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A Practical Multi-Area Bi-Objective Environmental Economic Dispatch Equipped with A Hybrid Gradient Search Method and Improved Jaya Algorithm

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Abstract:

Generation dispatch decision making integrated into a centralized wholesale electricity market has been always a challenging concern for transmission system operators and has progressively received significant attention in recent years. The reason lies mainly in the complex and highly-interconnected structure of the grid, escalated demand, and the crisis of the amount and price of energy. For the dispatch solutions to be highly reliable with an acceptable level of accuracy, several factors of notable importance need to be well taken into account, among which one can mention the valve-point effect, multiple fuel options and disjoint prohibited zones, up/down ramp rate requirements of generating units, as well as the spinning reserve constraints which, in turn, intensify the non-smoothness, non-convexity, non-linearity, and dynamic restriction of such combinatorial hard problems. This paper proposes a new optimization toolset for the bi-objective multi-area economic dispatch problem to determine the transmission interface power flow and power output of generating units while satisfying system demand and security constraints at each area. The proposed architecture builds upon an improved gradient-based Jaya algorithm to generate a feasible set of Pareto optimal solutions corresponding to the operation cost and fuel combustion emission calculated through a new robust bi-objective gradient based method. The projected algorithm is proved to be capable of finding the robust global or near-global Pareto solutions fast and accurate.

Keywords: Bi-objective gradient-based technique; economic dispatch; environmental; heuristic; improved Jaya algorithm, optimization.

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Nomenclature

A. Indices

ger	Iteration index of the gradient method (GM).
i, j	Generating unit indices.
$iter$	Iteration index of the proposed algorithm.
k, k'	Area index.
n	Particle index.
nf_i	Fuel type index for generating unit i .
obj, t	Objective function and time step indices, respectively.
κ	Disjoint prohibited zone (DPZ) index.

B. Constants

$a_{i,k}^{nf_i}, b_{i,k}^{nf_i}, c_{i,k}^{nf_i}, d_{i,k}^{nf_i}, e_{i,k}^{nf_i}$	Cost coefficients of generating unit i in area k for the fuel type nf_i .
$B_{ij,k,t}$	Loss coefficient of generating units i and j in area k at time t (MW^{-1}).
$B_{0i,k,t}$	Loss coefficient of generating unit i in area k at time t .
$B_{00,t}$	Loss coefficient parameter at time t (MW).
$c_{kk'}$	Cost coefficient of a tie-line located between area k and k' .
$D_{k,t}$	Load demand of area k at time t (MW).
$DR_{i,k}, UR_{i,k}$	Ramp down/up rate of generating unit i in area k , respectively (MW/h).
$ger^{\max}$	Maximum number of iteration for the GM.
$g_{i,k}^{\min}, g_{i,k}^{\max}$	Power capacity and maximum power output of generating unit i in area k , respectively.
$g_{i,k}^{L,\kappa}, g_{i,k}^{U,\kappa}$	Lower/upper boundary of the κ th DPZ for unit i in area k , respectively.
$iter^{\max}$	Maximum number of iteration for the proposed algorithm.
$N\kappa_i$	Number of disjoint prohibited zones (DPZs) for generating unit i .
$NF_{i,k}$	Number of fuel types for generating unit i in area k .
$NPop$	Number of particles in the population of the suggested algorithm.
NK	Number of areas.

NUK	Number of generating units in area k .
$Rand1_{m,n}^{iter}, Rand2_{m,n}^{iter}$	Random function generators in the range [0,1] for m^{th} member of the agent n at iteration $iter$.
$r_{k,t}^{up}, r_{k,t}^{dn}$	Required up/down spinning reserve for area k at time t , respectively (MW).
$Tie_{kk',t}^{\min}, Tie_{kk',t}^{\max}$	Minimum/maximum power flow limits of tie-line kk' at time t , respectively.
$\alpha_{i,k}, \beta_{i,k}, \gamma_{i,k}, \zeta_{i,k}, \lambda_{i,k}$	Emission coefficients of generating unit i in area k .
α^{ger}, m^{ger}	Constant parameters in the iteration ger of the GM.

C. Variables

$F_1(\mathbf{X})$	Function of the total operation cost.
$F_2(\mathbf{X})$	Function of the total emission.
$F_e(g_{i,k,t})$	Emission function of generating unit i in area k at time t (\$).
$F_g(g_{i,k,t})$	Fuel cost function of generating unit i in area k at time t (\$).
$F_{Tie}(Tie_{kk',t})$	Transmission cost function of a tie-line connecting between area k and k' at time t (\$).
$\mathbf{G}$	Vector of system generating units.
$\mathbf{G}_{k,t}$	Interchange power vector between area k and others at time t .
$g_{i,k,t}$	Power output of generating unit i in area k at time t (MW).
$\bar{g}_{i,k,t}, \underline{g}_{i,k,t}$	Upper/lower limit of i^{th} generating unit output power in area k at time t , respectively (MW).
$g_{k,t}^{vio}$	Power mismatch of area k at time t (MW).
$Loss_{k,t}$	Total real power losses of area k at time t (MW).
$r_{i,k,t}^{up}, r_{i,k,t}^{dn}$	Up/down spinning reserve of the generating unit i in area k at time t , respectively (MW).
$R_{k,t}^{up}, R_{k,t}^{dn}$	Total up/down spinning reserve of all generating units in area k at time t , respectively (MW).
$\mathbf{Tie}$	Tie-line power flow vector.
$\mathbf{Tie}_{k,t}$	Power flow vector for all tie-lines connecting to area k at time t .
$Tie_{kk',t}$	Power flow from area k to k' at time t .
$\mathbf{X}$	Vector of decision variables.

$\mathbf{x}^{worst,iter}$	The worst solution among all particles in iteration $iter$ of the proposed algorithm.
$\mathbf{x}^{best,iter}$	The best solution among all particles in iteration $iter$ of the proposed algorithm.
$x_{m,n}^{iter}$	The m^{th} member of particle n at iteration $iter$ of the proposed algorithm.
$x_m^{best,iter}, x_m^{worst,iter}$	The m^{th} member of the best and worst solutions found at iteration $iter$ of the proposed algorithm, respectively.
λ^{ger}	Lagrange multiplier in the step ger of the GM.

1. Introduction

Deregulation in nowadays electric power system operation, monitoring and control offers a power pool environment enabling different utility operators to participate in energy and reserve interchange from the areas with cheaper generations to those expensive ones through tie-lines. In this way, achieving the least operation cost and fuel combustion emission with optimum reliability and security performance compared to the isolated operation modes would be possible. Whilst the majority of existing research works focus on either the mono-area mono-objective economic dispatch (ED), or mono-area bi-objective ED (BED), or multi-area mono-objective ED (MED) formulations, this study deals with the multi-area bi-objective ED (MBED) through which fast and robust power generation schedules of different thermal generating units (TUs) as well as the tie-lines power flows would be potentially optimized while simultaneously lowering the operation cost and emissions subject to several operational and physical network constraints. In the classical ED formulation, the TUs' cost functions are assumed to be quadratic polynomials which are convex, differentiable, and smoothly augmenting functions. As a matter of fact, the valve point effect, multiple fuel options, disjoint prohibited zones (DPZs), up/down ramp rate limits, and the system security requirements are also other critical concerns bringing about additional complexities to optimal operation of the multi-area electric power systems. In the power pool electricity market environment, the economic, environmental, and technical characteristics of the grid as well as the reliability performance of power generation system can be further improved if spinning reserve restrictions in all the interdependent areas are well formulated. Consequently, providing the non-dominated Pareto optimal solutions is challenging when it comes to the MBED problems.

In general, the solution methodologies proposed in the existing literature for solving the ED formulations can be categorized into two major groups: mathematical programming techniques and meta-heuristic optimization methods.

In view of the former category, several approaches are available to solve the ED problems, among which one can mention the linear programming (LP) method [1], analytical techniques [2], and direct Newton–Raphson method [3] are also suggested to solve the BED formulations. A linear optimization process [4] and adaptive Lagrange relaxation approach [5] are suggested to solve the MED problems. While some of such mathematical algorithms are currently employed by some transmission system operators (TSOs) due to their higher convergence speed and unique solution sets offered, they majorly suffer from some notable bottlenecks as follows: (a) employing the derivative operations (b) Sacrificing the desirable accuracy using linearization; (c) Incapable in handling difficult inequality constraints; (d) Entrapping in local optimal positions; (e) High execution run-time in large scale electric power systems; and (f) Inability to effectively handle the complex bi-objective optimization problems (BOPs). To tackle one or two aforementioned issues, the method of reformulating the relaxation has attracted significant interests in recent years. A mixed-integer quadratic programming (MIQP) combined with the big M technique were suggested in [6] for the search of global optimal solution and complexity moderation. However, this model is unable to consider the transmission network losses constraints. A self-organizing computation architecture on the basis of distributed economic dispatch is presented in [7], [8] to handle the control and monitoring concerns of a smart micro-grid with minimum centralized data acquisition requirements. A decentralized and self-organizing approach to solve the ED problems is developed in [9]. Such frameworks are flexible, stable and scalable, and can be implemented for handling the ED problems with convex and smooth objective functions. Further attempts are made in [9] to incorporate the transmission line losses into the problem formulation through local agents governed by a central authority. Incorporation of transmission losses into a non-convex ED problem using a fully decentralized architecture is introduced in [10]. Albeit a compact formulation was presented in [11] to provide a continuous feasible region for the TUs with the restriction of DPZs, they would eventually find a local optimal solution. A formulation of vanishing restrictions on the basis of semi-definite programming (SDP) relaxation was also suggested in [12] which could not guarantee the global or near-global solution if the relaxation framework has a gap to the original one.

In response to all the mentioned concerns, many meta-heuristic techniques have been proposed in the literature. The Bacterial Foraging (BF) [13] is among such suggestions to solve the MED problem. In addition, multi-objective Particle Swarm Optimization (MOPSO) [13], strength Pareto evolutionary algorithm [14] and Non-Dominated Sorting Genetic Algorithm (NSGA) [15] are proposed to apply to the BED optimization problems. The dynamically

controlled PSO (DCPSO) [16], Harmony Search (HS) [17], an improved PSO [18], Teaching-Learning-Based Optimization (TLBO) [19], Artificial Bee Colony Optimization (ABCO) [20], and PSO [21] are developed to handle the MED problems. An Improved Differential Evolution (IDE) [22], Chaotic Global Best Artificial Bee Colony (CGBABC) [23] and PSO [24] are also developed to handle the MBED challenges. Due to the strong capability of the meta-heuristic techniques in dealing with the mentioned problems and their straight-forward implementation, they are widely employed to handle complex problems in electric power system domain [25]. However, there exists several disadvantages of such algorithms as follows: (a) slow and premature convergence; (b) sensitivity to the settings and parameters; and (c) trapping in the local optima.

