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Towards developing a systematic knowledge trend for building energy consumption prediction

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Abstract:

The rapid depletion of natural sources of energy, coupled with increasing global population has triggered the emergence of various techniques and strategies for building energy consumption prediction. According to information from existing body of knowledge, this paper systematically brings to fore the application areas of building energy consumption prediction (i.e. well-established and emerging), the relationships between these areas and the ways in which authors integrate the current spate of techniques. Based on direct implications of buildings on global energy consumption and CO₂ emissions, this information makes it possible to identify trends, strengths and limitations in this context, thereby enabling the centralisation of activities required for future studies. This study follows several well-documented guides for conducting logical reviews of primary articles concerning main topics of building energy consumption prediction within popular online databases. The definition of articles' search keywords as well as inclusion/exemption factors were governed by a combination of principles stipulated by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and Procedures for Performing Systematic Reviews (PPSR). In comparison to existing review articles in the studied field, the current study is novel in the sense that it provides a very holistic view to building energy consumption prediction, thereby minimising the need to consult multiple individualised studies that are limited to specific techniques, data sets, regions or types of buildings. Another unique feature of this study is its interrelationship network of articles which depicts a quick glance at some of the most influential studies as well as underrepresented areas, thereby aiding research planning, future directions and cross-disciplinary collaborations.

Keywords

Building energy; energy consumption; prediction; sustainability; systematic and meta-analysis

1. Introduction

The population of the world has experienced an unprecedented growth from 2.53 billion in 1950 to 7.16 billion in 2011. Based on the current growth rate of 1.2% per year, the world population is anticipated to reach 14.4 billion within the next 60 years [1]. This rapid growth in population, has led to a corresponding rise in global primary energy consumption (3701Mtoe in 1965 to 13511 Mtoe in 2017). At the current population growth rate, it is predicted that there could be a total depletion of all current primary energy sources in less than 134 years [2].

Buildings represent an immense proportion of global energy consumption and carbon dioxide (CO₂) emissions, due to rising human demands for housing and quality of living standards [3]. As a consequence, building and transport related activities are gradually becoming the main energy consumption sectors globally. In 2017, buildings construction and maintenance represented 36% of global energy usage and 39% of total CO₂ released [4], [5]: this proportion could be significantly greater in highly industrialised nations. For instance, the UK's domestic and services industries accounted for an estimated 44% of cumulative energy in 2018 [6]. Similarly, building energy usage in China rose by a magnitude of 1.7 between 2000 and 2014, and is predicted to represent 35% of cumulative national energy usage by 2020 [7]. The criticality of stable and reliable energy can never be overemphasised, which is perhaps why policymakers and governments across the world are continuously implementing regulations, policies and in some cases incentives that are aimed at promoting building energy saving initiatives. In the United Kingdom for instance, Climate Change Act of 2008 established a legal framework for reducing CO₂ emissions by 34% by 2020 and a further 80% by 2050 [8]. While such Acts and targets are immensely crucial drivers for change, their actualisation significantly hinges on the reliability of building energy usage predictions. In recent decades, a number of theoretical (statistic methods and artificial intelligence methods) [9] and practical (EnergyPlus, TRNSYS, eQuest, DOE-2) [10] analysis tools have been developed and applied to varying levels of success in this field.

While existing building energy consumption prediction approaches have significantly enhanced the understanding of energy trends as well as aided forecasting, the ever-increasing complexity of the energy systems associated with modern day buildings have made it imperative to continuously seek smarter and more reliable approaches. The complexity of prediction is further compounded by variations in occupant behaviour [11] with regards to the use of electrical appliances and/or devices, geographical location of buildings, age of buildings, function of building, etc.[12]. Owing to the rising popularity of building energy studies, coupled with the advent of high-power computational technologies, existing body of knowledge is adequately furnished with a spate of articles in this area but very few of them are solely based on knowledge trends development through detailed literature reviews of building energy consumption prediction, except for those by Amasyali and El-Gohary [13], Wei et al.[14], Ahmad et al.[15] as well as Lim and Zhai [16].

Amasyali and El-Gohary [13] reported a study based upon data-driven building energy usage prediction models. The study [13] primarily focused on investigating scope of predictions, data features, data pre-processing methodologies, roles of machine learning based prediction algorithms and evaluation performance measures. The study advocates the need to further focus on longer term building energy usage forecasts of residential buildings through better understanding of lighting patterns [13]. Similarly, Wei et al. [14] reviewed the emerging data-driven methods applied in building energy analysis for a range of archetypes and granularities, whereby the basic concepts, merits and demerits of existing applications of building energy analyses were discussed. The study [14] generated three core findings. The initial finding advocates that current data-driven frameworks should be streamlined to specific energy demands. The second finding highlights that building energy analyses need to encompass energy applications at varying scales as well as using several weather conditions. The third and final finding recommends the integration of multiple target indices into existing data-driven frameworks. Ahmad et al. [15] studied the forecasting mechanisms for electrical energy usage of buildings especially those that involved artificial intelligence (AI) techniques such as support vector machine (SVM) and artificial neural networks (ANN). The study [15] further highlighted the superior performance of hybrid methods such as least square-SVM (LSSVM) over the independent application of traditional ANN and/or SVM when predicting building electrical energy usage. Lim and Zhai [16] also provided a detailed review of commonly used mechanisms and techniques for building stock energy forecasting, whereby

specific emphasis was placed on comparing the strengths and weaknesses of existing primary stochastic engineering building stock energy models.

Although all classes of existing articles (literature reviews, case studies, short communications, editorials and regular articles) provide some insights on prevailing as well as previous status of building energy consumption prediction research, the approaches adopted for the reviews therein can be described as opinionated since they rarely explain the criteria used for selecting the included primary studies. Additionally, traditional literature-based studies offer little or no information about the timelines covered and the statistical distribution of primary studies (also referred to as meta-analysis), which is crucial to the understanding of energy consumption since outcomes may sometimes vary according to authors' geographical locations. Based on these premises, the current study aims to adequately compensate for the existing gaps through logical and well-structured classification of the findings of existing studies [17]. A systematic review (SR) attempts to identify and interpret contributions of existing studies that concern the investigated title, thereby synthesising existing work on the basis of fairness, precision and reliability. In contrast to standard literature reviews, SRs need considerably more efforts as well as provide further details about the specific impacts of certain principles across macroscopic settings and empirical methods. On the one hand, if several comparable studies generate consistent results, SRs offer proof that such principles are robust and transferable. On the other hand, if the findings from studies are inconsistent, sources of discrepancies are easily identified. With regards to quantitative studies, a systematic review can be used to detect the actual effects through meta-analytic techniques [18], which may be challenging or impossible through individual primary studies alone or standard literature reviews.

Based on a rigorously defined research protocol, the systematic review performed here examines all types of prediction methods (physical, statistical, artificial intelligence-based and hybrid methods) associated with building energy consumption prediction over 3 decades. Additionally, the classification of the prediction methods provides information such as overall developmental trends within the study area, building designs considered, temporal granularities, forms of energy usage forecasted, data structures, feature types, sample sizes, optimisation and improvement approaches considered within individual primary studies. The

remaining parts of this paper are structured thus; Section 2 provides the procedural details of the systematic review of building energy consumption prediction. Section 3 summarises widely applied prediction methods as well as explains the data classification approach adopted here, including a highlight of the advantages and disadvantages of individual methods. Section 4 describes the synthesis of major findings from included articles, particularly the data properties, data preprocessing and accuracy of the prediction methods. Finally, Section 5 provides the concluding remarks and future considerations.

The contributions provided by this systematic literature review are two-fold: firstly, it helps to identify the general developmental trends of building energy usage forecasting/prediction, based on logical but thorough examination of all related articles from 4 databases. Secondly, the extracted data and statistics provide a knowledge repertoire which offers guidance for future research, especially in the identification of opportunities that can enhance the accuracy and robustness of prediction outcomes.

2. Review Methodology

The SR is performed in line with both PRISMA and PPSR methodologies provided by Sharma and Oremus [19] and Kitchenham [17] respectively. PRISMA and PPSR are characterised by detailed items checklist and phase flow diagrams that enable transparent reporting during SRs and meta-analyses.

2.1 The research question

Formulating a representative research question is a fundamental step for adequately performing SRs. With regards to building energy consumption prediction, several of the existing regulations, instruments and guideline are still at development stages. This implies that some prediction procedures are sometimes determined based on personal experience and preference. In simpler terms, personal understanding of the interrelationships that exist between different prediction methods, building types as well as input parameters would be the most uncertain part of prediction. Therefore, tracking the totality of developmental history and trends of building energy consumption prediction offers a great opportunity for ascertaining research direction. Unfortunately, such holistic and all-encompassing reviews are very rare within existing body of knowledge, thereby necessitating the harmonisation of numerous independent studies. Based on this premise, the following research question was formulated for this study:

“To what extent do existing building energy consumption prediction literature reviews address the multi-dimensionality of knowledge management trends?”

2.2 Identification of relevant articles

The research area of energy consumption monitoring and prediction is quite diverse and widely studied across various disciplines. In order to create a representative spectrum of studies, 6 well-known multidisciplinary electronic databases (Web of Science, InSpec, Compendex, Geobase, GeoRef, Scopus) are used to generate the reviewed articles. Web of Science (WoS) and Scopus being two of the most comprehensive academic information management system broaden the wider reach of review while Engineering Village (which is made up of 4 engineering-specific databases) were used to complement each other. The review primarily comprised of several classes of inputs especially published journal articles, conference articles, conference proceedings, book chapters, dissertations as well as articles in press. The systematic search starts with identifying very important keywords. In order to enhance good coverage of articles but at the same time optimise the selection of directly linked articles, a combination of the SPIDER and PICO approaches suggested by Cooke et al. [18] was applied for defining the following keywords:

“building” AND “energy consumption” AND “prediction” AND “ageing” OR “existing” OR “retrofit” OR “old”.

The selected keywords indicated that this SR particularly focuses on existing buildings rather than new buildings. The rationale behind this class of buildings is due to the peculiar challenges associated with older buildings with regards to energy consumption prediction, due to their lack of up-to-date or totally unavailable data. Furthermore, since the term “existing” might not be comprehensive enough to capture all the relevant articles, alternative but related words such as “ageing” “retrofit” and “old” were included within the search string so as to enhance search quality.

2.3 Study Selection

While keywords are universally recognised as incredibly strong tools for guiding articles search within databases, their ability to adequately represent the interest of a reviewer is always a function of their origin. For instance, some authors misdefine keywords or even omit them completely, which raises the possibility of extracting several unrelated articles during reviews. Therefore, an additional layer of filtration is often required for further assessment of actual relevance. Additionally, the inclusion of all primary studies is

unreasonable, inefficient and could also lead to bias. Therefore, the definition of key inclusion criteria is imperative for the exclusion of irrelevant studies. The inclusion criteria defined for this systematic review are:

- i. Language of publication must be English language due to its global prevalence;
- ii. Research focus of article must be on building energy consumption prediction;
- iii. Full text of article must be available.

Table 1 shows the review protocol that was adopted for this study, which also summarizes the search string and exclusion.

