11.32424</td>
</tr>
<tr>
<td>d</td>
<td>0.22257</td>
<td>0.21102</td>
<td>0.262096</td>
<td>4.655831</td>
<td>0.216169</td>
<td>14.70195</td>
<td>16.64075</td>
</tr>
<tr>
<td>e</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 4-15 portrays EDEL visibility values which record the total duration the lines are operated above the static maximum continuous rating. As it is expected the recorded values for the non-TUS case-e are zero. By observing lines 23 and 28 for TUS case-b, EDEL exhibits visibility values greater than 90 hours/year. Given the fact, based on the recorded simulated results, that out of this duration the lines age for at least 14 hours per year, the difference between the EDEL (Table
4-15) and the EEAI (Table 4-14) visibility index can be used to establish the ageing resiliency duration: this is approximately 90 hours/year for line 28 and 82 hours/year for line 23.

<table>
<thead>
<tr>
<th>Line No.</th>
<th>6</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>23</th>
<th>28</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>3.0657</td>
<td>3.9865</td>
<td>3.2356</td>
<td>32.0976</td>
<td>7.6548</td>
<td>95.4643</td>
<td>108.6587</td>
</tr>
<tr>
<td>b</td>
<td>2.8644</td>
<td>2.2332</td>
<td>2.8576</td>
<td>30.9243</td>
<td>5.6442</td>
<td>93.6565</td>
<td>106.5433</td>
</tr>
<tr>
<td>c</td>
<td>2.5643</td>
<td>2.2907</td>
<td>2.9672</td>
<td>23.8763</td>
<td>5.6134</td>
<td>82.2332</td>
<td>95.3234</td>
</tr>
<tr>
<td>d</td>
<td>2.8644</td>
<td>2.2332</td>
<td>2.8576</td>
<td>30.9243</td>
<td>5.6442</td>
<td>93.6565</td>
<td>106.5433</td>
</tr>
<tr>
<td>e</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Utilities generally aim to minimise the durations for which lines may be operated above their maximum continuous static ratings. Therefore, the ageing resilience values calculated in the exemplified manner can inform reliability planners of the extra annual existing untapped capacity. However, interpreting this index solely may lead to misleading results. Consider TUS case-a, which exhibits approximately 95 and 108 hours/year of ageing resiliency for lines 23 and 28 respectively. These lines are highly resilient as their recorded ageing is zero. However, the benefit of this resiliency does not result in the best system adequacy performance according to earlier discussed results in Table 4-13. Therefore, the ageing resiliency must be interpreted in unison with the ageing of the lines as well as the corresponding system adequacy credits.

<table>
<thead>
<tr>
<th>Line No.</th>
<th>6</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>23</th>
<th>28</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0.8675</td>
<td>0.6865</td>
<td>0.2565</td>
<td>24.7757</td>
<td>1.6354</td>
<td>89.7182</td>
<td>99.3248</td>
</tr>
<tr>
<td>b</td>
<td>0.8497</td>
<td>0.6286</td>
<td>0.2142</td>
<td>22.3243</td>
<td>1.3423</td>
<td>87.0323</td>
<td>97.3494</td>
</tr>
<tr>
<td>c</td>
<td>0.8125</td>
<td>0.6143</td>
<td>0.1985</td>
<td>17.2463</td>
<td>1.2987</td>
<td>75.9432</td>
<td>86.5432</td>
</tr>
<tr>
<td>d</td>
<td>0.8497</td>
<td>0.6286</td>
<td>0.2142</td>
<td>22.3243</td>
<td>1.3423</td>
<td>87.0323</td>
<td>97.3494</td>
</tr>
<tr>
<td>e</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

These values are nearly as high the EDEL visibility values and subsequently suggest that the most important lines i.e., 12, 23 and 28 do not operate above the maximum continuous rate for more than 2 hours per-overload on average. The EDEL and EFEL visibility indices are valuable to system operators who need to know in advance how often and for how long they can reliably schedule emergency loadings in a given year. At present, operators simply rely on experience to make this decision. However, with the proliferation of uncertainties in demand and generation coupled the increased pressure to increase the utilisation of OHL, the reliance solely on experience to handle new operating situations would be a huge gamble on power system reliability. Therefore, these
newly proposed OHL indices can provide information (to aid in lowering the stresses of power system operators amid these novel operating scenarios) to help the selection of secure operating decisions.

4.4.2 Case Study-II: Risks of TUSs through Electro-thermal Reliability Model
Having studied the benefits of a TUS, this section studies the risk of a TUS and discusses how modelling TUS risks can be implemented into the electro-thermal simulation process.

4.4.2.1 Study Background
Reliability planners consider the reliability evaluation of power systems without considering the impacts of high temperature TUSs on OHL failures within right-of-ways (ROWs). This is because planners assume that it is perfectly maintained. However, this may not always be the case, as was ascertained in the 2003 US blackout post mortem analysis which reported that heavily loaded lines sagged into trees that were over grown [98]. However, it is still possible to reliably operate conductors at high ageing-based TUS temperatures, if these risks can be firstly quantified and then subsequently managed through a proper assessment which aids to guide the correct and economical AMAS implementation [14, 180].

Figure 4-15 typifies the relationship between sag and conductor operating temperature for homogenous (AAC, ACAR and AAAC) and heterogeneous (ACSR) conductor technology types[75]. The behaviour of the homogenous conductor is portrayed by the solid line, whereas the behaviour of non-homogenous type is illustrated by the dotted line. Figure 4-15 (left), typifies that in the attempt to uprate existing OHL conductors beyond their ageing threshold temperature, utilities must account for the limiting effect of conductor sag in order to adhere to statutory static sag limit as shown through the $T_{max}$ plots. Furthermore, Figure 4-15 (right) shows that sag limits are rather dynamic and change with time due to change of objects underneath and/or sideways to the OHL conductor (e.g. new structures, vegetation growth) [1]; as well as the conductor’s ageing over time such that even if it were to be operated at low non-aged temperature’s it would...
yield higher sag values compared to if the conductor was not aged at all [63]. Subsequently, this lower limit increases the risk of infringement at a selected $T_{\text{max}}$. Infringing sag limits corresponds to a system security blackout compromise (as earlier mentioned) and to ameliorate this compromise, either the $T_{\text{max}}$ must be lowered or the dynamic sag limit increased to its static limit through maintenance.

Lowering conductor $T_{\text{max}}$ operation reduces the adequacy of the power system. Consequently, the resulting adequacy at this lowered rating must be measured in order to justify the action of not enterprising in AMASs that enable the increment of the dynamic limit back to its previous static limit. Conversely, if the measured adequacy is established to lie outside acceptable unreliability load curtailment risk limits, the investiture in measures (i.e., optimal AMASs) to increase $T_{\text{max}}$ and the dynamic sag limit (back to its static limit) must be engaged. Examples of typical AMASs include (1) increasing the frequency of OHL ROW trimming and/or (2) increasing the frequency of OHL retensioning and/or (3) implementing OHL reconductoring.

### 4.4.2.2 Increased Failure Rate at Emergency Loading Design

To investigate the effect of increasing $T_{\text{max}}$ on blackout risk reliability, through the illustrations rendered in figure 4-15, the previous uprating scenarios are once again considered. In this scenario, according to Equation 3-5, $\lambda_{e,i}$ variables are stipulated for the emergency loading conditions based on $T_{\text{thresh}} = 95^\circ\text{C}$, $\theta = 1$, $\text{spanfailures\%} = 10$. The $k_{\text{loading\_factor},i}$ is computed based on network power flows and weather conditions evolved within the simulations. The $\alpha_{n,i}$ value for plant ‘$i$’ is evaluated using the reliability data in Appendix A.

### 4.4.2.3 Study Results

The effect of the ROW reliability is evident in Table 4-17 indicating now ‘TUS case-a’ as the best solution. This is because the thermal rating in ‘TUS case-a’ is designed to not operate above its $T_{\text{thresh}} = 95^\circ\text{C}$ value. Moreover, the influence of $\lambda_e$ under these stipulated conditions do not severely compound reliability to the point where any of the TUS cases (b-d) perform worse than not uprating at all; as it has been assumed that $\text{spanfailures\%} = 10$. Earlier results suggested that high frequency emergency loadings do not last longer than 2 hours per occurrence on average. Therefore, only those sampled portions from the $\lambda_{e,i}$ distribution which fail (on average) in less than two hours per occasion are able to compound reliability. Clearly, from the results, it can be inferred that this proportion which fails in less than two hours is low; and that the risk posed by those samples deemed to fail for durations larger than two hours is circumvented because after this time the system no longer needs to schedule emergency loadings.
Therefore, it is necessary for power system operators, when they operate at emergency loading, to forecast and subsequently schedule an emergency rating only if its anticipated time-to-fail will elapse the emergency loading duration. As a result of the impact of $\lambda_e$ on the TUS cases studied, it is unsurprising that the recorded ageing in Table 4-18, in comparison to the earlier case studies (in Table 4-14) drops in all (a-e) cases on average by approximately 19% for line 28, 21% for line 23 and about 57.7% for line 12. Therefore, these results expectedly suggest and hence confirm that as $\lambda_e$ increases, the ageing of the lines is reduced. More explicitly, when $\lambda_e$ increases then there is clearly no benefit from increasing the duration of elevated temperature operation and therefore there is no ageing, but instead there is an increase in EENS (Table 4-17). Therefore, $\lambda_e$ and ageing are mutually exclusive.

In this study it is assumed that utmost only 10% of the system is at risk of $\lambda_e$ based failures. Consequently, it could be clearly envisaged that if certain variables which compound the $\lambda_e$ parameter were to change then the measured reliability indices would most certainly be impacted. The composite $\lambda_e$ parameter is subsumed by many variables. Thus there are many ways to achieve a particular $\lambda_e$ value and these are based on the selected values of the tangible and intangible parameters.

To visualise this dependency a classification tree plot was developed as shown in Figure 4-16. In this figure, the oval shapes are termed as decision nodes and within them are decision questions about either the tangible or intangible parameter values. So, when at any given decision node, the branch protruding to the right implies that the decision outcome is suggestive of a higher value (than the decision node) while the left branch indicates a smaller (than the node) value.
The decision nodes are colour coded to denote their affiliation to one of the tangible or intangible parameters used to aid in computing the composite $\lambda_e$ parameter. This tree displays 10 terminal nodes denoted with the small red circles. The data used to fit this tree are produced by sampling the tangible or intangible parameters from their uniform continuous distribution within the stipulated ranges: the $\%_{\text{span_length}_i} [0 - 1]$ pu; $\beta_i = 1$; $\alpha_{n-i} = [1 - 3]$; $k_{\text{loading_factor}_i} = [0.5 - 3]$. The sample size was 10000. From this sampled size, data mining and learning algorithms (through in-built Matlab functions) were used to then produce the tree with its nodes and branches as shown in Figure 4-16.

The SMCS algorithm is oblivious to the particular tangible or intangible values and is instead more sensitive to the composite value $\lambda_e$ value. Therefore a sensitivity study was engaged on TUS case-d from the previous studies by varying $\lambda_e$ so as to establish its impact on system EENS and ECOST. Table 4-19 presents results to this study and clearly narrates how when the number of $\lambda_e$ failures/hour increases from 0 to 2.0 represents no relationship of OHL loading with failures while
the value of 2 failures/hour represents the increase in failure rate within a given hour due to the critical loading of the OHL. The critical loading of the OHL is by interaction of both the *intangible* and *tangible* factors.

Evidently, from Table 4-19 (as this $\lambda_e$ is varied from 0 to 2.5), the network EENS degrades by a staggering 765.52%. Moreover, beyond the 2 failures per hour mark, the reliability values remain constant; suggesting that all the lines that are at emergency loading fail within the first hour of their operation. This indicates that $\lambda_e$ values greater than 2 failures/hr are not realistic. It should be noted that system planners and asset managers can use these results to engage more efficient dialoguing’s in order to fully understand how different combinations of the tangible and intangible values affect the outputs on system reliability and thereby select appropriate AMASs to mitigate them.

### 4.4.3 Case Study-III: Mitigating the Risks of TUSs through Electro-thermal Reliability Model

There are a number of employable AMASs for mitigating blackout risk and these could be classed into those that require electro-thermal reliability modelling evaluation and those that do not. Reconductoring is an example of an AMAS which requires electro-thermal reliability modelling evaluation, whereas retensioning or ROW tree trimming AMASs do not. These issues and characteristics are further explored within a methodology framework in chapter 5. In this section, however, the aim is to showcase how the reconductoring AMAS can be modelled and investigated through an electro-thermal reliability modelling assessment.

#### 4.4.3.1 Study Background

When attempting to mitigate blackout risk through reconductoring, it is imperative (due to the fact that a plethora of conductor technologies have been designed) to perform comparative assessments in order to properly ascertain which is the optimal conductor to engineer into the power system. When an optimal reconductoring solution for an OHL system is considered, it is done on the basis of a postulated static ground clearance value [5]. Regrettably power system planners do not further investigate the performance of this selected candidate conductor on the whole system’s reliability performance. The comparative analysis currently performed to establish the optimal conductor solely considers plant level and thus excludes system level analysis.
4.4.3.2 STUDY DESIGN

Therefore, in this section the reliability performance evaluations of conductor candidates considered for reconductoring is undertaken. Full description of conductor types and technologies is given in [5, 75]. In this study, only lines 23 and 28 are reconductored as they are the most influential to the reliability of the system. TUS Case-d from the earlier studies is also used here. The conductor technologies compared are the ACSR, ACCC, AAAC and the ACCR.

4.4.3.3 STUDY RESULTS

The first sets of results are collated in Table 4-20. The first row in the table delineates the first five columns which describe various OHL reconductoring options candidate conductor properties: type, weight, diameter, RBS, and sag at EDT. The sixth column (still in the first row) describes the ROW $\lambda_e$ sag threshold value which is determined by considering a 95°C maximum operating temperature of ACSR Plover for the specified OHLs of the RTS network. As it can be noticed, this $\lambda_e$ threshold is a common constraint which all reconductoring candidates must adhere to. The seventh row shows calculated sag values of these candidate reconductoring options. If the values in column seven exceed that of column six, the $\lambda_e$ failure function is triggered. If the values in column seven do not exceed that of column six, then the $\lambda_e$ failure function is not triggered. Either way the corresponding influence of these $\lambda_e$ scenarios on power system-wide reliability are recorded in columns eight (EENS) and nine (ECOST).

<table>
<thead>
<tr>
<th>Cond. type</th>
<th>Weight kgs/Km</th>
<th>Dia, mm</th>
<th>RBS, N (EDT Tension, N)</th>
<th>Sag @ EDT</th>
<th>Sag @ $\lambda_e$ threshold</th>
<th>Sag at $T_{MAX}$ (m)</th>
<th>EENS MWh/yr</th>
<th>ECOST M$/yr</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACSR</td>
<td>2708.9</td>
<td>33.98</td>
<td>214013 (42802)</td>
<td>12.416938</td>
<td></td>
<td>16.190543</td>
<td>3072.07</td>
<td>3.325</td>
</tr>
<tr>
<td>AAAC</td>
<td>2753</td>
<td>41</td>
<td>293880 (44082)</td>
<td>12.25304</td>
<td></td>
<td>15.571543</td>
<td>2934.65</td>
<td>3.040</td>
</tr>
<tr>
<td>ACCC</td>
<td>2210</td>
<td>33.4</td>
<td>204010 (40802)</td>
<td>10.62697</td>
<td></td>
<td>11.02237</td>
<td>2924.75</td>
<td>3.035</td>
</tr>
<tr>
<td>ACCR</td>
<td>2242</td>
<td>34.3</td>
<td>171256 (34251)</td>
<td>12.86568</td>
<td></td>
<td>13.19079</td>
<td>2929.43</td>
<td>3.038</td>
</tr>
</tbody>
</table>

In Table 4-20, the ACSR Plover, AAAC Rubus, the ACCC London and ACCR 1238-T11 are considered as they are very similar to Plover. In the table the sag threshold at $T_{thresh} = 95^\circ$C is recorded in addition to their everyday tension (EDT) sags. By studying the recorded entries in the table it can be witnessed that operating the ACSR conductor at 1.2pu of its nominal thermal rating results in sag infringement, which further translates to an EENS of 3072.07 MWh/yr and a societal cost of 3.325 M$/yr. Since the AAAC obeys this limit, it results in better performance against the ACSR type. However, the ACCC and ACCR types perform marginally better on the merit of their low
reactive power losses. Moreover, when the sag limit drops (under the assumption of a tree overgrowth) by lowering the sag threshold value in Table 4-21, the ACCR conductor now results as the best performer based on the EENS and ECOST values. However, clearly, the ACCC conductor has a much larger sag buffer in comparison to the ACCR conductor. Therefore, the ACCC conductor can hedge against tighter ground clearances much better than its competing counter parts. For this reason it can be selected as the overall best performer.

Table 4-21 Reconductoring case study for $\lambda_e$ temperature threshold of 90°C

<table>
<thead>
<tr>
<th>Cond. name</th>
<th>Weight kgs/Km</th>
<th>Dia, mm</th>
<th>RBS, N (EDT Tension, N)</th>
<th>Sag @ EDT</th>
<th>Sag @ $\lambda_e$ threshold</th>
<th>Sag at $T_{MAX}$ (m)</th>
<th>EENS MWh/yr</th>
<th>ECOST M$/yr</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACSR</td>
<td>2708.9</td>
<td>33.98</td>
<td>214013 (42802)</td>
<td>12.416938</td>
<td>14.99137</td>
<td>16.190543</td>
<td>4145.37</td>
<td>4.264</td>
</tr>
<tr>
<td>AAAC</td>
<td>2753</td>
<td>41</td>
<td>293880 (44082)</td>
<td>12.25304</td>
<td>15.44920</td>
<td>11.02237</td>
<td>2924.75</td>
<td>3.463</td>
</tr>
<tr>
<td>ACCC</td>
<td>2210</td>
<td>33.4</td>
<td>204010 (40802)</td>
<td>10.62697</td>
<td>11.02237</td>
<td>13.19079</td>
<td>2929.43</td>
<td>3.035</td>
</tr>
<tr>
<td>ACCR</td>
<td>2242</td>
<td>34.3</td>
<td>171256 (34251)</td>
<td>12.86568</td>
<td>13.19079</td>
<td>13.19079</td>
<td>2929.43</td>
<td>3.038</td>
</tr>
</tbody>
</table>

This brief study demonstrated here to indicate how OHL designers and system planners can more closely work together to identify the true value of a reconductoring solution. Through this methodology OHL designers can more closely understand how their solutions affect reliability as power system planners compute their proposed solutions in order to test their reliability credits.

4.5 CONCLUDING REMARKS

In this chapter a series of validation exercises (to confirm the applicability of electro-thermal modelling to facilitate power system predictive reliability studies) have been completed. Studies incorporated the OHL conductor construction and weather conditions in the network studies. Weather model comparisons indicated that correlating the weather variables was more accurate exhibiting an error of less than 10% in all studied thermal rating modelling cases.

Monte Carlo method including thermal rating modelling was validated initially proving that it performed well—producing results within 5% tolerance but time consuming. Therefore, the speed of convergence was enhanced through the inclusion of two optimisation methods. The introduction of correlated sampling without altering the expected value computed through the crude method which optimised the computations by a factor of 3 and a chronological splitting method which further halved the computation time. Having validated all aspects pertaining to the espoused electro-thermal reliability model, it was further validated amid a variety of case studies in order to better understand the relationships between thermal rating performance and
reliability. The results proved that indeed certain solutions are more reliable than others—these conclusions were based on interpreting both the visibility and traditional indices.

Therefore, by comparing (the STR, PTR and DTR) TUSs it was found that DTR can theoretically provide more capacity to power systems; however, there are occasions when it increases the risk of system operation. This was more pronounced when the \( \lambda_e \) was modelled as a function of conductor rating, inadequate management of ROWs and/or insufficient sag clearances. Considering these TUSs the system ageing (EEAI) on the network was found to be 0 hours for the STR, 0 hours for the DTR and 38.853 hours for the PTR, with the maximum ageing developed on the line 28 being 16.64 hours. Network performance was improved when a more advanced method of rating is implemented from 8.526 GWh/yr in the base STR scenario to 2.934 GWh/yr (218%) with PTR and 2.498 GWh/yr (233.76%) with DTR TUSs respectively. Finally, it was realised that the increased benefit on network performance (due to applying an exceedence based DTR, recorded at 2.467 GWh/yr) indicates that implementing AMASs to mitigate the effects of the expected ageing could lead to significant improvement on network operating costs as well as its reliability. Thus, the decision to assess the viability of reconductoring AMAS on power system reliability has quantitatively shown the reliability value that the ACCC conductor renders to this system. More explicitly, when compared against both the ACSR and AAAC candidates, the results testified that ACCC was clearly a better performer.

Moreover, measurable correlations between ageing and its relations to EFEL, EDEL, EENS as well as ECOST were undertaken. The results plainly showed positive correlations between the EFEL and EDEL visibility indices and negative correlations between the EENS and ECOST indices. That is, for example, high EENS were recorded when the ageing was low and vice versa. The reliability of ageing was investigated as well. Results to this study showed the exact extent to which the _tangible_ parameters inherent to \( \lambda_e \) (i.e., span length %, \( T_{\text{thresh}} \), \( K_{\text{loading factor}} \) and or \( \alpha_{\text{r}} \)) could ably negatively influence reliability—by up to 765%, depending on certain conditions.

In general, the results stemming from this methodology have proven apt to help planners understand more on OHL conductor performance; and to henceforth propose decisions (based on the methodology) to designers and asset managers in regards to the exact ageing and \( \lambda_e \) value that is required in order to attain a particular system reliability target. Prior to this methodology, the planner’s role in regards to OHL utilisation decision making has been a passive one as historically, OHL designers have suggested ageing values with little understanding of their impact on reliability.
The planning steps which are required in order to select the optimal thermal uprating scenario (TUS) usually involves a joint holistic techno-reliability-economic exercise which most accurately evaluates the cost of ageing and not just its visualised ageing. For a given TUS the technical aspects relate to the electrical, thermal and mechanical aspects of OHL performance. Alongside, the reliability aspects relate to the corresponding system performance. Finally, the economic aspect relates to the costs to be incurred in order to realise a desired system reliability performance improvement (as a result of providing the technical OHL performance improvement). Balancing the technical cost in order to achieve a desired reliability benefit is an antithetical TUS challenge. This means that if investment into this technical cost is lowered then the expected reliability offered (by a utility) to the society at large will too be lowered—and will subsequently imbue high societal economic losses. Although the converse situation will, however, ensure reliability improvement in the provision of electrical energy, it will, nevertheless, also pose the risk of overinvestment and question the economic viability of the utility. Therefore an optimal TUS must be realised.

To realise an optimal ageing flexibility utilisation TUS, a novel holistic techno-economic TUS AMAS process framework incorporating the proposed electro-thermal power system reliability methodology is developed. In this AMAS process, the earlier developed EAI index is employed as a composite index to quantify the system’s OHL electrical, thermal and mechanical performances against mutually exclusive risks related to oversagging (leading to blackout risk) and ageing (leading to early reconductoring risk) while the EENS index is used to quantify the system’s reliability performance. Additional computations are employed to convert both the EENS and EAI indices into their monetary equivalents. The EENS monetary equivalent is retrieved from the design of a performance based regulatory (PBR) framework. EAI monetary equivalents are retrieved from the optimal asset management activity solutions (AMAS) available to mitigate the two aforementioned risks.
5.1 **A Holistic Optimal Ageing Flexibility Utilisation TUS and AMAS Selection Process Using the Electro-Thermal Methodology**

The TUS ageing flexibility utilisation selection process is a multifaceted process in which dialogues and decisions (stemming from various utility personnel) have to be jointly made in order to attain the optimal TUS decision for the lowest AMAS cost. Traditionally, this TUS selection process has been achieved through the EPRI model [1]. The EPRI model has, however, been found to possess some gaps which impede the optimal TUS selection process amid contemporary power system operating environments which are being encumbered with increasing levels of uncertainty. These gaps include (1) a lack of robust power system and OHL operational and reliability indices, and (2) a lack of a robust project costing computational abilities to overcome the inherent uncertainty encumbrances in projects. Thus, in order to fill these gaps, an improved TUS selection process methodology is proposed, and its flow chart depicted in Figure 5-1.

![Figure 5-1 An integrated computational and analytical ageing flexibility utilisation methodology to facilitate thermal uprating](image)

To start with, according to Figure 5-1, TUSs must be defined. TUSs are simply thermal uprating thermal rating candidate values (representable in either in MWs or in p.u.) for either the existing OHL conductors, or for reconductoring AMASs. Clearly, these TUSs are characterised by their inherent TUS capital project AMAS costs as shown above, and these costs are fraught with uncertainties. To account for these uncertainties, in this proposed methodology, distribution uncertainty modelling is undertaken, as shown in the figure. In addition to feeding data into the TUS capital project costs section, TUSs feed TUS candidate rating (as well as their electro-thermal) data into the electro-thermal reliability evaluation methodology (developed in chapter 3). As a result, for each TUS, results characteristic of the system reliability, OHL latent flow and ageing analysis are computed, as shown above.
The ageing indices for the lines in the system are then normalised in order to rank individual OHLs according their contribution made to system reliability improvement and consequently apportioned to each line within an arbitrary system. This ranking index formula is based on evaluating an arbitrary line’s age relative to its system counterparts in order to produce a normalised age. Thus, through this way, which leads to the proper meriting of an arbitrary line, the apportioned gains can be used to fund the required AMAS investment enterprises. These computed data are then, together with the modelled uncertain TUS capital project AMAS costs, used to develop robust decision trees. It is then through these decision trees that the optimally robust TUS and AMAS can be selected.

Mathematically, these processes (Figure 5-1) are defined by Equation 5-1; where Total Benefit Cost\textsubscript{OHL, year, i} is the composite index which represents the total benefit of a TUS solution in year\_i. The Risk Reduction Benefit\textsubscript{OHL, year, i} is characteristic of the OHL apportioned system-wide reliability improvement between an old and a candidate TUS. Its value is a function of the expected reward payment (ERP) from a PBR scheme, as agreed on between the utility and its governing regulator.

\[
Total\ Benefit\ Cost\textsubscript{OHL, year, i} = \left\{ \begin{array}{l}
Risk\ Reduction\ Benefit\textsubscript{OHL, year, i} \\
+\ Generation\ Dispatch\ Value\textsubscript{OHL, year, i} \\
+\ Latent\ Capacity\ Revenue\textsubscript{OHL, year, i} \\
-\ Oversagging\ Risk\ Cost\textsubscript{OHL, year, i} \\
-\ Thermal\ Uprating\ Risk\ Cost\textsubscript{OHL, year, i-1} \\
-\ Reconductoring\ Risk\ Cost\textsubscript{OHL, year, i} \\
-\ Weather\ Data\ Costs\textsubscript{OHL, year, i}
\end{array} \right.
\]

Equation 5-1

The Generation Dispatch Value\textsubscript{OHL, year, i} is the OHL apportioned system-wide reduction in out-of-merit costs minus the potential increase in system losses [174, 175, 195, 196] costs due to a candidate TUS. The Latent Capacity Revenue\textsubscript{OHL, year, i} is the OHL apportioned system-wide revenue which can be received from the market price of electricity, for unlocking more capacity from TUSs (in comparison to the presiding system thermal rating). Therefore, the Risk Reduction Benefit\textsubscript{OHL, year, i}, Generation Dispatch Value\textsubscript{OHL, year, i}, and Latent Capacity Revenue\textsubscript{OHL, year, i} characterise the extrinsic TUS benefit indices of a given TUS. In addition, the OHL apportioned system-wide Oversagging Risk Cost\textsubscript{OHL, year, i}, the Weather Data Costs\textsubscript{OHL, year, i} costs as well as the OHL apportioned Thermal Uprating Risk Cost\textsubscript{OHL, year, i-1} and Reconductoring Risk Cost\textsubscript{OHL, year, i} costs characterise the intrinsic AMAS cost indices for a candidate TUS. Both the extrinsic TUS benefit and intrinsic AMAS cost
indices, discussed in the following sections, are functions of particular prices, such as, the regulatory based maximum reward/penalty value, generation dispatch cost, electricity market price, oversagging risk cost, reconductoring risk cost, and weather data costs. In order to compute the *intrinsic AMAS cost plant* of a candidate TUS, its technical performance data are required alongside with the *extrinsic TUS benefit* influence on system performance data. These *extrinsic TUS benefit* system performance data are then converted to their monetary equivalents.

**5.1.1 System Analysis**

To convert the system delivery point reliability performance to a monetary value, further computations within a performance based regulatory (PBR) framework, illustrated in figure 5-2, should be invoked. This figure is more fully discussed earlier in chapter 2, and at this stage it will suffice to recall that it is composed of three zones defined by a finite linear combination of indicator functions of intervals; with a maximum reward cap interval (i.e., ranging from 0 to point a on the x-axis) and joined (i.e., at point a) to a negative gradient interval line which terminates at the dead zone value (i.e., of 0 pu at point b).

![Figure 5-2 A reward-penalty scheme](image)

The dead zone lasts for an interval which ranges from b to c, and the penalty zone is a mirror image to the reward zone (i.e., ranging from point c to d by a positive gradient function, and finally retains a maximum value beyond point d). The first step, however, requires to plot the finite linear combination of indicator functions of intervals requires the selection of a target risk index (i.e., as shown in the figure within the dead zone), and, then after, the computation of its standard deviation (i.e. S.D, as illustrated in Figure 5-2). These parameters (namely, the maximum reward, a, b, mean targeted value, c, d and maximum penalty) would normally be set through an exchange of discussions between the asset owner and the regulator. Furthermore, as it can be seen from the figure, an intermittent probability distribution function (*pdf*) characteristic of a system performance reliability index is superimposed on this PBR function. Subsequently, transmission asset owners can evaluate an expected reward payment/penalty (*ERP*)
remuneration value for the reliability offered by a candidate TUS by computing the relevant probabilities of the pdf lying within the zones using equations 2-50 to 52, as defined in chapter 2.