The key innovation of this study is to hybridize the mathematical gradient based method (GM) and improved Jaya algorithm (IJA) as a meta-heuristic approach to exploit their complementary and advantageous characteristics in finding the robust and optimal non-dominated solutions in Pareto frontier very fast. The essential concept of the new Jaya algorithm (JA) is designed in such a way that the existing solutions in the search space should constantly move towards the best agent and avoid the worst one [26]. The main feature of the proposed algorithm, which makes it unique in comparison with other similar meta-heuristic algorithms, is that it does not require tuning of any algorithmic parameter. Although the superiority of the JA algorithm over the 54 benchmark functions has been investigated in [26], it may steadily stop generating the successful solutions though the population when it comes to highly complex non-linear problems in electric power systems. Therefore, a new mutation strategy is added to the original structure to strongly improve the exploration and exploitation process of JA. On the other hand, the rapid convergence of the GM, by appropriately exploiting the gradient information and providing a robust solution compared to the IJA – that does not calculate gradient – offers motivations to combine it with the IJA. With such additions and modifications, the projected improved gradient based Jaya algorithm (IGJA) would provide attractive benefits in terms of considerably-fast convergence, efficient robustness, well-distributed and uniform Pareto optimal frontier, and scalable features for real-world implementations. To prune the repository containing the non-dominated solutions and select the best compromised solution, a fuzzy clustering method is employed as the final decision making mechanism. Case study results well verify the acceptable performance of the suggested algorithm and its interesting promises for real-world implementations.

2. Problem Formulation

The decision variables, objective functions and constraints of the proposed MBED are as follows:

$$\begin{aligned}
 \mathbf{X} &= [\mathbf{G} \quad \mathbf{Tie}] \\
 \mathbf{G} &= [\mathbf{G}_{1,t} \quad \cdots \quad \mathbf{G}_{k,t} \quad \cdots \quad \mathbf{G}_{NK,t}] \\
 \mathbf{G}_{k,t} &= [g_{1,k,t} \quad \cdots \quad g_{i,k,t} \quad \cdots \quad g_{NUK,k,t}] \\
 \mathbf{Tie} &= [\mathbf{Tie}_{1,t} \quad \cdots \quad \mathbf{Tie}_{k,t} \quad \cdots \quad \mathbf{Tie}_{NK-1,t}] \\
 \mathbf{Tie}_{k,t} &= [Tie_{kk+1,t} \quad \cdots \quad Tie_{kk',t} \quad \cdots \quad Tie_{kNK,t}]
 \end{aligned} \tag{1}$$

- Minimize operation cost [4], [19], [24]

$$F_1(\mathbf{X}) = \sum_{k=1}^{NK} \sum_{i=1}^{NUK} F_g(g_{i,k,t}) + \sum_{k=1}^{NK-1} \sum_{k'=k+1}^{NK} F_{Tie}(Tie_{kk',t}) \tag{2}$$

- Minimize emissions [22]:

$$F_2(\mathbf{X}) = \sum_{k=1}^{NK} \sum_{i=1}^{NUK} F_e(g_{i,k,t}) \tag{3}$$

Subject to:

$$F_g(g_{i,k,t}) = \begin{cases} \text{if } g_{i,k}^{\min} \leq g_{i,k,t} \leq g_{i,k}^1; & \text{Fuel type 1} \\ a_{i,k}^1 + b_{i,k}^1 g_{i,k,t} + c_{i,k}^1 (g_{i,k,t})^2 + |d_{i,k}^1 \sin(e_{i,k}^1 (g_{i,k}^{\min} - g_{i,k,t}))| \\ \text{if } g_{i,k}^1 \leq g_{i,k,t} \leq g_{i,k}^2; & \text{Fuel type 2} \\ a_{i,k}^2 + b_{i,k}^2 g_{i,k,t} + c_{i,k}^2 (g_{i,k,t})^2 + |d_{i,k}^2 \sin(e_{i,k}^2 (g_{i,k}^{\min} - g_{i,k,t}))| \\ \vdots \\ \text{if } g_{i,k}^{NF_{i,k}-1} \leq g_{i,k,t} \leq g_{i,k}^{\max}; & \text{Fuel type } NF_{i,k} \\ a_{i,k}^{NF_{i,k}} + b_{i,k}^{NF_{i,k}} g_{i,k,t} + c_{i,k}^{NF_{i,k}} (g_{i,k,t})^2 + |d_{i,k}^{NF_{i,k}} \sin(e_{i,k}^{NF_{i,k}} (g_{i,k}^{\min} - g_{i,k,t}))| \end{cases} \tag{4}$$

$$F_{Tie}(Tie_{kk',t}) = c_{kk'} Tie_{kk',t} \tag{5}$$

$$F_e(g_{i,k,t}) = \alpha_{i,k} + \beta_{i,k} g_{i,k,t} + \gamma_{i,k} (g_{i,k,t})^2 + \zeta_{i,k} \exp(\lambda_{i,k} g_{i,k,t}) \tag{6}$$

$$\sum_{i=1}^{NUK} g_{i,k,t} = D_{k,t} + Loss_{k,t} + \sum_{k'=1, k' \neq k}^{NK} Tie_{kk',t} \quad (7)$$

$$Loss_{k,t} = \sum_{i=1}^{NUK} \sum_{j=1}^{NUK} g_{i,k,t} B_{ij,k,t} g_{j,k,t} + \sum_{i=1}^{NUK} B_{0i,k,t} g_{i,k,t} + B_{00,t} \quad (8)$$

$$g_{i,k,t} - g_{i,k,t-1} \leq UR_{i,k} \quad i=1,...,NUK, k=1,...,NK \quad (9)$$

$$g_{i,k,t-1} - g_{i,k,t} \leq DR_{i,k} \quad i=1,...,NUK, k=1,...,NK \quad (10)$$

$$\underline{g}_{i,k,t} \leq g_{i,k,t} \leq \bar{g}_{i,k,t} \quad i=1,...,NUK, k=1,...,NK \quad (11)$$

$$\bar{g}_{i,k,t} = \min(g_{i,k}^{\max}, g_{i,k,t-1} + UR_{i,k}) \quad i=1,...,NUK, k=1,...,NK \quad (12)$$

$$\underline{g}_{i,k,t} = \max(g_{i,k}^{\min}, g_{i,k,t-1} - DR_{i,k}) \quad i=1,...,NUK, k=1,...,NK$$

$$g_{i,k,t} \in \begin{cases} g_{i,k}^{\min} \leq g_{i,k,t} \leq g_{i,k}^{L,1} \\ \vdots \\ g_{i,k}^{U,\kappa-1} \leq g_{i,k,t} \leq g_{i,k}^{L,\kappa} \\ \vdots \\ g_{i,k}^{U,N\kappa_i} \leq g_{i,k,t} \leq g_{i,k}^{\max} \end{cases} \quad \kappa=2,3,...,N\kappa_i, i=1,...,NUK, k=1,...,NK \quad (13)$$

$$\left(R_{k,t}^{up} = \sum_{i=1}^{NUK} r_{i,k,t}^{up} \right) \geq r_{k,t}^{up} \quad (14)$$

$$\left(R_{k,t}^{dn} = \sum_{i=1}^{NUK} r_{i,k,t}^{dn} \right) \geq r_{k,t}^{dn} \quad (15)$$

$$r_{i,k,t}^{up} = \begin{cases} g_{i,k}^{L,\kappa} - g_{i,k,t} & \text{if } g_{i,k}^{L,\kappa} < \left(g_{i,k,t} + \min(g_{i,k}^{\max} - g_{i,k,t}, \frac{UR_{i,k}}{6}) \right) < g_{i,k}^{U,\kappa} \\ \min(g_{i,k}^{\max} - g_{i,k,t}, \frac{UR_{i,k}}{6}) & \text{else} \quad \kappa=1,...,N\kappa_i, i=1,...,NUK, k=1,...,NK \end{cases} \quad (16)$$

$$r_{i,k,t}^{dn} = \begin{cases} g_{i,k,t} - g_{i,k}^{U,\kappa-1} & \text{if } g_{i,k}^{L,\kappa-1} < \left(g_{i,k,t} - \min(g_{i,k,t} - g_{i,k}^{\min}, \frac{DR_{i,k}}{6}) \right) < g_{i,k}^{U,\kappa-1} \\ \min(g_{i,k,t} - g_{i,k}^{\min}, \frac{DR_{i,k}}{6}) & \text{else} \quad \kappa=1,...,N\kappa_i, i=1,...,NUK, k=1,...,NK \end{cases} \quad (17)$$

$$Tie_{kk',t}^{\min} \leq Tie_{kk',t} \leq Tie_{kk',t}^{\max} \quad k, k'=1,...,NK, k \neq k' \quad (18)$$