Articles that meet these three basic criteria were further screened for eligibility. For instance, when conducting inter-database search for articles using the same keywords, there is always a possibility of creating duplicates, triplicates and quadruplicates that must be screened out since their contributions to knowledge is same. Figure 1 depicts the procedure used for streamlining the articles generated at different stages of the review. A total of 2493 articles were initially generated from all 6 databases, of which 181 of them were inaccessible. An additional 1835 articles were further excluded due to the misalignment of their core contents with the review context. The remaining 457 full-text accessible articles were then transferred into Mendeley reference management software, whereby 217 articles were identified and excluded due to duplicates, triplicates, quadruplicates and non-English text. Finally, 240 articles were retained for detailed contents review and eventual analysis.

3. Classification of methods for building energy consumption prediction

A comprehensive classification and reasonably standard nomenclature of prediction methods would ease the ability of readers or researchers to build a holistic building energy performance analysis knowledge network. Currently, there is a lack of uniform and clear consensus on the classification of prediction methods, which may lead to misconceptions and a corresponding lack of deep understanding of the peculiarities of individual prediction methods. For instance, Amasyali and El-Gohary [13], as well as Runge and Zmeureanu [20] simply classified methods as physical or data-driven while Suganthi and Samuel [21] applied 12 sub-categories for their classification. This broad classification of articles and techniques rarely reflect the key features of the individual methods. In addition, contradictory definitions of prediction methods could be observed across several review articles. For instance, Grillone et al. [22] deemed hybrid method (grey model or grey-box model) that making use of data-

driven techniques to optimize the results obtained with deterministic (physical based) methods, while subtle difference existed in [8], [13], [23]–[28] which simply defined hybrid methods as combination of physical models and data-driven approaches. According to [29] however, any combination of different methods can be regarded as a hybrid method. Simply designating hybrid methods as grey models can potentially lead to significant misinterpretation when such classifications are compared to the earlier grey prediction model introduced by Deng [30] over 4 decades ago, which had a primary aim of predicting system behaviours.

Based on inspirations from earlier works by Wei et al. [14], Bourdeau et al. [27] and Robert et al. [26], prediction approaches should have at least four basic classifications, namely; physical, statistical, AI and hybrid methods. The data-driven methods in their reviews [14], [26], [27] were fundamentally grouped into statistical and AI methods, due to the fact that both classes primarily investigate the relationships that exist between input and output data. However, while statistical methods mechanically seek to establish the input-output data relationships, artificial intelligence methods apply special characteristics such as self-learning, self-adjusting and generalization abilities to achieve similar outcomes more efficiently. In order to foster clarity and conciseness, Table 2 summarises the merits and demerits of the different classes of prediction methods described herein.

3.1 Physical methods

Physical methods (also referred to as engineering, deterministic or white-box approaches) [33], [34] are mainly based on the application of physical laws for modelling building systems and their associated components, as well as estimating thermal dynamics and energy patterns. The increased understanding of the characteristics of physical methods over the past decades has contributed to the creation of several building energy simulation platforms including EnergyPlus, DOE-2, eQuest and DesT. In addition to the relative simplicity of obtaining details of a building's performance through physical methods, impact of changes to a building can also be swiftly and clearly assessed from the relationships that exist between inputs and outputs. Physical methods are also good at simulating energy consumption throughout the life cycle of a building, which in turn offer asset owners and/or operators the highest degrees of flexibility with regards to implementing cost-effective improvement strategies. Such methods are more applicable at building design stages rather than predicting the performance of existing buildings. Furthermore, in terms of handling diverse predictive

situations as well as assessing new technologies for energy conservations, physical methods are far more flexible than statistical and AI method [16].

Despite the aforementioned advantages of physical methods, the possibility of significant deviations between predicted results and real-life situations is still considered a limitation. Such deviations are also referred to as performance gaps, which may be influenced by various factors as summarised by Lahrech et al. [35] and Simon [36]. The most prominent factors include uncertainties in building design parameters, uncertainties in operational data used for modelling, estimation errors as well as limitations in the underlying models [35], [36].

3.2 Statistical methods

Statistical methods (also known as statistical regression or regression methods) [9] mainly focus on estimating the relationships between variables. More specifically, statistical methods enable researchers understand the impacts of independent variables on the dependent variables by estimating the minimum mean square error (MMSE) for a given set of independent variables. The most common statistical methods are linear regression, stepwise regression, locally estimated scatterplot smoothing (LOESS), ordinary least squares regression (OLSR), multivariate adaptive regression splines (MARS) and logistic regression. Statistical methods are arguably the most widely applied for building energy prediction in practice, due to computational ease, speed and reasonable degree of accuracy [37]. Despite their ability to quickly generate predictive energy consumption data, this class of building energy prediction approaches have been criticized for their inability to adequately establish the nature of relationships between inputs and outputs, which necessitates thorough scrutiny of the influence of assumptions made during results generation. Studies have shown that statistical methods can accurately predict medium to long term energy consumption patterns of buildings [38]. Although reasonably acceptable, their performance with regards to short term prediction is less accurate [39]. The relative simplicity of implementation coupled with acceptable predicting performance outcomes of statistical methods is perhaps a fundamental reason for their widespread application as benchmarking tools for more advanced and complicated prediction methods [27].

3.3 Artificial Intelligence (AI)

During the last decade, the breakthroughs in computational technology has significantly elevated the capabilities of artificial intelligence (AI) methods. The concept of AI was initially coined by John McCarthy in 1956 who defined AI as the science and engineering of making intelligent machines [40]. Machine learning (ML) and neural networks (NNs) are two very common methods for automating intellectual tasks [41]. ML consists of applying mathematical and statistical approaches to automatically learn from experience[42]. ML algorithms are often categorised as supervised, unsupervised and semi-supervised algorithms. NN explores the prospects of techniques that can adequately mimic the operations of the human brain. The most representative and commonly used NNs are ANN and their deep learning derivatives.

3.3.1 Machine learning (ML)

3.3.1.1 Supervised machine learning algorithms

Supervised machine learning algorithms can utilise what has been learned in the past to new data using labelled samples to predict future events [42]. The most common supervised algorithms are SVM, DT, ensemble algorithms, Bayesian methods.

Support vector machine (SVM)

SVM can be described as a kernel-based machine learning technique [15]. Assuming a set of training samples, each of which belongs to one or more classes, SVM training algorithm can adequately allocate the new sample(s) into the appropriate categories by functioning as a non-probability binary linear classifier. The trained samples are represented by space points and the possible classes are distinguished by notable gaps. Consequently, new samples are mapped into the created spaces and simultaneously allocated to their respective categories, based on their relative positions from the gaps. While SVM outperforms other methods on the basis of linearly separable problems, it has also been criticized for the difficulties associated with data training and interpretation [43], [44].

Decision trees

Decision trees [45] are often considered one of the most popular amongst machine learning approaches. Their functioning is mainly based on application of tree-like structures to allocate datasets into several preconceived groups or target values [46]. Classification, boosted and regression trees are considered the most popular forms of decision trees. The most notable strengths of decision trees are their relative ease of interpretation and non-parametric nature. However, they have also been described as being susceptible to overfitting

problems as well as having high affinity for local minima. Another problem with decision trees is their lack of online learning capabilities.

Ensemble algorithms

Ensemble methods [28] are combinations of multiple learning algorithms, whereby the individual algorithms can be trained separately and their predictions combined in ways that depict an overall prediction. The main purpose of ensemble algorithms is to determine which of the weaker models can be combined as well as the best means by which such combinations can be performed [47], [48]. Random forest, bootstrapped aggregation, gradient boosting machines, boosting, stacked generalization and adaBoost [49] are some of the most notable examples of ensemble algorithms. While the combination approach adopted by ensemble algorithms allows for the strengths of certain individual algorithms to compensate for the weaknesses of others thereby improving overall prediction accuracy, tuning the different methods to ensure compatibility is often very challenging.

Bayesian algorithms

Bayesian methods [50] are explicitly based on the application of Bayes' theorem for solving classification and regression problems. Gaussian Naive Bayes, Naive Bayes, Bayesian network, Bayesian belief network and multinomial Naive Bayes are common examples of Bayesian algorithms. While Bayesian methods are universally recognized for their data processing speeds and training ease, the presence of correlated input variables is known to cause immense difficulties during analysis. This is often due to the fundamental assumption that the resultant output category is always a function of independent input variables, which is seldom the case under practical applications. Therefore, the performance of Bayesian methods (especially naïve Bayes) is best when the correlation attributes is minimal but could be unreliable when the number of variables is large.

3.3.1.2 Unsupervised machine learning algorithms

In contrast with supervised learning, unsupervised machine learning algorithms explore how to infer a function of describing hidden structures from unlabelled data [42]. The most common unsupervised algorithms are clustering algorithms and dimensionality reduction algorithms.

Clustering algorithms

Clustering algorithms [51] are used to establish pattern similarities so that data that exhibit similar characteristics can be classified into their corresponding target groups. Popular examples of clustering algorithms include hierarchical, expectation maximization, k-medians and k-means clustering approaches. Clustering algorithms are most suited for identifying linear correlations between data classes but their applications can be highly restricted by the non-linearities, noise, multi-dimensionality and significant variabilities often associated with real-life data. This is perhaps why several studies have explored alternative approaches for determining cluster compositions and efficiency [52].

Dimensionality reduction algorithms

Similar to clustering methods [53], dimensionality reduction methods are principally based on the utilisation of underlying data structure to summarise and/or explain data characteristics, but with significantly fewer information. This implies that dimensionality reduction algorithms can be useful for the visualisation, simplification or interpretation of highly dimensional data, prior to feeding such data into a typical supervised learning framework. Partial least squares regressions (PLSRs), principal components regressions (PCRs) and principal component analysis (PCA) are some of the most commonly used dimensionality reduction algorithms. Most dimensionality reduction approaches are multivariate statistical analysis tools that pose the capabilities to transform original interrelated variables onto alternative and new subspace with significantly lower dimensionality. The resultant subspace would then represent a set of uncorrelated variables that retained the maximum variations that exists in the original data set, thereby making them suitable for handling large datasets but less effective when dealing with non-linearities.

3.3.1.3 Semi-supervised machine learning algorithms

Semi-supervised machine learning algorithms (SSMLA) fall between supervised and unsupervised learning classes, thereby utilising both labelled and unlabelled data [54]. The most common examples of semi-supervised algorithms are generative models, low-density separation and graph-based methods.

Generative Models

Generative models assume that all data (whether labelled or not) are produced by the same underlying model [55]. This assumption ensures that the parameters of the underlying model can be used to associate the unlabelled data with the learning purpose, and the label of the unlabelled data can be regarded as the actual parameters of the model. The main advantages

of generative models are simplicity, ease of implementation and its ability to outperform other methods under limited labelled data scenarios. However, a key challenge often associated with SSMLAs is that the model assumptions must be accurate, that is, the hypothetical generative model must match the real data distribution, otherwise the use of unlabelled data will reduce the generalization performance. Unfortunately, it is often difficult to make accurate model assumptions in advance under real-life situations, unless sufficient and reliable domain knowledge exists [55].