Therefore, in the system analysis block (Figure 5-1), the electro-thermal SMCS computational tool earlier developed is employed to more accurately produce distributions about a computed reliability index of interest, and not solely on computing the expected value of a particular reliability index (as was the case in chapter 4). In subsequence to this computation, the Risk Reduction Benefit\textsubscript{OHL, year\_i} can be evaluated according to Equation 5-2; where ERP\textsubscript{new, year\_i} is the value computed due to a new candidate TUS and ERP\textsubscript{old, year\_i} is the value computed due to the present system-wide thermal ratings. Also, in Equation 5-2, π\textsubscript{Max. Reward Cap} is the agreed payment or penalty price resulting from the dialogue between a system OHL network owner and its governing regulator. From this, the OHL apportioned Risk Reduction Benefit\textsubscript{OHL, year\_i} can be evaluated as in Equation 5-3, based on the Normalised Age\textsubscript{OHL, year\_i} evaluated as in Equation 5-4.

\[
\text{Risk Reduction Benefit}_{\text{OHL, year\_i}} = \left( \text{ERP}_{\text{new, year\_i}} - \text{ERP}_{\text{old, year\_i}} \right) \times \pi_{\text{Max. Reward Cap}} \tag{Equation 5-2}
\]

\[
\text{Risk Reduction Benefit}_{\text{OHL, year\_i}} = \text{Risk Reduction Benefit}_{\text{sys, year\_i}} \times \text{Normalised Age}_{\text{OHL, year\_i}} \tag{Equation 5-3}
\]

\[
\text{Normalised Age}_{\text{OHL, year\_i}} = \frac{\text{EEA}_{\text{OHL, year\_i}}}{\sum_{m=1}^{N} \text{EEA}_{\text{OHL, m, year\_i}}} \tag{Equation 5-4}
\]

Furthermore within the system reliability analysis block (Figure 5-1), the Generation Dispatch Value\textsubscript{sys, year\_i} is evaluated by computing the difference between the total system generation dispatch cost (SGDC\textsubscript{new, year\_i}) at the new candidate TUS from the old system conditions (SGDC\textsubscript{old, year\_i}) as shown in Equation 5-5 and apportioned for an OHL as in Equation 5-6. These dispatch costs also account for system losses through the OHLs, which are supplied by increasing the generation output.

\[
\text{Generation Dispatch Value}_{\text{sys, year\_i}} = \left( \text{SGDC}_{\text{new, year\_i}} - \text{SGDC}_{\text{old, year\_i}} \right) \tag{Equation 5-5}
\]

\[
\text{Generation Dispatch Value}_{\text{OHL, year\_i}} = \text{Generation Dispatch Value}_{\text{sys, year\_i}} \times \text{Normalised Age}_{\text{OHL, year\_i}} \tag{Equation 5-6}
\]

5.1.2 OHL Latent Flow Analysis

Alongside the system performance analysis, OHL latent flow analysis also takes place during the electro-thermal SMCS computations. This latent capacity when exploited results in added revenue which mathematically is defined by Equation 5-7. In Equation 5-7, EDEL\textsubscript{new, year\_i} is the expected
THE VALUE AND RISK OF PROBABILISTIC THERMAL UPRATING SCENARIOS ON POWER SYSTEM RELIABILITY

duration of extra loading due to a candidate TUS and $EDE_{\text{year,old}_i}$ is the expected duration of extra loading for the old nominal system case.

$$\text{Latent Capacity Revenue}^{\text{OHL}_{\text{year,old}_i}} = \left( \frac{(EDE^{\text{new}_{\text{year,old}_i}} - EDE^{\text{old}_{\text{year,old}_i}}) \times \pi_{\text{electricity}}}{(EMEL^{\text{new}_{\text{year,old}_i}} - EMEL^{\text{old}_{\text{year,old}_i}}) \times \pi_{\text{electricity}}} \right)$$  \hspace{1cm} \text{Equation 5-7}

Also $EMEL^{\text{new}_{\text{year,old}_i}}$ is the expected magnitude of extra loading due to a candidate TUS, whereas $EMEL^{\text{old}_{\text{year,old}_i}}$ would inevitably relate to a nominal system case. Finally, $\pi_{\text{electricity}}$ is the nominated price of electricity for a given power system market.

5.1.3 OHL AGEING ANALYSIS

TUS risks can be modelled by considering the inherent risks to an existing OHL line due to reconductoring risk which could lead to early reconductoring activities (measured by the $EAI_{\text{max}}$ criterion) and oversagging risk which could lead to increased failures and blackout (measured by the $EAI_{\text{sag age}}$ criterion). Resultantly, each candidate TUS must be evaluated using the electro-thermal reliability evaluation methodology to produce, amongst many indices, the expected EAI (EEAI) visibility index which is then compared against the two mentioned risks in order to evaluate the particular costs associated with each candidate TUS.

This EEAI visibility index must always be evaluated because there is always a risk of exceeding the permitted ageing of an OHL due to oversight or a change in future projected values (e.g. global warming). The impacts of this risk could increase the line failures amid both heavy (i.e., high temperature operation) and low flows (i.e., low temperature operation), when subjected to heavy OHL mechanical loading [14]. Even if this risk is deemed to be low, it must still be ensured that the maximum ageing (i.e. $EAI_{\text{line}} \leq EAI_{\text{max}}$) value is not eclipsed.

Eclipsing this $EAI_{\text{sag age}}$ value would invariably activate the emergency failure rate $\lambda_e$ [197] solely during heavy flows (i.e., high temperature operation). Therefore, clearance buffers and the risks of breaking statutory mandates on electromagnetic fields must be assessed to control $\lambda_e$ [21]. Once any (or all) of these intimated technical risks are assessed, the economic cost associated with mitigating the effects of OHL ageing through various AMASs must be computed. Equation 5-8 presents a conditional equation to assess the $Over\ Sagging\ Risk\ Cost^{\text{OHL}_{\text{year,old}_i}}$ and a maintenance AMAS decision variable ($\lambda_{\text{maint\_decision}}$) is utilised to enable this assessment. This is to say that if $\lambda_{\text{maint\_decision}} = 0$, then the effect of not performing a maintenance AMAS to ameliorate the impact of emergency failure rate $\lambda_e$ due to the $EMEL^{\text{new}_{\text{year,old}_i}}$ exceeding its $EAI_{\text{sag age}}$ is computed and its

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158
associated expected reward payment/penalty, \( ERP^{\text{year_i}} \) (through the aforementioned PBR finite linear combination of indicator functions of intervals).

\[
\text{Over Sagging Risk Cost}^{\text{OHL year_i}} = \begin{cases} 
    ERP^{\text{year_i}} \times \pi^{\text{Max Reward Cap}} & \text{if } \lambda^{\text{maint_decision}} = 0 \\
    \text{Maint}^{\text{OHL Cost}} & \text{if } \lambda^{\text{maint_decision}} = 1 \\
    0 & \text{if } \text{EEAI}_{\text{lag age}} \leq \text{EAI}_{\text{lag age}} 
\end{cases}
\]  

Equation 5-8

This resulting value can then be compared (once multiplied with \( \pi^{\text{Max Reward Cap}} \)) against the cost (i.e., \( \text{Maint}^{\text{OHL Cost}} \)) associated with the decision (i.e., \( \lambda^{\text{maint_decision}} = 1 \)) to invoke a maintenance AMAS; and the cheaper of the two options will be adopted. Moreover, as Equation 5-8 shows, if \( \text{EAI}_{\text{lag age}} \) is not eclipsed then \( \text{Over Sagging Risk Cost}^{\text{OHL year_i}} = 0 \). Thus, in the final remark, it is clear to understand how the knowledge of an accurately computed EEAI visibility index is vital to engage a number of maintenance AMAS technical and financial decisions.

Moreover, the decision to uprate an existing line will include a thorough joints replacement as well as other AMAs, and an empirically evaluated present conductor age analysis and activity [11, 13, 14]. This may either require taking the line out of operation or performing live-line operations in \( \text{year}_{i-1} \) (in readiness for when it would be needed) in order to complete the necessary due diligence and engineering practice. Equation 5-9 is implemented to capture these two decisions and their corresponding AMAS costs. For live-line thermal uprating repair costs value of zero (i.e. \( \text{TURC}^{\text{decision live line}} = 0 \)), then \( ERP^{\text{year_i}} \) cost is computed to evaluate the impact of the line outage due to maintenance on system reliability performance. When \( \text{TURC}^{\text{decision live line}} = 1 \), then the live-line maintenance cost, \( \pi^{\text{OHL Live-Line}} \), is utilised. These two costs are thus compared in order to realise the least costly decision.

\[
\text{Thermal Uprating Risk Cost}^{\text{OHL year_i}} = \begin{cases} 
    ERP^{\text{year_i}} \times \pi^{\text{Max Reward Cap}} & \text{if } \text{TURC}^{\text{decision live line}} = 0 \\
    \text{OHL}^{\text{Live-Line}} \times \pi^{\text{Max Reward Cap}} & \text{if } \text{TURC}^{\text{decision live line}} = 1 
\end{cases}
\]  

Equation 5-9

If \( \text{EAI}_{\text{max}} \) (after considering the simulated predicted EEAI visibility index plus the empirically calculated present line age) is not expected to be eclipsed, then the top formulation in Equation 5-10 is utilised to, nevertheless, compute the cost of ageing (i.e., \( \text{Reconductoring Risk Cost}^{\text{year_i}} \)) in order to account for the increment that the decision to operate at \( \text{EMEL}^{\text{new}} \) for a duration of
EDEL will impose on the annual capital payment (ACP). The ACP is the fixed cost of the OHL throughout its life cycle[82].

\[
Reconductoring Risk Cost_{OHL}^{\text{year}_i} = \begin{cases} 
\left( \frac{EAI_{OHL}^{\text{year}_i}}{EAI_{max}} \right) \times \pi_{\text{Exist}} \times \left( \% \text{Ageing}_{\text{year}_i} \right) & \text{if } EEAI_{\text{Line}} < EAI_{\text{max}} \\
\pi_{\text{Recond}} \times \left( \% \text{Ageing}_{\text{year}_i} \right) & \text{if } EEAI_{\text{Line}} \geq EAI_{\text{max}} 
\end{cases}
\]

Equation 5-10

However, amid its life cycle unforeseen needs (for instance in this study the need to increase to EDEL may require shortening the OHLs life. Subsequently, this will result in the increment of the initial ACP value of the OHL; and this has been captured in Equation 5-10 top. Albeit, if \( EAI_{\text{max}} \) (after considering the simulated predicted \( EEAI_{OHL}^{\text{year}_i} \) plus the empirically calculated present line age) is exceeded then the bottom relationship in Equation 5-10 is utilised in order to implement AMAS reconductoring (a % portion) the OHL with either a like-for-like or with an unlike conductor technology. In Equation 5-10, \( \pi_{\text{Exist}} \) represents the existing ACP cost of the existing conductor, whereas \( \pi_{\text{Recond}} \) signifies the ACP cost of a new conductor which is to be installed in order to complete reconductoring activities.

5.1.4 Uncertainty Modelling of TUS Project Costs and Revenue

Although any distribution of uncertainty can be employed, within this methodology project cost and revenue uncertainties are modelled as normal distributions with the mean (\( \mu \)) representing a nominated (or expected) capital project cost and the standard deviation (\( \sigma \)) to represent the measure of dispersion uncertainty of the capital project cost with respect to its nominated value. Nominated capital project costs can be gleaned from company database websites [188], or from academic publications [1, 2]. The following parameters from Equations 5-1, 5-2, 5-7, 5-8, 5-9 and 5-10 respectively, are modelled with distributions to account for their uncertainties related with weather data cost uncertainty, \( \pi_{\text{Weather Data Costs}} \), needed to compute EEAI visibility index; regulatory uncertainty cost, \( \pi_{\text{Max. Reward Cap}} \), is used in Equations 5-8 and 5-9; electricity price uncertainty, \( \pi_{\text{electricity}} \); maintenance price uncertainty, \( \pi_{\text{Maint Cost}} \); live-line maintenance price uncertainty, \( \pi_{\text{Live-Line}} \); and the fluctuating discount rate \( \pi_{\text{Cond}} \) and the fluctuating conductor prices \( \pi_{\text{ACP}} \).

5.1.5 Robust Decision Tree Analysis

In this methodology, the distributions related to the aforementioned uncertain parameters are sampled in order to evaluate a particular Total Benefit Cost\(^{\text{OHL}}_{\text{year}_i} \) value, according to Equation 5-1. Inevitably, myriad Total Benefit Cost\(^{\text{OHL}}_{\text{year}_i} \) values can be attained. Therefore, to extract the
information required to make informed decisions, the varied outcomes that stem from the various sampled combinations of the aforementioned uncertain parameters can be fitted to a decision tree in order to reproduce a visual display of the varied paths to which the corporate asset manager could consider in order to realise the best candidate TUS investment. The decision trees employed to represent the data are validated by their re-substitution accuracies; i.e., their ability to correctly classify data stemming from this analysis, according to the methodology and practice discussed in [198].

5.2 Test System for the Holistic Optimal TUS and AMAS Selection Process

The application and validation of this methodology is completed on the 24-Bus IEEE-RTS system illustrated in Figure 5-3.
This methodology is holistic in nature and thus it considers concerns of the various stakeholders involved in the process of selecting an optimum TUS, by modelling and producing the key information requisite to foster amicable dialogues between these stakeholders (and thus enable them to quickly come to the most agreeable solution). This is implemented by producing system delivery point risk indices (i.e., the red arrows in Figure 5-3) for a candidate TUS that the asset owner can employ to negotiate PBR reward/penalty schemes available while by producing a variety of OHL performance indices (for each of the labelled blue lines in Figure 5-3). This is in order to ascertain $EAI_{max}$ and/or $EAI_{sag age}^{ONL}$ violations and use then to develop effective risk mitigating solutions for the $EAI_{max}$ and or $EAI_{sag age}^{ONL}$ violations. Consequently, these results can flag up lines (e.g. line 28 in Figure 5-3) with high risk of $EAI_{max}$ and/or $EAI_{sag age}^{ONL}$ violations. In this way lines can be ranked based on their criticality and their treatment prioritised.

5.3 EVALUATION OF THE HOLISTIC OPTIMAL TUS AND AMAS SELECTION ELECTRO-THERMAL METHODOLOGY

In this section the evaluation of the methodology is completed by focussing on the selected indices, namely, those relating to the system and ageing analysis computation block of Figure 5-1. These have been selected to infuse brevity in the discussions whilst still justify the validity of the methodology. This is because the system analysis is able to showcase how the extrinsic TUS benefit indices are assessed, and the ageing analysis is able to showcase how the intrinsic AMAS cost indices are assessed. When uncertainties are considered, however, all the indices described in Equation 5-1 are taken into account during the production of the decision tree analysis presented in 5.3.3. Section 5.3.1 discusses selected system performance analysis indices and 5.3.2 the selected ageing performance index analysis.

5.3.1 CASE STUDY-I: SYSTEM PERFORMANCE ANALYSIS

5.3.1.1 STUDY BACKGROUND

The first study within this section illustrates the communication between the system planner and the corporate asset owner process to optimally select an optimal ageing flexibility utilisation TUS from a list of candidate TUSs (defining the flexible range of ageing space). The planner must propose candidate TUS magnitude values to the corporate asset owner, through calculations of system risk indices (associated with each candidate TUS) within a scheduled reinforcement year. These risk indices presented must be fully inclusive of their inherent distributions. In this study the ENS reliability index is utilised. The list of candidate TUsSs considered are the thermal uprating’s of 1 pu, 1.05 pu, 1.1 pu, 1.15 pu and 1.2 pu of the 24-bus IEEE-RTS’s nominal ratings.
5.3.1.2 STUDY DESIGN
An electro-thermal reliability evaluation simulation is performed on all the five TUS cases. The first TUS simulation run takes 2500 simulation years in order to attain results within 5% covariance error. Consequent TUS simulations, however, were significantly speed up by the application of correlated sampling [149]. Convergence due to this approach was realised at about 500 simulations without affecting the distributions of the computed indices.

Finally, the computed system and OHL performance indices were plotted into distributions fitted to parametric distributions with up to 10% fitting error allowance and used for sequel analysis. The same systemic conditions (i.e., generation, load profiles, conductor construction, weather modelling etc.,) and procedures with those described in chapter 4 are employed.

5.3.1.3 STUDY RESULTS
System simulation is completed for the five competing TUSs with the results illustrated in Figure 5-4. The x-axis shows the energy not served (ENS) index, while the different lines illustrate the probability density functions (pdf) of the ENS values recorded from the simulations of the competing TUSs.

![Figure 5-4 System based ENS reliability index distributions peculiar to each thermal uprating candidate](image)

The table in the figure indicates the legends associated with the competing TUS plots as well as the summarised statistical data describing each pdf. From the results in Figure 5-4 it can be seen that the distributions follow negative exponential trends that corroborate with results in other literature [199-202]. Subsequently, these plots could be initially interpreted by realising that they characterise a highly reliable system than one that would be, for example, characterised by a normal distribution, albeit with the same EENS value. This is because for this (exponentially described ENS trend) system, 37.5% of the time the EENS will be exceeded. However, if these trends followed normal distributions, it would imply that the EENS values would be exceeded 50% of the time. These percentages are derived by computing the integral of the respective exponential and normal distribution functions between the limits ranging from 0 ENS to the
calculated EENS value for an arbitrary TUS. Then subtracting the calculated value from 1, and converting it to a percentage.

Furthermore, a system characterised by a normal reliability distribution may be more robust (when compared with the exponential case) against a total system wide blackout. This is because normal distributions have smaller dispersions (i.e., standard deviations) of observation about their mean values than do the exponential distributions (which are characterised by long tail ends, as the figure shows). In addition, if these (exponential) distributions were to be compared with power law distributions wherein about 20% of the values exceed the EENS; these exponential distributions would narrate a generally comparatively unreliable system. From Figure 5-4, it is also observable that the closer the distribution is to the ordinate the more reliable the system is. In particular this can be seen from the comparison of the 1 pu and 1.2 pu ratings with total 8.52 GWh/y and 2.93 GWh/y EENS respectively.

From the distributions in Figure 5-4 the evaluation of the Value-at-Risk (VaR) index can be used to measure of the probability of exceeding a particular threshold value of a given distribution of the TUS. Analysis based on VaR is commonly used within the financial sector in order to assess risks relevant to asset portfolios [184] and it is adopted within this study as a competent metric that system planners could use to convey information to the asset owners. Thus, the 5% VaR (probability of being exactly equal to or exceeding that value is 5%) for the 1.2 pu thermal uprating case is approximately 8.943 GWh/yr EENS with a 99.971% system reliability. The corresponding values for the 1 pu case are 20.323 GWh/yr at 99.918%. The closest competing case is the 1.15 pu TUS which results to 10.232 GWh/yr at 99.966%.

Thus, clearly, the 1 pu distribution exhibits a much larger variation and consequently, it can be discernibly shown to the corporate asset owner that higher TUSs present systems with indices that gravitate the system closer to their ordinates, through the analysis presented.

An additional benefit stemming from the computation of EENS pdf’s is found in their ability to be utilised within a PBR framework which is then used to evaluate the $ERP_{year,i}^{new}$ values for each competing TUS as discussed in the next case study.

### 5.3.2 Case Study-II: Applying PBR Schemes On TUSs

#### 5.3.2.1 Study Background

In this second study, the communication between the corporate asset owner and the governing regulator is simulated. Contemporarily, this is achieved through the efficient design of a reward-penalty scheme [167] that aims to monetarily compensate the regulated utility (for good
performance) as well as monetarily compensate the society. Social compensation is achieved by
distributing the proceeds accumulated from the process of penalising the utility when its
performance is inadequate to supply demand to the affected delivery points.

5.3.2.2 STUDY DESIGN
The design of an efficient performance-reward scheme is only possible through the computation
of a utility’s risk profile [167]. Thus, the EENS distributions that were estimated in section 5.3.1.3
retain their usage within this study. Moreover, in order to define the reward, dead and penalty
zones, a finite linear combination of indicator functions of intervals must be developed and
superimposed on the earlier discussed utility distribution plots [167]. As aforementioned, the first
step required to plot this function requires the selection of a target risk index. In this study, as an
example it is arbitrarily assumed that the EENS and the standard deviation are equal to the 1 pu
distribution results earlier presented in 5.3.1.3. Following these initial inputs, the finite linear
combination of indicator functions of intervals plot is completed according to Equations 2-49 to 2-
52, reproduced below (Equations 5-11 to 5-14) for convenience.

\[
ERP = \sum_{i=1}^{N} RPS_i \times P_i \tag{Equation 5-11}
\]

\[
P_i = \int_{x}^{x+i} f(x) \, dx \tag{Equation 5-12}
\]

\[
RPS = \begin{cases} 
1 & R_{ind} \leq a \\
(R_{ind} - b) \times \text{Slope}_{ab} & a < R_{ind} < b \\
0 & b \leq R_{ind} \leq c \\
-(R_{ind} - b) \times \text{Slope}_{ab} & c < R_{ind} < d \\
-1 & R_{ind} \geq d
\end{cases} \tag{Equation 5-13}
\]

\[
\text{Slope} = \frac{1 - 0}{(S.D. / 2)} = \frac{2}{S.D.} \tag{Equation 5-14}
\]

5.3.2.3 STUDY RESULTS
Figure 5-5 shows the finite linear combination of indicator functions of intervals (red plot)—in
addition to the distribution plots. This red line represents the computed results characteristic of
the regulator’s acceptable and non-acceptable reliability ranges (due to the initial assumptions
made in 5.3.1.6): i.e., the mean target is specified as ~8.5 GWh/yr; the higher edge of the dead
zone as ~13.5 GWh/yr; the lower end of the dead zone as ~4.6 GWh/yr; the higher end of the
positive ramp function as ~16.5 GWh/yr; and the lower end of the negative ramp function as ~0.5
GWh/yr. Moreover, the range of the maximum gain is a mere ~0.5 GWh/yr whereas the range of the maximum payment is a substantial ~14.5 GWh/yr.

The asset owner can then compute the $ERP_{\text{new,year}_i}^{\text{new}}$ total value for each competing TUS. The ERP loss, gain and total values for each candidate TUS results for this case study are shown in the table in Figure 5-5. The ERP gain values are those solely calculated from the reward region. Similarly, the ERP loss is calculated from the penalty region.

![Figure 5-5 System based ENS pbr computations peculiar to each thermal uprating candidate](image)

Thus, through these $ERP_{\text{new,year}_i}^{\text{new}}$ values, the ramifications of the financial monetary risk performance to the utility (i.e., the ERP loss) and that to the regulator (i.e., the ERP gain payable to the utility) can be most fully understood. Consequently, for a maximum reward-penalty agreement of 1 M$ (by both the regulator and asset owner) the payments of ~0.51M$ for the 1.2 pu case, ~0.50M$ for 1.15 pu, 0.08 M$ for the 1.1 pu case would be resulted. It is evident from the results that in all cases the utility is rewarded, albeit to varying degrees with the best performing candidate TUS being the 1.2 pu case ($ERP_{\text{new,year}_i}^{\text{new,1.2 pu}}=0.5091 \text{ pu/yr}$).

The total resulted benefit of the TUS 1.2 pu case is therefore computed as shown below:

$$ERP_{\text{benefit,sys,year}_i}^{\text{benefit,sys,year}_i} = (ERP_{\text{new,year}_i}^{\text{new,1.2 pu}} - ERP_{\text{old,1 pu}}^{\text{old,1 pu}}) = (0.5091 - 0.0392) = 0.4699 \text{ pu}$$

It must be mentioned that $ERP_{\text{benefit,sys,year}_i}^{\text{benefit,sys,year}_i}$ is minuscule in regard to its sensitivity to the assumed target value from which the PBR finite linear combination of indicator functions of intervals is developed. The disparities in the $ERP_{\text{benefit,sys,year}_i}^{\text{benefit,sys,year}_i}$ are due to the estimation error that occurs during the selection of the bin size on which to calculate the $ERP_{\text{benefit,sys,year}_i}^{\text{benefit,sys,year}_i}$ value. Irrespective of this inherent error, the closeness in the $ERP_{\text{benefit,sys,year}_i}^{\text{benefit,sys,year}_i}$ as the target value is altered within the range [-10% to +10%] of the nominal 8.52 GWh/yr value is clearly shown in Table 5-1 (left column). Therefore, irrespective of the set target index the $ERP_{\text{benefit,sys,year}_i}^{\text{benefit,sys,year}_i}$ is approximately the same and thus justifies the need, irrespective of the set target index, to thermally uprate to 1.2 pu in this case study.
Table 5-1 A sensitivity study on the effect of a selected reliability target on ERP benefits

<table>
<thead>
<tr>
<th>( \text{Benefit}_{\text{sys}} )</th>
<th>( \text{Target Value, MWh/yr} )</th>
<th>( % \text{ Change} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4685</td>
<td>0.5686</td>
<td>10</td>
</tr>
<tr>
<td>0.4624</td>
<td>0.5493</td>
<td>5</td>
</tr>
<tr>
<td>0.4699</td>
<td>0.5091</td>
<td>0</td>
</tr>
<tr>
<td>0.4703</td>
<td>0.4814</td>
<td>-5</td>
</tr>
<tr>
<td>0.4684</td>
<td>0.4672</td>
<td>-10</td>
</tr>
</tbody>
</table>

The assessment of the ageing risks involved with the 1.2 pu TUS should also be considered in order to investigate the investment cost AMASs to mitigate this risk. This is investigated in the next case study. When this risk is not assessed it is difficult to justify any risk mitigating investment; the consequence of which will reduce the system’s reliability, as a result of \( \lambda_e \) effect on cascading failures.

5.3.3 Case Study-III: OHL Ageing Analysis

5.3.3.1 Background
This study illustrates the communication of the key information requisite to engage in a successful dialogue between the system asset planner and the plant OHL designer and asset manager. Historically the data exchange between these two personnel has been sparingly completed; and in most cases OHL designers have provided their advice regarding the ideal TUS based on engineering judgement [1, 76]. This, engineering judgement approach, clouds the true TUS and it’s AMAS from being realised, because a wealth of data is simply not accounted for. In this study this challenge is overcome by the computation of a more accurate EEAI visibility index evaluation; leading to OHL ageing costing of the reconductoring, retensioning, and oversagging risks and their AMAS mitigation technical solution costs.

5.3.3.2 Study Design
During the simulation process for the 1.2 pu TUS, the thermal rating variables are simulated in accordance with the correlated model developed in chapter 4 and utilised to evaluate the ageing within each year for each line of the network. This is denoted as an observational year of ageing. All these observed years are then tabulated and fitted to parametric distributions with a 15% acceptability fitting error limit. The correlated weather variables are implemented assuming a real time thermal rating instrumentation in place.
5.3.3.3 STUDY RESULTS

The EEAI visibility index distributions for all the lines within the IEEE-RTS assuming the 1.2 pu TUS as an ideal scenario from the previous case studies have been computed. Figure 5-6 shows the EEAI visibility index distributions of the seven most critical ones. The bold caption in the figure documents the total network age as well as its standard deviation. The Tables within Figure 5-6 contain the mean and standard deviation values for each critical OHL. From Figure 5-6 it can be concluded that the EEAI visibility index variable follows an exponential distribution (suggesting that it is highly correlated with the earlier discussed delivery point indices), and is not a static value as previously considered (in chapter 4) and suggested in literature [1].

Moreover, the EEAI visibility index values in the plot are the expected EAI values and their corresponding standard deviations. Lines 12, 23 and 28 are described by distributions spread across a wider range of observable ages (i.e., beyond 10 hrs/yr for example) in comparison to the rest of the lines. For the rest of the lines, the probability of observing an ageing value of more than 10 hours per year is nil. It is important to clearly show results such as these (Figure 5-6) to OHL designers as these results would aid to justify the retro-designing of certain structures of the OHL system by for example increasing tower heights in order to increase the $EAI_{\text{agg age}}^{\text{OHL}}$ limit as well as other options narrated in [10], which can also be easily motivated by the results presented in Figure 5-6.

From these distributions, as well, the probability/risk of an OHL being either an asset or a liability can be computed for the first time. Consider that an OHL is designed for 30 years and has a maximum EAI value (i.e., $EAI_{\text{max}}$) of 1000 hours at a specified temperature. The annual allowable age per year is therefore ~ 33 hours/year (i.e., 1000/30). Consequently, an OHL is considered as an asset if its incurred age in a given operational year falls below (or equal to) this 33 hours/year value, as it does not increase its initial ACP value. Above this value, however, it is (initially) a liability and can only be deemed as an asset if the extrinsic benefit it provides to the system is far
greater than the increase it renders to its ACP value. Therefore, the distribution plots to lines 23 and 28 can be evaluated to ascertain exactly the probability of exceeding 33 hours per year; which in this case are 10.59% and 13.7% respectively. Considering the high $ERp_{\text{Benefit}}^{\text{sys}} = 0.4699 \text{ pu}$ benefit earlier computed these lines can be considered assets (as further results in 5.3.3 will confirm). Generally, it can be concluded that as long as the maximum EEAI is known and the EEAI distribution is known, its probability of being a liability (for a given line within a given predicted operational year) can be computed.

These recorded ageing values are only possible if blackout risk is mitigated. The mitigation of blackout risk is possible through the implementation of particular AMASs which must be applied on a line by line case. As shown in Figure 5-6, and expectedly so, different OHLs incur different ages in their bid to contribute to the reliable provision of electrical energy. Therefore, the contributed benefit (by each individual OHL) to system reliability improvement must be apportioned. Thus according to Equation 5-3, the EPR benefit of 0.4699 pu calculated in 5.3.1 must be apportioned to each line based on the amount of EEAI incurred (Figure 5-6) as shown in Table 5-2. This approach will aid to solve disputes that could potentially arise if these lines are owned by a number of asset owners. Resultantly, each owner could be compensated according to the portion of line aged relative to the other lines within the system.

<table>
<thead>
<tr>
<th>OHL</th>
<th>Normalised Age, pu</th>
<th>Apportioned Risk Reduction Benefit, pu</th>
<th>OHL</th>
<th>Normalised Age, pu</th>
<th>Apportioned Risk Reduction Benefit, pu</th>
</tr>
</thead>
<tbody>
<tr>
<td>28</td>
<td>0.4200</td>
<td>0.1974</td>
<td>11</td>
<td>0.0069</td>
<td>0.0032</td>
</tr>
<tr>
<td>23</td>
<td>0.3700</td>
<td>0.1738</td>
<td>10</td>
<td>0.0055</td>
<td>0.0258</td>
</tr>
<tr>
<td>13</td>
<td>0.0078</td>
<td>0.0037</td>
<td>6</td>
<td>0.0058</td>
<td>0.0027</td>
</tr>
<tr>
<td>12</td>
<td>0.1200</td>
<td>0.0564</td>
<td>Rest</td>
<td>0.0641</td>
<td>0.0301</td>
</tr>
</tbody>
</table>

These resulting values in Table 5-2 can then be utilised to evaluate the Total Benefit Cost $OHL_{\text{Benefit}}^{\text{sys}}$. The next study will compute Total Benefit Cost $OHL_{\text{Benefit}}^{\text{sys}}$ related solely to line 28 for exemplary purposes, as it has been isolated to be the described by the highest apportioned ERP from Table 5-2. In this sequel study the aim is to investigate conditions which result in a positive i.e., $Total Benefit Cost_{\text{Benefit}}^{\text{sys}} \geq 0$ score.
5.3.4 CASE STUDY-IV: ROBUST DECISION TREE AMAS FINANCIAL ANALYSIS TO MITIGATE BLACKOUT RISK

5.3.4.1 STUDY BACKGROUND

In order to compute the total benefit cost \( C_{\text{OHL,year}}^{\text{Total Benefit}} \), for the 1.2 pu TUS implementation on line 28 both the electro-thermal and the financial parameters have to be computed in order to evaluate the seven \( C_{\text{OHL,year}}^{\text{Total Benefit}} \) sub-indices defined in Equation 5-1. Table 5-3 shows the various electro-thermal and financial parameters as earlier defined in Equations 5-1 to 5-10 which are related to one of the seven the sub-indices of Equation 5-1. Particularly, it can be seen that electro-thermal parameters can be sub-divided into seminal and conditional parameters. The seminal electro-thermal parameters are tied to the extrinsic TUS benefit sub-indices, index 1, 2, 3a and 3b in the table. The conditional electro-thermal parameters are tied to the intrinsic AMAS cost sub-indices based on the decision parameters earlier discussed in Equations 5-8 to 5-10 and are indices 4a, 5a and 6a.

**Table 5-3 A complete list of the total benefit cost electrothermal and financial parameters**

<table>
<thead>
<tr>
<th>Index no.</th>
<th>Total Benefit Cost(^{\text{year,}}) Sub Index</th>
<th>Electro-thermal parameters</th>
<th>Financial parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Risk Reduction Benefit(^{\text{year,}})</td>
<td>( ERP_{\text{new,year,}} )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>2</td>
<td>Generation Dispatch Value(^{\text{year,}})</td>
<td>( SGDC_{\text{new,year,}} )</td>
<td>( \pi_{\text{electricity}} )</td>
</tr>
<tr>
<td>3a</td>
<td>Latent Capacity Revenue(^{\text{year,}})</td>
<td>( EDEL_{\text{new,year,}} )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>3b</td>
<td>Latent Capacity Revenue(^{\text{year,}})</td>
<td>( EMEL_{\text{new,year,}} )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>4a</td>
<td>Oversagging Risk Cost(^{\text{year,}}) ( \lambda_{\text{maint,decision}} = 0 )</td>
<td>( n/a )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>4b</td>
<td>Oversagging Risk Cost(^{\text{year,}}) ( \lambda_{\text{maint,decision}} = 1 )</td>
<td>( n/a )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>5a</td>
<td>Thermal Uprating Risk Cost(^{\text{year,}}) ( \lambda_{\text{TURC,decision}} = 0 )</td>
<td>( n/a )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>5b</td>
<td>Thermal Uprating Risk Cost(^{\text{year,}}) ( \lambda_{\text{TURC,decision}} = 1 )</td>
<td>( n/a )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>6a</td>
<td>Reconductoring Risk Cost(^{\text{year,}}) ( EEAI_{\text{line}} &lt; EEAI_{\text{max}} )</td>
<td>( n/a )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>6b</td>
<td>Reconductoring Risk Cost(^{\text{year,}}) ( EEAI_{\text{line}} \geq EEAI_{\text{max}} )</td>
<td>( n/a )</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>7</td>
<td>Weather Data Costs</td>
<td>( n/a )</td>
<td>( \pi_{\text{Weather Data Costs}} )</td>
</tr>
</tbody>
</table>

In this case study, the total benefit cost \( C_{\text{OHL,year}}^{\text{Total Benefit}} \) for line 28 is calculated by considering only the seminal electro-thermal parameters (i.e., index no’s 1, 2, 3a and 3b in Table 5-3) and their relevant financial parameters as well as the relevant financial parameters of the intrinsic AMAS costs. By omitting the electro-thermal influence of the intrinsic AMAS costs, it is assumed the Boolean decisions have been made according to Table 5-4, and this means index no’s 4a, 5a and...
6a are evaluated as shown by the dark purple highlights Table 5-3. The highlighted indices in Table 5-3 only depend on capturing the financial parameters and not electro-thermal parameters. These financial parameters capture the cost of implementing AMASs (i.e., live-line reconductoring, ROW and retensioning) to realise the benefits of the 1.2 pu TUS that have been previously studied and narrated.