While the fuel cost of the TUs is traditionally modeled as a quadratic function, there exists, in real world scenarios, several operation intervals and sinusoidal ripples in the cost function of modern TUs mainly due to existence of different fuel types and the steam admission through the valves (valve-point effect), respectively. As a result, the cost function of each TU is defined in constraint (4) considering various fuel types. Such considerations of valve-point effect brings about additional difficulties as the non-linear feature of the problem search space as well as the number of local optima would escalate. The sinusoidal and quadratic cost functions are compared in Fig. 1(a) and Fig. 1(b) in terms of two-unit cost function surface. Constraint (5) represents the transmission cost for the active power flow through the corresponding tie-line. The released emission of each TU is represented in (6) through a quadratic function plus an exponential term. For the sake of clarity, the exponential and quadratic types of emission functions are portrayed in Fig. 1(c) and Fig. 1(d), respectively. The power balance restriction of each area is referred to in (7). The transmission loss at each area is expressed in (8) using the Kron's loss formula [27]. This quadratic formulation converts the power network operating information with regard to the convoluted currents and voltages into data with reference to the real generation units' power and transmission line's losses employing the B-loss coefficients [27], [28]. As can be seen in (8), the losses are dependent on loading of each individual generating unit through a set of constants. Compared to other loss formula [29], this technique is extensively common in many literature [10], [14], [19], [20], [22], [23] and is derived by Kron [27] using tensorial methods, with a significantly lower computational and measurement requirements [29], [30]. The existence of off-nominal turn ratios and their illustration on an AC power network analyzer with several interconnected transmission systems are considered in tensorial techniques to drive (8). Moreover, Kron's formula is definitely appropriate for transmission networks as the practical computation of B-loss coefficients is based on the fact that the X/R (reactance/resistance) ratio is large [31], [32]. Constraints (9) and (10) impose the up and down ramp restrictions, respectively. Owing to the economical, physical, and practical constraints, the certain amounts of minimum and maximum output generations are represented in (11) and (12) for each TU. Due to some physical restrictions, the undivided feasible zone of some TUs is separated into several disjoint sub-feasible zones so that only one is active during each time interval and the TU could continuously change its operation set point within the selected sub-feasible zone. Constraint (13) represents the mentioned sub-feasible zones for each unit. For instance, the feasible solution plane of three TUs with two DPZs is highlighted with oblique black lines in Fig. 2(a). The demand of the system is $D_{k,t}$ and the upper and lower bounds of sub-feasible zones are determined with red, blue and green lines for the respective first, second, and

third TUs. As illustrated, the non-convexity and complicatedness of the problem are intensified considering the DPZs. The system up and down spinning reserve constraints are enforced in (14) and (15), respectively. Up and down spinning reserves are the indispensable requirements of each area to deal with unexpected fluctuations. However, the DPZs strictly pose the restrictions for TUs to participate in load regulations. In contrast to the traditional approach that the TUs with no DPZs were managed to corporate in up and down spinning reserve requirements [33], [34], constraints (16) and (17) illustrate that all the TUs are able to provide the 10-min up/down reserves for which the up and down ramping rates are rationally modeled as $UR_{i,k} / 6$ and $DR_{i,k} / 6$, respectively. As shown, the 10-min up and down reserve capabilities of each TU shrink to its sub-feasible region to avoid the load regulation from DPZs. The spinning reserve satisfaction with and without considering the DPZs for a typical TU is demonstrated in Fig. 2(b). The tie-line power flow limit is eventually reflected in (18).

Figures1 and 2

3. Improved Gradient based Jaya Algorithm (IGJA)

3.1. Overview of the Original Jaya Algorithm (JA)

The JA is a novel population-based optimization algorithm which is proposed in [26]. In this paper, the JA comprises a number of different individuals ($\mathbf{X}_n, n=1, \dots, NP_{op}$) with unlike fitness function values of $F(\mathbf{X}_n), n=1, \dots, NP_{op}$. The agents implement the position information of two solutions i.e. the best and the worst ones and update themselves as follows:

$$x_{m,n}^{new,iter} = x_{m,n}^{iter} + rand1_{m,n}^{iter} \left(x_m^{best,iter} - |x_{m,n}^{iter}| \right) - rand2_{m,n}^{iter} \left(x_m^{worst,iter} - |x_{m,n}^{iter}| \right); \forall m, n, iter \quad (19)$$

The fitness function of each agent n at iteration $iter$ ($F(\mathbf{X}_n^{iter})$) is determined as follows:

$$F(\mathbf{X}_n^{iter}) = \omega_1 \mu_1(\mathbf{X}_n^{iter}) + \omega_2 \mu_2(\mathbf{X}_n^{iter}) \quad (20)$$

To select the best solution during the JA implementation, the TSO assigns a weighting factor (ω_{obj}) to each objective function that is a given number in the range of [0, 1]. Moreover, each objective function is mapped into a pseudo-objective value using a fuzzy membership function ($\mu_{obj}(\mathbf{X}_n^{iter})$) as follows [15]:

$$\mu_{obj}(\mathbf{X}_n^{iter}) = \begin{cases} 1 & \text{for } F_{obj}(\mathbf{X}_n^{iter}) \leq F_{obj}^{\min} \\ 0 & \text{for } F_{obj}(\mathbf{X}_n^{iter}) \geq F_{obj}^{\max} \\ \Delta_{obj} & \text{else} \end{cases} \quad (21)$$

where,

$$\Delta_{obj} = \frac{F_{obj}^{\max} - F_{obj}(\mathbf{X}_n^{iter})}{F_{obj}^{\max} - F_{obj}^{\min}} \quad (22)$$

In (21) and (22), $obj \in \{1, 2\}$, $F_{obj}^{\min}$ and $F_{obj}^{\max}$ are the minimum and maximum acceptable values of obj^{th} objective function, respectively. In each step of the evolutionary algorithms, each candidate solution should be substituted with the new generated individual, obtained through the optimization procedure, if and only if the new one has a better fitness function value. In the JA approach, the new and old solutions are compared to each other according to (20). In this regard, the pseudo-objective value of each candidate solution is determined to normalize the objective function and map them from two discrepant spaces to the same range of [0, 1]. The TSO is then asked to determine his/her preferred pseudo-objective values, that illustrate the significance of objective function, called weighting factor (ω_{obj}). In this study, the equivalent value of 0.5 are chosen for both ω_1 and ω_2 . Then, equation (20) is deployed to select the better candidate solution which is anticipated to be the closest one with reference to the TSO's preference. The selected candidate solution is participated in the next step of the optimization algorithm (see Fig. 4).

3.2. Improved JA (IJA)

In order to enhance the accuracy of the Pareto optimal solutions and restrain the algorithm from a premature convergence, a new mutation strategy is added to the original JA. To implement the proposed strategy, the following procedure should be followed:

Initialize the population and name it as $\mathbf{P}^1$.

Set $q_1^1 = \dots = q_n^1 = \dots = q_{NPop}^1 = 0$; $\mathbf{A} = \mathbf{P}^1$.

While $iter \leq iter_{\max}$

Update the position of each particle using the JA as described in (19).

For $n = 1$ **to** $NPop$

Select $r_1 \neq r_2 \neq r_3 \neq r_4$ from the set $I = \{1, 2, \dots, NPop\}$, randomly.

If $q_n^0 < NPop / 2$

Let $\mathbf{X}_{r_1}^{iter}$, $\mathbf{X}_{r_2}^{iter}$, $\mathbf{X}_{r_3}^{iter}$, $\mathbf{X}_{r_4}^{iter}$ and $\mathbf{X}_n^{iter}$ be the r_1^{th} , r_2^{th} , r_3^{th} , r_4^{th} and n^{th} vectors of $\mathbf{P}^k$, respectively.

Else

Let $\mathbf{X}_{r_1}^{iter}$, $\mathbf{X}_{r_2}^{iter}$, $\mathbf{X}_{r_3}^{iter}$, $\mathbf{X}_{r_4}^{iter}$ and $\mathbf{X}_n^{iter}$ be the r_1^{th} , r_2^{th} , r_3^{th} , r_4^{th} and n^{th} vectors of $\mathbf{A}$, respectively.

End If

Generate a donor vector $\mathbf{V}_n^{iter} = \text{mutate}(\mathbf{X}_{r_1}^{iter}, \mathbf{X}_{r_2}^{iter}, \mathbf{X}_{r_3}^{iter}, \mathbf{X}_{r_4}^{iter})$ using (23).

Generate a trial vector $\mathbf{U}_n^{iter} = \text{xover}(\mathbf{X}_n^{iter}, \mathbf{V}_n^{iter})$ using (24).

If $F(\mathbf{U}_n^{iter})$ is less than $F(\mathbf{X}_n^{iter})$

$$\mathbf{X}_n^{iter+1} = \mathbf{U}_n^{iter};$$

$$q_n^{iter+1} = 0;$$

Update vector $\mathbf{A}$ with $\mathbf{U}_n^{iter}$.

Else

$$\mathbf{X}_n^{iter+1} = \mathbf{X}_n^{iter};$$

$$q_n^{iter+1} = q_n^{iter} + 1;$$

End If

End For (it refers to index n)

End While (it refers to index $iter$)

The mutate and xover are the mutation operators which are formulated in (23) and (24), respectively.

$$\mathbf{V}_n^{iter} = \begin{cases} \mathbf{X}_{r_1}^{iter} + \text{rand} \cdot (\mathbf{X}_{r_2}^{iter} - \mathbf{X}_{r_3}^{iter}) & \text{if } \text{rand} \leq 0.5 \\ \mathbf{X}_{r_1}^{iter} + \text{rand}1 \cdot (\mathbf{X}_{r_2}^{iter} - \mathbf{X}_{r_3}^{iter}) + \text{rand}2 \cdot (\mathbf{X}^{best, iter} - \mathbf{X}_{r_4}^{iter}) & \text{else} \end{cases} \quad (23)$$

$$u_{m,j}^{iter} = \begin{cases} x_{m,j}^{iter} & \text{if } \text{rand} \leq 0.5 \\ v_{m,j}^{iter} & \text{else} \end{cases} \quad (24)$$

where, $\mathbf{V}_n^{iter}$ is $[v_{n,1}^{iter} \cdots v_{n,j}^{iter} \cdots v_{n,N \text{ var}}^{iter}]$; q_n^{iter} is the number of recently consecutive unsuccessful updates for

the n^{th} agent in iteration $iter$; rand is a random number between 0 and 1, and $v_{m,j}^{iter}$ and $u_{m,j}^{iter}$ are the j^{th} element of

vectors $\mathbf{V}_n^{iter}$ and $\mathbf{U}_n^{iter}$, respectively. The suggested strategy improves the process of selecting the mutant vectors through storing the successful agents into the archive $\mathbf{A}$, and selecting them from $\mathbf{A}$ when stagnation is happened. It should be mentioned that constraints (7)-(18) must be all satisfied during the IJA process. The following steps 1 and 2 are proposed to handle such requirement.