Low-Density Separation

The fundamental concept of low-density separation methods (LDSMs) is quite similar to that of support vector machine. LDSMs consider applying various possible label assignments to unlabelled samples. This implies that attempts are made to use each unlabelled sample as a positive or negative example, after which one in all samples are divided into hyperplanes with maximal spacing. Once the partitioned hyperplane is determined, the final label assignment of the unlabelled samples becomes the predicted result [56].

Graph-Based Methods

Graph-based methods [55] map the data set into a graph whereby each sample within the data set corresponds to a node on the graph. If the similarity between two samples is very high (or the correlation is strong), then there is an edge between the corresponding nodes, and the strength of the edge is proportional to the similarity (or correlation) between the samples. The node corresponding to the labelled sample is regarded as dyed, and the node corresponding to the unlabelled sample has not been dyed. Therefore, semi-supervised learning corresponds to the process of "colour" spreading or spreading on the graph. Graph-based methods have the advantage of clear concepts and easy to explore the nature of the algorithm through matrix operation analysis. However, this method occupies a lot of memory space during calculations, and it is difficult to directly process large-scale data. In addition, it may be necessary to recalculate when receiving new samples [57].

3.3.2 Neural Networks (NNs)

Artificial neural network (ANN)

ANN owes its origin to biological neural networks of the human central nervous system and was initiated by McCulloch and Pitt [58]. ANN is primarily a sub-set of pattern identification techniques that can be used to visualise regression and/or classification challenges. A typical

ANN can be characterized by several hundreds of algorithms that possess wide variations that can be applied to different practical challenges. Some of the most frequently applied ANN approaches include Hopfield network, multi-layer perceptron, perceptron, and radial basis function networks (RBFN) [59]. The main advantages of ANN include: superior ability to solve non-linear problems that are associated with highly dimensional datasets, handling large and incomplete datasets (including those containing random noise) and self-adaption to dynamic scenarios [60]. Besides self-adaptation, self-organisation and real-time learning, basic ANN-based models are relatively easy to construct. A typical ANN model comprises of several simple processing elements that are joined via a complicated layer structure that allows the model to evaluate complicated tasks which are often characterised by multiple inputs and outputs. Figure 2 shows a typical ANN-based model with multiple inputs (IP) and several target outputs (TM). However, just like any other tool and technique, ANN has also had its fair share of criticism especially due to its requirement for large amounts of data, computational expense during data training as well as the difficulties associated with the selection of meta-parameters and network topology.

Deep learning

Deep learning methods [61] are updated forms of ANN that require more computer power than the traditional ANNs. In comparison with standard ANNs, deep learning methods apply far more complex neural networks and the most common types are AutoEncoder [62], recurrent neural network (RNN) [63], convolutional neural network (CNN) [64] and Generative adversarial network (GAN) [65]. In addition to their earlier stated characteristics, deep learning networks generally share very similar advantages and disadvantages with ANNs but better emphasise the depth of the model structure. On the one hand, a deeper model means better nonlinear prediction capability and can learn more complicated transformation, thereby allowing the model fit more complex input data. On the other hand, the more layers a model has, the fewer tasks required to be handled for each layer. Therefore, the model can better learn input data layer by layer.

3.4 Hybrid methods

Just as ensemble methods are based on the fusion of multiple learning algorithms, hybrid methods [66] also combine several methods, although their fusion approaches vary. For ensemble methods, the individual sub-models are homogeneous while hybrid methods combine completely different or heterogeneous machine learning methods to improve the

quality of reasoning as well as boost the adaptivity of the entire solution [33]. Besides the lack of in-depth knowledge about hybrid methods within existing literature, their perceived drawbacks are often attributed to the risk of overfitting and computational intensiveness. When sufficient amount of data are available, more complex methods generally provide more accurate prediction result [22]. However, the extent to which data amounts influence the performance (including accuracy, speed and complexity) of hybrid methods has not been studied in detail, which implies that it is yet to be fully founded as to whether hybrid methods will always outperform other individualised prediction methods. This systematic review shows that hybrid methods have been applied in 32 of the captured case studies and Table 3 clearly depicts the main functions of the respective hybrid methods as well as their sub-methods.

4. Extraction of data and synthesis of major findings from included article

Comprehensive and accurate statistics can help to accurately grasp the development trend of building energy usage to a large extent. Correspondingly, it should be reminded that due to the increasing complexity of the thermal environment of buildings, professional knowledge and rich practical experience are still indispensable even if various advanced and efficient prediction approaches are applied. In this section, this kind of experience will be summarized in detail.

4.1 Overview of included articles

Core developments in building energy consumption prediction research can be traced back to 2001. Figures 3 and 4 show the number of relevant articles published annually between 2001 and 2013. Interestingly, the SR conducted here revealed that the articles search sensitivity and precision is not always a function of the database size. For instance, Engineering Village databases, especially Compendex and InSpec, returned the highest percentage as well as volume of relevant primary articles in comparison to significantly larger databases such as WoS and Scopus. This finding could help save significant amounts of research time and efforts in the future. Research outputs in this field have been limited till 2010. However, exponential rises in total energy consumption due to building operational activities also led to publication surge from less than ten articles to about 20 articles per year for the next 4 year, until 2018 when output rates doubled to almost 40 articles. It is adjudged that the experienced growing trends could have been influenced by the implementation of initiatives such as the Kyoto Protocol [98]. as well as the growing expenditures or contributions of various

governments on education (including research) since 2009 as shown in Figure 5. Additionally, Figure 6 provides a distribution of articles by country, where it can be observed that the two biggest economies in the world (United States of America and China) contribute the most but contributions from other developing countries is also very significant. For instance, India and Malaysia are contributing immensely which may be attributed to their currently erratic and inadequate electric power supply shortage [99].

Only 24 of the 240 included articles qualified as literature review articles, which is not a representation of the global focus on building energy usage prediction. A further breakdown of the 24 literature review articles showed that 50% of them (articles [9], [13], [14], [22], [23], [25], [27]–[29], [93], [94], [95]) typically focused on the application of statistical and AI methods for building energy consumption prediction, which is a further attestation to their well-established popularity. The articles mainly iterated the advantages, disadvantages and application areas of the most common classes, with keen emphases on building types, temporal granularity of prediction, types of energy usage predictions and the characteristics of the training/testing data ([13], [23], [27]). Additionally, 4 review articles ([15], [20], [60], [103]) targeted ANN-based applications. A summary of their major findings revealed that Mohandes et al. [103], Runge and Zmeureanu [20] investigated the practicability of ANNs in analysing issues related to building energy, while Georgiou et al. [60] gave a brief review of the basic theory of ANNs as well as their specific applications to building energy management, systems control and energy prediction. Additionally, Ahmad and Hassan [15] reviewed the use of building electrical energy consumption prediction methods that were primarily based several artificial intelligence (AI) approaches especially ANN, SVM and their fusion. The 4 review articles by Kavgić et al. [8]; Liam and Zhai [16]; Li and Wen [10] as well as Yang et al. [104] were compilations of research outputs that applied physical methods. Kavgić et al. [8] compared as well as summarised the possible advantages and disadvantages of both top-down and bottom-up methods, with particular emphasis on the current stochastic building stock energy models. In general, their study [8] offered useful insights on the challenges and possible future directions of stochastic building stock energy modelling. The physical methods review by Yang et al. [104] on the other hand examined the relationship between building energy usage and thermal comfort especially the implications of such relationships on wider energy and environmental challenges such as socio-economic, carbon footprints and fuel mix. Liam and Zhai [16] provided a comparison of the performance of five distinct applications of bottom-up physical models on the UK building

stock. Li and Wen [10] tried to harmonise building operation and control mechanisms by providing a holistic review of whole building and building critical components modelling approaches. Some of the most intriguing highlights of the study are its details on how to achieve energy savings through short-term weather forecasting and diverse model-based optimal control methods.

Two review articles by Yildiz et al. [9] and Menezes et al. [105] respectively examined the application of statistical methods for building energy prediction. Yildiz et al. [9] presented various electricity load estimating models, with keen emphasis on regression models. Menezes et al. [105] however compared the benchmarking figures published in the 2nd and 3rd editions of CIBSE Guide F against actual power loads measured in UK office buildings. Rylatt et al. [106] reviewed current bottom-up methods to predict domestic energy requirements and introduced novel GIS tools to extract the plan form of dwellings from digital maps. Asadi et al. [107] performed a review of indoor environmental quality (IEQ) as well as energy usage within several buildings, based on occupant behaviours.

Eight of the 240 primary articles were case studies that investigated the impacts of climate change on the energy performance of buildings. Based on the climate change data from UKCIP02, the heating and cooling demand for the 2020s, 2050s, and 2080s in UK office buildings and housing stock was investigated [108]. For residential buildings in the UK, despite global warming being predicted to lead to increased energy demand in the summer, heating demand will still dominate cooling demand by the 2080s [109]. The fall in heating demand for office building is predicted to approximately cover the rise in cooling demand. Natural ventilation alone may fail to supply sufficient summer cooling especially for most existing office buildings that do not comply with the 2002 version of the Building Regulations or more recent versions [108]. Taking climate change and building age into consideration, a similar conclusion with regards to heating and cooling demand was drawn by Waddicor et al. [110], using IPCC predictive weather files to predict the future energy patterns of office blocks within Torino, Italy. Based on IPCC weather file, Daly et al. [111] investigated the influence of climate change on energy usage of commercial buildings across various Australian cities. The comparative study revealed slight changes (i.e. between -0.6% and +8.3% in heating demand and an increase from 9.1% to 25% in cooling demand) [111]. The building energy consumption during the 2020s, 2050s, and 2080s was simulated in [112]–[114], whereby a drop in heating demands with corresponding rises in cooling

demands were observed for all cases. According to Wong et al [115] the cooling loads of Hong Kong's residential sector during 2009-2100 would be 6.1%-9.8% more than 1979-2008 due to additional heat gained by the building envelope [115]. Full details of the scope, data properties, data sources, data sizes, temporal granularities, prediction algorithms, and performance metrics of the individual prediction models discussed within all articles are provided in Appendix A.

Figure 7 shows a detail breakdown of the information presented in Appendix A, where further classifications according to prediction approach and building types are provided. The existing methods cover residential, commercial, education & research and other buildings (1 article for mixed building, 8 articles for building sector and 8 not available). According to Figure 7(b), the use of physical methods was skewed towards residential buildings. This is mainly due to the challenges and time-intensiveness often encountered when using physical methods to evaluate the complexities and non-linearities associated with the indoor environment of commercial and educational buildings. Moreover, commercial buildings often have large amounts of historical energy consumption data available, which makes them the preferred target of artificial intelligence, statistical, and hybrid methods. In order to ease the determination of optimum data sampling frequency trends for existing studies, the temporal granularities of the studies are also shown in Figure 8, where it is observable that more than 50% of energy usage prediction research data were obtained on daily basis. Additionally, Figure 9 showed that predicted energy usage is mainly based on 4 categories - total energy consumption (18% of primary articles), heating and cooling load (28% of primary articles), electricity consumption (35% of primary articles) and others (19% of primary articles).