Table 5-4 Boolean table of AMAS decisions

<table>
<thead>
<tr>
<th>Decision Parameter</th>
<th>TURC \text{live line}</th>
<th>EEAI \text{Line} &lt; EAI_{\text{max}}</th>
<th>\lambda_{\text{EAI}}</th>
<th>\mu_{\text{EAI}}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boolean Value</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

5.3.4.2 STUDY DESIGN

The previous case studies have been completed by considering the electro-thermal \textit{extrinsic TUS benefit} analysis. Therefore, from the system analysis the indexes 1 and 2 in Table 5-3 have been computed while from the OHL latent analysis the indexes 3a and 3b in Table 5-3 have been evaluated. Finally, the OHL ageing analysis has identified the EEAI. The next step prior to computing the \textit{Total Benefit Cost}_{\text{OHL,year}_i} requires computing the \textit{intrinsic AMAS financial parameters} in Table 5-3. Since these parameters are highly uncertain, it is prudent to model their distributions of uncertainty.

The parameters in Table 5-5 have been modelled as normal distributions with the mean (\(\mu\)) representing a nominated (or expected) capital project cost and the standard deviation (\(\sigma\)) to represent the measure of dispersion uncertainty of the capital project cost with respect to its nominated value. Nominated capital project costs were gleaned from company databases [188] and academic publications [1, 2]. As can be noticed in the table, a large dispersion in \(\sigma\) was considered in order to capture a wide range of scenarios.

Table 5-5 Input data of financial parameter distributions

<table>
<thead>
<tr>
<th>Financial Parameter</th>
<th>mean ((\mu))</th>
<th>standard deviation ((\sigma))</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\pi_{\text{Max Reward Cap}}) (M$)</td>
<td>5.0</td>
<td>1.0</td>
</tr>
<tr>
<td>(\pi_{\text{electricity}}) (M$)</td>
<td>0.025</td>
<td>0.01</td>
</tr>
<tr>
<td>(\pi_{\text{TU,Cost}}) (M$)</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>(\pi_{\text{TU,Cost}}) (M$)</td>
<td>0.3</td>
<td>1.0</td>
</tr>
<tr>
<td>(\pi_{\text{Weather Data}}) (M$)</td>
<td>0.096</td>
<td>1.0</td>
</tr>
<tr>
<td>(\pi_{\text{Costs}}) (M$)</td>
<td>0.1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

In this analysis, the distributions related to the parameters in Table 5-5 are sampled in order to evaluate a particular value that is purely reflective of the \textit{Total Benefit Cost}_{\text{OHL,year}_i}. Moreover, the
sampling of these values does not account for correlation between these financial parameters, simply because these plants are not correlated. For each sample, a particular \( \text{Total Benefit Cost}_{\text{OHL, year}_i} \) is attainable; and subsequently, myriad \( \text{Total Benefit Cost}_{\text{OHL, year}_i} \) values can be attained. Moreover, the varied outcomes that stem from sampling the \( \text{Total Benefit Cost}_{\text{OHL, year}_i} \) financial parameters can be fitted to a decision tree in order to reproduce a visual display of the varied paths to which the corporate asset manager could consider in order to better understand the varied influences of the parameters in Table 5-5 on the \( \text{Total Benefit Cost}_{\text{OHL, year}_i} \). Consequently, by sampling the parameters in Table 5-5, 5000 \( \text{Total Benefit Cost}_{\text{OHL, year}_i} \) samples were computed which are produced using a decision tree plot to convey the results of this study [198].

5.3.4.3 STUDY RESULTS

Figure 5-7 illustrates the decision tree plot of this study. The oval shapes are termed as decision nodes and within them are decision questions [198]. These decision nodes are colour coded and exemplified in the key provided in the figure to denote their affiliation to one of the \( \text{Total Benefit Cost}_{\text{OHL, year}_i} \) sub-indices. Moreover, this tree has been pruned, to aid readability, to display only 16 terminal nodes i.e., the small circles in the plot. The accuracy of this tree at this pruned state is 99.68%, which is an exceedingly high level of accuracy [198]. The maximum number of terminal nodes computable is 24 as is shown in Table 5-6. The re-substitution error points to the error with which the tree is able to classify the data it is representing. The black circles in the tree represent the most probable decision outcome at that node whereas the red circles represent the definite decision outcome.

Having validated its accuracy, it can be confidently stated that this tree is a reliable source on which to study the strategic decisions available to the corporate asset owner. So, when at any given decision node, as shown in the figure, the branch protruding to the right of that node implies that the decision outcome is suggestive of a value that is higher than that within the decision node. Conversely, the branch protruding to the left of any decision node is indicative of a value less than the one within the node. Corporate analysts are always interested in realising the number of ways to achieve a positive i.e., \( \text{Total Benefit Cost}_{\text{OHL, year}_i} \geq 0 \) value. Out of the 16 terminal nodes, 8 achieve the acceptance status, (noted with ‘A’ in Figure 5-7) because they record a \( \text{Total Benefit Cost}_{\text{OHL, year}_i} \geq 0 \) and the other 8, the rejection status, (noted with ‘R’ in Figure 5-7) because they record a \( \text{Total Benefit Cost}_{\text{OHL, year}_i} < 0 \). Of the 8 ‘A’ terminal nodes one node is probabilistic (black circle). This means if the branch protruding from that node were to be investigated there would be some decisions node values that would result in rejection in the final analysis.
Therefore, it can be seen that one definite path out of the 7 to achieve an ‘A’ status path requires ensuring that the Reconductoring Risk Cost^{OHL}_i is less than 111 k$. In addition, the maximum Risk Reduction Benefit^{OHL}_i must not be less than 733 k$. This is, however, dependent on the fact that the Thermal Uprating Risk Cost^{OHL}_{i-1} be utmost 597 k$ and the Oversagging Risk Cost^{OHL}_i be utmost 546 k$. However, in case Risk Reduction Benefit^{OHL}_i is less than 733 k$, then asset owner must ensure that Oversagging Risk Cost^{OHL}_i and Thermal Uprating Risk Cost^{OHL}_{i-2} do not exceed 232 k$ or 11.2 k$ respectively. Clearly, since only one example has been discussed, a number of other alternative options could be explored as the figure demonstrates, and hence easing the difficulty of contending with uncertainties inherent in project expenses.

Figure 5-7 A holistic thermal uprating strategic decision making tree plot

Table 5-6 Rank table of the number of decision terminal nodes against their relative errors for holistic case

<table>
<thead>
<tr>
<th>Number of terminal nodes</th>
<th>1</th>
<th>4</th>
<th>7</th>
<th>9</th>
<th>16</th>
<th>18</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>Re-substitution Error, %</td>
<td>78.34</td>
<td>30.45</td>
<td>0.56</td>
<td>0.48</td>
<td>0.32</td>
<td>0.28</td>
<td>0.22</td>
</tr>
</tbody>
</table>
The decision tree results studied in this section can be compiled into a TU project ledger which the asset owner must present to the regulator in order to discuss the provisional receipt of a \( \text{Risk Reduction Benefit}^{\text{Line}_{\text{year},i}} \) payment. The decision trees utilised in these studies are able to suggest a number of plausible alternative regulator provisional \( \text{Risk Reduction Benefit}^{\text{Line}_{\text{year},i}} \) payment schemes. In so doing this approach aids to facilitate the fullest possible transparent disclosure of options; which is a key requisite to engender the regulator’s interest in dialoguing—to ensure that they do not over, but rather, rightly compensate the utility.

Therefore in addition to the regulator dialogue, these decision trees are robustly useful when the asset owner is negotiating contracts with external companies (e.g. for live-line reconductoring [2]); as they help to ensure that negotiation is engaged in a strategic manner that helps the asset manager adhere to its strategic corporate goals.

### 5.4 Electro-thermal AMAS Effects on Robust Decision Tree AMAS Financial Analysis

AMASs can either have a negative effect or a positive effect on the electro-thermal reliability performance on power system reliability. As the previous study has shown, the selected AMASs did not have a negative effect on the electro-thermal power system reliability (and hence financial) performance as live-line reconductoring, ROW and retensioning AMASs (i.e. the options earlier studied according to Table 5-4) have the effect of securing the reliability of an OHL and thus effectively mitigating blackout risk.

However, it is also worth to study the negative effects of certain AMASs on power system reliability in order to compare the performances of all possible AMASs on an objective basis. In this section, various AMAS cases are considered, as shown in Table 5-7. In each of the cases, investigations into how they affect the \( \text{Total Benefit Cost}^{\text{OHL}_{\text{year},i}} \) decision tree output for line 28 on the basis of the highlighted and bolded Boolean values shown in Table 5-7 are investigated.

<table>
<thead>
<tr>
<th>Case Study</th>
<th>( \text{TURC}_{\text{live line}} )</th>
<th>( \text{EEAI}<em>{\text{Line}} &lt; \text{EAI}</em>{\text{Line}} )</th>
<th>( \text{maint decision} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case Study 1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Case Study 2</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Case Study 3</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
5.4.1 Case Study-I: Effect of Electro-thermal Based Maintenance Outage Cost on Robust Decision Tree AMAS Financial Analysis to Mitigate Blackout Risk

5.4.1.1 Study Background

A line can either have implemented on it an AMAS which takes it out of service for a given duration of time or have a live-line AMAS to allow the TU project to be completed. Both approaches are characterised by their respective Thermal Uprating Risk Cost values. However, taking a line out of service imposes a very direct risk to system operation; and, therefore, based on this planners must quantify the true risk in order to implement solutions that would minimise interruption cost (such as increasing man-power if live-line work is not desired).

In the previous analyses this line outage cost is considered to be zero as live-line AMAS was instead adopted. In terms of the Total Benefit Cost index, the cost 5a instead of 5b (as was earlier assumed in the previous study in 5.3.3.) is assumed as highlighted in Table 5-8.

Table 5-8 A complete list of the total benefit cost electrothermal and financial parameters

<table>
<thead>
<tr>
<th>Index no.</th>
<th>Total Benefit Cost_{OHL}^{year_i}</th>
<th>Sub Index</th>
<th>Electro-thermal parameters</th>
<th>Financial parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>5a</td>
<td>Thermal Uprating Risk Cost_{OHL}^{year_i-1} ( \text{TURC}_{\text{decision live line}} = 0 )</td>
<td>( \text{ERP}_{\text{sys outage year_i-1}} )</td>
<td>n/a</td>
<td>( \pi_{\text{Max. Reward Cap}} )</td>
</tr>
<tr>
<td>5b</td>
<td>Thermal Uprating Risk Cost_{OHL}^{year_i-1} ( \text{TURC}_{\text{decision live line}} = 1 )</td>
<td>n/a</td>
<td>n/a</td>
<td>( \pi_{\text{sys outage year_i-1}} )</td>
</tr>
</tbody>
</table>

Therefore, this section, investigates the effect of performing an electro-thermal evaluation to the maintenance outage cost of line 28 (based on the thermal uprating decision to not adopt live-line work). As Table 5-8 (which is an excerpt from Table 5-4) shows, in the dark purple highlight, this requires calculating the \( \text{ERP}_{\text{sys outage year_i-1}} \) value, which requires performing an electro-thermal reliability simulation. From this simulation, the \( \pi_{\text{Max. Reward Cap}} \) from Table 5-5 of the previous case study from section 5.3.3 is reused, as are the rest of the parameters from the previous case study, to produce a decision tree which captures the effect of \( \text{ERP}_{\text{sys outage year_i-1}} \).

5.4.1.2 Study Design

To model the outage of line 28, two TTR values were simulated for each TTF value. The TTR_{norm} simulated the no maintenance scenario and the TTR_{maint} value is used to simulate the scenario that considers maintenance outage durations. The TTR_{maint} was simulated from a uniform distribution with a range of 168 - 1344 hours representing a repair duration between a week to two months based on practices from literature sources [10]. The TTR_{norm} from the original IEEE-RTS reliability data is used. These two cases were simulated in parallel and the ENS values and
their difference between the two cases was recorded for 2000 simulation years in order to sample as many scenarios as possible with 95% confidence. By running both TTR$_{\text{norm}}$ and TTR$_{\text{maint}}$ cases in parallel an algorithm was developed to then, based on the TTR$_{\text{norm}}$ and TTR$_{\text{maint}}$ case results, identify the periods in the year when an outage scenario would least compound the reliability of the system. Therefore, the ENS of the two scenarios were compared only when an outage occurred (i.e. when higher ENS values recorded than the no outage ENS case).

5.4.1.3 STUDY RESULTS

Figure 5-8 shows these results as a distribution of the maintenance scheduling risk profile which narrates (through its peak values) the hours of the year the reliability of the system would be least affected amid the outage duration period of line 28. These are roughly between 2000 and 3000 hours and 5000 and 6500 hours, which are the peaks of the curve shown in Figure 5-8. Therefore, a total of 2500 hours (roughly 3.7 months) the outage of line 28 can be scheduled with least risk, based solely on these peak values.

![Figure 5-8 An hourly distribution plot of the density of the likelihood of low system compounding risk scenarios](image)

It must be emphasised that this does not mean that the risk is not increased when line 28 is taken out, it means that the risk increment is minimised. In these studies the demand is set to 1.4 pu to illustrate that the thermal uprating outage AMAS was scheduled the year before in readiness for when it would be needed. Therefore, even though these peak values represent the least risk periods, the actual risk amid these periods must be evaluated as well. This was achieved by generating a distribution of all (and not just selected as in the earlier case in Figure 5-6) possible performance differences: i.e., relating to when the line was scheduled out in comparison to when it was not scheduled out. This outage period lasted during hours 2000 to 3000, to simulate one month and two week outage duration [2]. The result is rendered in the plots within Figure 5-9. Additionally, in Figure 5-9, a performance based regulated plot was designed based on the target ENS of the no outage TTR$_{\text{norm}}$ case plot.
On this basis, the ERP difference between the no outage \( TTR_{norm} \) and the outage \( TTR_{maint} \) cases was computed as shown in the figure and substituted into \( ERP_{sys\_outage} \) in order to compute the \( Thermal\ Uprating\ Risk\ Cost_{year\_i}^{\text{cht}} \) as given in Equation 5-7. This was then used to compute the \( Total\ Benefit\ Cost_{year\_i}^{\text{cht}} \) according to Equation 5-1. Subsequently, based on these aforesaid computations and keeping all parameters from the previous decision tree (Figure 5-7) constant, a second decision tree was computed and plotted in Figure 5-10.

Figure 5-9 performance based regulation comparative plot for the reliability amid hours Case 2000 to 3000

Table 5-9 Rank table of the number of decision terminal nodes against their relative errors for maintenance outage case

<table>
<thead>
<tr>
<th>Number of terminal nodes</th>
<th>1</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>13</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Re-substitution Error, %</td>
<td>58.34</td>
<td>12.45</td>
<td>5.74</td>
<td>1.45</td>
<td>0.63</td>
<td>0.45</td>
</tr>
</tbody>
</table>
It was pruned to 6 terminal nodes from its maximum of 16. Five out of its six terminal nodes resulted in probabilistic terminal nodes and the re-substitution errors for different tree terminal nodes are shown in Table 5-9. The most telling result from the figure is that the two options that lead to an ‘A’ rating require that the Thermal Uprating Risk Cost\(^{\text{CONV}}\)\(_{\text{year}_{i-1}}\) (at 1.4 pu) be less than 18.1k and that the Reconductoring Risk Cost\(^{\text{CONV}}\)\(_{\text{year}_{i}}\) (at 1.5 pu) be less than 72.4k. Clearly these options are not realistic and the tree in Figure 5-10 proves (by its poor options) that the outage maintenance option is exorbitantly costly than the live-line option for the line 28.

Table 5-10 A sensitivity study on the effect of a selected reliability target on ERP benefits

<table>
<thead>
<tr>
<th>ERP(^{\text{sys}})(<em>{\text{outage}})(</em>{\text{year}_{i-1}})</th>
<th>ERP(^{\text{sys}})(<em>{\text{outage}})(</em>{\text{year}_{i-2}})</th>
<th>ERP(^{\text{sys}})(<em>{\text{outage}})(</em>{\text{year}_{i-1}})</th>
<th>Outage Duration</th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-0.2069</td>
<td>0 weeks</td>
<td>-100</td>
<td></td>
</tr>
<tr>
<td>0.0244</td>
<td>-0.1825</td>
<td>1 week</td>
<td>-88.64</td>
<td></td>
</tr>
<tr>
<td>0.0325</td>
<td>-0.1744</td>
<td>2 weeks</td>
<td>-84.82</td>
<td></td>
</tr>
<tr>
<td>0.0436</td>
<td>-0.1633</td>
<td>3 weeks</td>
<td>-79.70</td>
<td></td>
</tr>
<tr>
<td>0.0567</td>
<td>-0.1502</td>
<td>4 weeks</td>
<td>-73.60</td>
<td></td>
</tr>
<tr>
<td>0.0864</td>
<td>-0.1205</td>
<td>5 weeks</td>
<td>-59.67</td>
<td></td>
</tr>
<tr>
<td>0.2148</td>
<td>0.0079</td>
<td>6 weeks</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

The effect of outage maintenance duration on ERP\(^{\text{sys}}\)\(_{\text{outage}}\) was completed and recorded in Table 5-10. It is clearly (and expectedly) recognised from this table that ERP\(^{\text{sys}}\)\(_{\text{outage}}\) falls exponentially with fall in outage duration. Physically this means the utilisation of extra man power capable of lowering the outage duration. Therefore, a cost benefit analysis must be employed in order to ascertain the optimum man-power numbers who can be employed to perform outage maintenance (for a cost which is less than that of live-line work). The values shown in the table at week 6 are illustrative of the comprehensive study that was engaged in this section.

5.4.2 CASE STUDY-II: EFFECT OF ELECTRO-THERMAL BASED OVERSAGGING ON RISK ROBUST DECISION TREE AMAS FINANCIAL ANALYSIS TO ACCEPT BLACKOUT RISK

5.4.2.1 STUDY BACKGROUND

The option of letting line 28 succumb to its emergency loading failure rates, \(\lambda_{e}\), instead of investing to maintain ROW and/or OHL retensioning AMASs, is investigated in this section. This means the ERP\(^{\text{sys}}\)\(_{\text{new}}\)\(_{\text{year}_{i}}\) is removed as an independent participator in Equation 5-1 and its value is instead taken up by the ERP\(^{\text{sys}}\)\(_{\text{year}_{i-1}}\)\(_{\lambda_{e}}\) participator in Equation 5-1. Therefore an increased failure rate is considered during the expected emergency loading of line 28. The modelling parameters are
shown in Table 5-11 which is an excerpt from Table 5-3. As can be seen when the decision to let line 28 succumb to its $\lambda_e$ the $ERP^{Str, \lambda_e}_{year,i}$ value has to be computed. If this value is computed it means the $ERP^{new}_{year,i}$ cannot be computed. This is because $ERP^{new}_{year,i}$ evaluates a TUS’s benefit, whereas $ERP^{Str, \lambda_e}_{year,i}$ evaluates a TUS’s risk and these parameters are mutually exclusive.

Table 5-11 A complete list of the total benefit cost electrothermal and financial parameters

<table>
<thead>
<tr>
<th>Index no.</th>
<th>Total Benefit Cost $^{Str}_{year,i}$</th>
<th>Sub Index</th>
<th>Electro-thermal parameters</th>
<th>Financial parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$Risk\ Reduction\ Benefit_{\lambda_e}^{\text{OHL}}_{year_i}$</td>
<td>$ERP^{new}_{year,i}$</td>
<td>$ERP^{old}_{year,i}$</td>
<td>$\pi_{\text{Max. Reward Cap}}$</td>
</tr>
<tr>
<td>4a</td>
<td>$Oversagging\ Risk\ Cost_{\lambda_e}^{\text{OHL}}<em>{year_i}$ ($\lambda</em>{\text{maint_decision}}=0$)</td>
<td>$ERP^{Str, \lambda_e}_{year,i}$</td>
<td>n/a</td>
<td>$\pi_{\text{Max. Reward Cap}}$</td>
</tr>
<tr>
<td>4b</td>
<td>$Oversagging\ Risk\ Cost_{\lambda_e}^{\text{OHL}}<em>{year_i}$ ($\lambda</em>{\text{maint_decision}}=1$)</td>
<td>n/a</td>
<td>n/a</td>
<td>$\text{Maint}^{\text{OHL\ Cost}}$</td>
</tr>
</tbody>
</table>

5.4.2.2 STUDY DESIGN

For this study a nominated value for $\lambda_e$ i.e., of 0.5 failures/hr (only for line 28) was utilised. At this $\lambda_e$ value the EENS was recorded at 7.89 GWh/yr. Further analysis showed that it followed an exponential distribution (as have all the results presented here). Consequently, the computed $ERP^{Str, \lambda_e}_{year,i}$ gain was a mere 0.0939 pu. Therefore, keeping all other values from the initial decision tree study (i.e., section 5.3.3) constant the final decision tree was plotted.

5.4.2.3 STUDY RESULTS

This plot is shown in Figure 5-11. It was pruned to five terminal nodes with a re-substitution error of 13.5% and therefore all terminal nodes are probabilistic. In stark similarity to the maintenance outage case, this decision tree renders very poor and unrealistic options in order to realise an ‘A’ class result.

In the first option, the tree suggests an ‘A’ result if the $\text{Thermal Uprating Risk Cost}^{\text{OHL}}_{year,i}$ is less than 9.26 k$ and the ageing less than 151 k$ and an alternative (more promising) option wherein $\text{Thermal Uprating Risk Cost}^{\text{OHL}}_{year,i}$ is utmost 64.9 k$ and the ageing cost is utmost 139 k$. It is, therefore, evident that due to the lowered $ERP^{Str, \lambda_e}_{year,i}$ value as a result of $\lambda_e$, implementing ROW and/or retensioning AMASs instead of foregoing these intimated AMASs, utilities can expect to perform poorly financially due to the heavy regulatory penalties they would incur due to blackout risk.
5.4.3 CASE STUDY-III: ROBUST DECISION TREE AMAS FINANCIAL ANALYSIS TO MITIGATE FUTURE ELECTROTHERMAL BASED EARLY RECONDUCTOR RISK

5.4.3.1 STUDY BACKGROUND

In the studies so far it has been assumed that line 28 is steeled with sufficient ageing capabilities. However, over time $EAI_{\text{max}}$ will be eclipsed. When $EAI_{\text{max}}$ is eclipsed it will then be incumbent on the asset manager to realise the most cost effective and robust conductor technology investment that will minimise the overall life cycle cost of the investment and thus mitigate future early reconductoring risk. Consequently, the benefit of this task, if well engaged in, will result in a system design that will require less reactive reconductoring activities during the project lifetime. This means that for a candidate OHL conductor technology, the OHL asset manager will have to calculate $n_{\text{Recond}}$ as shown in Table 5-13.

Table 5-13 A complete list of the total benefit cost electrothermal and financial parameters

<table>
<thead>
<tr>
<th>Index no.</th>
<th>Total Benefit Cost $^{\text{Sub Index}}<em>{\text{year}</em>{i}}$</th>
<th>Electro-thermal parameters</th>
<th>Financial parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>6a</td>
<td>$\text{Reconductoring Risk Cost}<em>{\text{上半年}} (EEAI</em>{\text{Line}} &lt; EAI_{\text{max}})$</td>
<td>$EEAI_{\text{年}}$, n/a</td>
<td>$n_{\text{Ex}}$</td>
</tr>
<tr>
<td>6b</td>
<td>$\text{Reconductoring Risk Cost}<em>{\text{下半年}} (EEAI</em>{\text{Line}} \geq EAI_{\text{max}})$</td>
<td>n/a, n/a</td>
<td>$n_{\text{Recond}}$</td>
</tr>
</tbody>
</table>
Calculating $n_{\text{ACP}}$ is not trivial and, therefore, combating this conundrum requires predicting an OHL candidate conductor’s long-term ageing performance, for the sake of annuitizing and justifying ageing amid the present time. To exemplify this challenge two study designs (A and B) are formulated.

### 5.4.3.2 STUDY-A DESIGN

This study engages purely in evaluating the reconductoring options with candidate conductor technologies for the line 28 case over a project life time of 30 years. The assumptions and methodology relating to the overall transmission line cost calculations used here to budget reconductoring costs are made according to [188]. From this an annuitized cost list (i.e., $n_{\text{ACP}}$) of potential candidates was completed and ranked. These costs were annuitized by evaluating their annual capital payment (ACP) values over the stipulated 30 year period at a discount rate of 8%.

### 5.4.3.3 STUDY-A RESULTS

Figure 5-12 shows the ranking of the candidate conductor technologies. The y-axis characterises the decision pertaining to the percentage of line 28 to be reconducted which is used to account for the reality of spatial ageing. The x-axis records the $n_{\text{ACP}}$ cost. The technological options are also labelled in the figure on an equal risk contour line. This equal risk contour function is developed in order to rank the candidate conductors in terms of how much of a line they could reconductor at a fixed cost. As shown in Equation 5-15 the $\text{Risk}_\text{cost}$ is a fixed cost, the $X_{\text{axis_conductor_cost}}$ is a candidate’s evaluated annual capital payment (ACP) cost considering a full line reconductoring investment—it is also a fixed value. Therefore $Y_{\text{axis_line%_value}}$ is suggestive of the % of a line that would be reconducted in order to adhere to the $\text{Risk}_\text{cost}$.

$$\text{Risk}_\text{cost} = X_{\text{axis_conductor_cost}} \times Y_{\text{axis_line%_value}}$$  \hspace{1cm} Equation 5-15

![Figure 5-12 A contour plot of thermal uprating candidates costs of ACSR and ACCC technologies](image-url)
From Figure 5-12 it is transparent that this x-y plot is a risk matrix with the equal risk $\text{Risk}_\text{cost}$ contour line depicted in the figure. For reconductoring lengths below the contour line the ageing of line 28 is improving system performance while for required reconductoring lengths above the contour the ageing of line 28 increases the total cost of network operation based on the assumptions. Spending an ACP of $\sim$0.58 M$ on 100 % for circuit reconductoring, the best option would be to engage in a like-for-like reconductoring option with Plover conductor. Alternatively, investing in more advanced high temperature low sag (HTLS) Aluminium Composite Core Conductor (ACCC) technological types, it must be ensured that utmost only about 42% of the line would require reconductoring—as shown in the figure through the Milan conductor. Figure 5-12’s plot, thus, conclusively shows that ACCC conductors are not as economically competitive as their ACSR counterparts. However, to fully capture the true costs, the operational ageing cost of the conductors over the assumed 30 year lifecycle must be evaluated as well in order to investigate its impact on $\text{ACP}^{\text{Recond}}$ cost.

5.4.3.4 STUDY-B DESIGN
To simulate this study, all original IEEE-RTS data (from chapter 4) was kept static over the multi-year period. Only the simulation of load growth on this system in order to characterise a system advancing in years was undertaken. A simple load growth model was developed for this study. This model assumed that the demand level at all busses grew at the same rate.

Clearly, load growth modelling is not as simplistic as this and it is possible that some busses may experience load recessions. However to model such behaviour was not within the focus of this study, as this study is merely trying to illustrate how advancing years affect ageing. Assuming load growth at all busses is one of many scenarios apt to model an advancement of years. Therefore, it would be prudent that engineers engaging this study apply the load growth model most befitting to their objective.

A further simplification to the load model was made to ensure that the computational burdens pertaining to the number of recursive simulations that were invoked were maintained within the available computational resources. Therefore, it was assumed that the demand level grew spontaneously at the end of every quinquennium (five year) period by a factor of 10%; and that prior to the end of the quinquennium, the demand would be maintained at the same level. Finally, the electro-thermal models to these ACSR and ACCC candidates are provided through [188].
5.4.3.5 Study-B Results

Results of the completed simulated conditions with the different conductor uprating options are capitulated in Figure 5-13. The y-axis records the total age at the end of a quinquiennium period and adds it to the age of the next quinquiennium. In this manner the total age of a candidate over the entire life of the project is accurately established. The x-axis plots the quinquiennium periods. Some of the basic conductor properties are also shown in the figure.

The red dotted lines are plotted to aid the interpretation of the results in the plot and is indicative of the total life thermal ageing limit points of each candidate conductor. Consequently the validity of the conclusions to be drawn from the proceeding analysis hinges on this assumption—i.e., the 500 hour age limit. Other conclusions would be attained if this assumption was different. Therefore, planners ought to be confident of the final ageing value available to them and used in their analysis. The ACCC conductors are not represented in this plot as they did not exhibit ageing at the temperatures for which they operated at amid this study. This additional benefit needs to be captured for the HTLS conductor technologies, however this study focus mainly on the ACSR conductors.

It is cognisable, on observation that four of the seven ACSR candidates eclipse the ageing limit at least more than twice amid the 30 year project duration. This means that reconductoring will take place at least twice for these conductor types—and more particularly thrice for the Bobolink conductor as it eclipses the 1500 hour mark. Moreover, it is noticeable that ageing behaviour is non-linear. That is, as the diameter (shown in inches in the figure) of the conductors increase, it should lead to the lowering of their resistance. The lowering of resistance lowers the temperature at which a conductor operates; and hence significantly lowers its ageing. However, the steel content of these conductor’s, serve to increase their resistance [2]. Therefore, even though an ACSR is typified by a large diameter, it is still susceptible to advanced ageing if its steel content is higher than a conductor with both a smaller diameter and lower steel content—this is more clearly shown between Kiwi and Bluebird; and Lapwing and Falcon.
Therefore, the fact that four of the seven candidates will have to be reconductored more than once during the project life time, will increase their project ACP value. Moreover, the ACP values of the other three i.e., Chukar, Bluebird and Kiwi will also increase, albeit at a lower rate, because even though their ageing does not eclipse the limit, its value is still sufficient to incur increased maintenance costs which has to be accounted for. Thus to grasp these phenomena more vividly, the contour plot in Figure 5-12 is recapitulated in Figure 5-14 and clearly shows that the candidates have shifted along this contour line—many of them falling into the ACCC range apart from Bluebird.

Consequently, these results infer that ACCC conductors can now compete with the ACSR conductors, in terms of overall investment cost, even though their direct costs are higher than ACSR. However, the results also suggest that the optimal conductor to select is Bluebird, as it possesses the least ACP cost (~ 1.18 M$) for the benefit of reconductoring 100% of the line. However, to adhere to the 0.58 M$ ACP constraint, Bluebird can utmost reconductor about 56% of the line.