Step 1: Handling Inequality and Dynamic Constraints: If an element of the agent is infeasible, then it freezes to its boundary values. Thus, this process is defined as follows:

$$g_{i,k,t} = \begin{cases} g_{i,k,t} & \text{if } \underline{g}_{i,k,t} \leq g_{i,k,t} \leq \bar{g}_{i,k,t} \\ \underline{g}_{i,k,t} & \text{if } g_{i,k,t} < \underline{g}_{i,k,t} \\ \bar{g}_{i,k,t} & \text{if } g_{i,k,t} > \bar{g}_{i,k,t} \end{cases} \quad (25)$$

$$Tie_{kk',t} = \begin{cases} Tie_{kk',t} & \text{if } Tie_{kk',t}^{\min} \leq Tie_{kk',t} \leq Tie_{kk',t}^{\max} \\ Tie_{kk',t}^{\min} & \text{if } Tie_{kk',t} < Tie_{kk',t}^{\min} \\ Tie_{kk',t}^{\max} & \text{if } Tie_{kk',t} > Tie_{kk',t}^{\max} \end{cases} \quad (26)$$

In addition, limitation (13) may be broken when the power output of a TU falls into its DPZs. In such circumstances, the power output of TU freezes to the closest lower or upper bounds of the DPZ. This process is formulated for the i^{th} TU in area k when its generation is settled in its κ th DPZ, $g_{i,k}^{L,\kappa} < g_{i,k,t} < g_{i,k}^{U,\kappa}$ as:

$$g_{i,k}^{Ave,\kappa} = \frac{g_{i,k}^{L,\kappa} + g_{i,k}^{U,\kappa}}{2} \rightarrow g_{i,k,t} = \begin{cases} g_{i,k}^{L,\kappa} & \text{if } g_{i,k}^{L,\kappa} < g_{i,k,t} \leq g_{i,k}^{Ave,\kappa} \\ g_{i,k}^{U,\kappa} & \text{if } g_{i,k}^{Ave,\kappa} < g_{i,k,t} < g_{i,k}^{U,\kappa} \end{cases} \quad (27)$$

Step 2: Handling Equality Constraints: The power balance feasibility in (7) and (8) should be first checked. The amount of power mismatch in each area can be calculated as follows:

$$g_{k,t}^{vio} = \sum_{i=1}^{NUK} g_{i,k,t} - \left(D_{k,t} + Loss_{k,t} + \sum_{k'=1, k' \neq k}^{NK} Tie_{kk',t} \right) \quad (28)$$

If $g_{k,t}^{vio} = 0$, return.

If $g_{k,t}^{vio} \neq 0$, determine the areas that have non-zero power mismatch and select one randomly. Then randomly select one TU in this area and subtract the $g_{k,t}^{vio}$. If any TU breaches constraints (9)-(13), step 1 is called upon. Next, update the power loss formula using (8). If all the TUs are tested and $g_{k,t}^{vio}$ is not yet zero, two TUs will be chosen as slack

TUs and would share the $g_{k,t}^{vio}$, and the same process goes on until all the areas meet their power balance requirements.

3.3. Gradient-based Method (GM)

One of the main features of the GM is its fast convergence. The strong exploitation capability of the GM is another feature that is employed to find the best solution in this study. If the best solution is improved by the GM, one can ensure that at least the near global Pareto optima have been obtained. In this context, the bi-objective Lagrange function is first formulated on the basis of (22) as follows:

$$L^{ger} = \omega_1 \frac{F_1^{\max} - F_1(\mathbf{X})}{F_1^{\max} - F_1^{\min}} + \omega_2 \frac{F_2^{\max} - F_2(\mathbf{X})}{F_2^{\max} - F_2^{\min}} + \lambda^{ger} \sum_{k=1}^{NK} \left(D_{k,t} + Loss_{k,t} + \sum_{k'=1, k' \neq k}^{NK} Tie_{kk',t}^{ger} - \sum_{i=1}^{NUK} g_{i,k,t}^{ger} \right) \quad (29)$$

The gradient of this function is calculated as follows:

$$\nabla L^{ger} = \begin{bmatrix} \frac{\partial L^{ger}}{\partial g_{1,1,t}^{ger}} \\ \vdots \\ \frac{\partial L^{ger}}{\partial g_{NUK,NUK,t}^{ger}} \\ \frac{\partial L^{ger}}{\partial Tie_{12,t}^{ger}} \\ \vdots \\ \frac{\partial L^{ger}}{\partial Tie_{NK-1NK,t}^{ger}} \\ \frac{\partial L^{ger}}{\partial \lambda^{ger}} \end{bmatrix} = \begin{bmatrix} \frac{\omega_1}{F_1^{\min} - F_1^{\max}} \frac{d}{dg_{1,1,t}^{ger}} F_g(g_{1,1,t}^{ger}) + \frac{\omega_2}{F_2^{\min} - F_2^{\max}} \frac{d}{dg_{1,1,t}^{ger}} F_e(g_{1,1,t}^{ger}) + \lambda^{ger} \left(\frac{d}{dg_{1,1,t}^{ger}} Loss_{1,t} - 1 \right) \\ \vdots \\ \frac{\omega_1}{F_1^{\min} - F_1^{\max}} \frac{d}{dg_{NUK,NUK,t}^{ger}} F_g(g_{NUK,NUK,t}^{ger}) + \frac{\omega_2}{F_2^{\min} - F_2^{\max}} \frac{d}{dg_{1,1,t}^{ger}} F_e(g_{NUK,NUK,t}^{ger}) + \lambda^{ger} \left(\frac{d}{dg_{NUK,NUK,t}^{ger}} Loss_{NK,t} - 1 \right) \\ \frac{\omega_1}{F_1^{\min} - F_1^{\max}} \frac{d}{dTie_{12,t}^{ger}} F_{Tie}(Tie_{12,t}^{ger}) + \lambda^{ger} \\ \vdots \\ \frac{\omega_1}{F_1^{\min} - F_1^{\max}} \frac{d}{dTie_{NK-1NK,t}^{ger}} F_{Tie}(Tie_{NK-1NK,t}^{ger}) + \lambda^{ger} \\ \sum_{k=1}^{NK} \left(D_{k,t} + Loss_{k,t} + \sum_{k'=1, k' \neq k}^{NK} Tie_{kk',t}^{ger} - \sum_{i=1}^{NUK} g_{i,k,t}^{ger} \right) \end{bmatrix} \quad (30)$$

It is noteworthy that the derivatives of $F_g(g_{i,k,t}^{ger})$ and $F_e(g_{i,k,t}^{ger})$ with respect to argument $g_{i,k,t}^{ger}$ and derivative of

$F_{Tie}(Tie_{kk',t}^{ger})$ with respect to $Tie_{kk',t}^{ger}$ are computed as follows:

$$\frac{d}{dg_{i,k,t}^{ger}} F_g(g_{i,k,t}^{ger}) = b_{i,k}^{nf_i} + 2c_{i,k}^{nf_i} g_{i,k,t}^{ger} + \frac{(-e^{nf_i} d_{i,k}^{nf_i} \cos(e^{nf_i} (g_{i,k}^{\min} - g_{i,k,t}^{ger}))) (d_{i,k}^{nf_i} \sin(e^{nf_i} (g_{i,k}^{\min} - g_{i,k,t}^{ger})))}{|d_{i,k}^{nf_i} \sin(e^{nf_i} (g_{i,k}^{\min} - g_{i,k,t}^{ger}))|} \quad (31)$$

$$\frac{d}{dTie_{kk',t}^{ger}} F_{Tie}(Tie_{kk',t}^{ger}) = c_{kk'} \quad (32)$$

$$\frac{d}{dg_{i,k,t}^{ger}} F_e(g_{i,k,t}^{ger}) = \beta_{i,k} + 2\gamma_{i,k} g_{i,k,t}^{ger} + \lambda_{i,k} \zeta_{i,k} \exp(\zeta_{i,k} g_{i,k,t}^{ger}) \quad (33)$$

By applying the differentiation formula for the absolute sinusoidal cost function and exponential emission function, their derivatives are respectively formulated in (31) and (33). They are graphically illustrated in Fig. 3(a), (b) and Fig.3(c), (d) corresponding to the two TUs for which the original functions' surface are shown in Fig. 1. It is clearly demonstrated that although the first absolute sinusoidal function is continuous in Fig. 1 (a), it is not differentiable at all points. As shown in (31) and Fig. 3 (a)-(b), there might be a TU for which the term $d_{i,k}^{nf_i} \sin(e_{i,k}^{nf_i} (g_{i,k}^{\min} - g_{i,k,t}^{ger}))$ in its derivative function would be equal to zero. This implies that the derivative is not defined when $d_{i,k}^{nf_i} \sin(e_{i,k}^{nf_i} (g_{i,k}^{\min} - g_{i,k,t}^{ger})) = 0$. If $e_{i,k}^{nf_i} (g_{i,k}^{\min} - g_{i,k,t}^{ger}) \in \{2n\pi, (2n+1)\pi\}$, where n is an integer number, then the derivative does not exist. Therefore, such points are fixed to their generation levels obtained from the IJA and remain fixed during the GM procedure. For the differentiable points, for which $e_{i,k}^{nf_i} (g_{i,k}^{\min} - g_{i,k,t}^{ger}) \in (2n\pi, (2n+1)\pi)$ and $((2n+1)\pi, (2n+2)\pi)$ is valid, the new agent in iteration ger of the GM is calculated as follows:

$$\begin{bmatrix} g_{1,1,t}^{ger} \\ \vdots \\ g_{NUK,NK,t}^{ger} \\ Tie_{12,t}^{ger} \\ \vdots \\ Tie_{NK-1NK,t}^{ger} \\ \lambda^{ger} \end{bmatrix} = \begin{bmatrix} g_{1,1,t}^{ger-1} \\ \vdots \\ g_{NUK,NK,t}^{ger-1} \\ Tie_{12,t}^{ger-1} \\ \vdots \\ Tie_{NK-1NK,t}^{ger-1} \\ \lambda^{ger-1} \end{bmatrix} + \alpha^{ger} \begin{bmatrix} \Delta g_{1,1,t}^{ger} \\ \vdots \\ \Delta g_{NUK,NK,t}^{ger} \\ \Delta Tie_{12,t}^{ger} \\ \vdots \\ \Delta Tie_{NK-1NK,t}^{ger} \\ \Delta \lambda^{ger} \end{bmatrix} \quad (34)$$

Where,

$$\begin{bmatrix} \Delta g_{1,1,t}^{ger} \\ \vdots \\ \Delta g_{NUK, NK, t}^{ger} \\ \Delta Tie_{12,t}^{ger} \\ \vdots \\ \Delta Tie_{NK-1NK,t}^{ger} \\ \Delta \lambda^{ger} \end{bmatrix} = m^{ger} \begin{bmatrix} \Delta g_{1,1,t}^{ger-1} \\ \vdots \\ \Delta g_{NUK, NK, t}^{ger-1} \\ \Delta Tie_{12,t}^{ger-1} \\ \vdots \\ \Delta Tie_{NK-1NK,t}^{ger-1} \\ \Delta \lambda^{ger-1} \end{bmatrix} + (1 - m^{ger}) \nabla L^{ger} \quad (35)$$

where, m^{ger} and α^{ger} are the GM parameters which can be updated as follows [35]:

If $L_t^{ger} < L_t^{ger-1}$

$$m^{ger} = 0.8; \alpha^{ger} = 1.1\alpha^{ger-1}$$

Else

$$m^{ger} = 0; \alpha^{ger} = 0.9\alpha^{ger-1}$$

End

Figure3

4. Bi-objective Optimization Methodology

In this study, MBED is formulated as a bi-objective optimization problem (BOP). Generally in such optimization formulations, no single solution is capable of simultaneously optimizing both objective functions. In this case, different Pareto optimal (also known as non-dominated) solutions may exist. It is called Pareto optimal as the solution worsens the condition of at least one objective function while improving the others. The optimization process would then select the most preferable solution through trade-offs. The bi-objective optimization approach has been introduced as an appropriate tool for handling incommensurable objectives with conflicting/supporting relations. As the problem dimension increases, it becomes infeasible to reach the global or near-global Pareto optimal solutions in which both objectives can be optimized simultaneously. Different methods are introduced in the literature to deal with such bi-objective optimization problems which can be classified to priori and posterior techniques [36], [37].