4.2 Data properties and data pre-processing

The recent proliferation of smart buildings, metering devices, sensors and sophisticated data acquisition devices is continuously enhancing the ability of researchers to amass building energy data at high frequencies. Irrespective of the field of study, the accuracy of prediction or forecasting activities is heavily dependent on the reliability and volume of datasets fed into the model. For building related studies, additional parameters such as data quality, geographic diversity, forecast horizon, customer segmentation and forecast origin also influence prediction performance [116]. This makes it crucial to ascertain the peculiarities of building energy prediction data as well as their processing regimes.

4.2.1 Data properties

Figure 10 shows a distribution of primary studies according to the types of data upon which their research was founded, which reveals that 61% (87) of studies were based on primary/real data, while 23% (33) and 10% (14) applied simulated and benchmarking datasets respectively.

The amount of the datasets applied for training, validation, and testing varies between 3 days [117] and 30 years[118] . In this review, the sizes of datasets are divided into 6 categories according to duration, as shown in Figure 11. Most of the primary studies applied between 1 month and 1 year, with approximately 25% collecting data for at least one year. Additionally, nine of the studies [38], [78], [79], [81], [82], [119]–[122] considered did not provide details on timeframe applied, owing to sole reliance on simulated datasets.

4.2.2 Data pre-processing and features selection

The primary building data acquired through experiments and/or surveys are often raw, incomplete and crucial features may be embedded in uncorrelated background noises, which could cause errors and inaccurate final results. Hence, some degree of pre-processing is required before model training. Data pre-processing can help improve the quality of data as well as boost accuracy of prediction outcomes. Cleaning, filtering, integration, normalization, reduction and transformation of datasets are common activities associated with data pre-processing. If accurately implemented, data smoothening and noise frequency bands identification can help identify and/or delete outliers, thereby helping to aiding the achieve the following objectives: data format standardisation, abnormal data clearing, error correction and duplicate data clearing. Once the raw data has been treated, the next step is data integration, which involves combining data from multiple sources so that redundant features can be identified and excluded prior to training. By removing non-discriminative features as well as reducing dimensionality of the dataset, computational efficiency and model performance can be significantly enhanced.

Based on the findings from this review, the most commonly used building energy prediction parameters can be divided into six main groups, namely; building features, time, outdoor weather conditions, occupancy/occupant energy usage patterns, indoor environmental conditions and historical energy consumption. More than 50 features were identified from the primary studies captured in this review as depicted in Table 4. In order to visualize the most

widely applied features, Figures 12-15 show the historical trends of parameter classes adopted by the 4 prediction methods and building types from which the data were acquired. In Figure 12, it can be deduced that outdoor weather conditions were the dominant parameter class adopted by all 4 prediction methods, which is closely followed by indoor environmental conditions and building characteristics respectively. It was also observed that historical energy consumption rates, time and occupancy/occupant energy use behaviour are the least applied parameters when employing physical methods. With regards to the application of the parameters to building types, Figure 13 shows that outdoor weather conditions and historical consumption data are two of the most widely applied parameter classes for all 3 types of buildings. Owing to the availability of relevant energy management systems and sensors, commercial and educational buildings offer more information for indoor environmental conditions. On the contrary, building characteristics is the most adopted parameter when studying energy consumption of residential buildings, due to the ease of their measurements. Figure 14 shows that solar radiation, relative humidity and outdoor air temperature are the most frequently used outdoor weather conditions by all the prediction methods, owing to the maturity of meteorological studies and availability of several open source weather databases. However, classifications according to individual methods further depicts that predictions based on physical and statistical methods are often performed using features such as building geometry, energy consumption and equipment load data while AI and hybrid methods have mostly relied on energy consumption data alone. The trend among the reviewed studies also suggests that the randomness of occupancy patterns makes it very challenging feature to accurately quantify especially for mixed purpose buildings. The elemental distribution in Figure 15 indicates that approximately 60% of features applied to all building classifications are related to building characteristics and outdoor weather.

4.3 Identification of influential studies and interrelation network

Irrespective of the field of study, researchers expend immense proportions of their time and efforts on the compilation and analysis of existing studies. The emergence of advanced computational technology and the recent push for environmental sustainability around the globe has immensely increased the rates at which research articles associated with the different facets of energy are published. While the rationale behind interactions with existing studies is unquestionable, it is vital to understand how researchers are able to fairly establish balance between quantity, quality and influence of such studies. This study has already exposed the unavailability of SR studies related to building energy consumption prediction

but besides just compiling relevant studies and presenting their core findings, a bibliometric network analysis is used to highlight the interrelationship that exists among the included articles. For instance, the 158 articles used here represent the most relevant to the defined research protocol, but their individual influence on the field cannot be easily ascertained from a traditional systematic review alone. Bibliometric analysis typically enables the mapping of interdisciplinary research on the basis of selected keywords in a specific database (for example WoS, Compendex, InSpec, GeoRef, Scopus and GeoBase) or within field-specific articles or a fusion of all approaches [123].

Several earlier bibliometric analyses were based on the application of manually generated binary strings for articles encoding [123]. In this study however, Vosviewer is used to automatically construct the bibliometric network of the data downloaded from well-known multidisciplinary databases (i.e. WoS, Compendex, InSpec and GeoBase). The constructed network then establishes concept-similarity among the 158 included primary articles through pair-wise comparisons of their keywords. The greater the commonality between two publications, the higher their correlation on the basis of concept-similarity which in turn determines their sub-field or cluster as depicted in Figure 16. The magnitude of a particular sub-field is a representation of the proportion of articles that belong to an entire field while the connecting lines indicate strong correlation between two sub-fields. Also, similar sub-fields or clusters are positioned in close proximity and dissimilar ones far from each other. With reference to Figure 16, some of the most influential sub-fields are energy consumption, energy efficiency, machine learning, sensitivity analysis, residential buildings, data mining, retrofit, occupant behaviour. Through a combination of the keywords, it is possible to create a dynamic strategic map that can illustrate the strengths of knowledge in a particular field and where such is domiciled in the world. Finally, one article was selected from each of the 19 most influential clusters and its major findings detailed in Table 5. Both Figure 16 and Table 5 provide a quick guidance of research hotspots for building energy consumption prediction, so as to aid research planning, future directions and cross disciplinary collaborations. The keywords distribution depicted in Figure 16 adequately demonstrates the main focal points of research within the studied discipline, which makes it easier to understand areas of strengths and underrepresentation at a glance.

This SR did not dwell on the underlying principles of individual methods or their applications, since such generic information are readily obtainable from the background reviews of several

existing articles and textbooks. The primary articles indicate that 6 types of variables (i.e. building features, time, outdoor weather conditions, occupancy/occupant energy usage patterns, indoor environmental conditions and historical energy consumption) are mostly applied. It is worth noting that the statistics of variables in this SR only reflected the frequency of variables applied within included primary articles, therefore, it is difficult to accurately evaluate the impact of each class of variables on the prediction process. For example, when using any of the four methods for prediction irrespective of building type, outdoor weather conditions are the most commonly used, while occupants' behaviour data is a rare parameter. The skewness in application towards outdoor weather conditions does not necessarily indicate its superiority as a parameter over occupants' behaviour but rather highlights availability. For instance, outdoor weather conditions can be obtained from various public databases, while variables such as occupant behaviour are particularly difficult to obtain due to privacy policies. In general, research on the influence of data types on prediction methods is still in its infancy. The SR indicates that current research efforts appear to be overwhelmingly directed towards implementation of AI methods which have been previously compared to black box models because of the difficulties associated with understanding the intermediate processes of their associated algorithms, which has been identified as a reason for the stratification of input variables and algorithms. Therefore, unless AI-based research paradigms shift towards developing deeper understanding of underlying governing principles, the representativeness of building energy predictions may still continue to rely on professional knowledge of building thermodynamics.

5. Limitations of the study

Some of the papers published on building energy prediction may have been left out of this SR owing to the inclusion and exclusion criteria that were defined as part of the research protocol to focus only on primary articles published in English language and accessible within Web of Science, Compendex, InSpec, GeoBase, GeoRef, Scopus databases. Also, the inclusion of ageing, existing, retrofit and old in the search string can be perceived as a limitation, since it can be argued that this approach potentially excludes articles that considered the sophistications associated with modern-day buildings. However, the authors believe that most building energy inefficiencies, data collection difficulties and prediction inaccuracies are more attributable to older buildings, thereby making the chosen study group substantial and very relevant. Besides, the lack of standard and universally agreed definition of what

constitutes old or ageing or existing building within existing body of knowledge is believed to have significantly broadened the review scope beyond that which was originally intended.

6. Concluding remarks and future considerations

A combination of population growths and rapid depletion of traditional energy resources in recent decades is continuously influencing energy planning and management research across the globe. The need to increase energy sustainability, while correspondingly reducing carbon footprints has led to enactment of various regulations that often rely on accurate predictions of current energy usage under varying scenarios. This has led to the emergence of numerous approaches within a spate of research contributions which must be collated for better optimization of the valuable information domiciled within individual primary article. This paper provides a systematic knowledge trend for building energy prediction, through the application of well-founded principles of PRISMA and PPSR methodologies for conducting systematic reviews. The paper compiles various descriptions of building energy prediction as well as reflecting their spread, principles and scope. This paper also presents a review of 240 primary research articles on building energy prediction over the past century, based on a rigorously defined research protocol. The review analyses articles' time distribution, author profiles, energy prediction methodologies, input data types, data sample sizes, sampling frequencies and building characteristics. Based on the synthesis of the findings extracted from individual articles, these conclusions can be inferred from this SR:

- Judging from the viewpoint of the immense global drive for energy conservation and carbon footprint reduction, one would assume that building energy prediction related literature reviews should account for a significant proportion of existing literature especially owing to the fact that buildings consume up to 40% of primary energy in some countries. However, based on the adopted search string for this systematic review, only 24 literature review articles were found and none of which is a systematic review. While traditional literature reviews also contribute significantly to the understanding of research trends, the decision to include or exclude certain articles is sometimes viewed as opinionated. Also, the lack of bibliometric analysis in such review articles limit the ability of researchers to swiftly ascertain answers to crucial research planning questions such as “who’s doing what, when and where”
- During articles retrieval, it was observed that search sensitivity and precision is not always a function of the database size. Engineering Village databases especially Compendex and InSpec returned the highest percentage as well as volume of relevant primary articles in

comparison to significantly larger databases such as WoS and Scopus. Additionally, the bibliometric network analysis provides a dynamic and strategic map of the interrelationship and frequency of research keywords utilised by the primary articles. A combination of these could be very valuable time-saving mechanism during future research planning activities.

- There are 4 dominant classes of building energy consumption prediction methodologies, namely: physical, statistical, artificial intelligence and hybrid methods. The physical methods are mainly based on the application of physical laws for modelling building systems and their associated components as well as estimating thermal dynamics and energy patterns. Statistical methods (also known as statistical regression or regression methods) are the most widely applied in practice, due to their computational ease, speed and reasonably acceptable degree of accuracy but often criticized for their inability to adequately show the underlying relationships that exist between inputs and outputs. AI based techniques such as Bayesian networks, deep learning, decision trees, ensemble algorithms, ANN, SVM and clustering algorithms are becoming more and more influential in the field, due to their ability to self-learn from historical data. Hybrid methods combine various heterogeneous machine learning methods into a single unified framework, thereby allowing the strengths of one class of techniques to compensate for the limitations of others. However, the confidence level in the technique is often undermined by the risk of overfitting and computational intensiveness. This is perhaps the reason for a lack of in-depth knowledge about hybrid methods within existing literature.