There are many constraints to thermal uprating which can be augmented to this study’s model in order to exemplify how the ACP value for candidate conductors is affected. The studies here focussed solely on modelling the ageing as a selection constraint. However, conductor weight is another factor that can be included (as a constraint) into the analysis. Thus, the weight of the Bluebird conductor would impede its selection. This is because it surpasses the Plover conductor weight by more than 5% and in this study it is assumed that a candidate conductor cannot exceed 5% of the weight of the existing conductor due to the tower strength constraints [75]. Consequently, Bluebird would be too heavy for the towers on which it would be erected. Conversely, the towers can be strengthened [1], but not without the risk of increasing the Bluebird’s ACP cost. If its cost can be ascertained to be less than that of the lighter ACCC
conductor’s ACP then it would qualify as the optimal candidate. However, due to lack of data on tower strengthening costs, it was assumed that the Milan ACCC conductor was the optimal choice.

As a consequence to the selection of Milan, only a block reconductoring policy of not more than 42% reconductoring can be engaged as opposed to the full reconductoring policy. This is because of the need to adhere to the 0.58 M$ investment cost constraint. Conversely, a total reconductoring solution of minimal cost would be realised at a value of Milan’s 1.4 M$ 100 % ACP cost—a difference of 0.82 M$ when compared against the 42% 0.58 M$ ACP cost (see Figure 5-14). However, if the Total Benefit Cost^{OH}, year_i (from Equation 5-1) can be ascertained to result in at least 0.82 M$, the utility can invest in a full Milan reconductoring activity, if the need to do so is justified.

Therefore, a decision tree was invoked to ascertain the managerial options that the asset owner could realise and this cost (i.e., Reconductoring Risk Cost^{OH}, year_i) was added to Equation 5-1, whilst keeping all the earlier value from the study in 5.3.3.2 the same. Thus, resulting from these computations a decision plot of 10 terminal nodes and four decision node participators (the oval shapes) was produced as in Figure 5-15. The re-substitution error is shown in Table 5-14 and of the ten terminal nodes in Figure 5-15, three register ‘A’ class status. Subsequently, an incision into the terminal with the ‘A’ status when it was arbitrarily assumed that the true Thermal Uprating Risk Cost^{OH}, year_i-1 lay (for example) between 54.6 k$ and 197 k$ resulted in Figure 5-16; which presents a distribution plot of Total Benefit Cost^{OH}, year_i observations. The table within the figure collates results to particular enquiries. Evidently, as the results show, the decision to engage full reconductoring becomes probabilistic. Therefore the probability of collecting enough monetary payments to incentivise reconductoring with Milan at the added cost of 0.82 M$ ACP is only ~12%, after having accounted for all possible uncertainties. In the end, it can be robustly concluded on the basis of the assumptions employed in this study that a block uprating policy is more economical than a full uprating policy. Moreover, under certain circumstances, the more expensive conductors can result in cheaper block investment enterprises in the long run.

Table 5-14 Rank table of the number of decision terminal nodes against their relative errors for reconductoring

<table>
<thead>
<tr>
<th>Number of terminal nodes</th>
<th>1</th>
<th>3</th>
<th>6</th>
<th>10</th>
<th>16</th>
<th>18</th>
</tr>
</thead>
<tbody>
<tr>
<td>Re-substitution Error, %</td>
<td>74.54</td>
<td>48.65</td>
<td>2.54</td>
<td>1.54</td>
<td>0.64</td>
<td>0.43</td>
</tr>
</tbody>
</table>
5.5 CONCLUDING REMARKS

This chapter has presented a novel holistic *techno-economic* assessment for optimal TUS selection process based on the computational electro-thermal power system reliability methodology developed in chapter 3. In this *techno-economic* assessment seven criteria through decision tree analysis are jointly utilised to aid the selection of the optimal ageing flexible utilisation TUS considering risk mitigating AMASs and their inherent financial uncertainties. In this methodology three possible AMASs have been identified and modelled: thermal uprating AMASs (TU AMASs), blackout risk AMAS (BR AMASs) and early reconductoring risk AMAS (ER AMASs). To model the scenario which captures the outputs capable of aiding the decision on whether to engage in a live-line or an offline TU AMAS, a line outage scenario based on the parallel sampling technique is
modelled. Furthermore, in order to decide on whether to engage in a retensioning/ROW or a do nothing BR AMAS, the $\lambda_e$ function is modelled to capture the blackout risk cost. Lastly, in order to decide on whether to engage in ER AMAS with either novel or conventional conductors, the corresponding (novel and conventional conductor) electro-thermal models are modelled. Therefore, based on these aforementioned models and accounting for their costs, it is possible to realise the optimal AMAS at a given stage of an OHL’s life-cycle.

Five TUSs ranging from 1 pu to 1.2 pu are used to create a flexible ageing space range. From this ageing space range the optimal flexible ageing utilisation TUS being the 1.2 pu as it recorded a 65.6% increase in EENS. Resultantly, this TUS increase was able to realise a 92.3% financial performance improvement when assessed under a performance based regulatory (PBR) framework. The evaluation of the AMAS risk cost were considered by accounting for the three identified AMASs. By studying various AMASs, it was found that when live-line thermal uprating and ROW and/or OHL retensioning AMASs were employed, a utility could invest within the range of $11.2k and $1.1M and still realise a profitable project. However, when different AMASs were employed, the profitability investment range shrunk by 98.3% to between $3.16k and $18.1k.

Clearly for the first time in open literature this methodology is able to show that for a 20% TUS increase in ageing flexibility utilisation, the least risk TUS-AMAS-PCCs and the TUS-AMAS-CCs must include live-line thermal uprating and ROW and/or OHL retensioning. Moreover, when deciding the conductor technology to implement in order to mitigate for future reconductoring risk it has been found that technologies that do not age become more attractive. In particular the ACCC technology was found more suitable to the commonly employed ACSR technology. These conclusions were robustly arrived at by taking into account the many sources of uncertainties in TU financial models which were accurately handled up to ~98% by the utilisation of decision tree based methods.
Reconductoring, retensioning, right-of-way (ROW) maintenance and OHL structural thermal uprating are multistage based AMASs. This means that they are implemented at some stage in a TUSs life-cycle [77]. Traditionally these AMASs have been scheduled to take place at set times and fixed intervals [2]. This schedule has been engaged with either little condition assessment or inaccurate (or partially sighted) condition assessment tools, which were mainly focussed at the OHL level analysis whilst making engineering based judgements about how the wider system would influence the particular OHL’s ageing behaviour throughout its lifetime [133]. OHL design engineers are fast realising that traditional approaches are flawed and costly and are thereby seeking to design OHLs at the outset by more accurately considering the dynamic multistage nature of AMASs, based on the actual ageing condition computation of the OHL [2, 76].

It has been shown in the previous chapters that an OHL’s ageing condition (and flexibility range) is best assessed through an electro-thermal power system reliability modelling. This chapter, therefore, extends the holistic TUS ageing flexibility utilisation evaluation process presented in the previous chapter to account for the multistage nature of OHL ageing behaviour in order to compute solutions which help OHL designers and asset planners to optimise the multistage implementation of the AMASs. This methodological enhancement is based on implementing the dynamic programming (DP) optimisation technique.

DP is an optimisation technique whose aim is to reconstruct a complex problem into a sequence of simpler problems requiring much less computational effort [203]. At each stage, DP evaluates and collates information necessary to enable the assessment of the consequences that a decision at that stage influences future decisions within prospective stages; and thus to achieve the aforesaid, DP must be modelled as a recursive optimisation which works up to a solution of the overall N-stage problem by initially computing a single stage problem and serially including and evaluating a new stage at a time until the overall optimal solution is yielded [203].
6.1 LIFE-CYCLE TUS ELECTRO-THERMAL BASED DP MULTI-STAGE AMAS IMPLEMENTATION METHODOLOGY

6.1.1 EMPLOYING DP TO THE HOLISTIC TUS ELECTRO-THERMAL METHODOLOGY

The application of the proposed DP method to the holistic electro-thermal TUS methodology is formulated initially by considering Figure 6-1; which illustrates the lifecycle problem as one requiring a two layer formulation. These layers are both represented by 2 dimensional universal (x, y) state spaces. Studying the 1st dimension’s state space reveals an x-axis representing the years of operation and a y-axis which is characteristic of the increasing rate magnitude of candidate rates. Moreover, within the state space are black circles which represent the positions of the discrete states inherent within the universal space, i.e., a thermal uprating scenario (TUS).

When viewed vertically (i.e. in the y-direction), the shapes can be collectively clustered to define a single discrete stage (year)—i.e., in this example it is four circles that cluster into a single discrete stage. Subsequently, when viewed horizontally (i.e. in the x-direction), these six circles form a series of discrete stages (i.e., multi-stages) running from left to right leading to a total of six stages in this figure. As individual points in space, these shapes denote those computations which must be invoked (for a particular TUS) in order to generate values that contribute to the realisation (at each particular stage) of the Total Benefit Cost\(_{\text{OHL}}\)\(_{\text{year}_i}\) (and its sub-indices introduced in chapter 5).

This cost is realised through the initial computation of system level reliability indices which are required to compute the ERP through the use of the PBR framework and thereafter also recording the OHL indices, including the EEAI visibility index.
The (holistic electro-thermal TUS) computational processes are then repeated across all points vertically within the cluster (i.e., along the y axis). The solutions rendered by each candidate (black circles) are compared against other candidates, and the most profitable result is selected (for example, as point A in the figure). This then completes the first stage’s computations. Moreover, to compute the next stage(s), which is/are representative of the multistage behavior, these computations are then progressed serially stage after stage. Subsequently, with each progression in time/stages, the realization of the optimal TUS to traverse to is incumbent on recollecting the results of previous stage and then adding these recollected results to each individually computed prospective TUS. In addition to the recollected costs, the recorded ageing (if it existed) associated with a previous stage is also added to the calculated ageing associated with the prospective optimal TUS of the prospective stage. This is performed in order to track the evolution of OHL ageing over time. In this repetitive manner, the traversal path between optimal TUSs is realized as shown in the figure, each time by establishing the optimal cost at a given stage and using this information to compute the cheapest traversal to a given TUS in the next stage. Consequently, the overall project cost is evaluated by summing up all the optimal TUS costs at the available stages.

The traversal, however, is not obvious because at some stages a given TUS within a given stage may cost less (or more) in comparison to its competing candidates than it would cost in other retrospective or prospective stages. This dynamic behavior of the costs of TUSs is due to both the Total Benefit Cost\textsubscript{\text{OHL, year}} being compounded by the dynamic ageing as well as other associated constraint costs which exacerbate with increasing years of operation. This point is better illustrated through the exposition of the 2\textsuperscript{nd} layer of the constraint matrix in Figure 6-1 where the arrows link a particular TUS with its constraints. In Figure 6-1 the 2\textsuperscript{nd} layer of the calculations represents a two-dimension (x,y) space of decision constraint variables of varying intensity represented by the variation of states along the y-axis; while the various classes of constraints are allocated on the x-axis, accordingly labeled in the figure. The blue circles represent various possible points (states) within the state space; which based on their position within the space convey the specific magnitude values inherent to each corresponding constraint. Therefore, the selection of the optimal TUS path must result on the basis of accounting for the various combinations of decision constraints inherent within the OHL network of circuits comprising arbitrary power systems.

The arrowed ties linking point A to the various blue circles clearly show how (one of the myriad possible combinatorial sets of) the constraints feed into the 1\textsuperscript{st} layer of calculations. These constraints model themselves in likeness to an artificial memory data bank within the DP
algorithm formulation. Therefore, by constantly recollecting information about these constraints whilst invoking calculations at each stage, the DP’s computations seek to establish the optimal TUS life-cycle traversal pattern which results in the most profitable overall project cost (as shown in the figure).

### 6.1.2 FORMULATING THE LIFE-CYCLE TUS DP-BASED OBJECTIVE FUNCTION

A policy is a precise course of action which must be implemented for the purpose of optimally managing resources. Therefore, the proposed methodology commences with the definition of the universal objective function, which is stated through Equation 6-1, wherein the aim is to identify the *Optimal TUS life-cycle Policy* from an array of contending policies—by searching out for the TUS life-cycle policy attributed by the maximum profit.

\[
\text{Optimal TUS life-cycle Policy} = \max_{\text{Policy}} \text{cost}
\]

Being oblivious to their actual inherent value, utilities must always devise diverse TUS life-cycle policies in order to consequently compute and compare which of these TUS life-cycle policies is most economical. Therefore, prior to the comparative exercise, these computed cost values must be stored in an array (of cost elements ranging from \( k = 1 \cdots K \)) as shown in Equation 6-2.

\[
\text{Policy}^{\text{cost}} = \begin{bmatrix}
\text{TUS Policy}_{k}^{\text{cost}} & \cdots & \text{TUS Policy}_{K}^{\text{cost}}
\end{bmatrix}
\]

Moreover, the particular objective function required to compute the cost (i.e., \( \text{TUS Policy}_{x}^{\text{cost}} \)) of any devised policy \( k \) is thus formulated in Equation 6-3 as a life-cycle profit maximisation DP algorithm which works similar to the description narrated in 6.1.1. In this Equation \( t \) is the stage number in years and \( M \) is the final stage value which signifies the project life-cycle. Whereas the outer summation symbol relates to modelling of the multi-stage/multi-year aspect problem, the inner summation symbol relates to the individual TUS computations performed according to the electro-thermal TUS methodology of chapter 5 (where \( x \) is the TUS and \( N \) is the final candidate value).

Within the large bracket of the equation are variables which are emblematic of either the revenue or cost aspects of a given TUS policy. More detailed (and similar to chapter 5), the revenue aspects of the \( \text{TUS Policy}_{x}^{\text{cost}} \) are the TUS performance based regulatory expected reward payment revenue (i.e., \( \text{PBR-ERP Revenue}_{x}^{t} \)) and the TUS capacity flow revenue (i.e., \( \text{Flow Revenue}_{x}^{t} \)) at a given time stage \( t \) for a particular TUS \( x \). The cost aspects are classed into multistage-based conditional and annuitized one off stage-based investment costs.
The value and risk of probabilistic thermal uprating scenarios on power system reliability

\[
TUS Policy_{x}^{cost} = \max_{\text{policy}} \sum_{t=1}^{N} \sum_{x=1}^{M} \left( PBR-ERP Revenue_{x}^{t} + Flow Revenue_{x}^{t} - \text{Ageing Damage Cost}_{x}^{t} - \text{Reconductoring Risk Cost}_{x}^{t} - \text{Thermal Uprating Risk Cost}_{x}^{t} - \text{Over Sagging Risk Cost}_{x}^{t} - \text{Weather Data Investment ACP Cost}_{x}^{t} - \text{Conductor Investment ACP Cost}_{x}^{t} \right)
\]

Equation 6-3

Thus at a particular time-stage \( t \) for a particular TUS \( x \), the conditional costs are the \( \text{Ageing Damage Cost}_{x}^{t} \), the \( \text{Reconductoring Risk Cost}_{x}^{t} \), the \( \text{Thermal Uprating Risk Cost}_{x}^{t} \) and the \( \text{Over Sagging Risk Cost}_{x}^{t} \) (as earlier introduced in chapter 5) and the \( \text{Ageing Damage Cost}_{x}^{t} \). The latter is discussed in the section 6.1.2.3). Furthermore, the conditional characteristics of these costs are, however, elaborated later in this chapter. Finally, only two annuitized one off stage-based investment costs are considered: (1) \( \text{Weather Data Investment ACP Cost}_{x}^{t} \) which is the cost of installing weather data collection instrumentation; and (2) \( \text{Conductor Investment ACP Cost}_{x}^{t} \) which is the initial cost of the conductor.

In the following sub-sections, the revenue and cost aspects in Equation 6-3 are further elaborated mathematically—exemplified through Equations 6-4 to 6-22.

6.1.2.1 PBR REVENUE

In Equation 6-4 \( ERP_{x}^{t} \) is the expected reward payment in pu peculiar to TUS \( x \) amid time stage \( t \) and \( \pi^{pu}_{\text{Max. Reward Cap}} \) represents the maximum reward-penalty cap variable (as agreed between utility and regulator) in pu. \( d \) is the discount rate (in %) which quantifies an OHL asset’s loss of value of time.

\[
PBR-ERP Revenue_{x}^{t} = \frac{ERP_{x}^{t} \times \pi^{pu}_{\text{Max. Reward Cap}}}{(1 + d^t)}
\]

Equation 6-4

6.1.2.2 FLOW REVENUE

In Equation 6-5 \( EMEL_{x}^{t} \) is the loading magnitude index in MWs whereas \( EDEL_{x}^{t} \) is the duration index in hours peculiar to candidate \( x \) amid stage \( t \). \( \pi^{pu}_{\text{electricity}} \) is in pu and is a cost variable related to the price of energy.

\[
Flow Revenue_{x}^{t} = \frac{EMEL_{x}^{t} \times EDEL_{x}^{t} \times \pi^{pu}_{\text{electricity}}}{(1 + d^t)}
\]

Equation 6-5
6.1.2.3 Ageing Damage Cost

The ageing damage cost is calculated from first principles as follows. When an investment in a conductor is made, the design operating temperature is such that over its lifetime its investment is maximised. Therefore, a conductor’s ageing must be controlled over its lifetime. The controlled age can be defined as:

\[ \text{Controlled Age} = \frac{\text{Total Conductor Age}}{\text{Project life}} \]  

Equation 6-6

This means, for example, that if a line has an allotted maximum age of 1500 hours and is designed for a project lifetime of 30 years, then its Controlled Age can be expected to be 50 hours per year. When for a given year, a utility ages this line at or less than its Controlled Age then the conductor can be deemed to be an asset, because it is adhering to its planned ageing thus keeping the early reconductoring risk value at zero. Conversely, the line becomes a liability when it ages more that the controlled age, simply because it increases the early reconductoring risk to a value above zero. In practice, it is not possible to operate a conductor in such a way that utilities can control its exact ageing on an annual basis. In some years a line may witness lesser ageing and in other years more ageing even beyond the Controlled Age annual value. Consequently, it becomes desirable to record ageing so as to track it and hence make more informed decisions based on the previous conductor ageing history. At present, there is no evidence in literature that utilities pursue this action and therefore the existing planning tools are inept to justify ageing.

Therefore this tool accounts for this as follows once the inherent ageing in year \( t \) peculiar to TUS \( x \) is computed from the electro-thermal tool, it can be converted to a monetary value (i.e., \( \text{Inherent Age Cost}_{\text{year}, t}^{\text{OHL}} \)) as shown below—where \( p \) denotes the invested conductor cost and \( \text{CRF} \) is the capital recovery factor and \( \text{perc} \) the percentage of the line length needing to be reconducted.

\[ \text{Inherent Age Cost}_{\text{year}, t}^{\text{OHL}} = \frac{\text{EEAI}_{\text{year}, t}^{\text{OHL}}}{\text{EAI}_{\text{max}}} \times p \times \text{perc} \times \text{CRF} \]  

Equation 6-7

The definition of the \( \text{CRF} \), is mathematically defined in Equation 6-8; where \( t \) denotes the average interest rate over the conductor lifetime and \( M \) is the total number of annuities (i.e. the total life time of the conductor in years) [82].

\[ \text{CRF} = \frac{t(1+t)^M}{(1+t)^M - 1} \]  

Equation 6-8
Similarly the controlled ageing cost can be computed below

\[
\text{Controlled Age Cost} = \left( \frac{\text{Controlled Age}}{\text{EAI}_{\text{max}}} \right) \times P \times \text{CRF} \quad \text{Equation 6-9}
\]

Subsequently, in a given planning year \( t \), a utility could predict the \( \text{Inherent Age Cost}^\text{ONL}_{\text{year_t}} \) for a TUS \( x \) and subtract from it the \( \text{Controlled Age Cost} \) through Equation 6-10 below in order to compute the \( \text{Ageing Damage Cost}^x_t \). If \( \text{Ageing Damage Cost}^x_t > 0 \) then it is added to the cost of TUS as given in Equation 6-3. If \( \text{Ageing Damage Cost}^x_t \leq 0 \) then \( \text{Ageing Damage Cost}^x_t \) is capped to a value of 0.

\[
\text{Ageing Damage Cost}^x_t = \text{Inherent Age Cost}^\text{ONL}_{\text{year_t}} - \text{Controlled Age Cost} \quad \text{Equation 6-10}
\]

### 6.1.2.4 RECONDUCTORING RISK COST

Whilst attempting to traverse from a present stage \( t \) to the next potential stage \( t + 1 \), it may be possible that a given OHL may be steeled with adequate clearance. However, it is still possible that the residual life may be eclipsed once the system operates within the stage \( t + 1 \) it traverses into. The constraint formulation to account for this concern is expressed in Equation 6-11:

\[
\text{EEAI}^X_t + \text{EEAI}^X_{t+1} \leq \text{EAI}_{\text{max}} \quad \text{Equation 6-11}
\]

Therefore, when the reconductoring constraint is observed, a Boolean variable is set as \( I_0 = 0 \), and conversely the Boolean variable is set as \( I_0 = 1 \) when Equation 6-11 is violated. This violation indicates that a reconductoring AMAS is warranted. Furthermore, if a utility is endowed with a blank reconductoring budget, then every time this constraint (Equation 6-11) is violated amid the project life-cycle, a reconductoring AMAS could be easily implemented. Nevertheless, some utilities may possess strict fixed budget constraints and therefore this must be accounted for, as is the case in Equation 6-12. In Equation 6-12 \( \text{Recon\_Counter}^x_t \) is the rolling count at stage \( t \) for TUS \( x \) and \( \text{Rec}^\text{freq}_{\text{const}} \) is the maximum budgeted reconductoring AMASs for candidate \( x \).

\[
\text{Recon\_Counter}^x_t \leq \text{Rec}^\text{freq}_{\text{const}} \quad \text{Equation 6-12}
\]

Therefore, by considering and accounting for these constraints, the \( \text{Reconductoring Risk Cost}^x_t \) can be computed based on the conditions in Equation 6-13. In Equation 6-13, \( \pi_{\text{Recond}}^\text{pu} \) is the cost of a single reconductoring activity and \( \text{Rec}^\text{budp}_{\text{const}} \) is the cost of associated with expanding a reconductoring budget after the constraint in Equation 6-12 has been violated.
Moreover, it must be noted that when a like-for-like replacement conductor AMAS is implemented at stage \( t \), it is expected that the ageing to be calculated in the prospective stages would be similar to the one calculated prior to reconductoring. Conversely, when a new replacement conductor AMAS is implemented, the new electro-thermal parameters characteristic of the implemented conductor are used in order to capture the new ageing characteristics in subsequent stage traversals of the TUS life-cycle policy. Therefore, in this manner, the impact of novel (i.e., HTLS) ageing free conductor technologies can be modelled considering the relevant techno-economical aspects within this DP-based reliability evaluation framework.

### 6.1.2.5 THERMAL UPRATING RISK COST

In the attempt to traverse between stages, it must be ascertained whether the next potential stage is typified by a higher thermal rating. If this event is established, it implies that a thermal uprating activity has been implemented and a Boolean variable is set to \( I = 1 \). Subsequently, the cost associated with this TUS is accounted for by initially invoking Equation 6-14:

\[
TR^*_t \leq TR^*_t+1
\]

In Equation 6-14 \( TR^*_t \) is the optimal thermal rating value of TUS \( X \) from the present stage \( t \) and \( TR^*_t+1 \) is the optimal thermal rating value of TUS \( X \) for the potential stage \( t+1 \). Moreover, within the methodology, every time a thermal uprating activity is embarked, a counter is updated and checked against the maximum number of allowable thermal uprating AMASs as constricted by a utility’s budget. This formulation is expressed in Equation 6-15, where \( TR_{Counter}^*_t \) is the rolling count at stage \( t \) for candidate \( X \), and \( TU^{freq}_{const} \) is the maximum thermal uprating value. Therefore, when equation 6-15 is violated \( Rec_{const}^{budg} \) is the ignited cost associated with expanding a TU budget.

\[
TR_{Counter}^*_t \leq TU^{freq}_{const}
\]

Subsequently, by accounting for the aforesaid factors the Thermal Uprating Risk Cost \( ^*_t \) for TUS \( X \) at stage \( t \) is made possible to evaluate through Equation 6-16. Moreover, in Equation 6-16, \( \pi^{pu}_{Live-line \ Cost} \) is the cost of live-line thermal uprating, \( ERP^{outage}_{year_i-1} \) is expected reward payment calculated through the electro-thermal tool and \( \pi^{pu}_{Max. \ Reward \ Cap} \) is the maximum reward-penalty cap variable (as agreed between utility and regulator) in pu.
The Value and Risk of Probabilistic Thermal Uprating Scenarios on Power System Reliability

6.1.2.6 Oversagging Risk Cost

Whilst attempting to traverse from a present stage $t$ to the next potential stage $t+1$, it must be ascertained whether the clearance of an OHL would be violated when it operates within the next potential stage $t+1$. This constraint is formulated below; where $EEAIX$ or $EEAIX_{r+1}$ is the expected EAI for TUS $x$ and $EAI_{sagage}$ is the maximum allowable ageing due to increased elevated temperature creep sagging.

$$EEAIX + EEAIX_{r+1} \leq EAI_{sagage}$$

When this constraint is respected, an integer decision variable $I$ is set to 0. Subsequently, the cost of violating this constraint is set to 0 and thereby eliminates its influence on the overall cost for that particular TUS $x$ amid the traversal to stage $t+1$. However, when this constraint is violated then the Boolean variable is set as $I = 1$. Subsequently, at the instant of violation, two cost functions can be invoked and these functions are subject to the decision the asset manager wishes to enforce: either to engage in ROW maintenance and retensioning AMASs to address the sag age (i.e., $\lambda_{maint\_decision}^{e} = 1$) or to do nothing (i.e., $\lambda_{maint\_decision}^{e} = 0$). Each option has its inherent cost, but more importantly each option has its influencing cost on the project. The AMAS cost related to $\lambda_{maint\_decision}^{e} = 1$ a positive influence on the overall TUS performance as it enhances the reliability of the system by lowering an OHL’s $\lambda_{e}$ value—subsequently raising the $PBR-ERP\_Revenue^{i}$ payment value.

Conversely, the $\lambda_{maint\_decision}^{e} = 0$ has no inherent cost but poses significant system reliability risk by raising the $\lambda_{e}$ value and it has been demonstrated in the earlier chapters that $\lambda_{e}$ lowers a utility’s $PBR-ERP\_Revenue^{i}$ earning potential. Therefore, when the decision variable $\lambda_{maint\_decision}^{e} = 1$ the AMAS maintenance cost is added to the traversal cost in Equation 6-3; while when $\lambda_{maint\_decision}^{e} = 0$ computations are rerun to obtain the $PBR-ERP\_Revenue^{i}$ influenced by the presence of $\lambda_{e}$, which is then appended to the traversal cost in Equation 6-3. Moreover, it is necessary to obey budgetary constraints related to the ROW maintenance and retensioning AMASs as shown in Equation 6-18 where $SagAge\_Counter^{i}$ is the rolling count at stage $t$ for TUS $x$, and $SagAge\_Maint^{freq\_Const}$ is the maximum thermal uprating value.
Therefore, when any of the discussed conditions manifest, the Over Sagging Risk Cost* at stage t for TUS x can be calculated using Equation 6-19. Moreover, in Equation 6-16, πROWRetConst is the cost of ROW maintenance and retensioning AMASs, ERP^{\text{sys, year}_t} is expected reward payment calculated through the electro-thermal tool due to the manifestation of λ, and π_{\text{Max. Reward Cap}} is the maximum reward-penalty cap variable (as agreed between utility and regulator) in pu.

Finally, in Equation 6-19, ROWRet\text{Budget} is the cost of associated with expanding the ROW maintenance and retensioning AMASs budget after the constraint in Equation 6-18 has been violated.

\[
\text{Over Sagging Risk Cost}_t^* = \begin{cases} 
0 & \text{if } l_t = 0 \& \text{SagAge}_t^* \leq \text{ROWRet}_t^\text{freq Const} \\
\text{ROWRet}_t^\text{freq Const} & \text{if } l_t = 1 \& \text{SagAge}_t^* = 1 \& \text{SagAge}_t^* \leq \text{ROWRet}_t^\text{freq Const} \\
\text{ROWRet}_t^\text{freq Const} & \text{if } l_t = 1 \& \text{SagAge}_t^* > \text{ROWRet}_t^\text{freq Const} \\
\end{cases}
\]

Equation 6-19

6.1.2.7 WEATHER INVESTMENT ACP COST

The cost of installing weather data collection instrumentation is given in Equation 6-20 as π_{\text{Weather Data Costs}} in order to compute the Weather Data Investment ACP Cost* at stage t for TUS.

\[
\text{Weather Data Investment ACP Cost}_t^* = \frac{\pi_{\text{Weather Data Costs}} \times CRF}{1 + d^t} 
\]

Equation 6-20

6.1.2.8 CONDUCTOR INVESTMENT COST

The initial cost of the conductor investment is given in Equation 6-21 as π_{\text{New Cond ACP}} in order to compute the Conductor Investment ACP Cost* at stage t for TUS.

\[
\text{Conductor Investment ACP Cost}_t^* = \frac{\pi_{\text{New Cond}} \times CRF}{1 + d^t} 
\]

Equation 6-21

The costs narrated through Equations 6-4 to 6-21 have been unitised to pu due to lack of realistic data. However, in light of real data, actual cost values can be imputed into these variables.

6.1.3 TUS OPTIMISATION SUB-OBJECTIVES

It must be postulated that some utilities may be interested solely in maximising ageing over the course of the TUSs life-cycle without ever having to implement reconductoring and/or ROW and retensioning AMASs prematurely. These interests are influenced by a particular overarching life-cycle policy a utility desires to implement, namely, time-based, condition-based, or reactive-based.
OHL life-cycle asset management policies [205]. These policies can be comparatively narrated through the Figure 6-2; which shows a plant’s actual failure date and a scheduled maintenance date, based on a time-based policy.

Clearly, according to the figure, this time-based approach is oblivious to the impending failure, as it is scheduled after the imminent failure date. When the failure occurs, a reactive-based maintenance activity is enacted; which could result in unintendedly high load curtailment costs. The time-based approach is adopted by utilities globally. Reactive-based strategies may aim to ameliorate the effects of time-based strategies, but sometimes their solutions may be found wanting. Implementing a condition-based policy able to predict the effect of ageing on both system reliability and maintenance costs is realised, significant cost savings would be gained. In this light, in order to account for a particular overarching life-cycle maintenance approach, a spectrum of policies as shown in Equation 6-22 would have to be programmed for each TUS’s life-cycle analysis.

\[
\text{Policy}_{\text{cost}}^{\text{array}} = \begin{bmatrix} \text{Policy}_{1}^{\text{cost}} & \cdots & \text{Policy}_{k}^{\text{cost}} \end{bmatrix}
\]  

Equation 6-22

So, when traversing between stages, it must be ascertained from a \( \text{Policy}_{\text{array}}^{\text{cost}} \) (Equation 6-22) whether there exist any profitable TUSs which can found in compliance with one of the three overarching life-cycle policies, namely, time-based, condition-based, or reactive-based.

6.2 TEST SYSTEM FOR LIFE-CYCLE TUS ELECTRO-THERMAL BASED DP MULTI-STAGE AMAS IMPLEMENTATION METHODOLOGICAL EVALUATION AND VALIDATION

The methodology proposed in this chapter is employed using IEEE-RTS 24 bus system discussed in chapter 4 and appendix A. The multiyear load growth model discussed in section 5.4.2.4 is imposed on this system in order to create the context in which the life-cycle multistage AMASs can be studied. Furthermore, the correlated weather model discussed in section 4.2.3.4 is used to model the long term behaviour of weather events. To further assume analytical simplicity the life-cycle TUS electro-thermal based DP multi-stage AMAS modelling analysis was focused on the ageing evolution of lines 12, 23 and 28—and as such it was assumed that the rest of the lines do not age. However, the ageing of other lines could be easily included into the analysis, but as
previous chapters have illustrated, their ageing behaviour is so low that it is be omitted for this study. The lines 12, 23 and 28 are highlighted in red in Figure 6-2, and the ageing threshold temperatures of 100°C for lines 23 and 28 and 75°C for line 12 where assumed. Furthermore, the ACSR Bobolink conductor was assumed to have been used for all lines.