- 1) In priori frameworks, such as weighted sum method or ε -constraint algorithm, a relative preference matrix should be provided with minimum knowledge on the possible outcomes. Thus, the preference matrix may

lead to a suboptimal consequence or an infeasible outcome. It is notable that this is extremely subjective to the TSO as the decision maker. Additionally, they may not only be a time-consuming and monotonous process, but also may lead to recurrence of the non-dominated solutions so that a good Pareto optimal curve might not be achieved [38]. Therefore, normal boundary intersection [38] and normalized normal constraint method [39] are developed to obtain a diverse and spread Pareto set. However, such methods involve handling the single optimization problem per Pareto point created. In other words, it mandates applying a numerical optimizer for solving the Pareto optimal points. Furthermore, the optimizer should work with a highly constrictive feasible sphere including a single line in three-dimensional space. In an extremely complicated optimization problem such as the MBED at hand, this may lead the optimizer to never discover its way back to the feasible area and therefore no true or near optimal Pareto frontier can be ever established. In addition, the CPU execution time of the normal boundary intersection technique increases in a larger rate with the growth in the number of decision variables, restrictions and of course number of Pareto optimal points to be extracted [40].

- 2) In contrast, the goal of posterior techniques is to find the Pareto-optimal solutions using the non-dominancy conceptions. All such optimal solutions can be fed into the decision making framework in order to find the final optimal solution considering the TSO's preferences [41]. Albeit the population-based techniques such as the non-dominated sorting genetic algorithm-II (NSGA-II) [42] and multi-objective particle swarm optimization (MOPSO) [43] technique can provide the entire Pareto optimal front all-at-once, they suffer from tuning of numerous algorithmic parameters for a suitable optimization process. For instance, the NSGA-II mandates setting up several parameters including the crossover type, its probability, mutation probability, etc. The MOPSO also needs to tune the cognitive parameter, social parameter, initial inertia weight factor, and final inertia weight factor. Consequently, the JA which is known as the algorithmic-parameter free of tuning technique is selected. Additionally, due to the heuristic nature of such algorithms, the same Pareto optimal solution is often not regenerated. In this paper, the heuristic-based mutation strategy and the mathematical-based GM can provide a balance between the global and local search characteristics of the IGJA and help to return the robust, fast and optimal solution in one trial run. The statistical evidence of producing such Pareto optimal fronts with acceptable execution time is provided in the next Section.

In general, the BOP is mathematically described as follows [14], [15]:

$$\begin{aligned}
 &\text{Min } F(\mathbf{X}) \\
 &\text{Subject to} \\
 &\quad G_{eq}(\mathbf{X}) = 0 \\
 &\quad H_{ine}(\mathbf{X}) \leq 0
 \end{aligned} \tag{36}$$

where,

$$\begin{aligned}
 F(\mathbf{X}) &= [F_1(\mathbf{X}), F_2(\mathbf{X})] \\
 eq &= 1, \dots, Neq \\
 ine &= 1, \dots, Nine
 \end{aligned} \tag{37}$$

In (36) and (37), $F(\mathbf{X})$ represents the vector of objective functions with two elements, $G_{eq}(\mathbf{X})$ function of the eq^{th} equality constraint, $H_{ine}(\mathbf{X})$ function of the ine^{th} inequality constraint, and Neq and $Nine$ the numbers of equality and inequality constraints, respectively. $\mathbf{X}^*$ is a Pareto optimal solution of the minimization problem defined by (36) if the following two conditions are valid for any $\mathbf{X} \in \Omega - \{\mathbf{X}^*\}$ in the search space of Ω :

$$\forall obj \in \{1, 2\} \quad F_{obj}(\mathbf{X}^*) \leq F_{obj}(\mathbf{X}) \tag{38}$$

and

$$\exists obj' \in \{1, 2\} \quad F_{obj'}(\mathbf{X}^*) < F_{obj'}(\mathbf{X}) \tag{39}$$

In order to select the best compromised solution out of a set of non-dominated points, a fuzzy decision making procedure is proposed. Let's assume that there are $NRep$ different non-dominated solutions in the repository of the BOP. To implement this procedure for r^{th} Pareto optimal solution $\mathbf{X}_r^*$ ($r \in \{1, \dots, NRep\}$), the $\mu_{obj}(\mathbf{X}_r^*)$ is first calculated in (21). Using this pseudo-objective value and corresponding weighting factor, the normalized membership index (ϖ_{obj}) for $\mathbf{X}_r^*$ is defined as follows [15]:

$$\varpi_{obj} = \frac{\sum_{obj=1}^2 \omega_{obj} \mu_{obj}(\mathbf{X}_r^*)}{\sum_{r=1}^{NRep} \sum_{obj=1}^2 \omega_{obj} \mu_{obj}(\mathbf{X}_r^*)} \tag{40}$$

where, ω_{obj} is the weighting factor assigned to obj^{th} objective function. It should be pointed out that the candidate with the maximum value of ϖ_{obj} is the best compromised solution. The block diagram of the suggested bi-objective IGJA approach describing the overall process is shown in Fig. 4.

Figure 4

5. Simulation Results

5.1. Test Systems and Parameters Adjustments

In order to examine the effectiveness and capability of the suggested IGJA, the multi-area mono-objective economic dispatch (MED1), multi-area mono-objective emission dispatch (MED2), and MBED problems with respective mono-, mono- and bi-objective functions are solved for five standard test systems with different number of areas, TUs, and constraints. The test system characteristics referring to MED1, MED2, MBED, transmission cost, valve-point effect, DPZ, multiple fuel option, transmission line losses, up/down ramp rate and reserve restrictions, values of NK , NUK and $D_{k,t}$ are presented in Table 1.

In case of the MED1 and MED2, the quality of the final solutions is assessed using the best, mean, worst, CPU computation time and convergence graph. The best, mean, and worst provide an outline of the concentration corresponding to the extracted solutions during 30 trial runs with respect to the central point of the distribution.

Table1

5.2. Test System 1: 2 Areas with 6 TUs

This renowned test system comprises of two areas with 6 TUs for which the data is taken from [19] and [20]. The MED1 is solved by IGJA and compared to the original JA and several recently presented algorithms such as Real Coded Genetic Algorithm (RCGA) [20], Evolutionary Programming (EP) [20], Differential Evolution (DE) [20], Artificial Bee Colony Optimization (ABCO) [20], Teaching-Learning-Based Optimization (TLBO) [19], and Chaotic Global Best Artificial Bee Colony (CGBABC) [23]. The results of the best solution are illustrated in Table 2. Almost all the techniques yield a comparable near-global optimum due to low dimension of this test system. The reported value for the system total loss is smaller than that in recent literature CGBABC [23], i.e. (13.6159 MW vs. 13.6161 MW). Moreover, the optimal power schedules of TUs and tie-lines in the cases of neglecting DPZs and

losses using IGJA are also reported in this Table. It is concluded that the network losses and objective functions may force the TUs of each area to generate electric power in different sub feasible zones. It is clear that ignoring such practical constraints would change the design variables and decreases the system operation cost leading to an inaccurate decision making by the TSO. Furthermore, the best, mean and worst solutions provided by IGJA are equal reflecting the fact that the IGJA is robust enough to provide equal solutions for 30 trial runs. According to the CPU computation time, the presented algorithm can provide the output solution much faster than others. More importantly, if the output design variables of CGBABC are recalculated by (2), then the resultant cost marginally differs from the reported costs which are shown in Table 2. Albeit there are minor power mismatches in the results of CGBABC, the proposed technique can provide more robust and fast solutions with no mismatch which is actually due to hybridizing the GM as a mathematical-based technique and heuristic-based IJA.

Fig. 5(a) shows the convergence graph of IGJA and original JA applications to this test system. It is strikingly observed that the convergence is reached in a considerably less number of iterations which leads to a reasonable execution time. It is also remarkable that the JA is susceptible to get stuck into local optima as it does not employ the mutation and GM strategies.

Table2

Figure5

5.3. Test System 2: 3 Areas with 10 TUs

This test system includes three areas with 10 TUs for which the data is given in [20]. The MED1 is solved by IGJA and compared to other state-of-the-art optimization approaches such as RCGA [20], EP [20], DE [20], ABCO [20], TLBO [19] and CGBABC [23] in Table 3. In addition, the results associated with the cases where network losses are neglected are appended to this Table for the sake of comparison. While the improvement in the best operation cost is only marginal in comparison with various techniques presented in recent literature, the suggested IGJA is definitely more robust. Unlike the developed algorithm, some of the other well-known algorithms are unsuccessful to perform constantly well as exposed in Table 3. As advocated for some heuristic methodologies which are stripped of convergence assurances, the proposed IGJA with the aid of GM is competent enough to converge to the near-global and acceptable solution. In other words, apart from being robust and fast, the suggested algorithm can converge to

the near-global optimum within 8 iterations, as portrayed in Fig. 5 (b). The suggested mutation strategy along with the GM can provide a balance between the diversity and convergence rate or diversification and intensification capacities of the IGJA which is an apparently critical requirement in providing a quality solution.