- Fundamental developments in building energy consumption prediction research can be traced back to 2001, but research publications were quite limited until 2010 after which a significant rise was observed, especially in 2018 when as much as 40 articles were obtained. This trend is believed to have been triggered by rises in total energy consumption resulting from building operational activities as well as the implementation of initiatives such as the Kyoto protocol. Also, sustained growth in educational expenditures and contributions of various governments since 2009 is adjudged a positive catalyst for the experienced publication trends.

- The emergence of research articles from different countries including USA, China, South Korea, UK, Malaysia, Spain, the Netherlands, Canada, India, Turkey, etc., suggests that building energy consumption prediction research is conducted across the globe. The distribution of articles by country also indicates that the two largest economies (i.e. USA and China) account for most of the published articles. Malaysia and India are also active contributors, perhaps owing to their currently erratic power supplies.

- Commercial buildings are widely used case studies, which is perhaps owing to the existence of relevant energy management systems and sensors that provide superior opportunities for research over educational and/or residential buildings.
- Historic energy usage, time, occupant energy usage patterns, outdoor weather conditions, building features and indoor environmental conditions are the six main groups of prediction parameters or features. Artificial intelligence, statistical and hybrid methods are heavily reliant on historical energy consumption data but on the average, outdoor weather condition is the most dominant parameter across all four classes of prediction methods, closely followed by indoor environmental conditions and building characteristics.

It is glaring that the quantity of published building energy usage prediction research is on an upward trajectory but future research endeavours need to also focus on diversity of data collection case studies and parameters. For instance, there is a stark under-representation of research on mixed purpose buildings, despite their popularity across the globe. Also, the use of building characteristics as a feature needs further attention especially for older buildings whereby energy management systems, sensors and building details are non-existent. So far, the application of AI and hybrid methods still highly relies on personal experience and preference. The SR reveals the application of multi-farious types and varying amounts of input data for prediction, which are very promising but it still remains a challenge to standardise the input variables to match different practical scenarios. Also, there is an underrepresentation of studies applying occupants' behaviours data when compare to publicly available information such as meteorological data, which may undermine the representativeness of existing outcomes. Perhaps one viable approach to the aforementioned challenges would be detailed exploration of the wider role of emerging approaches such as building information modelling within the premise of building energy consumption analyses, with keen interests on incorporating human factor analysis.

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Appendix A

List of Abbreviations

AI	Artificial intelligence
ARIMA	Autoregressive integrated moving average model
ANFIS	Adaptive neuro-fuzzy inference system
BPNN	Backward propagation neural network
BoostedT	Boosted tree
BaggedT	Bagged tree
CFD	Computational flow dynamics
CNN	Convolutional neural network
CRBM	Conditional restricted Boltzmann machine
DT	Decision tree
DBN	Deep belief network
DA	Discriminant analysis
DHN	Deep highway network
ERT	Extremely randomized trees
ELM	Extreme learning machine
EM	Expectation maximization
GIS	Geographical information systems
GA	Genetic algorithm
GAN	Generative adversarial net
GMMR	Gaussian mixture regression
GPR	Gaussian process regression
IPCC	Intergovernmental panel on climate change
k-NN	k – Nearest neighbor
LSSVM	Least square support vector machine
LOESS	Locally estimated scatterplot smoothing
LEAP	Long-range energy alternatives planning system
LSTM	Long short-term memory
MARS	Multivariate adaptive regression splines
MLR	Multiple linear regression
MA&ES	Moving average and exponential smoothing
OLSR	Ordinary least squares regression
OEM	Original equipment manufacturers
OPLS	Orthonormal partial least squares
PWARX	Piece wise auto-regressive eXogeneous inputs
PCA	Principal component analysis
PICO	Problem, intervention, comparison and outcomes
PSO	Particle swarm optimization
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
PPSR	Procedures for performing systematic reviews
QP	Quadratic programming
RBFN	Radial basis function network
SAE	Stacked auto-encoders
SARSA	State-action-reward-state-action

SPIDER
SVM
TB
TLBO

Sample, phenomenon of interest, design,
evaluation and research type
Support vector machine
Tree bagger
Teaching learning-based optimization

Fig.1. Systematic review process flow diagram.

Fig.2. Typical ANN-based model

Fig.3. Number of the articles found using research keywords

Fig.4. Number of articles found using building data collection as search term

Fig.5. Government expenditure on education

Fig.6. Distribution of articles by country of origin from 2001 to 2020

Fig.7. (a) composition of the building type. (b) prediction methods for each building type

Fig.8. (a) Temporal granularity, (b) Temporal granularity with different prediction methods, (c) Temporal granularity with different building types

Fig.9. Composition of energy type

Fig.10. Types of data

Fig.11. Size of datasets

Fig.12. Distribution of the usage of 6 main classes of parameters by common prediction methods

Fig.13. The frequency of the 6 kinds of parameters used in 3 types of buildings

Fig.14. The frequency of parameters used in a) Physical methods, b) Statistical methods, c) AI methods, d) Hybrid methods

Fig.15. Frequency of parameters used in a) Residential building, b) Educational and research building, c) Commercial building

Fig.16. Cluster of influential building energy consumption prediction keywords

Table 1. Review Protocol for the systematic review

Item	Description
Keywords	Building AND energy consumption AND prediction AND ageing OR existing OR retrofit OR old
Search fields	All fields
Inclusion criteria	In English language; focus on buildings; aimed at predicting building energy consumption; full text is available.
Publication type	Journal articles, conference articles, conference proceedings, articles in press, book chapters, dissertations
Time window	1990-

Table2. Summary of core characteristics of the prediction methods and examples

Method	Advantages	Disadvantages
Physical methods [8], [9], [13], [14], [16], [26], [27], [31]	- The relationship between input and output variables is very clear. - Good at simulating the energy consumption at the design phase.	- Assumptions - The physically-based model may not be appropriate for all scenarios - Often requires detailed/exhaustive building information - Time-consuming and labor-intensive
Statistical methods: [8], [14], [16], [21], [26], [31], [32] Ordinary Least squares regression [41], Linear regression [37], [121], [163], Logistic regression [41], [101], Stepwise regression, Multivariate adaptive regression splines [128], Locally estimated scatterplot smoothing.	- Straightforward and fast - Provide reasonable accuracy	- The relationship between input and output variables are unknown - The input data have a significant influence on the prediction results - Requires precise assumptions - Lack of tolerance for uncorrelated noise
Hybrid method [14], [26], [27], [29]	Can be used to harmonise the strengths of individual methods	- Overfitting problems - May also incorporate the weaknesses of individual methods if not adequately processed
Artificial intelligence: [9], [13], [32], [14], [21], [25]–[29], [31] Machine learning:		
Support vector machine [61], [116], [164] [167], [187], [189], [204]	Outperforms other methods on linearly separable problems	Challenging to train and interpret information
Decision trees: Classification tree [41], [199], Regression tree [9], [33], [124], [199] Boosted tree [33], [41] [124]	Easy to interpret and non-parametric	- Tends to over-fit - May get stuck in local minima - Not an online learning
Ensemble algorithms: Boosting [4], [33], [38], [41], [48], [90], [125], [139] Bootstrapped aggregation [21], AdaBoost [48], [196], Stacked generalization [41],	Capitalises on the merits of individual methods	Adequate combination and refinement of different methods is often challenging

Gradient boosting machines, Random forest [45], [75], [85] [86], [116], [187], [195]		
Clustering algorithms: k-Means [41], [50], [69], [71], [207], k-Medians, Expectation maximization [50], [73], Hierarchical clustering [41], [50], [207]	Useful for making sense of data	• Results are sometimes difficult to interpret • Very limited when dealing with unfamiliar datasets
Dimensionality reduction algorithms: Principal component analysis [41], [64], [73], [79], [83], [131], [135], [165], Principal component regression [41], Partial least squares regression [21]	Good for handling large datasets without necessarily making assumptions on data	• Not effective when dealing with non-linear data • It is sometimes difficult to understand the meaning of the results
Bayesian algorithms: Naive Bayes [41], Gaussian naive Bayes [37] Multinomial naive Bayes, Bayesian belief network [46], Bayesian network [9], [52], [146]	Fast and easy to train	Could be extremely challenging when the input variables are correlated
Neural network:		
Artificial neural network: Back-propagation [45], [122], [137], [141], [204], Hopfield network [54], Radial basis function network [54], [74], [78], [116]	• Superior in solving non-linear problems with high-dimensional datasets • Can handle large and incomplete datasets • Self-adapting, self-organizing and real-time learning network • Easy to construct the network models	• Requires large amount of data • Extremely computationally expensive to train • Full details of the internal working principles could be challenging to understand • The meta parameter and network topology selection is challenging
Deep learning: Deep Boltzmann machine [41], [57], [174], Deep belief networks [41], [61] Convolutional neural network [41], [118], Stacked auto- encoders [41], [74] [125]	• Superior in solving non-linear problems with high-dimensional datasets • Can handle large and incomplete datasets • Self-adapting, self-organizing and real-time learning network • Easy to construct the network models	• Requires a large amount of data • Extremely computationally expensive to train • The internal working is unknown • The meta parameter and network topology selection is hard

Table 3. Summary of articles that explored hybrid methods, their associated sub-methods and functions

Reference	Algorithm	Function
[67]	Physical	Simulates the building energy performance
	Genetic Algorithm	Identifies the buildings' internal mass model parameters
[68]	GM (1,1)	Predicts the buildings' energy consumption
	Radial basis neural network	Revises the residual errors of the grey model
[69]	RReliefF	Accounts for interdependencies between variables so as to select the optimal variable