![Figure 6-3 IEEE RTS – 24 Bus Network Schematic](image)

As this is a first time study, gleaning data on which to test the method proved arduous. Therefore, the constraint database shown in Table 6-1 is chosen as a starting point for this study. In practical situations, when planners find it difficult to obtain realistic data, the closest option is to develop data as realistically as possible. However, this data is inevitably characterised by uncertainty. Hence to cope with such uncertainty, sensitivity analyses about the nominal data are engaged in order to establish the variable that influences the model’s output most as well as least. Furthermore, sampling methods are more robust against sensitivity analytical methods; because a wide range of constraint combinations can be formulated and statistical tools such as decision trees can be enforced. These tools can be used to evaluate patterns and rules peculiar to the data.
and thereby make more informed decisions. Thus, decision trees used in previous chapter are retained in this study to handle the uncertainty about the nominated constraint database.

The multiplication factors that are required for the calculation of the cost functions (in Equation 6-3) within this study are given in Table 6-2 below. The costs within this methodology are simplified and developed to be functions of the reconductoring cost as also shown in Table 6-2. The costs narrated through Table 6-2 have been unitised to pu due to lack of realistic data. However, in light of real data, actual cost values can be imputed into these variables. Moreover, sampling methods are discussed later in the study to deal with the uncertainty about the data. A discount factor of 8% was assumed in this study to quantify an asset’s loss of value over time [110].

<table>
<thead>
<tr>
<th>Table 6-1 System level base case constraint database</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>EAI&lt;sub&gt;max&lt;/sub&gt; Hrs</strong></td>
</tr>
<tr>
<td>Value</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 6-2 Table of cost functions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cost Name</strong></td>
</tr>
<tr>
<td>π&lt;sub&gt;Max. Reward Cap&lt;/sub&gt;</td>
</tr>
<tr>
<td>π&lt;sub&gt;New Cond&lt;/sub&gt;</td>
</tr>
<tr>
<td>π&lt;sub&gt;Recond&lt;/sub&gt;</td>
</tr>
<tr>
<td>π&lt;sub&gt;Live-line Cost&lt;/sub&gt;</td>
</tr>
<tr>
<td>π&lt;sub&gt;ROWRet Cost&lt;/sub&gt;</td>
</tr>
<tr>
<td>π&lt;sub&gt;Weather Data Costs&lt;/sub&gt;</td>
</tr>
<tr>
<td>π&lt;sub&gt;electricity&lt;/sub&gt;</td>
</tr>
</tbody>
</table>

### 6.3 APPLICATION OF DP-BASED TUS METHODOLOGY ON TUS LIFE-CYCLE AGEING RISK AND MULTI-STAGE AMAS IMPLEMENTATION STUDIES

In this section the constructed methodology is validated through a series of case studies to illustrate how a utility might perform financially if certain policies and investments are carried out.

The state space representation of the 1<sup>st</sup> layer of traversal option states of the two-dimension problem which was defined in Figure 6-1 is evaluated in Table 6-3; which records the system EENS values labeled in black with the system EEAI visibility indices shown in brackets. Each cell of the values represents a static value which recurs yearly over a five year period. For instance for a
selected thermal rating of 1 pu, in the first quinquennium, a value of 2.023 MWh/year for EENS and of 0 Hrs/year of ageing occurs annually over this (five year) period.

Table 6-3 1st dimension results of the TARM model state space

<table>
<thead>
<tr>
<th>Thermal Rate Candidate, pu</th>
<th>0-5 years</th>
<th>6-10 years</th>
<th>11-15 years</th>
<th>16-20 years</th>
<th>21-25 years</th>
<th>26-30 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00</td>
<td>2.023</td>
<td>2.321</td>
<td>2.542</td>
<td>6.287</td>
<td>8.377</td>
<td>13.352</td>
</tr>
<tr>
<td>1.05</td>
<td>2.021</td>
<td>2.319</td>
<td>2.482</td>
<td>5.123</td>
<td>6.874</td>
<td>10.379</td>
</tr>
<tr>
<td>1.10</td>
<td>2.013</td>
<td>2.310</td>
<td>2.391</td>
<td>4.679</td>
<td>5.878</td>
<td>9.245</td>
</tr>
<tr>
<td>1.15</td>
<td>2.009</td>
<td>2.307</td>
<td>2.385</td>
<td>3.345</td>
<td>3.412</td>
<td>5.728</td>
</tr>
<tr>
<td>1.20</td>
<td>2.001</td>
<td>2.302</td>
<td>2.362</td>
<td>2.834</td>
<td>2.934</td>
<td>4.871</td>
</tr>
</tbody>
</table>

Corresponding to the entries in Table 6-3 are the results of the performance based expected reward payment factors which are collated in Table 6-4. It is these payment factors which are subsequently multiplied by the maximum reward capping value of 5 pu, which was earlier presented in Table 6-2. Moreover, it is evident within the first three quinquenniums i.e., (0-5, 6-10 and 11-15) that all examined TUSs characterised by expected reward payments. However, as the demand grows over the latter three quinquenniums, the ability of some TUSs to provide adequate reliability falls off as is demonstrated by the negative values in red.

Table 6-4 PBR ERP results to the 1st layer TARM model state space

<table>
<thead>
<tr>
<th>Thermal Rate Candidate, pu</th>
<th>0-5 years</th>
<th>6-10 years</th>
<th>11-15 years</th>
<th>16-20 years</th>
<th>21-25 years</th>
<th>26-30 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.00</td>
<td>0.322</td>
<td>0.0673</td>
<td>0.0667</td>
<td>-0.3706</td>
<td>-0.3859</td>
<td>-0.5916</td>
</tr>
<tr>
<td>1.05</td>
<td>0.0368</td>
<td>0.0816</td>
<td>0.0734</td>
<td>-0.2652</td>
<td>-0.3224</td>
<td>-0.5041</td>
</tr>
<tr>
<td>1.10</td>
<td>0.0411</td>
<td>0.0836</td>
<td>0.0839</td>
<td>-0.1773</td>
<td>-0.2974</td>
<td>-0.4794</td>
</tr>
<tr>
<td>1.15</td>
<td>0.0770</td>
<td>0.0865</td>
<td>0.0919</td>
<td>-0.0356</td>
<td>-0.0761</td>
<td>-0.2612</td>
</tr>
<tr>
<td>1.20</td>
<td>0.0954</td>
<td>0.0936</td>
<td>0.1173</td>
<td>0.0541</td>
<td>0.0375</td>
<td>-0.1617</td>
</tr>
</tbody>
</table>

In the sixth quinquennium, all TUSs are unable to expectedly adhere to the 99.99% expected reliability target and subsequently should expect to be penalised—as the results clearly illustrate. However, the utility, if able to realise an attractive policy, will still be able to successfully manage a thermal management project that yields profitability over the stipulated 30 year period. Within contemporary project management, projects are presumed to last (and are subsequently
designed) for a period of 30 years. Thus, it is for these reasons that a project life of 30 years was implemented.

In light of the results in Tables 6-3 and 6-4, it becomes necessary to engage in a suite of financial, traversal, ageing condition and sensitivity analyses over a spectrum of long term TUSs as well as policy scenarios (PSSs) to enable proper justification of the optimal solution. PSSs consider that over an OHLs life-cycle a variety of thermal ratings can be scheduled, whereas TUSs consider that over an OHLs life-cycle a constant nominated thermal rating can be scheduled. Therefore, financial analyses showcase how either a TUS or PS is likely to perform over an OHL’s lifecycle. Traversal analyses showcase how either a TUS or PS traversal history over an OHL’s life-cycle evolves.

Ageing condition analysis aids the documentation of either a TUS or PS in order to classify it into an overarching asset management policy. This ability to classify is vitally useful in aiding a utility correlate a particular (including the optimal) TUS or PS into its appropriate overarching asset management policy; and then assessing whether the utility is justified to maintain its current overarching asset management approach or to transition to an overarching asset management approach which is more financially profitable. Therefore, in this study five ageing flexibility utilisation TUS and five ageing flexibility utilisation PSs are conceived and their financial performance assessed.

6.3.1 CASE STUDY-I: FINANCIAL LIFE-CYCLE TUS AND PS PERFORMANCE ANALYSIS
6.3.1.1 STUDY BACKGROUND
The identification of the optimal ageing flexibility utilisation TUS or PS requires the analysis of even inconceivable ageing flexibility utilisation TUSs or PSs so as to create a spectrum of ageing flexibility utilisation TUSs or PSs so as to fully showcase ascertain the value of the optimal ageing flexibility utilisation TUS or PS [184]. Therefore, in this study five ageing flexibility utilisation TUSs and five ageing flexibility utilisation PSs are conceived and their financial performance assessed. The PS group specialises on forcing the algorithm to make decisions at each stage based on different objective mandates as typified through the sole manipulation of Equation 6-22 in section 6.1.3.

6.3.1.2 STUDY DESIGN
The first objective mandate, O1 PS, forces the algorithm to select the least profitable solution at each stage irrespective of the TUS (and its ageing based consequences) or PBR-ERP scheme enforced; this is the highest ageing risk averse ageing flexibility utilisation PS. In like manner, the second objective mandate, O2 PS, forces the algorithm to select the second least profitable
solution at each state. Similarly, $O_3$ PS, $O_4$ PS and $O_5$ PS objective mandates select the third, fourth and fifth least profitable solutions at each stage. Since there are a total of five candidates per stage, the selection of $O_5$ PS will always result in the most profitable solution; this is the least ageing risk averse ageing flexibility utilisation PS. Conversely, within the ageing flexibility utilisation TUS group, five TUSs are investigated: the 1, 1.05, 1.1, 1.15 and 1.2 pu cases. Thus, throughout the life of the OHL these TUSs are mandated to be scheduled all the time.

### 6.3.1.3 Study Results

Figure 6-4 presents results to the life-cycle financial performances of the ageing flexibility utilisation TUSs and PSs. The y-axis to these plots records the collected project revenue in pu. The legends within the figure clearly annotate the manner in which each TUS and PS cumulatively performs over the project life. This project life is recorded in years as typified by the x-axis within these plots. By interpreting the general behaviours characteristic of all the TUSs in the figure, it can be observed that all of them exhibit growing revenue over the first 15 years of the project and then these TUSs and PSs exhibit reductions in revenue gains for the remainder of the project life. This revenue growth over the initial half of the TUS and PS life-cycle evidently depends on the ageing flexibility utilisation TUS or ageing flexibility utilisation PS implemented.

![Figure 6-4 Lifecycle financial assessment of the competing ten thermal rating policies](image)

In the case of the 1.2 pu TUS and the $O_5$ PS (respectively), these ageing flexibility utilisation approaches cumulatively earn over 5 pu by the end of year 15. Conversely, the least profitable $O_1$ PS produces earnings of 2 pu. The general reason for this relatively admirable performance over the first three quinquenniums is that no $EAI_{avg,SAI}$ or $EAI_{max}$ constraint is met. Additionally,
these (1.2 pu and O₅) ageing flexibility utilisation TUS and PS result in decisions to schedule higher thermal ratings (than the other TUSs and PSs), the consequence of which result in the highest possible *PBR-ERP Revenue* gains. However, these TUS and PS (1.2 pu and O₅) still have to pay for the *Ageing Damage Cost*. Nevertheless, as the final revenue at year 15 shows, the *PBR-ERP Revenue* benefit of ageing far outstrips its *Ageing Damage Cost* and thus overall, the line is extrinsically an asset to the system in spite of whether it is intrinsically a liability.

For the period of year 16 to year 25 the 1.2 pu TUS and O₅ PS experience receding revenue growth in the order of approximately 32% and 35% respectively. Thus by the end of the 25th fiscal year the project NPV for both the aforesaid TUS and PS are just above 5 pu, while most of the other TUSs and PSs (Figure 6-4) are either already operating at a loss or starting to. Clearly, for these TUSs and PSs, because the scheduling of thermal rating up until year 25 is generally conservative, they have not being able to accrue as much *PBR-ERP Revenue* gains in order to tackle the *EAI*ₕₘₖₐₓ and *EAIₜₐₗₜₐₕ* constraint costs which they inevitably meet post the 15th year of operation. The last quinquennium period of project proves detrimental to the gains of all the TUSs and PSs. This results from the heavy costs pertaining to increased reconductoring, retensioning, ROW maintenance, thermal uprating and inspection AMASs, as well as lowering *PBR-ERP Revenue* gains (as earlier shown in Table 6-4) collectively compound the TUSs—including on the TUS and PS of 1.2 pu and O₅ respectively. In the end, TUS 1.2 pu and PS O₅ record final losses of 1.96 and 2.58 pu respectively.

Since PS O₅ was designed to realise the most optimal path among the ten investigated policies, it is expected that the final value should be at least equal to that recorded by the 1.2 pu—but evidently, it is considerably lower. The reason for this is that in year 17 instead of engaging reconductoring subsequent to the eclipsing of *EAIₜₐₗₜₐₕ* the computation instead opts to conserve the age that year (as it seemed cheaper at that stage to the optimisation algorithm) and thus defer reconductoring for a year. To correct this short-sightedness of the algorithm, a look-ahead constraint must be formulated as shown in Equation 6-23. Therefore, only when the revenue to be made in the present also supersedes the cost deferment, can the algorithm schedule deferment.

\[
\left( \text{OptimalPolicyRevenue}^{t+1}_t - \text{Reconductoring Risk Cost}^{t+1}_t \right) < \text{OptimalPolicyRevenue}^t_t
\]

*Equation 6-23*
6.3.2 **Case Study-II: Life-Cycle TUS and PS Traversal Analysis**

Figure 6-5—presents the traversals due to the intimated TUS and PS candidates and illustrates the technical perspective to the discussed financial view. Evidently, each TUS and PS results in a unique traversal path.

For example, for the (1 pu to 1.2 pu) ageing flexibility utilisation TUSs, as expected, a single rating from the beginning to the end of the project will be scheduled (not shown in figure). Conversely for the O₁ to O₅ ageing flexibility utilisation PSs (shown in figure), multiple ratings (TUSs) are scheduled during the project’s lifetime. Moreover, for the O₁ to O₅ PSs, it can be generally noticed that from year 18 and onwards, the thermal rating scheduled is 1.1 pu and above—however for O₅ ageing flexibility utilisation PS, the rating is 1.15 pu and above. This is because it is not profitable for the utility to preserve the asset at the expense of incurring PBR-ERP Revenue reliability.
The value and risk of probabilistic thermal uprating scenarios on power system reliability

Penalty costs payable to the regulator. Therefore, irrespective of the TUS or PS strategy embraced, beyond year 18 it is in most cases justifiable to incur heavy Ageing Damage Cost and AMAS costs (i.e., Reconductoring Risk Cost, Over Sagging Risk Cost and Thermal Uprating Risk Cost) as these are more affordable than the PBR-ERP Revenue penalty costs. However, prior to year 18, the proclivity to incur losses based on the scheduling of lower (than 1.15 pu) rates is much lower; and this can be clearly noticed from the resulting scheduling of thermal ratings between years 1 and 17 for all the ageing flexibility utilisation PSs.

It must be stressed, however, that prior to year 18 the resultant scheduling of the thermal ratings in a dynamic fashion stems from the short-sightedness purposely built into the algorithms (as earlier discussed), resulting into bad decisions made at particular stages, and, thus, negatively and seriously influencing the outcomes of the subsequent decisions. Therefore, asset management project planners can not only use this methodology to realise the optimal policy but also to investigate and understand more fully the consequences of a spectrum of decisions.

6.3.3 Case Study-III: Life-cycle TUS and PS Ageing Condition Analysis

6.3.3.1 Study Background

An OHL conductor contributes a single component to a complete OHL structure. This structure and its components are shown in Figure 6-6. Furthermore, each of these plants are characterised by their failure rates as shown in the figure. Traditionally, in order to holistically maintain an OHL, the time-based overarching asset management policy has been scheduled in order to synchronise the holistic maintenance of the entire structure as much as possible. For this reason, traditionally, thermal ratings have been lowly scheduled to preserve the time-based maintenance policy. However, as these individual components undergo their specific ageing mechanisms over their lifetime, there is increasing imperative to transition to a condition-based overarching asset management policy.

Resultantly, there is increasing interest amongst OHL designers to provide initial OHL design solutions that promise to minimise the maintenance cost (of the solution) over its lifecycle by synchronising the activities within condition-based overarching asset management policy [2]. To do so, however, requires OHL designers to possess fairly accurate projections regarding how the designed line will be used over its lifetime. This is so that the legal permit paper work; subcontracting processes; optimised OHL and ROW designs; and/or other pertinent decisions related to OHL conductor maintenance can be fully deliberated both economically and reliably throughout the project’s life. The ageing analysis engaged in this study will be useful to project
how an OHL will be used in order to map the optimal LT-TUS to its appropriate condition-based overarching asset management policy.

![An OHL Structure and its major constituent plants](image)

**Figure 6-6 An OHL Structure and its major constituent plants**

### 6.3.3.2 Study Design

In this study the collation of the lifecycle ageing performances of the earlier TUSs is therefore engaged and subsequently studied in order to draw inferences that would be useful to aid the initial OHL design process: by computing the number of times a given policy will require reconductoring, retensioning, ROW maintenance activities and thermal uprating inspection exercises and suggesting how these results could influence the synchronisation of an OHL conductor’s AMASs with the broader AMAS of the entire OHL structure.

### 6.3.3.3 Study Results

Results to this collation process are presented in Figure 6-7, which documents the evolution of the line’s age overtime for the 10 ageing flexibility utilisation TUSs and PSs. In particular the horizontal axis of the plots denotes the years of anticipated life-cycle operation. The y-axis denotes the ageing scale of the OHL. The top figure represents the ageing flexibility utilisation PSs and the bottom figure the ageing flexibility utilisation TUSs. By observing the two plots in Figure 6-7 multiple peaks inherent to a particular TUS or TS are revealed.

These peaks indicate when reconductoring activities must be enforced. It can be seen that reconductoring occurs in all cases when the ageing is less than the 200 hour $EAI_{max}$ ageing constraint. This indicates that reconductoring is enforced whilst there is still residual age. This is because the decision to enforce reconductoring is made on the basis of a future look ahead to ascertain whether this residual age will meet the next year’s ageing requirements. If it does not meet the requirement, live-line reconductoring (as it is cheaper than scheduling a line outage) is engaged at the end of that operational year.
Conversely, it is possible to defer reconductoring till the next year until ageing is fully consumed in that year, but this decision must be made with a full quantification of the risk of shifting the line into the third stage of the reliability bathtub curve (discussed in section 2.1.5.2). This is an untapped area of research at the plant level and is subsequently not investigated in this chapter.

In addition, Figure 6-7 also shows the unique life-cycle ageing behaviours as engendered by their correspondingly unique TUSs and PSs. Revealingly, the reconductoring frequency-counts (and stages/years) are different between these policies as their residual ages are too. For example, the $O_5$ ageing flexibility utilisation PS over its lifecycle is generally the least wasteful residual ageing; as it is the ageing flexibility utilisation ageing flexibility utilisation PS which most maximises its ageing prior to reconductoring. In summary the total reconductoring frequency-counts and stages for the studied policies from Figure 6-7 can be more vividly captured through Figure 6-8 which are indicated as black dots.

It, therefore, is clear for the ageing flexibility utilisation PSs (top figure of Figure 6-8) that they would have to fit into a condition-based overarching asset management policy as the intervals of scheduled reconductoring activities are generally non-cyclical. The same is true of the 1.2 and 1.15 pu ageing flexibility utilisation TUSs. However, for the rest of the ageing flexibility utilisation TUSs, there is no need to schedule any reconductoring activity. However, further results pertaining to the sag-ageing performance of these policies, which is not clearly portrayed within Figure 6-7 can be recapitulated into Figure 6-9 to more vividly depict the stages (i.e., year) and corresponding frequency-counts pertaining to retensioning and/or ROW AMAS implementations.
It is thus noticeable in Figure 6-9 that the O₅ PS 1.2 and 1.15 pu TUS cases engage in an equal total of three activities, whereas the rest have less. Thus three is highest count rendered by any of the ageing flexibility utilisation strategies.

To the OHL designer, these results are valuable to aid the design of a condition-based overarching asset management policy; as they suggest that AMASs on both the ROW and the line will be dormant for the first 15 years. However, post 15 years, the required AMASs of retensioning (Figure 6-9) as well as reconductoring (Figure 6-8) escalate. Therefore, the OHL designer will be obligated to propose a flexible design which will not require major investments within the first half of the project but will require intense activity amid the second half of the project, based on solutions such as those proposed in [2].

This, for example, means designing lines in a manner that will enable an easy acquisition of access paths to the ROW in such a manner that it will not interfere with the environment or the settlers within the area. This may motivate the designer to liaise with town planners in order to
understand how future design plans for the area within which the OHL resides will be able to place constraints on the design problem. Furthermore, in order to ensure that these AMASs are synchronised with the AMASs of the other structural plants, stronger tower designs, for example, less susceptible to short term rusting and mechanical wear and tear can be designed. Moreover, more initially expensive, yet durable, insulators requiring few maintenance activities for a long time can be invested into.

Finally, stronger, rust resistant and high operational temperature fittings and connectors can be installed to ensure the long term reliability of an OHL and thus synchronise its maintenance with the TUS or PS AMASs. Clearly, it has been shown that by understanding these issues, can the designer then propose solutions such as those mentioned and more mentioned in [2] that comply with particular constraints. Although these aforementioned example solutions will increase the initial investment of an OHL structure as a whole, the profitability potential for scheduling higher thermal ratings over an ageing flexibility utilisation TUSs’ or PSs’ life-cycle (in this study the 1.2 pu and O₅ TUS and PS) will pay for this increased investment and still guarantee profitability if the value of the optimal TUS or PS can be enhanced, as is further discussed.

6.3.4 Case Study-IV: Enhancing the Financial Value of a Life-cycle TUS and PS

6.3.4.1 Study Background

The financial analysis performed in section 6.3.1.3 revealed that all TUSs and PSs performed poorly; as O₅ PS recorded final NPV of -2.58 pu and the best performing 1.2 pu TUS recorded just -1.96 pu in NPV at the end of the project life-cycle. In this study, four approaches to enhance the value of a particular policy are designed and investigated, (1) sensitivity studies, (2) PBR policy adjustments, (3) reconductoring policy adjustment and (4) sag-age policy adjustment.

6.3.4.2 Life-cycle TUS and PS Sensitivity Studies

Due to the fact that over a TUS’s or PS’s life-cycle changes (both good and bad for project profitability) can occur, a sensitivity study is necessary to investigate how a project parameter is likely to either improve or worsen a TUS’s or a PS’s joint reliability-economic-technical life-cycle performance. These changes which can either severely or favourably influence a TUS’s or a PS’s joint reliability-economic-technical life-cycle performance broadly class into political, economic, social, technological, regulatory and environmental (PESTRE).

Political influences are closely tied to regulatory policies. Economic influences are closely tied to the price of electricity; social influences are tied to the societal demand for electrical energy which if high drives the price of electricity high and vice versa. Technological influences are closely tied with the ability of existing techniques (such as OHL greasing and cost effective tower height
engineering) to increase the $EAI_{\text{sag age}}$ and $EAI_{\text{max}}$ constraints and thus lower the AMAS cost performance of a TUS or PS over its life-cycle. Regulatory influences are closely tied with regulatory penalties and rewards and environmental to the factors such as global warming which threaten to exacerbate a TUS’s or PS’s ageing.

Subsequently, a sensitivity analysis about a particular TUS or PS strategy must be engaged in order to study the various PESTRE influences on a TUS or PS so as to study how the value of an ageing flexibility utilisation TUS or PS can be increased: in this study an illustrative example is engaged with respect to the O$_5$ PS. The results are plotted in Figure 6-10 with the y-axis indicating the revenue cost in pu and the horizontal axis indicating the variation of altered parameter values in percentages of their base case values. The parameters altered are the positive $EAI_{\text{max}}$ and $EAI_{\text{sag age}}$ parameters as well as $\pi_{\text{Recond}}^{\text{pu}}$ and $\pi_{\text{Live-line Cost}}^{\text{pu}}$ signifying the technological parameters; $\pi_{\text{electricity}}^{\text{pu}}$ signifying the social-economic parameter; the $\pi_{\text{Max. Reward Cap}}^{\text{pu}}$ signifying the political-regulatory parameters; and the negative $EAI_{\text{max}}$ and $EAI_{\text{sag age}}$ values signifying the environmental parameters (Figure 6-10). Each of these parameters was produced by keeping all other parameters at their base case values and changing the values about the nominated parameter, one at a time.

![Figure 6-10 Sensitivity of final revenue to various project revenue and cost parameter value changes](image)

Therefore, by studying the figure, it is vivid that even though the $EAI_{\text{sag age}}$ constraint, $\pi_{\text{Recond}}^{\text{pu}}$ or $\pi_{\text{Live-line Cost}}^{\text{pu}}$ costs are lowered by up to 50% (i.e. if both technological and environmental factors improve), the O$_5$ life-cycle PS will not result in profitability. This is also true for the case when the $\pi_{\text{electricity}}^{\text{pu}}$ (i.e., the social-economic factor) is increased by up to 50%. However, the most influential parameters to the project are both the $EAI_{\text{max}}$ and $\pi_{\text{Max. Reward Cap}}^{\text{pu}}$ candidates (i.e., the technological and political-regulatory factors). This is because it can be seen in the figure, that it requires at least one of these parameters to increase by at least 35% in order to collect revenue that will
allow the project to breakeven. Beyond the 35% increment for the $\pi^{\text{Max. Reward Cap}}_{\text{cap}}$ or the $EAI_{\text{max}}$ parameter changes, the project makes a profit—which culminates for both parameters at 1 pu when these intimated parameters increase by 50%. Moreover, whereas the $\pi^{\text{Max. Reward Cap}}_{\text{cap}}$ parameter (i.e., the political-regulatory factor) exhibits a smooth linear rise, the $EAI_{\text{max}}$ parameter (i.e., the technological factor) exhibits an irregular rise. These irregularities witnessed with the $EAI_{\text{max}}$ parameter result from the irregularities rendered by varying residual ages as the $EAI_{\text{max}}$ value is changed and recomputed with each % increment.

In conclusion, it has been gleaned that political-regulatory and selected technological factors can help significantly improve the $O_5$ life-cycle PS performance. The political-regulatory factors as earlier mentioned are linked with the regulator. However, if the social-economic factors do not directly improve, as has been shown, the $O_5$ life-cycle PS, it may indirectly improve it. This is discussed next.

### 6.3.4.3 Life-cycle TUS and PS PBR Policy Adjustment

The effect of altering the PBR policy on the project performances of the ten candidate cases is investigated in this study. So far the expected reward payment (ERP) values in the previous studies have been calculated based on the mandate to accommodate the reliability target value of 99.99%. In some cases, the need for reliability may not be high if the society can find a cheaper substitute for electrical energy through for example demand response and energy efficiency programs; thus it may be worthwhile to investigate the effect of accommodating other target values which could broadly reflect the behaviour of demand response.

![Table 6-5](image)

<table>
<thead>
<tr>
<th>Case</th>
<th>$O_1$</th>
<th>$O_2$</th>
<th>$O_3$</th>
<th>$O_4$</th>
<th>$O_5$</th>
<th>PBR Case, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenue, pu</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1.05$ pu</td>
<td>$-9.89$</td>
<td>$-7.54$</td>
<td>$-6.49$</td>
<td>$-1.64$</td>
<td>$7.66$</td>
<td>99.90</td>
</tr>
<tr>
<td>$1.10$ pu</td>
<td>$-5.73$</td>
<td>$-3.32$</td>
<td>$-1.61$</td>
<td>$6.23$</td>
<td>$14.12$</td>
<td>99.00</td>
</tr>
</tbody>
</table>

![Table 6-6](image)

<table>
<thead>
<tr>
<th>Case</th>
<th>1.00 pu</th>
<th>1.05 pu</th>
<th>1.10 pu</th>
<th>1.15 pu</th>
<th>1.20 pu</th>
<th>PBR Case, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenue, pu</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1.00$ pu</td>
<td>$-32.46$</td>
<td>$-25.04$</td>
<td>$-21.67$</td>
<td>$-8.38$</td>
<td>$-1.96$</td>
<td>99.99</td>
</tr>
<tr>
<td>$1.05$ pu</td>
<td>$-30.38$</td>
<td>$-21.56$</td>
<td>$-18.34$</td>
<td>$-2.26$</td>
<td>$8.29$</td>
<td>99.90</td>
</tr>
<tr>
<td>$1.10$ pu</td>
<td>$-27.94$</td>
<td>$-18.89$</td>
<td>$-14.63$</td>
<td>$5.39$</td>
<td>$15.62$</td>
<td>99.00</td>
</tr>
</tbody>
</table>
Subsequently, the results to this study are collated in Table 6-5 and Table 6-6 for three target PBR reliability cases: the base case (99.99%) and two other cases as shown. Thus, by observing the tables, it is clear, that if the target value is low (i.e., if the society is able realise substitutes for electrical energy), the project profitability can be improved. This is because utilities can gain more ERP payments for highly reliable thermal rating solutions.

6.3.4.4 LIFE-CYCLE TUS AND PS RECONDUCTORING POLICY ADJUSTMENT

Considering that the PBR target is retained to its nominal 99.99% value, this section investigates the value of adopting an optimal reconductoring policy so as to minimise the project cost and hence maximise its profit. This study is engaged only with the O₅ life-cycle PS. Furthermore, prior results engaged to this O₅ life-cycle PS showed that (when $EAI_{\text{max}}$ was eclipsed) performing like-for-like reconductoring was a liability toward the realisation of project profitability. Thus, in this study, a variety of competing conductor types has been conjured up.

This is in order to thoroughly investigate how other conductor types can affect the O₅ life-cycle PS. The details pertaining to their modelled parameters and investment costs are narrated in [188]. Each of these candidate conductors have different mixes of attributes pertaining to both their investment costs and ageing capabilities.

Figure 6-11 illustrates the reconductoring cost, relative ageing and project NPV of this study. The NPV has been calculated as the final value of Equation 6-3 which accounted for the following project parameters: $\text{PBR-ERP Revenue}$, $\text{Flow Revenue}$, $\text{Ageing Damage Cost}$, $\text{Reconductoring Risk Cost}$, $\text{Thermal Uprating Risk Cost}$, $\text{Over Sagging Risk Cost}$.
Weather Data Investment ACP Cost and Conductor Investment ACP Cost. These parameters have been thoroughly discussed earlier. The y-axis describes the value in pu for each of the different calculated outputs (cost, ageing, revenue) for each conductor. The x-axis documents the name and type of the candidate conductors with the colour code indicating the same technology type, to aid readability.

From the results it can be seen that reconductoring with certain types of AAC conductors will exacerbate the O₅ project losses; in spite of their initial low cost in comparison to their equivalent ACSR, ACCC, ACCR alternatives. It is also evident that AAC conductors generally develop the most ageing compared to other technologies. Contrarily, the initially expensive HTLS technologies lower project losses, and thereby help to convert the entire project into a profitable one—on the merit of their superior anti-ageing design features at the simulated temperatures. Therefore, in summary, it can be inferred that in spite of their relatively high investment costs (as shown), HTLS conductors can aid to improve the O₅ life-cycle PS—which in this case is realised through the Munich ACCC conductor, the plot in the far right hand of the figure.

### 6.3.4.5 Life-cycle TUS and PS Sag-Age Policy Adjustment

The prior results in 6.3.2.3 suggested that retensioning and other activities to increase ROW clearances were engaged three times for the O₅ life-cycle PS. Within a business case justification, it is also important to investigate the impact of a *do nothing* action [184]. In the context of eclipsing EAIₗₑ, the do nothing option presents an opportunity for the λₑ risk to manifest. The composite λₑ value is employed within this study with little respect to its *tangible* values.