Table3

5.4. Test System 3: 4 Areas with 16 TUs

This test case considers two types of 4-area 16-unit systems for which the characteristic, data, TUs and tie-line constraints are borrowed from [17], [23] and [24]. Unlike the previous test cases, all three problems, i.e., MED1, MED2, and MBED, are solved to comparatively check the efficiency of the projected IGJA. Tables 4 to 6 presents a comparison of the results provided by IGJA with those achieved with other techniques presented in the state-of-the-art literature in three cases; case1: first 16-unit system; case2: second 16-unit system neglecting valve-point effect; and case3: second 16-unit system considering valve-point effect. Different scenarios are taken into account in this case study to clarify the superiority of the projected method in satisfying different types of restrictions and constraints. In order to incorporate the valve-point effects of TUs, the optimal generation outputs of TUs are changed resulting to an increase in operation cost as well as emission growth [(\$2,127.5925 and 5.78778 ton) to (\$2,235.99277 and 5.81572 ton)] for the second test case. One can see that the suggested IGJA can still provide better results with the highest rate of execution efficiency compared to other algorithms especially in case of considering hard constraints. In general, the meta-heuristic algorithms are on the basis of population and, therefore, the optimal candidate solution may change in different simulations, while the GM is a mathematical-based technique and is able to dramatically enhance the robustness of the selection process. Additionally, it can theoretically guarantee the near global optimality of the proposed algorithm in shorter time. Besides, with the enhanced simulation time of the proposed approach, the CPU computation time is much better than others for all the studied optimization problems.

As the boundary points of the trade-off surface are provided, the MBED problem is solved to achieve the Pareto frontier. This curve allows the TSO to have the databank of several non-dominated solutions between the probable optimal operation cost and the possible optimal environmental effect. Figs. 6(a), (b), (c) bear witness to the attribute development of the suggested technique and displays the Pareto optimal frontiers obtained by the IGJA for three abovementioned cases. As shown, the IGJA struggles to keep up the uniformity and smoothness of the solutions

along the curve, especially around the edges. However, the Pareto frontier of the first case study which is portrayed in Fig. 6. (a) is not uniform. This benchmark bi-objective test problem (case1) is selected to explore different characteristics, e.g., tie-line cost (Table 1) and discontinuity in the shape of true Pareto front. In order to further clarify, the NSGA-II [42] and MOPSO [43] techniques are also employed in this case study for which the results are demonstrated in Fig. 7. It is clear that the aforementioned two algorithms have resulted in a discontinuity in their Pareto curves. Moreover, they fail to discover the extreme points of the Pareto surface and the optimal non-dominated points are more crowded in other parts rather than the edges.

The best compromised solutions of the above cases (Fig. 6) are listed in Tables 4 to 6 in which all the solutions have lower operation cost as well as emissions compared to other well-known algorithms such as [case1: (IGJA: \$6,697.69791 and 7,471.11752 ton) vs. (CGBABC [23]: \$9,569.40579 and 7,227.110436 ton); case2: (IGJA: \$2,137.68910 and 3.45047 ton) vs. (CASE I [22]: \$2,152.21264 and 4.65918 ton); and case3: (IGJA: \$2,151.69601 and 3.02967 ton) vs. (CASE I [22]: \$2,161.6991 and 3.08730 ton)]. Furthermore, the CPU simulation run time of the IGJA is enhanced with respect to CGBABC [23] and CASE I [22].

Figure6

Figure7

Tables4 to 6

5.5. Test System 4: 4 Areas with 40 TUs

This test system consists of 40 TUs which are equally distributed in 4 areas. The problem search terrain of this test system is characterized by uncountable local minimum points. To efficiently tackle such hard problems, the proposed IGJA is applied on MED1 and MED2 and the results are compared with other state-of-the-art approaches in Table 7. As one can infer from this Table, although other techniques might seldom provide an optimal solution which is near to that of the suggested one, the IGJA returns the robust, fast and optimal solution in one trial run. In order to verify the superiority of the suggested bi-objective methodology, the IGJA is implemented to derive the Pareto solution frontiers in two different cases with and without DPZs considerations (Fig. 8(a), (b)). The Pareto optimal surfaces of both subcases achieved by utilizing the IGJA have great diversity and distribute uniformly in

two dimensions space. The figure illustrates that the proposed algorithm can provide the near global non-dominated solutions within 30 iterations, so rendering a practical and scalable alternative strategy.

Table7

Figure8

5.6. Test System 5: 2 Areas with 120 Units

In order to further confirm the applicability and scalability of the suggested IGJA, a practical case with enormous 120 units is considered that aggravate the hurdles of optimization procedure. In concordance with the previous results for four test cases, the proposed IGJA minimizes the operation cost outstandingly superior in the MED1 problem. The corresponding results in 30 trial runs are noticeably less than JA and IJA and also compared with the results of classical optimization program (CM) [44] and GBABC [23] in Table 8. In addition to the impressive outputs, there is a competency in the capability of the suggested technique to converge to a solution with quality properties. This claim is clarified by the convergence characteristic in Fig. 8(c) where one can confirm that the IGJA can quickly converge to an optimal and robust solution. While it is almost advocated for meta-heuristic approaches that they are deprived of a convergence guarantee, suffering from the premature convergence and entrapping in local optima, the proposed IGJA puts the JA, mutation strategy, and GM together to successfully surpass the original JA, escape from local optima, and eventually halt to an acceptable solution in all 30 trial runs.

Table8

6. Conclusion

The IGJA algorithm hybridizes the GM, JA and mutation strategies and has been set up in this study to more accurately solve the complex MBED problems with practical constraints on several small and large scale test systems. Recall that on one hand, the bi-objective GM is introduced with deep-seated mathematical characteristics appropriate for improving the robustness of the main algorithm. With respect to other approaches that use Lagrange relaxation concept, the proposed method competitively considered the lambda as the decision variable for the JA. On the other hand, JA is known for its algorithmic-parameter free of tuning. In this paper, a new mutation strategy is integrated in the JA to enhance its exploitation and exploration, simultaneously. Moreover, the proposed Pareto-based bi-objective approach was proved that does not deteriorate when confronted with multimodal and deceptive

problems. The effectiveness, flexibility and scalability of the suggested algorithm were verified by the complexity and convergence analysis as well as experimental studies. The developed framework can be also employed in other combinatorial bi objective optimization problems within the electric power system domain such as optimal power flow, unit commitment, etc.

7. References

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Figure Captions

Figure 1. (a) and (b): Surface of the sinusoidal and quadratic cost functions of a 2-unit system in a typical area, respectively; (c) and (d): Surface of the exponential and quadratic emission functions of a 2-unit system in a typical area, respectively.

Figure 2. (a) Diagram for the sub-feasible regions of three units and their feasible solution planes; (b) Spinning reserve of a typical TU with and without considering DPZs.

Figure 3. (a) and (b): First order derivations of the first and second units' fuel cost functions, respectively; (c) and (d) First order derivations of the first and second units' emission functions.

Figure 4. Flowchart of the proposed bi-objective IGJA.

Figure 5. Convergence graph of the proposed IGJA compared to JA for (a) test system 1, (b) test system 2.

Figure 6. Pareto frontier of the proposed IGJA for (a) test system 3, Case1, (b) test system 3, Case2, and (c) test system 3, Case3.

Figure 7. Pareto frontiers obtained by proposed IGJA, MOPSO and NSGA-II for test system 3, Case1.

Figure 8. (a) and (b) Pareto frontiers found by the proposed IGJA for test system 4 with/without considering DPZs and (c) Convergence graph of the proposed IGJA compared to JA for test system 5.

Fig. 1. (a) and (b): Surface of the sinusoidal and quadratic cost functions of a 2-unit system in a typical area, respectively; (c) and (d): Surface of the exponential and quadratic emission functions of a 2-unit system in a typical area, respectively.

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Fig. 8. (a) and (b) Pareto frontiers found by the proposed IGJA for test system 4 with and without considering DPZs and (c) Convergence graph of the proposed IGJA compared to JA for test system 5.

Table 1. Different test systems and their characteristics

Test Systems	Scenarios	NK	NUK	$D_{k,t}$	Tie-line cost	Valve-point effect	DPZ	Multiple fuel	Transmission line losses	Up/down ramp rate	Reserve
1	MED1	2	3 and 3	757.8 and 505.2	No	No	Yes	No	Yes	No	No
2	MED1	3	4, 3 and 3	1350, 675 and 675	No	Yes	No	Yes	Yes	No	No
3	MED1, MED2, MBED	4	4, 4, 4, and 4	400, 200, 350 and 300	Yes	No	No	No	No	No	No
				0.3, 0.5, 0.4 and 0.6	No	Yes	No	No	No	No	Yes
4	MED1, MED2, MBED	4	10, 10, 10 and 10	1,575, 4,200, 3,150 and 1,575	No	Yes	Yes	No	No	No	No
5	MED1	2	70 and 50	18,200 and 9,800	No	No	No	No	No	Yes	No

Table 2: Results obtained by different techniques on test system 1

Units (MW)	Algorithms								
	RCGA [20]	EP [20]	DE [20]	ABCO [19]	TLBO [19]	CGBABC [23]	JA	IGJA	IGJA without DPZs and loss
$g_{1,1}$	500.0000	500.0000	500.0000	500.0000	500.0000	499.9999884	500	500	500
$g_{2,1}$	200.0000	200.0000	200.0000	200.0000	200.0000	200	200	200	200.0000000
$g_{3,1}$	149.6328	149.9919	150.0000	149.9997	150.0000	149.9999954	150	150	150.0000000
$g_{1,2}$	205.9398	206.4493	204.3341	204.3358	204.3271	204.3246584	203.4071084	204.3341003	180.1847317
$g_{2,2}$	155.8322	154.8892	154.7048	154.9954	154.7095	154.7091226	154.7163822	154.7048164	178.6608502
$g_{3,2}$	65.2209	65.2717	67.5770	67.2915	67.5795	67.5823479	68.5015109	67.57701863	54.1544181
T_{12}	82.4135	82.7652	82.7731	82.7728	82.7731	82.77312	82.7727750	82.7731350	92.2000000
$Loss_1$	9.4193	9.4267	9.4269	9.4269	9.4269	9.4268646325	9.42686500	9.42686500	-
$Loss_2$	4.2064	4.1754	4.1890	4.1955	4.1892	4.1892497863	4.19777643	4.18907033	-
$Error_1$	-3.1341×10^{-6}	1.8960×10^{-6}	3.5000×10^{-5}	4.1181×10^{-5}	3.5000×10^{-5}	-8.3251×10^{-7}	0	0	0
$Error_2$	-3.6074×10^{-5}	3.4102×10^{-5}	-6.9426×10^{-5}	1.3154×10^{-5}	-3.6045×10^{-5}	-8.8629×10^{-7}	0.65008×10^{-7}	0	0
Fuel cost from generation (\$)	12,255.66898	12,255.42970	12,255.38496	12,255.38663	12,255.38526	12,255.38527	12,255.39526	12,255.38527	12,130.24111
Reported fuel cost (\$)	12,256.23	12,255.43	12,255.42	12,255.39	12,255.39	12,255.38527	12,255.39526	12,255.38527	12,130.24111
CPU Computation Time (s)	9.6094	8.8906	5.9219	10.9844	5.0734	0.8800	0.0985	0.0386	0.0301