		subset
	SVM	Predicts the buildings' energy consumption
[70]	Improved real coded genetic algorithm	Determines the free parameters of LSSVM in a more effective manner by optimizing free parameters simultaneously from the training data
	Least squares support vector machine approach	LSSVM solves a set of linear equations instead of the QP problems solved in standard SVM, thereby significantly reducing the computational time of the learning process
	Latin Hypercube Monte Carlo sampling algorithm	Obtains a set of plausible solutions by varying each key building parameter
[71]	Physical	Simulates the buildings' energy performance
	Particle Swarm Optimization	Trains and adjusts the weights and threshold values of ANN model
[72]	ANN	Predicts the buildings' energy consumption
	Physical	Simulates the buildings' energy performance
	Bayesian calibration	Effectively derives the coefficient of performance and deterioration, as well as applies such to building energy models when calculating building energy consumption
[73]	Reinforcement learning	Predicts the energy consumption at the building level using unlabelled historical data
	Deep Belief Network	For continuous states estimation and automatic features extraction in a unified framework
[74]	SVM	Predicts the buildings' energy consumption
	Genetic algorithm	Optimizes the performance of SVM based on radial basis function kernel
[75]	Least square curve fitting method	Fits the polynomial to the preceding part of the analysed data set
	Fourier series	Refines all the parameters to yield the best data fit
[76]	K-means algorithm	Investigates representative end-user groups within buildings
	ANN	Predicts energy usage for the identified end-user groups
	K-nearest neighbour	Selects an appropriate set of historical data for network training
[77]	ANN	Predicts the energy consumption based on continuous inputs
	Decision tree	Predicts the energy consumption based on discrete inputs
[78]	Statistical method	Predicts the buildings' energy consumption
	K-means algorithm	Classifies the electricity and gas consumption data into groups
	k-modes clustering	Derives behaviour patterns directly from the database
[79]	Probability neural network	Associates occupants' characteristics with the clustered behaviour types
	First-order inhomogeneous Markov chain	Synthesizes the occupants' activity schedules
[80]	Expectation Maximization (EM)	Data clustering
	Principal Component Analysis (PCA) and	Extracts the most significant information from the data, reducing the dimensions of data and dealing with the multi-collinearity issues within the experimental data-set
	Adaptive Neuro-Fuzzy Inference System	Predicts the buildings' energy consumption
[81]	Stacked autoencoders	Extracts the buildings' energy consumption features
	Extreme learning machine	Functions as a predictor for obtaining accurate prediction results
[82]	Random Forest	Aids the building of forecasting models based on historical data. It includes working-day and non-working day modes
	Auto Regressive Moving Average algorithm	Serves as the benchmark for improving the presented model as well as addresses the challenges of switching between working mode and non-working modes
[83]	Convolutional neural networks	Detects buildings in the imagery forms and then extracts features from those building annotations
	Random forests regression	Estimates building energy consumption
[84]	ANN	Predicts the building energy consumption
	Minute-controlled resampling	Generates the training data for ANN
[85]	Energy-consuming pattern	Represents the periodicity property of building energy consumption and can be extracted from the observed historical energy consumption data
	Deep belief network	Predicts the building energy consumption
[86]	Principal component analysis	Reduces the dimensionality of the data to create an efficient and low-complexity data representation as well as eliminates subspaces occupied by uncorrelated noises
	Orthonormal partial least squares	Reduces the dimensionality of the data to create an efficient and low-complexity data representation as well as eliminates subspaces occupied by uncorrelated noises
[87]	SVM	Predicts the building energy consumption
	Jaya algorithm	Determines the resultant weights of SVM configurations
[88]	K-means clustering	Classifies the electricity and gas consumption data into groups
	Discriminant analysis	Features recognition and text mining
[89]	Particle swarm optimization	Determines optimal weights and bias values for neural network training so as to provide the most accurate prediction results

	ANN	Predicts the building energy consumption
[91]	Teaching learning-based optimization	Searches for globally optimised weights and threshold values of the ANN models
	ANN	Predicts the building energy consumption
[92]	Particle swarm optimization	Optimal weights and bias values for neural network training to hence the most accurate prediction results
	BPNN	Predict the building energy consumption
[93]	Quantile regression	Estimate arbitrary intervals instead of single values to forecast the building energy consumption
	D-vine copula method	Predict conditional quantiles of heating energy consumption after retrofitting is presented and implemented
[94]	Random forest	Classifies the electrical load data based on pattern similarity
	Multilayer Perceptron	Predicts the building energy consumption
[95]	Multi-Decomposition	Analyses similar signals and extracts features
	Deep Learning	Predicts the building energy consumption
[96]	Piece Wise Auto-Regressive eXogeneous inputs	Extracts the discrete modes from the collected measurements and associates each regression data to one of these functioning modes.
	Support Vector Machine	Identifies the optimum hyperplanes that separate the data within the regression space
[97]	Long short-term memory	Predicts the building energy consumption
	Genetic algorithm	Improves accuracy of prediction of LSTM method by searching for fine window sizes and appropriate number of hidden neurons.
[65]	Generative Adversarial Nets	Applies small proportions of the original data series to generate parallel data sets
	BPNN/SVM/ELM	Predicts the building energy consumption

Table 4. Main classes of building energy prediction parameters and their associated features/variables

Category	Variable
Outdoor weather conditions	Air pressure, climate zone, cloud cover, daylight level, illuminance contribution, dimming level, dew point temperature, dry-bulb temperature, ground temperature, monthly degree days, relative humidity, solar radiation, visibility, wet-bulb temperature, wind direction, wind velocity.
Indoor environmental conditions	Equipment schedule, gas volume, pressure, gas temperature, heated area, heating/cooling set-point, humidity set-point, HVAC system properties, HVAC system type, indoor air temperature, indoor CO2 concentration, indoor humidity latent heat gain from people, sensible heat gained from people, ventilation rates.
Building characteristics	Building age, building geometry, building material properties, building orientation, building type, compactness, air infiltration rate.
Time	Date, day of the week, day of the month, holidays, time of day.
Occupancy and occupant energy use behavior	Education level, family size, gender, occupant rate, occupant schedule, occupation, age, income.
Historical consumption	Energy consumption, sub energy consumption

Table 5. Findings and limitations of the articles from clusters

Reference	Prediction methods	Building types	Findings	Limitations
[124]	ANN	Office building	1) The number of parameters used in the prediction has a significant impact on the accuracy of prediction. Too many parameters may lead to overfitting problems and in turn diminish accuracy of prediction. 2) Integrating occupancy as an input can improve the accuracy of the proposed models.	The lack of indoor sensors made it difficult to capture the dynamics of the entire indoor environment. The model performance was only validated during the summer.
[82]	Hybrid method (stacked autoencoders and the extreme learning machine)	Retail	1) The proposed extreme SAEs approach has the greatest ability to deal with uncertainties associated with building energy consumption data. 2) In comparison to other methods, the residual errors of extreme SAE approach are usually the lowest.	The simultaneous utilization of data and prior knowledge of periodicity to construct the DNN is extremely difficult.
[125]	Stochastic method	Office building	CRBM is a powerful probabilistic method which outperformed other	The determination of parameters such as number of hidden units and

			state-of-the-art prediction methods (including ANN and hidden Markov models).	learning rates must be carefully managed.
[74]	Hybrid method (Deep belief network with Reinforcement learning)	Residential and commercial buildings	The extension of SARSA and Q-learning by incorporating DBN for states estimation is more robust as well as offers lower prediction error (approximately 20 times lower than obtainable from un-extended versions)	A more extensive investigation still needs to be conducted at different Smart Grid levels prior to full transition to future energy systems.
[126]	Deep highway networks (DHN) and extremely randomized trees (ERT)	Hotel	Both ERT and DHN models marginally outperform the SVR algorithm in predicting hourly heating, ventilation and air conditioning (HVAC) energy consumption of a hotel building	1) Obtained performance is optimal and no further improvements could be achieved 2) Network complexity significantly influences performance 3) Some variables of interest are missing 4) Historical data is required for reliable training of deep learning models, which could be challenging when dealing with new buildings.
[127]	Statistical methods	Office buildings	Glass type, building occupancy schedule and shape of buildings have the highest influence on energy consumption. H-shaped buildings recorded the highest consumptions, based on results from 7 different regression models.	The effects of building design parameters and shapes in different climate regions still need to be investigated
[122]	Extreme learning machine and Online sequential ELM	N/A	The proposed models learn better and outperform other popular machine learning approaches (including ANNs, SVM, RBFN and RF).	Some improvements can still be achieved by incorporating more information about building structure/attributes. It is also envisaged that gradual migration from shallow to deep architectures of deep learning prediction models would enhance accuracy.
[128]	ANN	Residential buildings	This study stipulates that ANN models can accurately (i.e. $R^2 = 97.7\%$) predict heating loads of buildings, based on just four input data. With the exception of the U-value, all other parameters are geometric properties which are still obtainable even in the absence of architectural details of the buildings.	N/A
[129]	Support vector machine	Office building	A comparison between the SVM model predictions and actual energy consumption figures were very identical.	N/A
[130]	Tree bagger, Gaussian process regression, multiple linear regression, bagged tree, boosted tree and neural network.	Office building	The simulation results implied that the precisions of TB, BoostedT, GPR, NN and BaggedT are better than the MLR model. The prediction performance was better in case of 7-day and 14-day period and the model can predict short-term energy consumption accurately.	This performance can further be improved by taking occupant behavior into account due to occupant behavior having a very dominant impact on lighting energy consumption
[37]	Binary decision tree, Compact regression, Gaussian process, Stepwise Gaussian processes regression and Generalized linear regression.	Office building	1) The multi linear regression performed worse than other methods. 2) The prediction performance is more suitable for short-term rather than long-term.	This method is most suitable for buildings that possess adequate monitoring and meteorological data. Additionally, such buildings shouldn't have undergone any form of retrofitting during the period of estimation.
[91]	Hybrid method Teaching learning-based optimization and ANN	School library	The proposed model performed better than previously reported GA-ANN and PSO-ANN methods, especially with regards to convergence speed and prediction accuracy.	The algorithms developed in this research rely heavily on the degree of correlation that exists among days to be predicted and the historical reference data
[131]	Fully connected auto-encoders,	Educational building	The features extracted by the fully connected autoencoders are	Most of the outliers identified were due to public holidays, excluding

	Convolutional auto-encoders and Generative adversarial networks		nonlinear transformations of the original data. One-dimensional convolutional autoencoders are capable of extracting useful temporal relationships in time series data used for predictive modeling, while the GAN-based feature engineering method adopts a generative approach for feature extraction.	Sundays and the days adjacent to those public holidays. While the approach eases prediction, its overall outcomes could become less representative.
[132]	Change-point regression, Gaussian process regression, ANN and Gaussian mixture regression	Office building	1) The accuracy of ANN was the least, due to lack of sufficient training data. 2) Besides ANN, all the methods can be used as baseline models since they meet the criteria stipulated by ASHREA Guidelines	The obtained outcomes can be further improved by accounting for occupants' behavior, owing to its dominant impact on energy consumption
[133]	Hybrid method (Particle swarm optimization + Radial basis function NN)	National	Through the incorporation of PSO for RBFNN optimization, the prediction accuracy of the hybrid method was far superior to that of RBFNN alone.	N/A
[134]	Statistical methods	Residential building	The study identified inaccuracies within application of climatic data, especially when such data are obtained from limited locations within a given region. Therefore, the influence of variability on prediction accuracy can be alleviated by collecting weather data from different locations within the studied region	Accessible network of meteorological sensors that are capable of collecting and sharing weather data required for energy consumption prediction is scarce.
[135]	GM (1,1) model, DGM (2,1) model, Regression, Polynomial model, Polynomial regression and ANN	Residential building	The ANN model outperformed all other five models in terms of MRPE and other statistical results.	N/A
[136]	Statistical method	School buildings	Including the school schedule as a regressor in the model can improve the accuracy of prediction results significantly. Including the dew point temperature did not improve the results. In contrast, the results deteriorated in some school.	There are no established standards for selecting input parameters, which implies that the adequacy of the fewer parameters applied here couldn't be established.
[137]	Hybrid methods (Principal component analysis + Auto regression)	N/A	Principal component analysis was used to reduce data dimensionality; thereby retaining only datasets that contain the highest variability. The harmonization of PCA and autoregressive approaches improved computational speed as well as prediction accuracy.	N/A
[89]	K-means clustering algorithm and Discriminant analysis	Residential buildings	1) The combination of K-means clustering and discriminant analysis achieved a very impressive 97.9% classification accuracy. 2) Occupant behaviors was observed to greatly impact building energy consumption	N/A