<table>
<thead>
<tr>
<th>Case</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>Modified O₅</th>
</tr>
</thead>
<tbody>
<tr>
<td>λₑ</td>
<td>0.2</td>
<td>0.4</td>
<td>0.6</td>
<td>0.8</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Revenue, pu</td>
<td>-1.99</td>
<td>-2.81</td>
<td>-4.23</td>
<td>-5.30</td>
<td>-7.11</td>
<td>-1.96</td>
</tr>
</tbody>
</table>

Results to this study are collated in Table 6-7 and emphatically show that the revenue of the O₅ life-cycle PS is worsened for all the λₑ values studied in the table. Therefore, it is more economical to instead incur the cost of ROW maintenance in order to attain a more profitable O₅ life-cycle PS.

### 6.4 Life-cycle TUS and PS Probabilistic Sensitivity Studies

TUS and PS life-cycle assessment and management is a process characterised by abundant uncertainty. The previous study hinged on the utilisation of an assumed (hence uncertain) dataset of costs and constraints. To overcome the uncertainty of the generated results about this data,
the previous chapter varied these datasets one at a time. This section however presents a robust TUS and PS life-cycle analysis which varies these parameters at the same time and uses decision trees to draw out meaningful data to aid meaningful analysis.

6.4.1 Case Study-I: Probabilistic Life-cycle TUS and PS Financial Sensitivity Analysis Considering Data Uncertainty

6.4.1.1 Study Background

Four studies were devised in 6.3.3 to showcase those opportunities whereby project planners could add more value to an underperforming TUS or PS life-cycle. These devised case studies are by no means exhaustive as it is also possible to propose solutions based on the combined application of these approaches. This approach could further lead to an even higher performance from an already well performing TUS or PS life-cycle. However, it must be emphasised that in all these studies, only one constraint is changed whilst keeping the other’s constant. Therefore, the resulting analysis fails to capture the influence of simultaneously changing constraints on the outputted TUS or PS life-cycle results. To overcome this, a probabilistic simultaneous sampling treatment of these constraints is required.

6.4.1.2 Study Design

The datasets earlier presented in Table 6-1 and 6-2 are converted to uniform distributions in Table 6-8 and 6-9 in order to perform the uncertainty analysis about them and robustly understand its impact on the project success. In Table 6-8 the range of the uniform distributions is shown as well as in table 6-9 as is encapsulated within the brackets. Once values from these distributions are sampled, a decision tree based on these values is produced in order to visual display the results.

This tree is produced by sampling parameters from their uniform continuous distribution within the following ranges illustrated in Table 6-8 and Table 6-9. In this study the sample size was 10000—this means that the 1st dimension space rendered in Table 6-3 was traversed 10000 times based on the various combinations of the values of the attributes sampled from within their distribution bounds.

<table>
<thead>
<tr>
<th>Table 6-8 Selected modified system level base case constraint database</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Range</strong></td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td>50 - 1500</td>
</tr>
</tbody>
</table>
216

Table 6-9 Modified table of cost functions

<table>
<thead>
<tr>
<th>Cost Name</th>
<th>(\alpha)</th>
<th>(\beta)</th>
<th>(\psi)</th>
<th>(\delta)</th>
<th>(\varepsilon)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max ERP Cost Range, pu</td>
<td>[0.5 - 10]</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>MVA Flow Cost Range, pu</td>
<td>-</td>
<td>[0 - 1]</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Reconductoring Cost Range, pu</td>
<td>-</td>
<td>-</td>
<td>[0.5 - 5]</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Thermal Uprating Cost Range, pu</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>[0 - 5]</td>
<td>-</td>
</tr>
<tr>
<td>ROW and retensioning Cost Range, pu</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>[0 - 5]</td>
</tr>
</tbody>
</table>

6.4.1.3 STUDY RESULTS

The resulting plot for O₅ life-cycle PS is shown in Figure 6-12 representing 34 pruned terminal nodes with an acceptable resubstitution accuracy of 93.4%. The terminal resulted nodes are clustered final project revenue values; with cluster A laying between \([21 \ldots 40]\) pu; cluster B between \([1 \ldots 20]\) pu; cluster C between \([-21 \ldots 0]\) pu; and cluster D between \([-41 \ldots -20]\) pu. Clearly from these defined clusters, only A and B realise profitable solutions. It can therefore be observed from this figure that 13 paths realise B status, 16 the C status and just 4 for the D status and no path was able to realise an A status solution.

![Figure 6-12 Decision tree plot of a variety of clustered project revenue paths](image)

Evidently, these results demonstrate the flexible nature of this O₅ life-cycle PS problem; and as such there is no single golden-cut or break-even solution for those results residing within cluster B. Therefore, it is inferable that when project parameters change course amid the project life-cycle, a variety of other parameters could be adjusted to ensure project profitability according to PESTRE analysis, as earlier discussed in 6.3.3.2. For example, in Figure 6-12 it can be seen that one scenario is forecasted to have \(EAI_{\text{max}}\) higher than 458 hours per lifecycle.
This scenario would achieve B status in three ways. The first way entails that initially the Thermal Uprating Risk Cost is less than 1.28 pu and the $\pi_{\text{Max. Reward Cap}}^{\text{DU}}$ must exceed 1.39 pu. The second option follows similar path but its $\pi_{\text{Max. Reward Cap}}^{\text{DU}}$ value does not exceed 1.39 pu and the $EAI_{\text{max}}$ should be 911 hours or more. The third option results to profitability when the Thermal Uprating Risk Cost rises above the 1.28 pu value and the $\pi_{\text{Max. Reward Cap}}^{\text{DU}}$ and the $EAI_{\text{max}}$ exceed the 2.73 pu and 810 hours values respectively. As discussed earlier, ageing is composed of inextricably interwoven competing environmental and thermal aspects; thus if environmental influences of ageing (such as conductor greasing and other activities [2]) can be engaged, higher $EAI_{\text{max}}$ values can be realised.

6.4.2 Case Study-II: Optimal Probabilistic Life-cycle TUS and PS Policy Selection Sensitivity Analysis Considering Data Uncertainty

6.4.2.1 Study Background
Section 6.3.1 presented a policy performance analysis of five TUSs and five PSs in which the 1.2 pu TUS was established as optimal. The analysis of those TUSs and PSs is further robustly assessed here by the inclusion of the distributive behaviours of policy constraint attributes earlier presented in Table 6-8 and Table 6-9 and simultaneously sampling them.

6.4.2.2 Study Results
Each TUS and PS was examined across all initial 10000 scenarios—which led to a total of 100 000 state-sequences for all the five TUSs and five PSs combined. In the next step, the TUS or PS which scored the most profitable solution from each of the 10000 scenarios was selected as a candidate for the decision tree. In this way the robustness of a selected TUS or PS could be studied over a broad range of scenarios. This solution tree is reproduced in Figure 6-13 with 24 pruned terminal nodes.

The accuracy of the tree outputs at this pruned level is 90.54%. This implies that the results gleaned from studying this plot are 90% true. Under pruning further the plot a more accurate output can be achieved, however, the additional number of branches leads to same outcomes as already shown in the plot. Therefore, it can be inferred that 11 out of 24 terminal nodes indicate that the optimal result is that characterised by the 1.2 pu life-cycle TUS, while 12 out of 24 terminal nodes indicate the O5 PS as optimal. Only in 1 out of 24 nodes the 1 pu TUS is selected as optimal. A more detailed study of the figure will reveal that in a number of cases, the 1.2 pu TUS is optimal as $EAI_{\text{sag age}}$ increases. Clearly, this places increased impetus on project planners if they intend to implement the 1.2 pu TUS to ensure that an OHL will be steeled with adequate $EAI_{\text{sag age}}$ values or, conversely, that the Over Sagging Risk Cost is sufficiently low.
If this cannot be assured then it would be more profitable to implement the O₅ PS. Moreover, it must be recapped from the previous studies that the O₅ PS attempts to identify opportunities for reconductoring deferment. Therefore, a deeper understanding of the results in Figure 6-13 will lead to assuring project planners of the high likelihood of deferring a reconductoring investment activity by at least a year (based on prior results).

6.4.3 CASE STUDY-III: OPTIMAL PROBABILISTIC LIFE-CYCLE TUS AND PS RECONDUCTORING POLICY SENSITIVITY ANALYSIS CONSIDERING DATA UNCERTAINTY

6.4.3.1 STUDY BACKGROUND

In section 6.3.3.4 a policy performance analysis of 24 reconductoring candidate options was engaged—and the Munich ACCC conductor was selected as the best candidate to enhance the value of the O₅ PS. In this section, this analysis is repeated taking into account the distributive behaviours of policy in order to clearly and robustly establish the conditions under which the Munich ACCC conductor would still materialise as the selected candidate.

6.4.3.2 STUDY DESIGN

The constraint attributes earlier presented in Table 6-8 and Table 6-9—in order to study the robustness of the selected Munich ACCC conductor. Therefore each policy was examined across all initial 10000 scenarios—which led to a total of 240 000 scenarios (i.e., 24 candidate policies multiplied by 10000 scenarios). In the next step, the policy which scored the most profitable solution from each of the 10000 scenarios was selected as a candidate for the decision tree. In this way the robustness of a selected policy could be studied over a broad range of scenarios.
6.4.3.3 Study Results

This solution tree is reproduced in Figure 6-14 with 32 pruned terminal nodes. The re-substitution accuracy is 88.43% at this pruned level. This implies that the results gleaned from studying this plot can be trusted with 88% confidence.

![Figure 6-14 Decision tree plot of a variety of TARM reconductoring policy project revenue paths](image)

Similar to the previous plot there is, however, little value to be gained by over-fitting the tree. Therefore, from this tree it can be shown that the robustness of the Munich ACCC conductor as a solution is realised in 11/32 terminal nodes i.e., 34.3%. Studying the plots in a more ruminate manner will reveal the varied unrelated paths engendered by the varied combination of constraints to which these terminal nodes could be traversed. Consequently, it is pivotally important to track the particular parameters which influence the traversal paths to the various terminal nodes in order to increase the likelihood of ascertaining the exact conductor to invest in; by adapting to changes in these parameters.

As the results show, it is difficult to pin point the exact parameters which influence the selection of the Munich ACCC, but it can be, nevertheless computed with 40.6% confidence that reconductoring with Munich ACCC will be the most optimal solution. Given such a low confidence it may be worth to wait closer to the reconductoring time when more of the influencing parameters shown in Figure 6-14 are more certain in order to compute with more confidence the optimum conductor to invest in.
6.5 Concluding Remarks

This chapter presented a dynamic programming (DP) based TUS and PS optimisation methodology and it was implemented to assess a spectrum of TUSs and PSs in order to realise the optimal stages in a TUS’s and PS’s life-cycle when AMAS policies were to be scheduled.

To fully validate this methodology a number of TUS and PS ageing flexibility utilisation policies were compared against each other (techno-economically) for their life-cycle performance. From the analyses it was shown (compared to the non ageing 1 pu TUS strategy) that up to 88.23% life-cycle financial improvement was realisable for the 1.2 pu PS strategy. This financial improvement derived by scheduling a high TUS or PS over its life-cycle with a condition-based overarching asset management policy. Therefore, to ensure the profitability of shifting to a condition-based policy, by predicting the actual stages wherein an AMAS was required, this stage could be synchronised with when AMASs on other OHL structures would need to be engaged as well. A plethora of scenarios of PESTRE factors are performed due to their uncertainty on their value and decision trees are made to identify their importance on the project’s economic viability. Such decision trees could be used by utilities to indicate the most optimum and flexible TUS or PS and therefore reduce the project risk on PESTRE factor changes.

The study of PESTRE uncertainty factors which influence the profitability of the optimal TUS’s or PS’s life-cycle duration was also investigated. It was found that when the $EAI_{sag\ age}$ constraint, $\pi^{\text{Recond}}_{\text{sub}}$ or $\pi^{\text{Live-line Cost}}_{\text{sub}}$ costs were lowered by up to 50%, life-cycle TUSs and PSs were not profitable. This was also true for the 50% increase in the $\pi^{\text{electricity}}_{\text{sub}}$ (i.e., the social-economic factor) case. The most influential parameters to the project’s profitability were the $EAI_{\text{max}}$ and $\pi^{\text{pu_max Reward Cap}}_{\text{sub}}$ variables (which describe the technological and political-regulatory factors). Consequently, an increase by at least 35% of one of these parameters is required to collect revenue that will allow either the 1.2 pu TUS or the O_5 PS strategies to breakeven. From the reconductoring study it was found that ACCC Munich increased life-cycle profitability by 64.9% appearing to be the most optimum. Alternatively, when demand response was implemented and the regulated reliability target policy was reduced by 0.99% the project’s profitability improved by a staggering 94%. It was also shown that when AMASs are not scheduled at the appropriate stages the life-cycle TUS or PS performance was reduced by up to 72%.
CHAPTER 7

REAL-TIME THERMAL OPERATING STATE MONITORING AND MANAGEMENT

The previous chapters have studied how to optimise the overall TUS’s life-cycle performance by capturing its EEAI visibility index as well as its related AMAS costs in order to ascertain the optimal AMAS implementation frequency and stages throughout the TUS’s life-cycle amid PESTRE uncertainties. This utilises the steady state OHL thermal behaviour model. The profitability of a TUS can be further improved by monitoring—in real-time—an OHL’s thermal operating state (TOS). This is because TOS monitoring allows for the opportunity to further flexibly increase the TOS’s magnitude and duration (beyond pre-planned TUS—as in the previous chapters’—values). This is due to the ability to exploit an OHL’s thermal inertia behavioural property, wrought through the employment of a conductor’s transient state OHL thermal behaviour model. A handful of papers have attempted to present tools which take advantage of an OHL’s thermal inertia, through transient thermal modelling, in order to increase the magnitude and duration of an OHL’s TOS [206-208]. However, these papers have failed to account for OHL ageing and have thus been limited to low temperature operation.

This chapter, subsequently, presents a novel approach based on real-time electro-thermal modelling to aid monitor, manage and identify further opportunities for TOS increments (and/or decrements) by including an ageing and its corresponding cost function. The benefit of TOS increments (and/or decrements) rendered through this novel methodical approach to real-time operation results in enhancements to both power system security and economical operation actions.

7.1 REAL-TIME TOS MONITORING AND MANAGEMENT METHODOLOGICAL APPROACH

Economically speaking, during real-time operations, it is more costly to enforce preventive actions. Preventive actions are actions designed to compute solution(s) which will instruct the system operator to maneuver a power system’s present pre-contingent system operational state to a new post-contingent state (through unmeritorious generation dispatches), such that if any pre-determined contingencies were to materialise at that point, the system would remain secure [36]. However, in spite of the high cost, operators have traditionally opted to maintain power
systems through preventive actions [36], as they are clearly more secure, because they constrict a power system’s operation to the normal security state after a contingency has arisen. Nevertheless, the panorama is shifting: contemporary power systems (due in part to the need to augment stochastic renewable generating sources to the grid) are increasingly required to deal with uncertain and highly polarised operational modes; which subsequently force the system to operate very close to, and sometimes at, system limits [209, 210].

Clearly, this action pushes power system operation from the normal to the alert security state. In order to effectively cope with these manifesting challenges, operators must be able to (more frequently) develop corrective action sequence plans. Corrective action sequences, as opposed to preventive action plans, invoke actions after the contingency in question has arisen— and not in anticipation to it. [209]. This subsequently requires utilising more corrective control plant technologies—such as generation re-dispatch; flexible AC transmission system (FACTS) devices, such as static var compensators (SVCs) and thyristor controlled series compensators (TCSCs); breaker and line switching; phase shifting transformers (PSTs), on-load tap changing transformer and/or system integrity protection schemes (SIPS)—in a cooperative, chained and time-series coordinated manner to alleviate any manifesting security violations, such as, voltage and thermal violations [210]. Co-ordination of these control technologies is not easy, as the time it takes for them to complete their action in a given sequence as illustrated in Figure 7-1 significantly varies.

One idea capable of engendering the coordinated implementation of these control technologies is to provide the power system operator with the flexibility of implementing TOSs of varying magnitude and durations in real-time into the corrective action sequence formulation process. Therefore, the flow chart of the proposed method is simply outlined in Figure 7-2. Hence, in response to a manifesting contingency (step 2) at a given/selected pre-contingent operating point (step 1) which has resulted in a static system violation (voltage or overload in step 4), the corrective action sequence formulation process begins at step 5 and ends at step 11. At step 5 a control action sequence, based on the availability of control action technologies and their implementation time constraints (Figure 7-1) in order to alleviate manifesting violations and thus
take the power system to a new secure operating state must be defined. Following this (step 6), the TOS magnitude and duration constraints must be defined.

These constraints determine the extent to which the control technologies within a given sequence may operate within the power system. More explicitly, if a generator, for example, can produce \( A \) MWs but a line can only accept \( B \) MWs, and if \( B < A \), then the generating unit will be constrained to outputting \( B \) MWs and the difference between the two (i.e., \( A \) and \( B \)) will be the society loss of energy. Therefore, the societal cost constraint function (step 7) must be included into the methodology as shown in Figure 7-2. If this societal cost is high it would justify re-evaluating
whether the TOS of $B$ MWs can be increased to $B'$ MWs so as to allow more power from the generator to flow through it. This will mean defining (at step 7) a TOS constraint cost function (i.e., its ageing cost function) to aid with the TOS magnitude and/or duration increase justification. Both these cost functions are then input as constraints (at step 8) together with the operational cost minimisation objective function (defined at step 7), in order to optimise power system operation over a TOS duration period.

Moreover a power system operator can also establish the optimal TOS which facilitates the cheapest control strategy by formulating new TOS of particular magnitude and duration (as shown through the iterative loop in the figure in step 10). Finally, the total cost of any given TOS-strategy (TOSS) can be computed by summing all the earlier discussed cost plants as defined in Equation 7-1. This is the final result computed from the optimisation process (Figure 7-2). In Equation 7-1, $\text{Op}_{\text{cost}}$ is the total system generation dispatch cost, $\text{ENS}_{\text{cost}}$ is the total system energy not served cost and $\text{EAI}_{\text{cost}}$ is the equivalent ageing index cost.

$$\text{Total}_{\text{cost}} = \text{Op}_{\text{cost}} + \text{ENS}_{\text{cost}} + \text{EAI}_{\text{cost}}$$  \hspace{1cm} \text{Equation 7-1}

### 7.1.1 Mathematical Formulations

During power system operation, the objective is to minimise the operation cost (Equation 7-2) by scheduling the most economical generators in a manner which satisfies the system power balance state Equation 7-3 (i.e., KVL and KCL) and its constraints Equation 7-4 (i.e. flow limits, voltage limits, plant mechanical limits etc.). Thus, when the constraints are satisfied, the inequality equation is given as in Equation 7-4.

In Equation 7-2 $f(x_k, u_k)$ is the total cost function (for a pre-contingent i.e., $k=0$ or a single contingency i.e., $k=[1, \ldots, c]$ or a multiple contingency i.e., $k=k$ operating state) of the vector of power outputs produced by all the generating units in the system. $c$ represents the total number of plants within the system. In Equation 7-3 and 7-4, $x_k$ is the vector (for a pre-contingent i.e., $k=0$ or a single contingency i.e., $k=[1, \ldots, c]$ or a multiple contingency i.e., $k=k$ operating state) of system state variables such as voltage and angle magnitudes and $u_k$ is the vector of system controls (for a pre-contingent i.e., $k=0$ or a single contingency i.e., $k=[1, \ldots, c]$ or a multiple contingency i.e., $k=k$ operating state) such as generator active power, switching options, phase shifting etc.; and is formulated to facilitate the implementation of various control, as well as corrective strategies. A detailed explanation of these formulations is given in [210].
\[
\min f_k(x_k, u_k) \quad \text{Equation 7-2}
\]

subject to

\[
g_k(x_k, u_k) = 0 \quad k = \begin{cases} 
0 & \text{if no contingency} \\
1, \ldots, c & \text{if singular contingency} \\
k & \text{if multiple contingency}
\end{cases} \quad \text{Equation 7-3}
\]

\[
h_k(x_k, u_k) \leq h_k^{\max} \quad k = \begin{cases} 
0 & \text{if no contingency} \\
1, \ldots, c & \text{if singular contingency} \\
k & \text{if multiple contingency}
\end{cases} \quad \text{Equation 7-4}
\]

When a contingent state \( k > 0 \) arises (whether singular i.e., \( k = 1, \ldots, c \) or multiple i.e., \( k = k \) ) and leads to violations in Equation 7-4 (indicating that a violation of either voltage or thermal rating (or both) have occurred and thus instigated a transition the system to the emergency state), it is vital that planners develop effective defence strategies in order to return to the condition \( h_k(x_k, u_k) \leq h_k^{\max} \) i.e., either the normal or the alert security state. Failure to do so in time will eventually lead to cascading line failures which will lead to the violation of Equation 7-3; and subsequent to this violation the system will transition to the extreme-emergency state in which partial or total load will be inevitably curtailed.

The development of effective defence strategies is achieved by selecting a set of corrective action TOS-strategies (i.e., TOSSs) \( \Omega_{\text{tot}} = \left[ \Omega_1 \cdots \Omega_n \right] \) and then one TOSS (i.e., from \( \left[ \Omega_1 \cdots \Omega_n \right] \) ) at a time evaluate the ability of that strategy \( \Omega_n \) (where \( n = 1 \cdots N \) ) to return to the system to the \( h_k(x_k, u_k) \leq h_k^{\max} \) condition, i.e., a new normal or alert state. The costs of these TOSSs \( \Omega_{\text{tot}} = \left[ \Omega_1 \cdots \Omega_n \right] \) are then evaluated in order to determine the least cost and most reliable TOSS. The TOSS with the least cost is then recommended to the operator (Figure 7-2).

7.1.2 ACCOUNTING FOR TOSS CONSTRAINTS AND COSTS

Since TOSSs may include a combination of line switching and/or generation re-dispatching actions (for example) co-ordinated and instigated at specified intervals, these actions and their time constraints such as breaker switching time and/or generator ramp and or down constraints must be accounted for and hence modelled as in Equation 7-5. This means that the state changes (for any of the given plants in a power system) between a pre-contingent \( u_k \) and a post-contingent state \( u_k \) must not exceed a plant’s inherent maximum state change \( \Delta u_k^{\max} \) within a given time window.
\[ |u_k - u_k| \leq \Delta u_k^{\text{max}} \quad k = \begin{cases} 0 & \text{if no contingency} \\ 1, \ldots, c & \text{if singular contingency} \\ k & \text{if multiple contingency} \end{cases} \quad \text{Equation 7-5} \]

Moreover, the impact of the instigation of plant control technologies on expediting a power system to the extreme-emergency state must be accounted for in a TOSS formulation as well. This is because improper operation could increase system risk of blackout and blackouts have a cost designated as the energy not served (ENS) cost. Mathematically, it means that the power balance Equation 7-3 is violated, and may consequently warrant a mathematical term to model ENS-based load shedding. To model load shedding within this methodology, virtual generators at the load points are modelled with their cost per unit MWh set based on the value of lost load (VOLL) at each demand bus, and are, therefore, only scheduled when generation re-dispatch is limited by the ramp rates of the actual units comprising the system. The virtual units are thus easily incorporated into the cost function defined in Equation 7-6; where \( N \) is the total number of busses experiencing load shedding within the system.

\[ \text{ENS}_{\text{cost}} = \sum_{j=1}^{N} \left( \text{voll} \left( t_j \right) \times \text{ENS} \times \text{time} \right) \quad \text{Equation 7-6} \]

### 7.1.3 TOSS CONSTRAINT AND COST FUNCTION

When formulating a particular TOSS in which a set of corrective actions are gathered in order to be implemented as a series of events in time, the appropriate TOSS magnitude and duration must be utilised so that after a given duration, as the system finds a new economical and secure operating point, during that same time the TOSS will be controlled to not operate beyond its magnitude and durational limits [211].

Therefore, historically, the definitions of system security states have aided power system operators in deciding which TOSS magnitude and duration to schedule when formulating a TOSS. This is shown in Figure 7-3 depicting TOSSs termed as the normal (or maximum continuous) rating i.e., N-TOS, the short term emergency (STE) rating i.e., STE-TOS and the long term emergency (LTE) ratings i.e., LTE-TOS [7, 83, 212]. Evidently, these ratings are scheduled on the basis of a given system’s security state. Thus when the system is residing within the normal state, margins must be enforced. Consequently, the power flows within this state will always be much less than the N-TOS. However, residence within the alert state implies that the system is operating close to or at its N-TOS limit.

The STE-TOS and LTE-TOS are applied to extend the duration of the emergency security state within which a system is residing. This is in order to reduce the possibility of transitioning to a
more insecure extreme emergency state. This is because it offers the power system operator time to realise a TOSS that would aid to manoeuvre the system to a new normal or alert state without load curtailment (when the system is in the emergency state) or with reduced load curtailment (when the system is in the extreme emergency state).

The STE-TOS is always higher in magnitude than the LTE-TOS, but shorter in duration. Therefore, the STE-TOS is designed for system contingent states that requires the securement of large thermal capacities albeit for short durations [58, 211-213], whereas LTE-TOSs are designed for system contingent states that mainly require the securement of thermal ratings for long(er) durations [7, 83].

Traditionally, as TOSS attempts to steer a power system to a new securer operating point, it does so by adhering to strict pre-set TOS magnitude and durational limits which are ubiquitously set based on engineering judgment and not on the actual evaluation of the ageing state of the TOS. Ubiquitously LTE-TOSs are limited to 24 hours and STE-TOSs are limited to 15 minutes. Therefore, the impact of selected TOSSs on the cost of TOS ageing must be included in the TOSSs selection process in order to evaluate the viability of relaxing a pre-set TOS magnitude and durational limit both reliably and economically.

The modeling of TOS limits within Equation 7-4 is based on defining an inequality constraint, \(|P_i| \leq P_i^{\text{max}}\); where \(P_i^{\text{max}}\) is the TOS limit in power ratings. In reality there are four cases to consider when assessing TOS rating inequality constraints, but the state-of-the-art models [206-208] only consider case 1 (see Equation 7-7) because in these models, conductor temperature is not monitored but rather assumed based on worst case conditions; which may be wrong and thus lead to TOS ageing (as shown in case 3 of Equation 7-7) even though an operator is supposedly yielding to a TOS rating constraint [1].

Figure 7-3 Power system security states [29]
In this methodology, however, because conductor temperature is monitored, it is possible to capture all possible inequality cases (shown in Equation 7-7), by monitoring both the power and temperature constraints. Hence, those cases when a TOS (i.e., whether they be N-TOS, LTE-TOS or STE-TOS depending on the operating security state of a power system) ages can be captured and costed according to Equation 7-8. Moreover, higher TOSs can be investigated beyond LTE-TOSs and STE-TOSs; and if their ageing cost is acceptable, they can be scheduled and aid to enhance a power system’s security. In Equation 7-8, the cost of ageing \( EAI_{\text{cost}} \) is a function of \( \pi_{\text{cost}} \) i.e., the cost of reconductoring with an equivalent conductor. Moreover, \( EAI_{\text{max}} \) is maximum ageing of an OHL. \% Ageing is the length of the given OHL. It must be stressed that as the utilisation increases, the ageing cost of the conductor will depend on both the historical as well the present ageing and has thus been accounted for as well in Equation 7-8.

\[
EAI_{\text{cost}} = EAI_{\text{historical cost}} + \left( \frac{EAI_{\text{actual}}}{EAI_{\text{max}}} \right) \times \pi_{\text{cost}} \times \left( \% \text{ Ageing} \right) \tag{7-8}
\]

### 7.1.4 Accounting for Thermal Transient State Change

It must be stressed that computing \( T_c \) in Equation 7-7 requires considering the transient behaviour of a TOS when a power system changes state, for example, from an intact state i.e., \( k > 0 \) to the contingent state (whether singular i.e., \( k = 1, \ldots, c \) or multiple i.e., \( k = k \)) . The behaviours that occur are explained in more detail.

When a conductor experiences an instantaneous change in its power flow, the resulting maximum change in its operating temperature will not rise instantaneously. Rather, the thermal inertia of the conductor will impede its instantaneous temperature rise. Subsequently, the final temperature corresponding to the new power flow will manifest after a particular time lag. Thus, by taking advantage of this time lag, higher power ratings can be implemented for short durations without operating the conductor at high temperatures. This is the basis for STE-TOSs [206, 212, 213].

The STE-TOS is a thermal (transient) rating which yields a specific maximum allowable conductor temperature \( T_{\text{max}} \) within a specified time ‘t’ after a step change in electrical current from some
CHAPTER 7: REAL-TIME THERMAL OPERATING STATE MONITORING AND MANAGEMENT

initial current $I_e$ [57]. The principle of transient thermal rating is depicted in Figure 7-4 (left) which further shows that the power flow must be reduced within an allotted time frame so as to not exceed the conductor accelerating ageing temperature ($T_{elev}$), where $T_{elev} = T_{max}$. However, it may be prudent to apply less conservative assumptions during emergency conditions so that conductors could be rated to operate above their maximum design temperatures $T_{max}$ whilst accepting a certain amount of annealing (i.e., conductor ageing) as shown by the shaded region in Figure 7-4 (right) as $T_{max} > T_{elev}$ (where $T_{elev} = T_{max}$). This is because even higher power ratings can be realised.

![Figure 7-4 Pictorial relationships between temperature rise and the latent consequential temperature rise (left) and the high temperature ageing (right) [57]](image)

7.1.5 THERMAL TRANSIENT MATHEMATICAL MODEL

In reality the OHL conductor is never in thermal equilibrium due to the constantly changing weather conditions and loading patterns and thus the transient state temperature model accounts for this. Its mathematical definition is given in Equation 7-9; where $mC_p$ represents the total heat capacity of the OHL and the other parameters have been earlier defined in chapter 3.

$$I^2R(T_c)\frac{dT}{dt}mC_p = Q_c(T_c, T_o) + Q_n(T_c, T_o) - Q_c$$  \hspace{1cm} \text{Equation 7-9}$$

Transient state temperature is time dependent and this means that the next state weather conditions will have an effect on the time it takes for an OHL to transition to another temperature state. To capture this behaviour Equation 7-10 presents a solved differential equation from Equation 7-9, and is used to estimate the instantaneous temperature $T_c(t)$ of an OHL.

$$T_c(t) = T_f + \left(T_f - T_i\right)(1 - e^{-t/\tau})$$  \hspace{1cm} \text{Equation 7-10}$$

$$\tau = \frac{(T_f - T_i)mC_p}{R(T_c)(I_f^2 - I_i^2)}$$  \hspace{1cm} \text{Equation 7-11}$$
Where $\tau$ is the time-constant given by the relation $mC_p$ is the conductor heat capacity. Moreover, $T_f$ is the final steady state temperature of the conductor’s response assuming the $T_i$ is the initial steady state temperature of the conductor prior to the step change and $R(T_i)$ is the instantaneous resistance of the conductor. $I_f$ is the final conductor ampacity during the step change and $I_i$ is the initial conductor ampacity prior to the step change.

### 7.1.6 Remarks

By considering the presented models it is possible to assess and optimise the utilisation of OHL conductors during real-time operations when formulating corrective action sequences. More explicitly, by considering, evaluating and costing OHL ageing amidst real-time power system operation, this can undoubtedly aid operators to more accurately assess more flexible ways to enhance power system security (for the first time in open literature).

### 7.2 Test System for Real-Time TOS Monitoring and Management Methodological Evaluation and Validation

The system used in this chapter’s study is the modified 230kV section of the IEEE-RTS network—as there is now a large amount of wind connected at the Bus 18 and Bus 21 shown in Figure 7-5.

In this event the operator notices about 1.28 GW (point A, Figure 7-5 right) of power output provided from Bus 18 and Bus 21 due to unanticipated high wind production. This scenario is used to compare the traditional and flexible TOS-based action strategies which take OHL ageing into account.
7.3 Application of Real-Time TOS Monitoring and Management Methodology for Comparison Between Traditional and Flexible TOSs

Based on the modified system conditions three case studies are formulated: Case study-I models the status quo TOS formulation approach which reliant on adhering to tight TOS constraints (i.e., case 1 of Equation 7-7); case study-II critiques this approach (and exposes its risk due to the inability to account for the other three cases) and proposes an augmented ageing cost function; and case study-III, consequently enhances the operator’s TOS formulation approach, through realising the optimal relaxed/flexible ageing based TOSs.