Table 3: Results obtained by comparing the application of different techniques on test system 2

Units (MW)	Algorithms									
	Fuel	RCGA [20]	EP [20]	DE [20]	ABCO [20]	TLBO [19]	CGBABC [23]	JA	IGJA	IGJA without loss
$g_{1,1}$	2	239.0958	223.8491	225.4448	225.9431	224.3088	225.3498851	222.9568323	224.2737546	216.0353437
$g_{2,1}$	1	216.1166	209.5759	210.1667	211.1594	210.6642	211.9047558	212.39824593	212.1547045	210.9166909
$g_{3,1}$	2	484.1506	496.0680	491.2844	489.9216	491.6998	489.3519339	491.2078688	489.3573007	484.1809807
$g_{4,1}$	3	240.6228	237.9954	240.8956	240.6232	240.6247	240.6273431	240.7623494	241.4331992	238.8802026
$g_{1,2}$	1	259.6639	259.4299	251.0049	254.0397	249.5648	250.8118968	253.0298414	251.1733064	247.5757457
$g_{2,2}$	3	219.9107	228.9422	238.8603	235.4927	235.8978	235.7646232	235.7592783	235.7641984	234.4205841
$g_{3,2}$	1	254.5140	264.1133	264.0906	263.8837	263.7414	265.2630376	262.3542148	266.3883687	261.6482147
$g_{1,3}$	3	231.3565	238.2280	236.9982	237.0006	237.1327	237.2683096	238.6092132	236.3271037	234.1772066
$g_{2,3}$	1	341.9624	331.2982	326.5394	328.7373	332.5910	330.3871385	327.6373410	328.1833087	324.8619016
$g_{3,3}$	1	248.2782	246.6025	250.3339	248.8607	249.4628	248.8701406	251.0296595	250.5946558	247.3031294
T_{12}		-93.1700	-100	-99.4680	-99.8288	-100	-99.9999853	-100	-100	-99.9883396
T_{13}		-93.8739	-100	-100	-99.7334	-100	-99.9676498	-100	-100	-99.9984426
T_{23}		-43.7824	-32.5231	-30.2810	-31.2615	-35.4599	-32.9091621	-33.63174840	-31.46384784	-31.3437951
$Loss_1$		17.0297	17.4884	17.2680	17.2095	17.3000	17.201559419	17.325296399	17.218959016	0
$Loss_2$		9.7010	10.0085	9.7688	9.8488	9.6639	9.748743954	9.775082843	9.789721383	0
$Loss_3$		8.9408	8.6056	8.5905	8.6037	8.7266	8.648836621	8.644465373	8.641220439	0
$Error_1$		8.24×10^{-5}	9.49×10^{-5}	2.98×10^{-5}	-1.15×10^{-4}	8.36×10^{-5}	-6.42×10^{-6}	0	0	0
$Error_2$		-2.46×10^{-5}	1.39×10^{-4}	4.75×10^{-5}	-6.66×10^{-5}	-5.96×10^{-5}	-9.55×10^{-6}	0	0	0
$Error_3$		9.23×10^{-5}	3.24×10^{-5}	-2.87×10^{-5}	4.50×10^{-5}	-9.80×10^{-6}	-5.98×10^{-5}	0	0	0
Fuel cost from generation (\$)		658.19294	655.97796	654.82991	654.81318	654.80495	654.70521	654.82073	654.62970	637.60276
Reported fuel cost (\$)		657.3325	655.1716	654.0184	653.9995	653.9977	654.70521	654.82073	654.62970	637.60276
CPU Computation Time (s)		83.8438	78.0625	65.0351	90.4381	61.6719	21.1100	0.2472	0.1014	0.0891

Table 4. Results obtained by comparing the application of different techniques for MED1, MED2 and MBED on test system 3-Case1

Units (MW)	Algorithms									
	MED1						MED2		MBED	
	CGBABC [23]	NFP [4]	PSO [18]	HS [14]	HHS [14]	IGJA	CGBABC [20]	IGJA	CGBABC [23]	IGJA
$g_{1,1}$	150	150	150	150	150	150	66.5207067	66.75718759	126.87540954	67.46083526
$g_{2,1}$	100	100	100	100	100	100	52.8691908	53.08948295	86.48162611	60.21294191
$g_{3,1}$	67.01425464	66.9700	67.3660	66.9700	66.8600	67.00854493	79.2482258	79.47373997	67.56408245	58.57822370
$g_{4,1}$	99.99999904	100	100	100	100	100	76.2889865	76.77491697	92.92597095	69.86866418
$g_{1,2}$	57.0015744	56.9700	56.6130	56.9700	57.0400	57.00813804	77.4657093	77.71182637	90.72876565	50
$g_{2,2}$	96.25963305	96.2500	95.4740	96.2500	96.2200	96.26020420	77.8002257	78.13719245	81.46985325	66.21283596
$g_{3,2}$	41.88030945	41.8700	41.6170	41.8700	41.7400	41.88009766	93.213952	93.45839235	51.20626706	45.25743083
$g_{4,2}$	72.50238905	72.5200	72.3560	72.5200	72.5000	72.50672370	83.8241036	84.19042498	68.52046897	59.56527929
$g_{1,3}$	50	50	50	50	50	50	90.1575617	90.32309784	61.75648809	50
$g_{2,3}$	36.25534412	36.2700	35.9730	36.2700	36.2400	36.25336106	63.7014978	63.85971118	48.95709899	36.00731531
$g_{3,3}$	38.50292424	38.4900	38.2100	38.4900	38.3900	38.50404047	94.4779301	94.6372598	54.66231557	48.84729669
$g_{4,3}$	37.31077863	37.3200	37.1620	37.3200	37.2000	37.31078584	94.4319083	94.83198679	41.80756184	37.98917688
$g_{1,4}$	150	150	150	150	150	150	86.1495095	85.14209639	130.12753749	150
$g_{2,4}$	100	100	100	100	100	100	59.0007298	58.41447890	86.68294222	100
$g_{3,4}$	57.00777352	57.0500	57.8300	57.0500	56.9000	57.00803572	73.2077956	72.72781412	69.25955138	100
$g_{4,4}$	96.26501822	96.2700	97.3490	96.2700	96.2000	96.26006839	81.6419652	80.47039135	90.97406045	100
T_{12}	7.35339×10^{-7}	0	0	0	0	0	-82.933808425	-39.96253632	-28.63191791	-45.33910605
T_{13}	19.697889742	18.1800	22.5880	18.1800	16.8600	19.05044664	-52.139081496	-72.40896772	2.47893078	1.45977108
T_{41}	2.683635835	1.2100	5.1760	1.2100	0	2.04190171	-9.999999449	11.53316848	-7.619 $\times 10^{-5}$	100
T_{23}	68.23306259	69.7300	66.0640	69.7300	70.6100	68.88136599	-10.629817346	1.428089353	63.28892961	75.69644003
T_{42}	0.589155905	2.1100	0.0040	2.1100	3.1100	1.22620240	-60	-92.10721048	-0.0045074	100
T_{34}	100	100	100	100	100	100	70	77.32882276	77.04867513	100
$Error_1$	-9.6234×10^{-7}	0	-4.6×10^{-2}	-6×10^{-1}	0	0	-2.72×10^{-7}	0	0	0
$Error_2$	0	-1×10^{-1}	0	0	0	0	-4.79×10^{-7}	0	0	0
$Error_3$	-6.78×10^{-7}	-1×10^{-1}	-3×10^{-3}	-3×10^{-2}	-7×10^{-1}	0	-9.42×10^{-7}	0	0	0
$Error_4$	0	0	-1×10^{-3}	1×10^{-1}	-1×10^{-2}	0	-4.51×10^{-7}	0	0	0
Fuel cost from generation (\$)	7,337.01396	7,336.81028	7,336.67492	7,332.26326	7,329.44283	7,337.01396	9,828.91530	9,857.842548	9,569.40572	6,697.69791
Reported fuel cost (\$)	7,337.01396	7,337.00	7,336.93	7,333.26	7,329.85	7,337.01396	9,828.91530	9,857.842548	9,569.40572	6,697.69791
Emission from generation (ton)	17,184.756610	17,184.63519	17,189.65121	17,186.07735	17,180.87943	17,184.72200	5,697.70548	5,697.14486	7,727.110436	7,471.11752
Reported emission (ton)	17,184.756609	NA	NA	NA	NA	17,184.72200	5,697.70548	5,697.14486	7,727.110436	7,471.11752
CPU Computation Time (s)-MED1	6.0200	17.8000	8.1560	11.5800	0.4000	0.0273	-	-	-	-
CPU Computation Time (s)-MED2	-	-	-	-	-	-	6.3600	0.0245	-	-
CPU Computation Time (s)-MBED	-	-	-	-	-	-	-	-	NA	0.0281

NA: Not available

Table 5. Results obtained by comparing the application of different techniques for MED1, MED2 and MBED on test system 3-Case2