Appendix B

Table 1. Scope, data properties, algorithms and performance of the energy consumption prediction models

Reference	Country	Building type	Scale	Prediction method	Energy type	Date source	Date size/Time scale	Temporal granularity	Performance metric
[119]	China	Office	Single	Multiple linear regression	Cooling load	N/A	173	Annual	R2
[138]	Canada	Office	Singe	Physical	Lighting	Measured	2months	Daily	N/A
[139]	Turkey	Residential	Single	Physical	Heating natural gas consumption	BOTAS database	2 years	Annual	N/A
[140]	Greece	N/A	N/A	Physical	Heating oil and electricity consumption	Simulated	1 year	Annual	N/A
[141]	Canada	Office	Single	ANN	Electricity	Simulated		Hourly	CV 0.25-0.46
[142]	Italy	School	138	Statistical	Heating load	Measured/database	6 months	Seasonal/monthly	Deviation 95%
[67]	China	Office	Single	Hybrid (Physical+ GA)	Cooling/heating load	Survey/database	2 weeks	Weekly	Relative error 8%
[143]	USA	Hotel	Single	ANN	Equipment load	Measured	3 weeks	Hourly	Case1 R 0.912-0.957
									Case2 R 0.822-0.917
[144]	Brazil	School	Single	Physical ANN	Total energy consumption	Measured	4 months	Daily	Relative error 13%
[145]	USA	School	Over 100	ANN	Steam load	School department	3 years	Daily	Relative error 10%
[146]	Poland	Hospital	2	Statistical	Heating load	Measured	4 years	Monthly	N/A
[118]	Belgium	Residential	Single	Physical	Heating load	Measured	30 years	Annual	N/A
[68]	China	Building sector	National	Hybrid (GM+ Radial basis NN)	Total energy consumption	China Statistical Yearbook from 2001 to 2008	7 years	Annual	Relative error 0.906%
[147]	China	Residential	City	ANN	Total energy consumption	Database	8 years	Annual	Relative error 3%
[148]	UK	Residential	National	Statistical	Total energy consumption	The household employment status data	N/A	Annual	MAE 9.4%
[149]	China	N/A	N/A	ANN	Equipment electricity load	Measured	1 year	Monthly	N/A
[150]	USA	School	Single	ANN	Electricity	Measured	20 days	Hourly	MAE 33.4 MAPE 5% standard deviation 34.9
[151]	USA	Residential	3	Linear regression/SVM/Least squares-SVM	Electricity	Tennessee Valley Authority	1 year	Hourly	N/A
[152]	USA	School	Single	Gaussian process	Chilled water and steam use	Measured	9 days	Hourly	R2 0.82-0.9
[69]	South Korea	Government	175	Hybrid (RReliefF+ SVM)	Electricity	2003 Commercial Buildings Energy Consumption	1 year	Hourly	N/A MAE 12.3333, RMSE 16.74, MAPE 34.88

						Survey (CBECS) database			
[153]	USA	Hospital	Single	Physical EnergyPlus	Electricity	Measured	N/A	N/A	Relative error 12%
[154]	Brazil/The Netherlands	Commercial	Single	ANN	N/A	Simulated	N/A	N/A	R2 0.99 Mean error 0.7 standard deviation 5.1
[155]	The Netherlands	Residential	National	Physical (energy label)	Total energy	AgentschapNL	1 year	yearly	N/A
[156]	Turkey	Residential	National	Physical	Heating load	Database	N/A	Yearly	N/A
[157]	Hungary	Residential	National	Physical (degree day)	Heating load	Agro-Meteorological Observatory Debrecen	20 years	yearly	N/A
[136]	USA	School	225	Statistical	N/A	Web-based energy information system	2 years	Monthly	R2 2%
[158]	Finland/China/USA	Swim center	Single	Physical	N/A	Measured	13 months	Daily	R2 >0.9
[159]	China	Public	Single	Artificial fish swarm	N/A	N/A	131 days		Relative error 1%
[160]	USA	School	Single	Physical eQuest	Heating load	TMY	2 years	Monthly	RMSE 1.1%
[125]	The Netherlands	Office	Single	Conditional restricted Boltzmann machine	Electricity	Measured	7 weeks	Hourly	Lighting RMSE 1.11 R 0.96 Total energy RMSE 1.76 R 0.98
[161]	USA	Residential	1355	Physical	Total energy	Survey	1 year	Hourly	Natural gas R2 0.31 Electricity R2 0.65
[162]	China	Commercial	Single	Physical DeST	Cooling/heating load	Database/TMY	1 year	Hourly	N/A
[163]	China	Mixed function	Single	Ensemble model	Electricity Peak power demand	Measured/Hong Kong Observatory	1 year	Daily	MAPE 2.32% MAPE 2.85%
[164]	United Arab Emirates	N/A	City	Multiple regression	Peak load	Database	1 year	Hourly	RMSE 1.54%
[135]	China	Residential	City	GM (1,1) model DGM (2,1) model Regression analysis polynomial model polynomial regression ANN	Total energy	The Statistical Yearbook of Chongqing Questionnaire Survey	12 years	Annual	MAPE 0.47% 0.85% 0.44% 0.65% 0.91% 0.09%
[165]	Spain	Bioclimatic	Single	ANN	Electricity	Measured	17months	Hourly	Mean error 11.48%
[127]	USA	Office		Multiple linear regressions	Total energy	Simulated	N/A	Annual	R2 0.94-0.95
[128]	Turkey	Residential	148	ANN	Heating load	Simulated		Annual	R2 97.7%
[133]	China	Building sector	National	Hybrid (PSO+RBF+NN)	Electricity	Chinese society database	2 years	Monthly	MSRE 0.139%
[166]	China	School		Hybrid (GA+BPNN)	N/A	Simulated	3 months	Daily	Average relative error 1.37%
[167]	China	Experiment	Single	Physical Conditional transfer function model Physical Combined	Total energy	EnergyPlus Weather Data	1 year	hourly	Relative error-1.3%-6.3% 4.4%-8.7%

				heat and moisture transfer model					
				Physical Effective moisture penetration depth model					N/A
[168]	USA	School	Single	Hybrid (Bayesian inference +LRM) +Calibration	Total energy	Measured	35 months	Daily	NMBE 0.01 CVRMSE 0.12
				Hybrid (Bayesian inference +LRM)					NMBE 0.18 CVRMSE 0.45
[169]	USA	Office		Multi linear regression	Heating/cooling load	Simulated		Annual	Maximum error 5%
[170]	France	Office	Single	SVM	Heating load	Data acquisition system	7 months	Hourly	R2 0.69-0.88 RMSE 50-140
[171]	Canada	Institutional	Single	Case-based reasoning	Electricity	Measured	4 months	Hourly	Relative error 12.79%-44.42%
[70]	South Korea	Business	Single	Hybrid (Least-squares SVM+ direct search optimization)	N/A	Telecommunication Corporation's building energy management system (BEMS)	4 weekdays	Hourly	Average RMSE 7.5994-11.1758
				Change-point regression					R2 0.55 0.88 CV-RMSE 14.96% 28.32% NMBE 1.79% 5.31
				Gaussian process regression					0.62 0.87; 13.90%
				Gaussian Mixture Regression					28.66%; 0.29% 2.8%
				ANN					0.58 0.88; 14.60%
									27.90%; 1.87% 4.30%
									0.54 0.86; 15.47%
									32.35%; 2.76% 4.8%
[172]	Portugal/Mexico /Slovenia	Residential	768	Genetic programming	Heating load Cooling load	N/A	N/A	N/A	MAE 1.02-1.31
									MAE 1.47-5.55
[72]	China	N/A	N/A	Hybrid (PSO + ANN)	Electricity	the Great Building Energy Predictor Shootout	5 months	Hourly	CV 0.0259-0.0268 MAPE 0.0169-0.0177
[173]	China	N/A	N/A	SVM	N/A	Measured	1 month	Hourly	MSE 0.0186-0.091 R2 82.17-84.27
[174]	South Korea	Hotel	Single	ANN	Cooling load	N/A	N/A	N/A	CVRMSE 21.32%
[175]	USA	Residential	173	Multivariate Autoregressive (M-AR)	Electricity	Pecan Street data	3 months	Hourly	MAE 0.8287-1.1196 RMSE 1.1928-1.3549 NRMSE 11.88%-14.06%
[176]	The Netherlands	Office	Single	SVM	Lighting	Measured	5days	Daily	Relative error less than 0.05
[177]	China	Hotel	Single	Statistical STIRPAT	Energy use intensity	Hotel system	1 year	Monthly	Average error 1.415%
[129]	USA	Office	Single	SVM	Lighting	Database	60 days	Daily	CV 6.83%

[73]	South Korea	Commercial	3	Hybrid (Physical+ Bayesian calibration)	N/A	Database	N/A	Monthly	Error 1.52%
[178]	France/SPAIN/UK	Experiment	Single	SVM	Electricity	Measured	1 year	Monthly	NRMSE 14.88%-15.75%
[120]	South Korea	N/A	N/A	ANN	Heating load Cooling load	Reference	768 datasets	N/A	RMS 0.19 RMS 1.42
[179]	Malaysia/Iran	Residential	N/A	Extreme learning machine	Heating and cooling load	Simulated	N/A	Annual	R2 0.9958-0.998777
[74]	The Netherlands	Residential and commercial	5	Hybrid (reinforcement learning + Deep belief network)	Total energy consumption	Baltimore Gas and Electric Company	7 years 25days	N/A	RMSE 96.5%
[63]	The Netherlands	Residential	Single	Conditional Restricted Boltzmann Machined/Factored Conditional Restricted Boltzmann Machine	Electricity	Individual residential customer	4 years	15min/hour/daily	N/A
[180]	China	Office	Single	ANN SVM ARIMA	N/A	Database	2 months	Hourly	RMSE, MSE, MAPE 0.0681, 0.0045, 0.1710 0.0714 0.0051 0.2030 0.0711 0.0051 0.2071
[75]	China	Office	Single	Hybrid (GA+ SVM)	Electricity	Simulated	N/A	Annual	R2 0.987
[181]	China	Laboratory	Single	Markov decision processes	Electricity	Measured	4 days	Hourly	Average error 52.4%
[76]	China	Library/office/residential	3	Hybrid (polynomial-Fourier series model)	Electricity	Measured	4 years	Monthly	Variation of roughly 5% to 17%.
[182]	South Korea	Office	Single	ANN SVM Gaussian Process	Chiller electricity demand	Measured	8 days	Daily	RMSE, CVRMSE, MBE 9.6, 10.5%,2.2% 10.2, 11.2%, 0.8% 10.0, 11.0%, 1.4%
[183]	USA	N/A	N/A	Statistical	N/A	the National Institute of Standards/ Technology (NIST) Net-Zero Energy Residential Test Facility (NZERTF)	1 year	N/A	Relative error 3.0%
[134]	USA	Residential	426305	Statistical	natural gas /electricity	Database/weather station	3 years	Monthly	N/A
[184]	China	Office	Single	Echo state networks	N/A	Measured	4 years	Hourly	CVRMSEs 3.72%-4.97%
[185]	China/USA	Office	Single	Statistical	Total energy	Measured	1 year	Hourly	CVRMSE 15%
[186]	USA	Residential	Single	ANN	House and heat pump energy consumption	Measured	72 days	Daily	Coefficients of determination within 0.87-0.91
[187]	Italy	Office	Single	ANN	Heating load Cooling load	Simulated	N/A	N/A	Relative errors 8.0% 8.1%
[188]	USA	Commercial	Single	System Identification	N/A	Measured/local	50 months	daily	R2 74.77%