7.3.1 Case Study-I: Generation of Traditional TOSs

7.3.1.1 Study Background

As earlier mentioned, it is generally acceptable to operate OHLs with emergency ratings. These ratings are realised in two ways: (1) by increasing the duration of long term operation i.e., long term emergency rating (LTE), and (2) by increasing the maximum temperature for a short time i.e., short time emergency rating (STE). This case study takes these tight TOS-LTE and TOS-STE ratings into account in developing a variety of TOSSs.

7.3.1.2 Study Design

By observing the security nomogram (for the test system earlier defined and drawn in Figure 7-5) on the right in Figure 7-6, lines 23 and 28 are operating at their maximum thermal limit (i.e., operating point is above the dotted line). These lines are also indicated in red in the one-line diagram in Figure 7-5.

![Figure 7-6 230kV Section of the IEEE-RTS and its Security Nomogram](image)

Thus the operator must manually curtail wind generation through re-dispatching conventional units, and also by requesting the wind utility company to ramp down its production. This operating point B is shown in the nomogram as the case considering that the operator has curtailed 0.28 GW of generation from busses 18 and 21; and re-dispatched generation from the
rest of the system (i.e., the x-axis on the nomogram). As can be seen, the lines would still be maximally loaded and the system cost would increase by 5.5% from 110k$ to 116k$. Further wind generation curtailment from busses 18 and 21 will shift the operating point further to the right, at point C; and relieve the maximum loading of line 28 (albeit to within 98% of its nominated maximum continuous rating)—but will still maintain a maximum continuous load on line 23 i.e., point C on the nomogram. Subsequently, the operator is made aware that the attempts to further curtail generation will result in increased operational (pre-contingent) costs. Moreover, the operator is now apprehensive that the system is operating in the alert state because results from the DC power-flow contingency analysis have shown that failures due to lines 23, 25, 26 and/or 28 during this operating hour for which the prevailing conditions are assumed to last, will result in overloads on selected healthy lines.

This will lead the system to operate in either its emergency or extreme-emergency state. Thus, the operator must come up with TOSSs i.e., \( \Omega_{\text{tot}} = [\Omega_1 \cdots \Omega_n] \) and then one TOSS (i.e., from \( [\Omega_1 \cdots \Omega_n] \)) at a time evaluate the ability of that strategy \( \Omega_n \) (where \( n = 1 \cdots N \)) to aid the decision pertaining to whether the current operating system point (i.e., A) could be secured either through the availability of plants to alleviate overloads or through ageing the OHLs. If any of TOSSs are not possible to implement, then the operator would have no choice but to curtail generation regardless of the cost. This is in order to manoeuvre to the more secure (albeit more expensive) pre-contingent points B or C—from its current point A. In coming up with TOSSs, the operator must comply to TOS magnitude and durational constraints, as shown in Table 7-1. Additionally, the operator is sentient of the fact that when the TOS-STE value given in Table 7-1 is exceeded, drastic actions are to be taken immediately, and consequently the operator may have to invoke load shedding. Therefore, line loadings that materialise above TOS -STE limits are termed as TOS drastic action limits (TOS-DAL) [214].

<table>
<thead>
<tr>
<th>Mins</th>
<th>Rating Classification</th>
<th>Rating MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/A</td>
<td>Normal (norm.)</td>
<td>500</td>
</tr>
<tr>
<td>1440</td>
<td>Long term emergency (LTE)</td>
<td>600</td>
</tr>
<tr>
<td>15</td>
<td>Short term emergency (STE)</td>
<td>625</td>
</tr>
</tbody>
</table>

The system is assumed to operate at point A, prior to line 25’s failure event. After the failure, with no post-contingent action, line 28 would operate at 678 MVA i.e., within its TOS-DAL range. In this case the protection scheme will immediately trip line 28 (Figure 7-5). The operator cannot contend with this potential situation, because flows will be redistributed to the healthy lines, with
high potential of overloading them (i.e., above their TOS-DAL range). This will consequently increase the risk of cascading trips throughout the system; and this could be further compounded through protection system sympathetic tripping—resulting in a faster progression of cascading events. Sympathetic trips are those which manifest when protection systems incorrectly operate [120, 215]. Therefore, to hedge against the potential cascading event scenario, one TOSS deemed as A-1 could be implemented by the operator. Moreover, in this study a total of four action TOSSs have been realised and named as in Equation 7-12.

\[
\Omega_{TOS} = [\Omega_{A-1}, \Omega_{A-2}, \Omega_{B-1}, \Omega_{C-1}]
\]  

Equation 7-12

7.3.1.3 STUDY RESULTS

The \( \Omega_{A-1} \) TOSS implies that the operator could implement the set of actions in the sequence depicted in Figure 7-7. The actions in black text are those that the operator takes amid the system’s extreme-emergency operating state. The system enters this state because in order to prevent line 28 from operating within its DAL range, an initial switching-out of line 23 is performed within the first minute of the failure.

Figure 7-7 A time sequence diagram of events and action for the A-1 TOSS

However, in order to maintain balance between generation and load, the operator must simultaneously shed some load as well as re-dispatch generation so as to realise a new operating point that allows for the reconnection of line 23 as soon as possible. Figure 7-7 shows that the re-dispatch action to facilitate this reconnection is completed within 15 minutes—as this is the most expeditious time available to the operator amid all possible system operation constraints. The red text in the figure illustrates the operator’s actions occurring during the emergency state.

By observing the time the events occur in Figure 7-7, one can see that the extreme-emergency state lasts for 5 minutes; i.e., between 00:01 and 00:05 (counting the first minute as well). At time
00:05, as the generation is still re-dispatching, the operator is able to realise a new secure operating point which consequently allows for the reconnection of the electrical load. Overall, under $\Omega_{A}\cup$ TOSS the operator is able to complete all possible actions within 35 minutes.

If the operator is not confident in implementing the switching action of line 23 inherent to $\Omega_{A}\cup$ TOSS (for fear of experiencing stuck breaker conditions), the $\Omega_{A}\cup$ TOSS can be alternatively deliberated. During this TOSS, while the relay trips line 28, a simultaneous generation re-dispatch is performed from the first minute of the manifestation of the contingency (Figure 7-8). It should be noted that these operator actions do not immediately transition the system into the extreme emergency state—as it was with the $\Omega_{A}\cup$ TOSS.

![Figure 7-8 A time sequence diagram of events and action for the A-2 TOSS](image)

However, considering the ramp rate constraints of the generators during the re-dispatch action, generation-load imbalance manifests after 5 minutes, and consequently the load shedding protection schemes accordingly act in order to curtail some load. This extreme-emergency state lasts for 10 minutes, which is 5 minutes longer in comparison to $\Omega_{A}\cup$ TOSS. After 15 minutes from the initial line outage the system is able to realise a new operating point that securely accommodates both the reconnections of the load and line 28. The operator’s $\Omega_{A\cup}$ TOSS is completed after 40 minutes—due to the generator re-dispatch action. This is 5 minutes longer than the $\Omega_{A\cup}$ TOSS. In total this strategy requires the utilisation of 7 actions, one action less than the $\Omega_{A\cup}$ TOSS.

In light of the evidence that the prior TOSSs transition the power system to the extreme-emergency state, the operator may decide to implement pre-contingent preventive security actions; by constraining the generators $G_{37}$ and $G_{41}$ at busses 18 and 21 respectively. Resultantly, this action shifts the pre-contingent operating point from A to B. Expectedly, the operating cost of this pre-contingent scenario is higher than the operating point at A, as discussed earlier (Figure 7-
However, considering the \( \Omega_{B,1} \) TOSS illustrated in Figure 7-9, it can be immediately noted that the operator does not require switching out any of the lines 23 and 28; and more importantly the system does not transition to the extreme emergency state for more than a minute. This scenario is not shown to aid the readability of the figure. Obviously, this result is most desirable (compared to the other TOSSs), to the operator in spite of securing this action at a pre-contingent cost which is increased by 5.5%. From Figure 7-9, it can be seen that the operator only requires invoking a total of four actions; which could prove advantageous to the operator in the event when only a limited number of actions (that could be implemented) are available.

Moreover, given the improved results rendered through shifting the pre-contingent operation from point A to point B, the operator might prefer to investigate the security offered through operating at point C. It is found, however, that the post-contingent \( \Omega_{C,1} \) TOSS actions required are exactly the same as those performed under the \( \Omega_{A,2} \) TOSS (Figure 7-8). It is important to note that even though point C should logically result in a more secure post-contingent \( \Omega_{C,1} \) TOSS compared to the points A and B, point C instead operates for 5 minutes within the extreme-emergency state. This, therefore, indicates that it is possible for a system operating point that is more secure at a pre-contingent state, to be more insecure at its post-contingent state. This observed behaviour is due to the non-coherent nature of non-linear power systems [81].

### 7.3.2 Case Study-II: Security and Financial Evaluation of Traditional TOSSs

#### 7.3.2.1 Study Background

Penultimate to selecting the most appropriate TOSS an assessment of the line flows to the narrated TOSSs must be engaged. This is to confirm and ascertain how these TOSSs adhere to TOS magnitude and durational constraints as the power system is steered to the most secure post-contingent state.
7.3.2.2 STUDY RESULTS

These results are plotted in Figure 7-10. This figure embodies plots characteristic of the TOSSs discussed earlier (in 7.3.1.3). Subsequently, A-1 TOSS is described through the label (i); A-2 TOSS and C-1 TOSS, through label (ii); and B-1 through label (iii). Throughout the employment of these strategies only lines 23, 26 and 28 experienced loadings at their TOS-STE boundaries. The y-axis scale records power flow values in MWs, and the x-axis records the times under which these flows are sustained.

Figure 7-10 A pictorial chronological representation of power flows through healthy lines consequent to operator corrective actions and initial system operation points

Clearly, it can be seen that the A-1 TOSS ensures that line 28 does not operate within its TOS-DAL range whilst line 23 is out. Rather, as illustrated, lines 28 (as well as 26) are slowly ramped up until line 28 attains its TOS-STE limit. Furthermore, it is shown that the complexity of system operation in this case is such that it cannot allow the operator to maintain TOS-STE flows on line 28 for longer than a minute. Maintaining TOS-STE flows on line 28 would minimise dispatch costs. However, because line 23 must be switched back into operation (for security reasons) the generating units will be ramped down in order to guarantee generation and load balance when line 23 is restored. Consequently, when line 23 is reclosed after 15 minutes the flows within line 28 (as well as 23 and 26) will reside between their TOS-LTE and TOS-STE limits as shown.

However, considering Figure 7-10 (ii), it is clear that invoking A-2 or C-1 TOSSs results in the maximal TOS-STE loading of line 26 i.e., between times 0 and 10 minutes. Furthermore, line 28 also operates for 12 minutes at its TOS-STE limit i.e., between 15 and 27 minutes; and hence it is clear that the system resides at its TOS-STE boundaries (amid the A-2 or C-1 TOSSs) longer than the A-1 TOSS. Finally, observing Figure 7-10 (iii) which typifies flows pertaining to the B-1 TOSS, it
can be clearly noted that no line operates beyond its TOS-LTE limit; with only line 28 operating at its TOS-LTE limit (i.e. below the STE thermal-security boundary) for the entire duration of 60 minutes.

Thus, these results serve to show the complexity of managing flows pertaining to the implementation of various post-contingency corrective action TOSSs. This behaviour is clarified because it can be clearly witnessed from Figure 7-19 how this system rapidly steers across many thermal-security boundaries as it seeks an optimal operating point. Regardless, however, it has been shown how all these strategies adhere to the thermal-security magnitude and durational limits. Therefore, the operator would be satisfied to implement any of these strategies, subject to a cost review of these actions.

Finally, the costs of the narrated strategies is summarised in Figure 7-11. These costs are delineated as follows: the out-of-merit costs, due to the shifting of the pre-contingent operating point from A to either B or C; the energy not served costs, due to load curtailment amid the re-dispatch and/or switching actions; and the re-dispatch cost, amid the re-dispatching action and/or switching actions. These cost calculations have been made according to Equation 7-1 and are scaled on the y-axis of Figure 7-11.

An initial study of the figure will show that the TOSS resulting in the lowest overall operating and security cost (i.e., the combined pre- and post-contingent) is A-1 TOSS. This is followed by B-1, A-2 and then C-1 TOSSs. Moreover, the overall operating and security costs for C-1 TOSS also shows that deciding to operate at C through solely judging its pre-contingent security state is not a prudent approach. This is because of the fact that due to the system’s non-coherency characteristic, its pre- and post-contingent costs significantly rise. A further ruminate study of the figure will reveal that all TOSSs (save for the B-1 TOSS) manifest energy not served costs which are superlatively higher than $1500. Conversely, due to its momentary load shedding, B-1 manifests a mere comparative cost of ~$1000. According to NERC’s N-1 criteria, the system must be secured by ensuring that any manifesting N-1 failure will not result in load shedding; or if does, with
minimal load shedding. Therefore, to comply to this directive, the best pre-contingent operating point would have to be selected as point B. Resultantly, this solution would prompt the operator to shift from point A to B (Figure 7-6).

7.3.3 Case Study-III: Security Risk Evaluation of Traditional TOSSs

7.3.3.1 Study Background
In developing the TOSSs so far and by only accounting for the power rating, the operator is only able to capture case 1.

\[
\text{Case}_j = \begin{cases} 
0 & \text{if } |P_l| \leq P_l^{\text{max}} \text{ and } T_c \leq T_{\text{age}} \quad j = 1 \\
0 & \text{if } |P_l| \geq P_l^{\text{max}} \text{ and } T_c \leq T_{\text{age}} \quad j = 2 \\
EAl_{\text{cost}}^j & \text{if } |P_l| \leq P_l^{\text{max}} \text{ and } T_c \geq T_{\text{age}} \quad j = 3 \\
EAl_{\text{cost}}^j & \text{if } |P_l| \geq P_l^{\text{max}} \text{ and } T_c \geq T_{\text{age}} \quad j = 4
\end{cases}
\]

Equation 7-13

However, as equation 7-13 shows it is possible (i.e., through case 3) to incur ageing despite adhering to the power flow ratings, as was the case in the previous case study. This study, therefore, assesses this risk.

7.3.3.2 Study Design
In this study, for a given power rating, to calculate the equivalent operating temperature \( T_c \) the following weather conditions are assumed: ambient temperature 40°C and 0.61 m/s perpendicular wind with solar radiation of 14 W/m². Equations 7-9 to 7-13 are then utilised to compute the relevant temperatures (accounting for the transient thermal behaviour) which are then plotted for further analysis.

7.3.3.3 Study Results
Consequently, Figure 7-12 produces the conductor temperature-time plots representative of the earlier discussed TOSS—clearly described by the legends in the figure. A-1 TOSS is described through the label (i); A-2 and C-1 TOSSs, through label (ii); and B-1 TOSS through label (iii). The y-axis scale records the temperature values and the x-axis scales the operating time progression for a given TOSS. It is immediately evident from this plot that the thermal behaviour of the lines is not correlated to their flow behaviours, from earlier studies (i.e. Figure 7-10).

This is because the linkage between instantaneous power flow perturbations and the corresponding thermal response is governed by the line’s thermal inertia property; this property which is further subsumed by a conductor’s diametric, heat capacity and material properties as was shown in Equations 7-9 to 7-13 [57]. Consequently, it is evident that although power flow changes are instantaneous in all TOSSs (Figure 7-10), rather than experience immediate step
changes in temperature, these lines (Figure 7-12) instead follow initial linear temperature rises or fallings that exponentially saturate as time elapses. Also it was observed in most of the TOSSs in Figure 7-10 that lines constantly ramp up or down—instead of maintaining their MW flows.

![Figure 7-12 A plot of conductor temperature transient rises amid the application of various corrective actions](image)

Logical intuition must expect the effect of this ramping up and down of MW flows to result in the cyclic cooling and heating of the conductors. However, this is not particularly evident in the results shown in Figure 7-12. This is simply because the thermal inertia of the conductor works to both slow the rate of change of either temperature cooling or rising, amid the cyclic MW flows. Thus, even though MW flows are constantly changing amid the implementation of various actions, the thermal inertia property, nevertheless, slows the response of conductor temperature. This, therefore, serves to produce more smoothed out plots as is evidenced in all the cases in Figure 7-12. Therefore, operators can take full advantage of this thermal inertia behaviour in order to increase MW flows without incurring excessive levels of ageing. Moreover, it can be noted that switching lines out has the added benefit of cooling the lines—see for example line 23 in Figure 7-12 (i) or line 28 in Figure 7-12 (ii). In Figure 7-12 (ii) line 23’s drop in temperature is driven by the switching of line 28 and not of the aforesaid line. This is why the observed drop (in conductor temperature) is not as much as that shown in Figure 7-12 (i)—i.e., when line 23 is truly switched out.

In summary, it can be noted that the lines in Figure 7-12, depending on an implemented TOSS, will eventually exceed the 100°C ageing threshold. This necessitates the need to assess the ageing of these lines in order to cost them to their particular strategies, and hence realise solutions that result in enhanced operator decisions. This costing has been completed according to Equation 7-7. Consequently, Figure 7-13 portrays bar charts characteristic of the lines earlier discussed—
The value and risk of probabilistic thermal uprating scenarios on power system reliability described by the legends in Figure 7-13. The x-axis records the instigated action-strategy. The top bar-chart plot in the figure records each line’s age in minutes. The black text above the bar chart represents the total system age in minutes for each TOSS. Similarly the bottom bar-chart plot records the corresponding ageing costs to these narrated TOSSs—based on their ageing minutes recorded above.

![Figure 7-13 A graphical representation of line ages and costs pertaining to the application of various strategies](image)

Also, it can be observed from Figure 7-13 (top) that in all cases, no line ages more than 5 minutes (blue text) in spite of accommodating high power flows. These low ageing values are due to the thermal inertia behaviours of the conductors. Therefore, the importance of a conductor’s thermal inertia as a characteristic that aids the conductor to be more resilient against ageing is worth noting—as has been earlier discussed. Finally, the ageing costs are augmented to the earlier costs from Figure 7-11—as collated in Table 7-2. Clearly, by observing column four it is evident that the ageing costs have imposed little influence on the total cost of the tabulated TOSS

<table>
<thead>
<tr>
<th>Action Strategy</th>
<th>Operating and Security Cost, $</th>
<th>Total System Ageing Cost, $</th>
<th>Total Operating and Security and Ageing Cost, $</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-1</td>
<td>131 057</td>
<td>726</td>
<td>131 783</td>
</tr>
<tr>
<td>A-2</td>
<td>231 834</td>
<td>783</td>
<td>232 617</td>
</tr>
<tr>
<td>B-1</td>
<td>152 577</td>
<td>700</td>
<td>153 277</td>
</tr>
<tr>
<td>C-1</td>
<td>131 057</td>
<td>783</td>
<td>131 840</td>
</tr>
</tbody>
</table>

(when compared with column two). This suggests that the cost of ageing is low (see column three) compared to the operating and security costs (column to). Evidently, this result, thus, presents the opportunity to further increase/relax thermal-security ratings beyond the values considered in the study thus far i.e., case 3 from equation 7-13.
7.3.4 CASE STUDY IV: EVALUATION OF FLEXIBLE TOSSs

Earlier results instructed the operator to shift the system’s initial operating point from A to B due to the need to adhere to tight thermal-security margins (i.e., case 3 from equation 7-14), based on Table 7-1. Given that prior results have showcased that these tight thermal-security margins could be relaxed and their ageing costed (i.e., case 4 from equation 7-14), the operating point at A is, therefore, once again considered.

\[
Case_j = \begin{cases} 
0 & \text{if } |P_j| \leq P_{l}^{\text{max}} \text{ & } T_c \leq T_{\text{age}} \quad j = 1 \\
0 & \text{if } |P_j| > P_{l}^{\text{max}} \text{ & } T_c \leq T_{\text{age}} \quad j = 2 \\
EAI_{\text{cost}}^j & \text{if } |P_j| \leq P_{l}^{\text{max}} \text{ & } T_c > T_{\text{age}} \quad j = 3 \\
EAI_{\text{cost}}^j & \text{if } |P_j| > P_{l}^{\text{max}} \text{ & } T_c > T_{\text{age}} \quad j = 4 
\end{cases}
\]

Equation 7-14

7.3.4.1 STUDY DESIGN

In this case study, the operator aims to study the effect of increasing the TOS-DAL (i.e., by operating at the initially rejected 678 MVA i.e., case 4 from Equation 7-14) loading time for line 28. Resultantly, it is assumed in this study that the protection system settings have been reconfigured in order to allow for this action to be investigated. Moreover, it must be emphasised that increasing the TOS-DAL extends the time frame for which actions must be implemented. And in all the considered TOS-DAL cases, only re-dispatch action was considered.

7.3.4.2 STUDY RESULTS

The results from this study are presented in Figure 7-14. Figure 7-14 encapsulates (for ease of comparison) the total post-contingent system cost (i); the ENS cost (ii); and the EAI cost (iii) for different TOS-DAL operation times (at the 678MVA magnitude). The zero TOS-DAL time in Figure 7-14 (i), represents the system cost of the case at the pre-contingent operating point B. Thus, from Figure 7-14 (i), it is clear that the total system cost reduction is achieved when the TOS-DAL operation time is increased. By further observing Figure 7-14 (i), and focussing on the 60 minute TOS-DAL time it can be noted that up to approximately 4.9% improvement in system cost can be realised if the system is operated pre-contingently at A and if the post contingent 678 MVA TOS-DAL duration is increased to 60 minutes. Moreover, at this value, the need for re-dispatching (and hence any operator corrective action) is completely eradicated. Further study will also show that a 100% reduction in ENS cost can be achieved (when the TOS-DAL duration is increased to 60 minutes—Figure 7-14 (ii)). And this is at the expense of a 105% increase in EAI cost (Figure 7-14 (iii)). However, when the total cost is considered there is an overall reduction of the order of ~4.9% realised; hence, re-proving that the impact of the ageing cost on the total cost is minimal. Therefore, this cost comparison shows that the operator will not have to operate at point B due to the flexibility that can be afforded by increasing the TOS-DAL magnitude and operation time.
Figure 7-14 The changes in total system cost, ENS cost and EAI cost with respect to increasing DAL durations

This also means that with the particularly increased TOS-DAL time of 60 minutes, the system does not transition to the extreme-emergency (EE) state as clearly shown also in figure 7-15 (b). Figure 7-15 (a) which is in is direct contradiction to Figure 7-15 (b) shows that there will always be a risk of transitioning to the extreme-emergency state when the TOS-DAL time is less than 60 minutes. Finally, Figure 7-16 shows the maximum temperatures (i.e., $T_{\text{MAX}}$) at which the OHLs will have to be operated at in order to facilitate this TAS-DAL magnitude and durational increase.

Figure 7-15 Security transition diagram comparing staTOS quo approach to thesis approach to thermal-security

Figure 7-16 A temperature versus DAL operation time relationship

### 7.4 The Effect of Multiple Contingencies on the Evaluation of Flexible TOSSs

In contrast to the single contingency analysis invoked in 7.3, a system is always at risk of being subjected to multiple contingencies. For this reason it is of prime necessity to evaluate the effect of multiple contingencies on the selection of flexible TOS-DALS. In this section, this effect is investigated. This investigation makes use of the state-based Monte Carlo (MC) algorithm to
generate multiple contingencies. The consequence of the utilisation of the MC results in the generation of a wealth of data encompassed within a probabilistic state space. The data from this state space can be analysed by either considering all the data in the state space or by considering a portion of the state space data i.e., by pruning out the irrelevant data in the state space through a probabilistic criterion as will be later discussed. In this section, therefore, two TOSSs-based case studies in accordance with the two ways of analysing state spaces are developed. In so doing, the first case study models an analytical process for which operators that are risk averse can utilise and the second case study models an analytical process for which operators who are less risk averse can utilise in assessing a TOSS’s robustness to multiple contingencies.

7.4.1 CASE STUDY-I: FULL PROBABILISTIC TOSS STATE ANALYSIS

7.4.1.1 STUDY BACKGROUND

In a contemporary power system operating environment which is largely uncertain in nature (i.e., due to load forecast errors, random plant failures etc.) and is projected to further increase in uncertainty due to the proliferation of stochastic generation i.e., wind, solar etc., the need for a probabilistic indicator which evaluates a probability density function of possible operator response times and their likelihood for a given TOS-DAL $T_{\text{max}}$ in order to aid decision making inevitably arises. The aim of this indicator must be to alert operators of system risk of exceeding a TOS-DAL $T_{\text{max}}$ at a given operating point and to help operators make decisions in regard to the optimal time required to initiate (and complete) a TOSS-based action (or set of actions) such as alarming/activating SIPS, FACTs devices or scheduling re-dispatch for a given TOS-DAL $T_{\text{max}}$.

By realising opportunities to safely increase overloading durations, significant cost savings could be realised and system security enhanced. Furthermore, this indicator should be able to measure risky operating system states that offer less overloading time margin opportunities. In these cases, the operator would be justified to instigate expensive actions to ensure the security of the system. Thus it could be claimed that this probabilistic indicator facilitates decision making by a risk/opportunity approach. The development and application of this indicator is the focus of this section.

7.4.1.2 STUDY DESIGN

Once again in this study the system is assumed to be pre-contingently operating at A. The worst case weather conditions invoked in the earlier study are assumed as well. 1000 random MC outages are simulated to model the various possible paths to which the system is able to transition from its present alert state to the emergency state. No operator actions are engaged in...
this study, so as to ascertain the maximum loading times till a TOS-DAL $T_{\text{max}}$ is attained in order to determine a distributed probabilistic loading risk profile; and consequently the duration indicator which is able to show the most likely emergency state residence period.

### 7.4.1.3 STUDY RESULTS

The results resident in Figure 7-17 (top) are descriptive of the results of the full state space of the 1000 simulated time to TOS-DAL $T_{\text{max}}$ cases that were computed. Evidently, the plots within this figure depict graphs represented by negative exponential distribution trends. Additionally, the mean action times for each corresponding TOS-DAL $T_{\text{max}}$ are recorded in the figure. The interpretation of the distributive risk profile shown in Figure 7-17 (top) is twofold. First is that it facilitates the study of the effect of a TOS-DAL $T_{\text{max}}$ over all the possible times within which the operator is expected to react and complete an action, as shown in the x-axis of the figure.

![Mean Time Legend](image)

![Density](image)

**Figure 7-17** Plots of operator action time distribution (top) and the classified probability of implementing a particular action for a given $T_{\text{max}}$ (bottom)

Alternatively, it is indicative of the average time within which the system is able to reside within the emergency state before transitioning to the extreme-emergency state. These two interpretations are interrelated because the operator must effectuate an action before the time to a TOS-DAL $T_{\text{max}}$ elapses. And similarly, the time to TOS-DAL $T_{\text{max}}$ is indicative of the emergency state residence duration before automatic control schemes take over and operate by tripping the line and thus send the power system to the extreme emergency state. Nevertheless, the top figure must be interpreted jointly with the bottom figure (in Figure 7-17). The probability plots of
the bottom figure are computed through Equation 7-15; where \( \mu \) is the mean time to a TOS-DAL \( T_{\text{max}} \) and \( t \) is the duration in minutes.

\[
p = \int_{t=0}^{t=\infty} e^{-\mu t} \, dt
\]

Equation 7-15

Therefore, by studying the bottom figure and employing Equation 7-15 it becomes clear that the probability of having to instigate and complete an action, for instance when \( T_{\text{max}} = 90^\circ \text{C} \), in less than 10 minutes is 0.54—this value has been calculated by adding the values associated with the black bars within the clustered time frames portrayed in the x-axis of Figure 7-17 (bottom). Additionally, by observing Figure 7-17 (bottom), it can be gathered that the operator will need to have sufficient fast ramping generators or highly reliable system integrity protection schemes (SIPS) and/or flexible AC transmission system (FACTS) devices ready to be activated. Furthermore, the probability (i.e., \( P(F \cap S_r) \)) that the SIPS or FACTS or fast ramping unit is required and fails is given in Equation 7-16, where \( P(F/S_r) \) is the probability that the equipment fails given it is required; and these values can be gleaned from historical reliability data—as discussed in chapter 2.

\[
P(F \cap S_r) = P(S_r) \times P(F/S_r)
\]

Equation 7-16

On the other hand \( P(S_r) \) is the probability that the equipment/action is required at a given TOS-DAL \( T_{\text{max}} \) and this is ascertained from the probability plot in Figure 7-17 (bottom). Therefore, for instance, \( P(S_r) \approx 0.37 \) when the activation of SIPS/FACTS is required in less than 5 minutes and when the setting of \( T_{\text{max}} = 90^\circ \text{C} \). Implicitly this means that if the aforementioned actions are available i.e., if \( P(F/S_r) \) is sufficiently low, then the operator can conveniently operate at \( T_{\text{max}} = 90^\circ \text{C} \). However, when the reliability of the fast actions is a concern i.e., \( P(F/S_r) \) is high, the slow ramping units may be utilised as they generally tend to be more reliable. Nevertheless, to utilise these units, the operator will approximately need a 20 minute time to TOS-DAL \( T_{\text{max}} \) allocation (or in other words emergency residence duration of 20 minutes).

Therefore a TOS-DAL \( T_{\text{max}} \) value that will on average allow for a response time of 20 minutes must be selected and any value above \( T_{\text{max}} > 110^\circ \text{C} \) will suffice (as can be evidenced in Figure 7-17 top). However, higher TOS-DAL \( T_{\text{max}} \) values increase the risk of conductor annealing and care must be exercised in their selection—in order to minimise ageing, for ageing risk averse operators. Consequently, TOS-DAL \( T_{\text{max}} \) is limited to 110\(^\circ\)C in this example. It can be seen from Figure 7-17 (top) that \( T_{\text{max}} = 110^\circ \text{C} \) yields an average response time of 24.75 minutes. With this selection of a
TOS-DAL $T_{\text{max}}$ value, the probability $P(S_r)$ of operating less reliable equipment (i.e., SIPS/FACTs, fast and average ramping units) drops from 0.66 by a factor of 2.0625 to 0.32. Therefore, to further drop $P(S_r)$ would require an increase in TOS-DAL $T_{\text{max}}$, but this increase will increase the OHL’s operating temperature.

In the previous case study (in section 7.3.4.2) it was shown that it is economical to operate the Plover conductors at 140°C. And clearly, the results generated in Figure 7-17 (top) support the idea of realising 55.47 minutes in order to complete an action at this (140°C) temperature. This is hugely beneficial toward relieving the operator’s stress amid contingent environments. In terms of security states this implies that the operator can on average operate within the emergency state for 55.47 minutes after the system has transitioned from the initial alert state.

However, in practical cases the operator would normally requires a 60 minute time to TOS-DAL $T_{\text{max}}$ allocation (instead of the 55.47 minute value) because system planning is normally realised within lumped time blocks such as 15, 30 or 60 minutes. Additionally, the conductor must not exceed the 140°C temperature of the conductor. Therefore, Figure 7-18 (top) presents the probability distributions to facilitate this study.

These plots are best fitted with lognormal distributions and to convey trends, the figure embodies distributions encompassing time to TOS-DAL $T_{\text{max}}$ allocations between 5 and 60 minutes. It is evident, that as the time to TOS-DAL $T_{\text{max}}$ allocation increases, so too does the probability of exceeding the 140°C limit. This is true for all cases—including the 5 minute time to TOS-DAL $T_{\text{max}}$ case. Nevertheless, this case also manifests the lowest exceedence probability as shown by the red intermittent line in Figure 7-18 (top). The exceedence probabilities are evaluated through Equation 7-17, where $\sigma$ represents the standard deviation of the distributions, $\mu$ the mean temperature $t$ and the temperature random variable used to define the limits of the integral below. The evaluated exceedence values are provided in Table 7-3 with results to the 60 minute time to $T_{\text{max}}$ highlighted.