Units (MW)	Algorithms							
	MED1			MED2			MBED	
	PSO [24]	CASE I [22]	IGJA	PSO [24]	CASE I [22]	IGJA	CASE I [22]	IGJA
$g_{1,1}$	0.1320	0.1400	0.1400000	0.1277	0.1004	0.11836915	0.1115606	0.14000000
$g_{2,1}$	0.0649	0.0999	0.1000000	0.0625	0.1000	0.10000000	0.0943248	0.10000000
$g_{3,1}$	0.1201	0.0397	0.0400000	0.1188	0.1006	0.11956406	0.0850709	0.09166400
$g_{4,1}$	0.1128	0.1199	0.1200000	0.0945	0.0988	0.11701390	0.0383869	0.12000000
$g_{1,2}$	0.2047	0.2497	0.2500000	0.1684	0.1449	0.13895918	0.1738436	0.19862765
$g_{2,2}$	0.0657	0.1199	0.1200000	0.0677	0.0793	0.07347976	0.1188736	0.12000000
$g_{3,2}$	0.1316	0.0606	0.1049999	0.1891	0.1235	0.11792123	0.1992356	0.10246391
$g_{4,2}$	0.1503	0.1494	0.1050001	0.1604	0.1266	0.12130768	0.0746936	0.10726303
$g_{1,3}$	0.0572	0.0008	0.0005000	0.0619	0.1242	0.11991663	0.1103756	0.07709005
$g_{2,3}$	0.0971	0.0005	0.0005000	0.0722	0.1218	0.11711100	0.0153371	0.06171960
$g_{3,3}$	0.0663	0.1824	0.1830000	0.0901	0.1174	0.11338182	0.0409648	0.07658940
$g_{4,3}$	0.2278	0.3000	0.3000000	0.1948	0.1203	0.11602852	0.2996616	0.26850719
$g_{1,4}$	0.0759	0.1068	0.1100000	0.0900	0.1100	0.11000000	0.0071000	0.11000000
$g_{2,4}$	0.1123	0.0006	0.0005000	0.1172	0.1143	0.10963045	0.1935572	0.05629710
$g_{3,4}$	0.0520	0.2286	0.2250000	0.0595	0.0909	0.08676283	0.1205024	0.08696574
$g_{4,4}$	0.1402	0.0005	0.0005000	0.1498	0.1262	0.12055379	0.1165175	0.08281234
T_{12}	-0.0316	-0.0599	-0.0600000	-0.0469	0.0292	-0.00505290	-0.0591709	-0.00833600
T_{13}	-0.0088	-0.0398	-0.0400000	-0.0020	-0.0400	-0.04000000	-0.0397930	-0.04000000
T_{14}	0.1699	0.1995	0.2000000	0.1427	0.1107	0.20000000	0.1283090	0.20000000
T_{23}	-0.0320	-0.0350	-0.0350000	-0.020	-0.0350	-0.01800434	-0.0349508	-0.03498142
T_{24}	-0.0516	-0.0547	-0.0550000	-0.0499	-0.0386	0.03538070	-0.0424251	-0.05500000
T_{34}	0.0048	0.0090	0.0090000	-0.0089	0.0090	0.00843362	-0.0084042	0.00892482
R_1^{up}	0.0602	0.0902	0.0900000	0.0865	0.0900	0.03505289	0.1606569	0.03833600
R_2^{up}	0.1977	0.1702	0.1700000	0.1644	0.2755	0.29833215	0.1833536	0.22164542
R_3^{up}	0.7516	0.7161	0.7160000	0.7810	0.7160	0.73356203	0.7336609	0.71609377
R_4^{up}	0.5296	0.5733	0.5740000	0.4935	0.4684	0.48305293	0.4723229	0.57392482
R_1^{dn}	NA	NA	0.3980000	NA	NA	0.45294711	NA	0.44966400
R_2^{dn}	NA	NA	0.5780000	NA	NA	0.44966785	NA	0.52635459
R_3^{dn}	NA	NA	0.4820000	NA	NA	0.46443797	NA	0.48190624
R_4^{dn}	NA	NA	0.3340000	NA	NA	0.42494707	NA	0.33407518
$Error_1$	3×10^{-4}	-3×10^{-4}	0	9.7×10^{-3}	-1×10^{-4}	0	-1.9×10^{-6}	0
$Error_2$	1.1×10^{-3}	0	0	8.8×10^{-3}	-1×10^{-4}	0	1.2×10^{-6}	0
$Error_3$	2.8×10^{-3}	-1×10^{-4}	0	5.9×10^{-3}	-3×10^{-4}	0	-5×10^{-7}	0
$Error_4$	6.7×10^{-3}	-3×10^{-4}	0	2×10^{-4}	-1×10^{-4}	0	7×10^{-6}	0
Fuel cost from generation (\$)	2,163.5927	2,127.4654	2,127.5925	2,178.2248	2,169.5898	2,169.12458	2,152.21266	2,137.68910
Reported fuel cost (\$)	2,166.82	2,127.6741	2,127.5925	2,178.20	2,169.8057	2,169.12458	2,152.21264	2,137.68910
Emission from generation (ton)	3.26430	5.89636	5.78778	3.18285	2.46932	2.44286	4.65918	3.45047
Reported emission (ton)	3.3152	5.8993	5.78778	3.230	2.47252	2.44286	4.65918	3.45047
CPU Computation Time (s)-MED1	NA	NA	0.0243	-	-	-	-	-
CPU Computation Time (s)-MED2	-	-	-	NA	NA	0.0212	-	-
CPU Computation Time (s)-MBED	-	-	-	-	-	-	NA	0.0296

NA: Not Available

Table 6. Results obtained by comparing the application of different techniques for MED1, MED2 and MBED on test system 3-Case3

Units (MW)	Algorithms					
	MED1		MED2		MBED	
	CASE I [22]	IGJA	CASE I [22]	IGJA	CASE I [22]	IGJA
$g_{1,1}$	0.1400	0.1400000	0.1183773	0.11836915	0.1399720	0.1400000
$g_{2,1}$	0.1000	0.1000000	0.1000000	0.10000000	0.0986082	0.1000000
$g_{3,1}$	0.0457608	0.0400000	0.1195736	0.11956406	0.0983318	0.0954115
$g_{4,1}$	0.1199994	0.1200000	0.1170255	0.11701390	0.1197505	0.1199313
$g_{1,2}$	0.2500000	0.2500000	0.1389808	0.13895918	0.1816420	0.1800899
$g_{2,2}$	0.1200000	0.1200000	0.0734976	0.07347976	0.0744027	0.1200000
$g_{3,2}$	0.2000000	0.0785273	0.1179339	0.11792123	0.1261824	0.1077175
$g_{4,2}$	0.0042327	0.1314727	0.1213222	0.12130768	0.1144656	0.1163627
$g_{1,3}$	0.0005000	0.0005000	0.1199036	0.11991663	0.0818219	0.0792306
$g_{2,3}$	0.0005000	0.0005000	0.1170986	0.11711100	0.0629645	0.0808021
$g_{3,3}$	0.1829997	0.1830000	0.1133690	0.11338182	0.1175823	0.0985387
$g_{4,3}$	0.2999999	0.3000000	0.1160152	0.11602852	0.1997273	0.2252466
$g_{1,4}$	0.1100000	0.1100000	0.1100000	0.11000000	0.0592040	0.1099008
$g_{2,4}$	0.0005000	0.0005000	0.1096131	0.10963045	0.0397950	0.0560058
$g_{3,4}$	0.1999942	0.2250000	0.0867518	0.08676283	0.1159061	0.0798857
$g_{4,4}$	0.0255122	0.0005000	0.1205377	0.12055379	0.1696448	0.0908766
T_{12}	-0.0542329	-0.0600000	0.0277957	-0.00505290	-0.0134335	-0.0046571
T_{13}	-0.0399995	-0.0400000	-0.0355024	-0.04000000	-0.0199525	-0.0400000
T_{14}	0.1999930	0.2000000	0.1626831	0.20000000	0.1900481	0.2000000
T_{23}	-0.0350000	-0.0350000	-0.0346740	-0.01800434	-0.0345699	-0.0350000
T_{24}	-0.0550000	-0.0550000	-0.0142043	0.03538070	-0.0178287	-0.05451300
T_{34}	0.0090000	0.0090000	-0.0037900	0.00843362	0.0075737	0.0088180
R_1^{up}	0.0842398	0.0900000	0.0350236	0.03505289	0.0333376	0.0346571
R_2^{up}	0.1757673	0.1700000	0.2982655	0.29833215	0.2533073	0.2258299
R_3^{up}	0.7160004	0.7160000	0.7336136	0.73356203	0.7379040	0.7161820
R_4^{up}	0.5739936	0.5740000	0.4830974	0.48305293	0.5254502	0.5733310
R_1^{dn}	NA	0.3980000	NA	0.45294711	NA	0.4533429
R_2^{dn}	NA	0.5780000	NA	0.44966785	NA	0.5221701
R_3^{dn}	NA	0.4820000	NA	0.46443797	NA	0.4818180
R_4^{dn}	NA	0.3340000	NA	0.42494707	NA	0.3346690
$Error_1$	-4×10^{-7}	0	0	0	4×10^{-7}	0
$Error_2$	-2×10^{-7}	0	-1×10^{-7}	0	4×10^{-7}	0
$Error_3$	1×10^{-7}	0	0	0	-1×10^{-7}	0
$Error_4$	-6×10^{-7}	0	0	0	4×10^{-7}	0
Fuel cost from generation (\$)	2,136.40511	2,135.99277	2,177.55342	2,177.55164	2,161.69911	2,151.69601
Reported fuel cost (\$)	2,140.27270	2,135.99277	2,177.55345	2,177.55164	2,161.69906	2,151.69601
Emission from generation (ton)	5.93165	5.81572	2.44286	2.44286	3.08730	3.02967
Reported emission (ton)	5.93165	5.81572	2.445	2.44286	3.08730	3.02967
CPU Computation Time (s)-MED1	NA	0.0250	-	-	-	-
CPU Computation Time (s)-MED2	-	-	NA	0.0212	-	-
CPU Computation Time (s)-MBED	-	-	-	-	NA	0.0307

NA: Not Available

Table 7. Comparison of the results achieved by comparing the application of different algorithms on test system 4

Solution technique	Objective function value			CPU Computation Time (s)
	Best	Mean	Worst	
MED1 (\$)				
RCGA [20]	129,911.8	NA	NA	160.5300
ABCO [20]	124,009.4	NA	NA	126.9300
EP [6]	123,591.9	NA	NA	NA
DCPSO [16]	121,948.8	NA	NA	64.8000
DE [20]	121,794.8	NA	NA	NA
TLBO [19]	121,760.5	NA	NA	NA
CGBABC [23]	121,595.7782	121,804.3390	122,393.1171	52.9100
JA	122,193.8780	122,259.1133	122,355.9162	3.1401
IJA	121,603.5225	121,609.9522	121,616.7124	2.0155
Proposed IGJA	121,595.7468	121,595.7468	121,595.7468	1.2617
MED2 (ton)				
CGBABC [23]	176,682.2646	176,682.2943	176,684.8232	45.9700
Proposed IGJA	176,682.2646	176,682.2646	176,682.2646	1.0019
MBED				
	Cost (\$)	Emission (ton)		
CGBABC [23]	124,576.5766	254,489.6408		-
Proposed IGJA	124,278.5422	254,478.0396		1.5612
NA: Not Available				

NA: Not Available

Table 8. Comparison of the results achieved by comparing the application of different algorithms on test system 5

Solution technique	Objective function value			CPU Computation Time (s)
	Best	Mean	Worst	
MED1 (\$)				
CM [44]	399,130	NA	NA	5,089.0000
GBABC [23]	377,958.3312	378,284.5146	382,657.0553	105.2100
JA	380,669.5400	382,181.4434	383,393.0733	4.7743
IJA	377,968.2507	378,299.5853	378,669.8543	3.8566
Proposed IGJA	377,958.2985	377,958.2985	377,958.2985	2.8149

NA: Not Available