				Process		airport			
[77]	South Korea	School	7	Hybrid(k-means+ANN+k-nearest)	Total energy	Survey/measured	145 days	Hourly	CV-RMSE 7.5%-20%
[189]	Italy	Residential	363	Multiple regression	Heating load	Survey	4 years	Annual	Relative error apartments 12.46%/ detached houses 9.71%
[190]	Egypt	Office Academic	2	Multiple Regression	Electricity	Database	5 years	Hourly	NRMSE 12% 13%
[78]	Australia	Residential	Single	Hybrid (ANN+ DT)	N/A	Simulated	4435 datasets	Annual	MSE 0.6
[191]	Singapore	School	Single	Physical EnergyPlus	Plug and lighting load	Measured	180 days	hourly	CV-RMSE 6.9-7.7%
[79]	South Korea	Office	Single	Hybrid (regression+ clustering)	electricity gas	Meteorological Agency	1 year	Daily	R2, MBE, CV 0.8623, 3.96%, 8.65% 0.9766, -0.67%, 17.62%
[46]	UK	Hotel	Single	ANN Random Tree	HVAC energy consumption	Building energy management system/reservation system/a nearby weather station	1 year 106 days	Hourly	RMSE 4.97 Relative error 6.10%
[80]	China	Residential	city	Hybrid (the k-modes clustering +demographic-based probability neural networks)	N/A	American time use survey/Residential energy consumption survey/weather station	1 year	Monthly	N/A
[81]	Malaysia/Iran	Residential	Single	Hybrid (Adaptive Neuro-Fuzzy Inference System+ clustering)	Heating load Cooling load	Energy Efficiency dataset	768 datasets	N/A	MAE 0.16 0.52
[82]	China	Retail	Single	Hybrid (Stacked autoencoders + the extreme learning machine)	N/A	Website database	34939 datasets	30min/hourly	MAE, MRE, RMSE 33.7168, 3.642%, 59.1812
[38]	USA	Commercial	73388	Gradient boosting regression	Fuel, or the combination of electricity, natural gas, and fuel oil, consumption	the Commercial Buildings Energy Consumption Survey (CBECS)/The New York City Benchmarking Law.	6720/13,223 datasets	Annual	R2 0.82
[192]	Italy	Residential	Single	Linear regression SVM Random Tree MLP Neural Networks	air-conditioning (AC) load	Pecan Street Inc.'s Data port	1 year	Hourly/daily	R2 84.7%/74.4% 85.6%/79.7% 87.3%/83.2% 87.3%/80.6%
[193]	France/Palestine	Residential	84	ANN	Heating consumption	Lille Metropole Habitat	4 years	Annual	R2 0.58-0.74
[194]	USA	Office	N/A	Linear Regression Lasso Regression	Energy Use Intensity, HVAC,	Commercial Building Energy	1 year	N/A	N/A

				Support Vector Machine Artificial Neural Network Gradient Boosting Random Forest	plug and lighting load	Consumption Survey (CBECS) 2012 microdata			
[195]	USA	Office	3	ANN	N/A	the local standards and survey	simulated	N/A	r 0.9985-0.9995
[95]	South Korea	Commercial	Single	Hybrid (Deep learning +multi-decomposition)	Electrical	Measured	N/A	Daily	MAPE 0.71%-5.96%
[122]	India	N/A	N/A	Extreme learning machine	Heating load Cooling load	Database	768 datasets	N/A	MAE 0.1433 0.2548
[137]	China	Experience	Single	ANN	Lighting	Measured	1 Month	Hourly	MAE 0.0249 RMSE 5.6778,
[196]	China	Public	Single	ANN	Electricity	Measured	42 days	Hourly	Relative error 1.4
[83]	China	Commercial	Single	Hybrid (Random Forest+ Auto Regressive Moving Average)		Measured	23 days	Hourly	
[197]	UK	School	Single	Bayesian networks	Electricity	Measured	11 days	N/A	MEA 30.73-35.898
[93]	Germany	Residential	N/A	Hybrid (D-vine copula method+ quantile regression)	Heating load	German EN-OP- Institute	N/A	N/A	N/A
[198]	India	Residential	City	Statistical	Electricity	Survey	1 year	Yearly	percentage deviation 1.2%-5%, 7%-9%
[199]	South Korea	N/A	N/A	Recurrent Neural Network	N/A	N/A	3 months	Daily	RMSE 0.1335
[200]	USA	Community	30000	Hybrid (CNNs+ Random Forest Regression)	Total energy consumption	the Alachua County Property Appraiser	1 year	Yearly	R2 0.95
[201]	USA	School	Single	Long Short-Term Memory (LSTM) neural networks	HVAC energy consumption	BAS system	3 months	N/A	CVRMSE LSTM 11.17% AdaBoost 22.63% SVM 29.50%
[117]	Czech Republic	Experiment	2	Auto Regressive Particle swarm algorithm	Heating load	Measured	3 days	Daily	Relative error 0.3-1.6 0.1-1.1
[202]	Spain	Hospital	Single	Multilayer perceptron (MLP) M5Rules algorithm Tree ensemble learner	Electrical	Database	5 years	Daily	R2 0.6614-0.9015 0.6713-0.9930 0.6529-0.9434
[85]	Canada	Residential	Single	Hybrid (Ensemble- based ANN framework with minute-controlled re-sampling technique and robust integration)	Electrical	Database	2 years 9 months	Daily	MAPE 11.3952%- 15.9396%

[86]	China	Retail	Single	Hybrid (the contrastive divergence algorithm +deep belief network)	N/A	Measured	1 year	Hourly	MRE, R, R2 5.03%, 0.94, 0.89
		Office					2 years 4 months		11.62%, 0.97, 0.93
[203]	USA	Residential	N/A	Multi-objective genetic programming	Heating/cooling load	Simulated	768 datasets	N/A	R 0.8
[204]	Pakistan/South Korea	Residential	N/A	Hidden Markov Model	N/A	Measured	1 years	Hourly	RMSE 2.62
								Daily	1.54
								Weekly	0.46
[130]	China	Office	Single	Tree bagger	heating and cooling load	Measured	1 month	Weekly	MAPE 3.544%
				Gaussian process regression					0.405%
				Multiple linear regression					1.703%
				Bagged tree					1.928%
				Boosted tree					2.592%
				Neural network					13.503%
[87]	Spain	Healthcare	2	Hybrid (PCA+ Autoregressive orthonormal partial least squares	Electrical	Database	8 years	Daily	MAPE 5.06%-5.96%
[205]	South Korea	South Korea	N/A	Lambda-based data processing	Electricity	Database	2 years	Hourly	N/A
[206]	USA	School	N/A	Gaussian Process Regression	Total energy	Database	N/A	Weekly	94.38%
								Hourly	99.26%
[88]	Pakistan	Residential	N/A	Hybrid (SVM+ Jaya algorithm)	Electricity	Database	1 year	Daily	MAPE 5.521
							9 days	Hourly	3.769
[89]	China	Residential	40	Hybrid (K-means clustering+ discriminant analysis)	Heating load	Measured	1 year	Daily	MBE 6.5% CVRMSE 6.59%
[90]	South Korea	Residential	4	Hybrid (PSO-based neural networks)	Electricity	Measured	1 year	Hourly	99.45%
[37]	China	N/A	City	Binary Decision Tree	Total energy	Database	2 years	Monthly	MAPE, CV 0.601%, 0.873%
				Compact Regression					1.058%, 1.402%
				Gaussian Process					1.529%, 1.983%
				Stepwise Gaussian Processes Regression					1.784%, 2.333%
[207]	China	Office	2	Generalized Linear Regression	N/A	Database	1 year	N/A	R 1.11-1.24
[208]	UK	Residential	322	Multiple regression model					
[208]	UK	Residential	322	Regression	Heating load	Survey	N/A	Yearly	R2 60.6
[91]	China	Library	Single	Hybrid (teaching learning-based	Electricity	Measured	1 month	Monthly	CV 0.0733

				optimization+ ANN)					
[121]	India	Residential	N/A	Online sequential extreme learning machine	Heating load	N/A	768 datasets	N/A	MAE, RMSE 0.3229, 0.7772
					Cooling load				0.2746, 0.3243
[209]	China	Building sector	National	SVM	N/A	Chinese National Bureau of Statistics	14 years	Yearly	R2 0.991
[92]	China	Commercial	Single	Hybrid (Enhanced particle swarm optimization + ANN)	Lighting	Measured	8 months	Hourly	MAE 0.7607-4.1532, RMSE 0.9947-5.4712
				Least mean square					R2(S) 0.888 R2(M) 0.806
				Normalized least mean square		Simulated			0.880, 0.791
[39]	USA	Commercial	2	Recursive least square	N/A		1 years	Hourly	0.893, 0.799
				Gaussian mixture model regression		Measured			0.985, 0.925
[210]	Italy	Residential	Single	Physical EnergyPlus	Heating/cooling load	Database	1 year	Annual	
[211]	Germany	Building sector	City	Statistical	Electricity	Database	N/A	Monthly	Average coverage error -0.0231 - 0.0184
[94]	South Korea	School	Single	Hybrid (random forest +multilayer perceptron)	Electricity	Database	6 years	Daily	N/A
				Randomized trees					R2 0.8427
[126]	UK	Hotel	Single	SVM	HVAC energy consumption	Database	1 year	Hourly	0.8453
				Deep highway networks					0.8491
[96]	France	Experiment	Single	Hybrid (Piece Wise Auto-Regressive eXogeneous + SVM)	Heating load	Measured	1 year	N/A	79%
				Total Consumption Pattern Matching (TCPM)/Hourly Consumption Pattern Matching (HCPM) model					
[212]	Germany	Commercial	59		N/A	Commission of Energy Regulation (CER) in Ireland	8 months	Daily/hourly	Relative error 17.70%- 24.02%
[97]	USA	Residential	Single	Hybrid (GA+ Long Short-Term Memory)	Electricity	Database	4 years	Hourly	CV 17.526%
		Commercial					1 year		8303%
[213]	Canada	Residential	Single	Statistical	Electrical	Measured	N/A	Hourly	NMAE 75%
[214]	China/USA	Convenience store	600	Multiple regression	Total energy	Database	1 year	Yearly	R2 0.7
[65]	China	Commercial	2	Hybrid Generative Adversarial Nets	N/A	Database	24 days	Daily	R, MAPE 0.940, 5.83%
							240 days		0.952, 13.63%
				Multiple linear regression					CV-RMSE 26.4%- 34.3%
[131]	China/Japan	Educational	Single	ANN	Cooling load	Database	1 year	Daily	20.2%-25.3%
				SVR					20.1%-25.1%

				Extreme gradient boosting trees					17.7%-19.3%
[215]	South Korea	Residential	12000	ANN	N/A	Simulated	N/A	Yearly	R 0.62886