Observing the clustered probability plots within Figure 7-18 (bottom) again, it is evident that the probability of further increasing the ageing of the lines within the accelerated annealing cluster is 0.53 for the 60 minute time to $T_{\text{max}}$ case whereas this is 0.48 for the 30 minute time to $T_{\text{max}}$ case. Moreover, this heightened probability will increase the likelihood of flash over amid dynamic clearance concerns. However, as earlier stated this will not be a problem for temperatures less than 140°C, but will be for those exceeding 140°C.
Figure 7-18 Plots of $T_{\text{MAX}}$ distribution (top) and the classified probability of experiencing a temperature for a given emergency state residence -or operator action time- duration (bottom)

\[
P(x) = \int_{-\infty}^{x} \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt
\]

Equation 7-17

<table>
<thead>
<tr>
<th>Required Operator Time, mins</th>
<th>Probability of $T_{\text{MAX}}$ exceedence</th>
<th>% change</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0.0125</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0.0151</td>
<td>-20.8</td>
</tr>
<tr>
<td>15</td>
<td>0.0207</td>
<td>-65.6</td>
</tr>
<tr>
<td>20</td>
<td>0.0268</td>
<td>-114.4</td>
</tr>
<tr>
<td>30</td>
<td>0.0319</td>
<td>-155.2</td>
</tr>
<tr>
<td>60</td>
<td>0.0405</td>
<td>-224.0</td>
</tr>
</tbody>
</table>

The analysis embarked on so far has not accounted for the probability of the assessed states and consequently it is worth investigating whether it is possible to justify employing the 60 minute to $T_{\text{max}}$ allocation if it can be ascertained that the true exceedence probability is lower than that which has been evaluated in this study. In order to do this risk based clustering methods must be employed in order to segregate events characterised by low probabilities of occurrence.
7.4.2 CASE STUDY-II: PRUNED RISK BASED PROBABILISTIC TOSS STATE ANALYSIS THROUGH CLUSTERING TECHNIQUES

7.4.2.1 STUDY BACKGROUND
Risk based decision making is a process designed to take into account the probability of the events (of interest) in order to enforce a final decision—through the omission of those events deemed highly improbable. For example, if a study can show that the likelihood of a particular event is low, it can be discarded from the decision making process—this hence allows the decision maker to facilitate decisions with due consideration solely to those events possessing a higher likelihood of occurrence. Generally, there are two risk based decision methods which are designated as the probability only and the risk only methods. Defined through the context of this study, the risk only method enforces decision by taking into account the product of the probability of the system state and its temperature consequence, whereas, the probability only method omits the consequence of the event and focuses solely on the true probability of the manifesting event. Within power system research risk based analysis have been tackled albeit not limited to [88, 216-218] and more importantly to thermal rating in [6, 219].

7.4.2.2 STUDY DESIGN
In order to achieve apt decision making, it is immensely helpful to employ clustering techniques which allow the operator to make decisions based on risk (or probability) thresholds. In this study, the probabilities of failures for the 1000 simulated Monte Carlo cases are the values through which the state space is sampled and clustered. Moreover, the risk only values are also included within this state space as well. A variety of clustering techniques can be employed. However, in this study the K-means clustering technique fully housed within the Matlab Software environment has been employed. Furthermore to study the effect of weather transitions on clustering, another 1000 correlated Monte Carlo cases were simulated and clustered using both the risk only and probability only methods.

A Markov weather model was utilised in order to account for the weather transitions that occur within a given operation hour and thus improve ageing calculations. A Markov model is a special rendering of the ARMA model i.e., ARMA (1,0). This means a present state defined through a Markov model is solely described by only its past and no moving average value(s). Naturalistically, in the previous study’s weather conditions, the transitions are rendered as illustrated through Figure 7-19 (left) where the red shaded box represents the conditions under which the previous analysis was undertaken and the light green box characterises the coolest weather conditions.
However, based on the analysis of the weather data introduced in chapter 4 it was realised that ambient temperature variability was low; and consequently the probability of observing large drops in temperature was low. More specifically, at the studied worst case conditions, the temperature drop was not more than 5°C; and also the calculated maximum likelihood estimation (MLE – through the Matlab environment) differential value was 2°C. This indicated (irrespective of the wind value) that the most likely transition of ambient temperature states was to be from 40°C to 38°C i.e., from either state 1 or 2 to either state 3 or 4 (see Figure 7-19 left). This difference in temperature state transition values coupled with the conductor’s thermal (transient temperature rise) inertia property did little to affect the temperature rise due to an MVA step change. Therefore, considering the aforementioned limited influence of ambient temperature, albeit notwithstanding the high influence of wind; the resulting model was sufficient to solely account for the transitions between wind states at a static MLE temperature state of 38°C as described in figure 7-19 right.

Therefore, in this study, four risk based decision making criteria are developed, compared and contrasted. These are delineated into either the non-Markov (NM) or the Markov (M) weather types (to account for weather transition probabilities as earlier discussed). Moreover, within each classification, both the risk only and probability only methods are employed. In short-hand form the clustered cases are the NMP designated as the non-Markov probability, the NMR designated as the non-Markov risk, the MP designated as the Markov probability and the MR designated as the Markov risk. Twenty clusters in all the aforementioned cases were established as the optimum; however, eighteen clusters were omitted for the probability only cases as all these cases all fell short of the $3.9954 \times 10^{-5}$ probability of occurrence threshold arbitrarily assumed in this study calculated through Equation 7-18. Moreover, for comparative purposes, 18 clusters were also omitted from the risk only cases. Furthermore, the full sample (non-clustered) data for both the Markov (short-hand M) and non-Markov (NM) methods were included in the study for comparative purposes.

\[
P = 1 - e^{(-\lambda t/8760)}
\]

Equation 7-18
7.4.2.3 Study Results

The full results to these cases are described within Figure 7-20. The figure shows that with the MR case, the system can reside within the emergency state for an average duration of 72.86 minutes, which is approximately 17 minutes longer than the NM case. Clearly, by not fully accounting for the realistic weather transitions within an hour coupled with not employing an adequate threshold below which the probability of failures could be omitted based on their low values, (e.g. in this case $3.9954 \times 10^{-5}$), results from the NM case skewed the computed distributions to narrate that the system emergency residence duration was 55.47 minutes—as shown in the figure.

![Figure 7-20 Optimal operator action times under different clustered and non-clustered computed cases](image)

Evidently, the MR case is closer toward the representation of the true operation of the power system, as it only accounts for the most probable of system failure states and captures more accurate weather behaviour. Consequently, results computed via the MR case are able to instil confidence in the operator of the near-true operation of the system—as it is assumed that those events with probabilities less than $3.9954 \times 10^{-5}$ are to be omitted. This means that under this assumption, the system is secured under N-1, N-2 and selected N-3 failures.

Furthermore, the 140°C exceedence threshold, for these newly computed cases, is once again examined. Results are plotted in Figure 7-21; which shows clearly that the MR model is able to lower the initial risk from the NM case. The actual values computed through Equation 7-17 are described within Table 7-4—with the MR case highlighted as the algorithm that computes the lowest exceedence probability (i.e., 0.0241) especially when compared to the initially computed NM case (i.e., 0.0405). Manifestly, as can be seen from the table, this represents a 40.5% change in exceedence probability.
A robust probabilistic analysis in regard to how increased resiliency could be built into the power system (by justifiably increasing TOS-DAL $T_{\text{max}}$ values) when it transitions into the emergency state in order to contain it within the aforementioned state so that it does not transition to a more detrimental extreme-emergency state has been completed. This robust analysis has for the first time within the context of short term (i.e., less than an hour) emergency rating research studies, accounted for a wide range of possible system failure states which state-of-the-art tools are unable to capture.

Through the presented clustering and Markov weather transition modelling techniques, it has been possible to show how exogenous yet opportune high TOS-DAL $T_{\text{max}}$ operation modes (through the rejection of low probability clustered states) could be realised. These clustering techniques can be employed by operators who are less risk averse. It was also shown that by being risk averse, it will force the operator to realise less emergency state durational resilience.

In summary, a security state space for the less risk averse MR case (left) and the risk averse M case (right) is plotted in Figure 7-21. In the MR the system is able to be resilient for ~72 minutes with a probability of 0.9759 and with a traversal (to the extreme emergency state) probability of 0.0241. Equally for the M case, the probability of residing in the emergency state is 0.969, whereas the probability of traversing to the extreme-emergency is 0.031.
7.5 **CONCLUDING REMARKS**

In this chapter a TOSS methodology has been developed to provide operators with increased flexibility when completing an action (based on which security state a power system operates in). Resultantly, operators can maintain (or improve) a power system’s security state, and hence avoid transitioning to a more detrimental security state. This methodology extends the methodology discussed in the chapter 3 by including an OHL’s transient thermal model which is coupled with the Markov weather model so as to enable more detailed short time OHL analysis within security studies to be completed. The introduced indices computed from this methodology are implemented within a risk-based analytical framework to provide additional solutions to the operator. This methodology is implemented using the most applicable current methods for power system state modelling (i.e., the N-1 and Monte Carlo techniques) with DC power flow calculations. Two new emergency state security indices have been developed for the TOSS methodology. The first index, namely, the *expected resiliency duration* measures a power system’s ability to maintain its current security state for a certain duration whilst not traversing to a more detrimental state. However, due to the probabilistic nature of this *expected resiliency duration* index, it is also important to measure the probability of a power system traversing to a more detrimental state sooner than the expected resiliency duration—this probability is the *traversal risk* index.

The primary aim of this methodology is to aid power systems to more effectively avoid disastrous operational modes by implementing the available OHL ageing flexibility during critical operating situations. This methodology is compared against the state-of-the-art alert state security assessment tools which incorporate deterministic OHL ratings. Resultantly, the TOSS methodological tool increased (the IEEE-24 bus) network performance due to operator flexibility by reducing the total operating costs by 4.9 % whilst enhancing resiliency against traversing to the extreme-emergency security state by 400% (i.e. 60 minutes from the 15 minutes originally implemented) with 0% traversal risk. This also led to a 100% EENS reduction. All these benefits were realised, however, at an OHL ageing incremental cost of 105% due to increase in emergency operating conductor temperature of up to 140°C (which recorded an equivalent ageing value of...
7.74 minutes). Even though this increase in ageing is not negligible (although it could have been higher if its thermal inertia was not accounted for) its resultant cost was computed to be much lower than the overall benefits gained through the reduction of operating costs. Consequently an overall improvement of 4.9% was realised.

Still accounting for a 140°C emergency operating conductor temperature, when a probabilistic DC (power flow) based TOSS assessment was undertaken in order to consider the network’s true stochastic nature, the resiliency reduced to 55.47 minutes (from 60 minutes), and the risk traversal probability rose to 3.98% (from 0%). However, by implementing the risk-based clustering algorithm in order to omit the most improbable states from the analysis, the resulting analysis demonstrated an improved performance (rising to 64.36 minutes) in resiliency with a 2.83% transversal risk. Furthermore, as a consequence to the inclusion of Markov weather transition modelling, a further improvement of the network performance was achieved; this time recording 72.86 minutes of resiliency and 2.41% transversal risk. Finally, these results clearly demonstrated the efficacy of employing risk-based clustering and Markov weather modelling techniques.
Integrating the ever expanding generation sector to transmission and distribution (T&D) grids is increasingly becoming difficult to accomplish through new OHL builds. This is mainly due to the high cost of new builds (coupled with and public and political opposition to their investment). The option of further utilising existing OHLs through increased exceedances (which consequently increases the risk of thermal ageing) manifests as a plausible thermal uprating solution (TUS). To justify this TUS, planners are compelled to address the question of how to effectively manage this ageing risk without compromising power system reliability. This thesis has examined various TUSs and has considered TUS thermal ageing risk management (TUS-TARM) methodologies to visualise and flexibly mitigate ageing risk. As a result, the contributions made through this work were due to the completion the objectives of the research. These objectives are restated:

- To review the current probabilistic power system reliability evaluation framework, namely, the state of the art sequential Monte Carlo simulation (SMCS) tool and technique used to evaluate system-wide reliability and to critically assess its OHL plant behavioural model
- To review the OHL plant level electrical, mechanical and thermal modelling related to OHL behaviour and to subsequently integrate an appropriate OHL electro-thermal model into the SMCS based power system reliability evaluation framework
- To further improve the electro-thermal SMCS by developing a more holistic and accurate simulation process of power system-and-OHL-plant behaviour in order to capture both early reconductoring and blackout risks, and to develop new OHL plant visibility and performance indices to measure and quantify these aforementioned risks
- To test and validate the novel electro-thermal power system reliability tool by the traditional coefficient of variation (cov) method in order to validate the ability of the tool to acceptably measure both early reconductoring and blackout risks
- To appropriately model a techno-economic framework by which to select the optimal AMASs needed to mitigate OHL early reconductoring and blackout risks
- To model uncertainties related to both the AMAS and electro-thermal SMCS power system reliability evaluation frameworks
To model a framework based on decision trees by which to extract the knowledge necessary to develop strategies which help to mitigate risks due to both AMAS and electro-thermal modelling uncertainties

To integrate (1) the holistic power system-and-OHL-plant SMCS electro-thermal reliability evaluation tool framework and its uncertainty model, (2) the AMAS framework and its uncertainty model and (3) the decision tree framework into a multifaceted holistic asset management framework; incorporating regulatory constraints, life-cycle considerations, multistage decision making strategies, and PESTRE (political, economic, social, technological, regulatory and environmental) concerns

To integrate the novel holistic multifaceted asset management framework into a multistage optimisation algorithm in order to strategize ways to optimise OHL life-cycle AMAS implementations in a manner which maximises (amid uncertainties) both long term power system reliability and OHL life-cycle utilisation.

To develop real-time monitoring and evaluation tools to aid the real-time management of OHL thermal ageing (amid uncertainties) and to thus provide the means by which the decision to age an OHL can be effectively made by the operator in real-time in a manner which adheres to the optimised holistic long term asset management based ageing strategy

8.1 Main Contributions

8.1.1 A Two-Level TUS-TARM Computational Methodology

A two-level TUS-TARM methodology is developed and includes an ageing visibility TUS-TARM methodology and an ageing utilisation flexibility TUS-TARM methodology.

Ageing Visibility TUS-TARM Electro-thermal Power System Reliability Evaluation Methodology

The ageing visibility methodology models four possible OHL electrical loading operating states: the normal operating state, the pre-contingency high operating state, the post-contingency high loading state and the failure state. This detailed modelling aids to realise high visibility of OHL performance due to either its normal $\lambda_n$ or its emergency failure rate $\lambda_e$ (which models the blackout risk due to cascading failures). Additionally a creep function (specific to a conductor type) is used to model (and capture the visibility performance) of the mechanical performance of a specified OHL so as to evaluate an OHL’s ageing (and to consequently assess its early reconductoring risk). These models are integrated to the traditional reliability evaluation methodology to produce both novel and traditional reliability indices In order to realise this visibility. The following novel visibility indices are computed: the expected magnitude of extra
loading (EMEL), the expected frequency of extra loading EFEL, the expected duration of extra loading EDEL, and the expected equivalent ageing index EEAI.

**AGEING UTILISATION FLEXIBILITY TUS-TARM METHODOLOGY**

The ageing utilisation flexibility TUS-TARM methodology allow utilities to realise both long and short term solutions which aid the relevant strategic decision making between stakeholders, namely, power system planners, operators and OHL designers. Long term solutions particularly allow power system planners (in collaboration with OHL designers) to make decisions about the optimum frequency and stages in which to implement AMASs, as well as the maintenance policy, over an OHL’s life-cycle. Short term solutions particularly allow power system operators to make decisions about the optimum thermal operating state strategy (TOSS) to implement whilst operating a power system.

1. **AMAS Modelling Process for Long Term Analysis**

Modelling the AMAS process takes into account the steady state IEEE 738 OHL thermal model. This is in order to enhance computation speed whilst calculating the EEAI ageing visibility index to be used in AMAS studies. In this methodology three possible AMASs are identified and modelled: thermal uprating AMASs (TU AMASs), blackout risk AMAS (BR AMASs) and early reconductoring risk AMAS (ER AMASs). To model the scenario which captures the outputs capable of aiding the decision on whether to engage in a live-line or an offline TU AMAS, a line outage scenario based on the parallel sampling technique is modelled. Furthermore, in order to decide on whether to engage in a retensioning/ROW or a do nothing BR AMAS, the $\lambda_e$ function is modelled to capture the blackout risk cost. Lastly, in order to decide on whether to engage in ER AMAS with either novel or conventional conductors, the corresponding (novel and conventional conductor) electro-thermal models are modelled. Therefore, based on these aforementioned models and accounting for their costs, it is possible to realise the optimal AMAS at a given stage of an OHL’s life-cycle. Moreover, in order to compute the optimal AMAS implementation frequency indices for an arbitrary OHL’s TUS at various stages over the course of its life-cycle, a dynamic programming computational algorithm is developed. Furthermore, uncertainty computation through Monte Carlo sampling and analysis through decision trees is modelled in order to facilitate more robust analysis.

2. **TOSS Modelling Process for Short Term Analysis**

Modelling the TOSS process takes into account the transient IEEE 738 OHL thermal model and the Markov weather model. This is in order to capture increased resolution of the short time changes
to the OHL as well as other plants as the operator attempts to maintain the integrity of the power system in order to avoid transitioning to the extreme-emergency state. The short time changes which must be modelled include generator ramp up and down times, plant and demand side switching on and off times, as well as the conductor thermal inertia model. The outputs of the TOSS modelling aids a power system operator to understand both the system benefit and risk involved when selecting to operate and subsequently age an OHL by operating it at a particular temperature. These outputs which aid the operator are the expected resiliency duration and the traversal risk indices. Furthermore, risk-based clustering techniques are employed to enhance the analysis of these aforementioned indices.

8.1.2 Computational Results from the Two-Level Methodology

The results produced using the TUS-TARM tools are related with the ageing visibility of the network and the benefits that could arise from its utilisation amid both long term network planning and short term emergency operation. The results obtained are based both on some network and plant assumptions.

Main Study Assumptions

The widely consented IEEE 24 bus reliability test system was selected as the test system on which to engage a variety of ageing visibility and operating flexibility with TARM studies. All network plants are assumed to be repairable. There was no uncertainty about the exponential failure rate data and the demand at any delivery point is 100% correlated with the other delivery points within the network, due to lack of realistic data [83]. Conductor data was derived from actual conductor sizes in order to fit them as precisely as possible to the provided IEEE-RTS system thermal rating values. Thus, the base case considered Plover ACSR conductor for the 230kV and Drake ACSR for the 138 kV network sections. Other conductor technologies (ACSS, ACCC) of similar properties were also considered. Weather data from National Grid TANSCOs CAT-1 monitoring stations in Canterbury site has been used to model the case studies which were engaged in this thesis. Most of the AMAS costs stated in the report are obtained from company databases and academic publications [1, 2][190].

Main Case Study Outputs

1. Long Term Strategic OHL TUS and AMAS Implementation through Visibility Assessment

By comparing (the STR, PTR and DTR) TUSs it was found that DTR can theoretically provide more capacity to power systems; however, there are occasions that it increases the risk of system operation. This is more pronounced when the \( \lambda_e \) is modelled as a function of conductor rating,
inadequate management of ROWs and/or insufficient sag clearances. Considering these TUSs the system ageing (EEAI) on the network was found to be 0 hours for the STR, 0 hours for the DTR and 38.853 hours for the PTR, with the maximum ageing developed on the line 28 being 16.64 hours. Network performance is improved when a more advanced method of rating is implemented from 8.526 GWh/yr in the base STR scenario to 2.934 GWh/yr (218%) with PTR and 2.498 GWh/yr (233.76%) with DTR TUSs respectively. Finally, it was realised that the increased benefit on network performance (due to applying an exceedence based DTR, recorded at 2.467 GWh/yr) indicates that implementing AMASs to mitigate the effects of the expected ageing could be lead to significant improvement on network operating costs as well as its reliability.

2. **Long Term Strategic OHL TUS and AMAS Implementation through Flexibility Assessment**

By accounting for the effects of ageing on OHLs due to TUSs selected by a network planner, increased flexibility can be provided for both long term and short term time horizons. In this thesis five different TUSs (1 pu, 1.05 pu, 1.1 pu, 1.15 pu, and 1.2 pu) are compared to identify the impact of increased TUSs with increased ageing on the network. The 1.2 pu is found to be the optimal solution for the specific network with an impressive 65.6% increase in EENS. This TUS resulted in a 92.3% financial performance improvement when assessed under a performance based regulatory (PBR) framework. This is achieved at the expense of 38.853 hours of total system (EEAI) ageing. This financial improvement is achieved when the AMASs considered include live-line uprating with OHL retensioning and ROW maintenance to mitigate for blackout risk. Furthermore, it was found that ACCC conductor technology is more suitable to implement as a reconductoring AMAS in order to mitigate for future reconductoring risk compared to cheaper and commonly employed ACSR technology. Decision tree based modelling indicated that the conclusions of the analyses performed for the 1.2 pu TUS, under many modelling uncertainties in TU financial models, have an accuracy of ~98%.

In order to capture uncertainties related to (political, economic, social, technological, regulatory and environmental) PESTRE factors, which affect the techno-economic performance of the TUS, analyses are carried out with varying PESTRE factors up to ±50% from their selected nominal values (presented in Chapter 6). The study identified that all the investigated TUSs increased the network costs in response to a 50% increase in the retension needs (due to increased ageing) or a 50% reduction in either the reconductoring cost, or the live-line maintenance costs, or a 50% increase in electricity price. The most influential parameters to the TUS profitability are found to be the reconductoring costs (due to maximum ageing of the conductor is reached) and the
expected reward payment (from improved performance) that describe the technological and political-regulatory factors. Consequently, an increase by at least 35% of one of these parameters is required to collect revenue that will allow the project to breakeven.

3. Short Term Strategic OHL TUS and AMAS Implementation through Visibility and Flexibility Assessment

TOSS flexibility studies, based on the operator’s ability to extend emergency security state rating up to 1.35 pu (from 1.25 pu) for a maximum duration of 60 minutes (from 15 minutes) showed a 4.9% reduction in total network costs. The reduction in costs is achieved through the reduction of the network operating (by 19%), the reduction of energy not served (by 100%) and increase in ageing of the network OHL conductors cost (by 105%). Therefore, the 4.9% reduction in costs is due to the increase in ageing of only 7.74 minutes of Line-28 of the network when N-1 deterministic analysis is performed.

Under probabilistic network analysis, the emergency state action flexibility studies resulted in a reduced emergency duration of 55.47 minutes (from 60 minutes) with an increased traversal risk to 3.98% (from 0% in the deterministic case). When the failures with extremely low probability of occurrence are not considered, the performance of the network is improved (rising to 64.36 minutes with a 2.83% transversal risk). When Markov weather transition algorithm included in the modelling, a further improvement of the network performance (of 72.86 minutes with a 2.41% transversal risk) is achieved.

8.2 Future Research Work

In addition to the realised contributions of this work, some areas for future work to improve the electro-thermal methodology have been identified and discussed next.

Smarter Electro-Thermal Tool

The developed holistic electro-thermal computational tool can be easily extended to perform further applicatory enhancements beyond those considered in this thesis. In the near future power systems will be increasingly expected to transition into a smart grid. This is in order to be more economical. Consequently, the smart grid will inevitably facilitate the inclusion of many solution and technological candidates, for example, ageing of overhead lines (OHLs); demand response (DR) and side management (DSM); special protection systems (SPSs); flexible AC transmission systems (FACTS); and energy storage (ES) into the reliability evaluation and planning process. Therefore, there will be an increasing need to adapt the electro-thermal reliability evaluation tool to consider and thus augment relevant models which consider flexible solution
and technological candidates (i.e., leading to a smarter electro-thermal reliability evaluation tool). Subsequently, results from this smarter electro-thermal reliability evaluation computational tool can be used to encourage the synergistic adoption of these proposed solutions, namely, SPSs, ES, FACTS, OHL ageing etc., through the more accurate quantification of the benefits realisable from these synergies.

Further alternative solutions which could be investigated, in addition to those earlier mentioned through this smarter electro-thermal reliability evaluation tool, including those which aim to either minimise plant downtime or maximise plant uptime; or both simultaneously maximise and minimise plant uptime and downtime respectively. This facilitation is shown in Figure 8-2 where the Non-TUS candidates could comprise either maintenance improvement candidates or smart grid candidates, whereas TUS candidates could include either PTR with AMASs and/or reconductoring with novel HTLS conductor technologies or other competing technologies. Therefore, each non-TUS candidate can be modelled with a TUS candidate’s electro-thermal characteristics into the smarter reliability evaluation framework so as to evaluate relevant traditional indices as well as appropriate and relevant novel indices so as to facilitate the production of results that encourage the fostering of efficient and synergistic non-TUS and TUS based system reinforcement decisions. Consequently, through this approach corporate managers can easily realise the justified solution as shown in the figure.
CHAPTER 8: CONCLUSION

ELECTRO-THERMAL MODELLING DATA ENHANCEMENTS

The results from this work are entirely tested on a test system with sufficient reliability data. It is a matter of great interest, nevertheless, to test the efficacy of this methodology on real systems with more realistic data. This is in order to test its reliability and ageing predictability capabilities. In particular, it is highly important to glean weather data from reliably operating weather instrumentation in order to compare the value of weather instrumentation reliability on ageing and reliability. Subsequently, results from real systems can then be used to expose some of the weaknesses of the methodology, and thus motivate further relevant improvements.

ELECTRO-THERMAL COMPUTATIONAL ENHANCEMENTS

Four possible computational enhancements have been identified and are discussed further.

1. Increasing Electro-thermal Computational Efficiency

It has been discussed already that reliability evaluation of power systems requires capturing a sufficient number of states prior to estimating a reliability index. It is a matter of great interest, therefore, to test this computational tool with modern state selection techniques, such as, particle swarm, genetic algorithms, and/or support vector machine state sampling. Once the efficacy of the ability of these techniques to compute both system and OHL indices is realised, computational power can then be released to do more computations; per sampled state. Performing more computations within a given state can lead to more accurate computations of the dynamic behaviour of OHL capacitance, resistance and induction values.

2. Enhanced Electro-thermal Dynamic Resistance, Capacitance and Inductance Modelling

To improve the calculations of power system losses for a given TUS, a formulation of the dynamic resistance, capacitance and inductance model is required. This was omitted from this thesis; instead static resistance, capacitance and inductance models were adopted as they significantly sped up the computational process within each sampled power system state. However, if faster sampling techniques are utilised, then more accurate losses could be calculated because more computational resources would be expended to performing more calculations within a given state.

3. Electro-thermal MILP Formulation and Optimisation

Another set of calculation steps which could be added within a given sampled state computational step is that of mixed integer programming (MIP). With a MIP formulation it is possible to optimise load curtailment whilst minimising both the ageing and generation dispatch costs. In this thesis, load curtailment was optimised by solely considering the minimisation of
generation dispatch cost within a single integer programming (SIP) formulation. Therefore, it would be of great interest to study the results that would be computed from this MIP model and to subsequently compare them with those produced by the SIP model in order to aid the instigation of more informed decisions.

4. Electro-thermal Load Forecast Uncertainty Modelling

Within this thesis, it was assumed that both the generating outputs and the load demand models were 100% certain. This may not always be the case in practical power systems and their operating environments. Therefore, there is an imperative need to research, identify and include appropriate models to account for both generation and load forecast uncertainty models for all TUS-TARM time scales.
But by the grace of God I am what I am, and his grace to me was not without effect. No, I worked harder than all of them—yet not I, but the grace of God that was with me (1 Corinthians 15:10)
REFERENCES

APPENDICES


APPENDICES


[81] W. Li. Risk Assessment of Power Systems - Models, Methods and Applications


In this appendix the system data presented is from the IEEE Reliability Test System, as narrated within by the IEEE Reliability Test System Task Force of the Applications of Probability Methods Subcommittee, in the publication: "IEEE reliability test system-96," IEEE Transactions on Power Apparatus and Systems, Vol. 14, No. 3, Aug. 1999, pp. 1010-1020. The system MVA base is 100

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### The Value and Risk of Probabilistic Thermal Upgrading Scenarios on Power System Reliability

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APPENDIX B: CUSTOMER SECTOR DAMAGE COST FORMULATIONS

In this appendix, data pertaining to the customer sector allocations for the IEEE RTS load buses are detailed.

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Agri – Agricultural Users; Lrg U – Large Users; Res – Residential Customers; Govt – Government Institutional offices; Ind – Industrial Customers; Com – Commercial Customers and Off – Office and Building Customers. The values arrayed under these designated sectors are in per cents (%) of the total demand at the given bus.
In this appendix, it will be shown from first principles how the correlated sampling technique discussed in Chapter 4 is modelled. As earlier discussed, the correlated sampling method is possible to compute with high accuracy if and only if there is a high level of correlation between a known reliability index and the new index to be evaluated.

If $Y$ is a known random variable (RV) is correlated either positively or negatively with an unknown RV, $X$ and has a known expectation $\mu$, it must follow then that the RV (i.e., $X_c$) given by Equation C1-1 should have to be an unbiased estimator of the yet to be computed mean of $X$ for an arbitrary real number $a$. This arbitrary number $a$ is termed as the control variate coefficient.

$$X_c = X - a(Y - \mu) \tag{Equation C1-1}$$

The variance of $X_c$ in Equation C1-1 can be computed as illustrated in Equation C1-2

$$Var(X_c) = Var(X) + a^2Var(Y) - 2aCov(X,Y) \tag{Equation C1-2}$$

It can be observed that $X_c$ will exhibit a lower variance than $X$ solely based on the special condition narrated through Equation C1-3

$$2aCov(X,Y) > a^2Var(Y) \tag{Equation C1-3}$$

Moreover, it can be recognised thus far that $a$ will need to be tuned to a value that ensures the optimal performance of this variance reduction algorithm. The case of assuming $a = 1$ has been commonly employed. However, other static values for $a$ between 1 and -1 can be assumed in order to tune the algorithm. Moreover, it is possible to develop an algorithm which can dynamically tune the value of this control variate in order to enhance the variance reduction computation process. This algorithm is developed as follows:

$$a^* = \frac{Cov(X,Y)}{Var(Y)} \tag{Equation C1-4}$$

In Equation C1-4 $a^*$ is the equation which describes how the optimum value for $a$ is computed.
On this basis the variance computed in Equation C1-2, can be reformulated through the substitution of $a = a^*$ into Equation C1-5 and further simplified in Equation C1-6, where $\rho_{xy}^2$ describes the correlation between $X$ and $Y$

$$\text{Var}(X^c) = \text{Var}(X) - \frac{[\text{Cov}(X,Y)]^2}{\text{Var}(Y)}$$  \hspace{1cm} \text{Equation C1-5}$$

$$\text{Var}(X^c) = (1 - \rho_{xy}^2)\text{Var}(X)$$  \hspace{1cm} \text{Equation C1-6}$$

From here on estimating $\text{Cov}(X,Y)$ and $\text{Var}(Y)$ will require imputing their sampled equivalents into them. Therefore, let $n$ be the number of simulation years, then by invoking the computations represented through Equations C1-7 to C1-11, it can be finally realised that estimates of $\text{Cov}(X,Y)$ and $\text{Var}(Y)$ can be given by $\overline{C}_{xy}$ and $\overline{\sigma}_y^2$.

$$\overline{X}(n) = \frac{\sum_{j=1}^{n} X_j}{n}$$  \hspace{1cm} \text{Equation C1-7}$$

$$\overline{Y}(n) = \frac{\sum_{j=1}^{n} Y_j}{n}$$  \hspace{1cm} \text{Equation C1-8}$$

$$\overline{C}_{xy}(n) = \frac{\sum_{j=1}^{n} [X_j - \overline{X}(n)][Y_j - \overline{Y}(n)]}{n - 1}$$  \hspace{1cm} \text{Equation C1-9}$$

$$\overline{\sigma}_y^2(n) = \frac{\sum_{j=1}^{n} [Y_j - \overline{Y}(n)]^2}{n - 1}$$  \hspace{1cm} \text{Equation C1-10}$$

$$a^* = \frac{\overline{C}_{xy}(n)}{\overline{\sigma}_y^2(n)}$$  \hspace{1cm} \text{Equation C1-11}$$

$$\overline{X}_c(n) = \overline{X}(n) \cdot a^*(n)[\overline{Y}(n) - v]$$  \hspace{1cm} \text{Equation C1-12}$$