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A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models

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ABSTRACT

Building energy use prediction plays an important role in building energy management and conservation as it can help us to evaluate building energy efficiency, conduct building commissioning, and detect and diagnose building system faults. Building energy prediction can be broadly classified into engineering, Artificial Intelligence (AI) based, and hybrid approaches. While engineering and hybrid approaches use thermodynamic equations to estimate energy use, the AI-based approach uses historical data to predict future energy use under constraints. Owing to the ease of use and adaptability to seek optimal solutions in a rapid manner, the AI-based approach has gained popularity in recent years. For this reason and to discuss recent developments in the AI-based approaches for building energy use prediction, this paper conducts an in-depth review of single AI-based methods such as multiple linear regression, artificial neural networks, and support vector regression, and ensemble prediction method that, by combining multiple single AI-based prediction models improves the prediction accuracy manifold. This paper elaborates the principles, applications, advantages and limitations of these AI-based prediction methods and concludes with a discussion on the future directions of the research on AI-based methods for building energy use prediction.

1. Introduction

Population growth and economic development in many ways propelled energy and material consumption to a greater degree that threatens the very existence of our Earth. Globally, buildings account for nearly 30% of global energy usage [1]. Needless to say, any effort toward decreasing building energy use considerably reduces the reliance on global energy. With a significantly large stock of buildings still put to use by, in some cases, over-extending their useful life by retrofitting through material upgrades, the importance of building energy efficiency cannot be understated. For one, the insulation requirements for most of the buildings built in the mid-twentieth century lack insulation requirements that may have prevented heat loss or gain. Besides, the inaccuracy or lack of calibrated sensors to control energy and lighting pose a continuous struggle to effectively track, control, and reduce energy use. Thus, with existing buildings posing a threat to overall energy efficiency, recent decades have seen an increase in research activities in the field of energy use prediction particularly using Artificial Intelligence (AI) techniques. This necessity has attracted many researchers attempting to predict energy use in a rapid manner. Among others, energy use prediction contributes to effective building energy management and conservation, energy systems commissioning through detecting system faults, and building energy control and operation [2].

Researchers have developed various simulation tools to predict building energy use since the early 1990s. These tools can be further classified as engineering method, AI-based method, and hybrid method [3]. The engineering method estimates energy use by using thermo-

Abbreviations: ANFIS, Adaptive Network-based Fuzzy Inference System; ANN, Artificial Neural Network; ARIMA, Autoregressive Integrated Moving Average; ARMAX, Autoregressive Moving Average with Exogenous inputs; BC, Bayesian Combination; BNB, Bernoulli Naïve Bayes; BSS, Blind Source Separation; BT, Boosting Tree; CART, Classification and Regression Tree; CHAID, CHi-squared Automatic Interaction Detection; CR, Case-based Reasoning; DHC, Double-layer Hierarchical Combining; DS, Dynamic Selection; DSR, Dempster-Shafer Regression; DT, Decision Tree; EN, Ensemble Node; FFNN, Feed Forward Neural Network;; GA, Genetic Algorithm; GA-ANFIS, Genetic Algorithm - Adaptive Network-based Fuzzy Inference System;; GENLIN, Generalized Linear model; kNN, k-Nearest Neighbors;; LEW, Least-squares Estimation-based Weighting; MA, Median-based Averaging; MAPE, Mean Absolute Percentage Error; MARS, Multivariate Adaptive Regression Splines;; MLP, Multi-Layer Perceptron; MNB, Multinomial Naïve Bayes; MS, Multi Staging; MV, Majority Voting; PCA, Principal Component Analysis; PNN, Probabilistic Neural Network; RBFNN, Radial Basis Functions Neural Networks; RC, Resistor–Capacitor;; RF, Random forest; RIPPER, Repeated Incremental Pruning to Produce Error Reduction; RMS, Reverse Multi Staging; RNN, Recurrent Neural Network;; SA, Simple Average; SARIMA, Seasonal Autoregressive Integrated Moving Average; SASOM, Structure Adaptive Self-Organizing Map; SOM, Self-organizing Map; SVM, Support Vector Machine; SVR, Support Vector Regression; WA, Weighted Average; WPA, Weighted Probability Averaging; WV, Weighted voting

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dynamic equations to represent the physical behavior of systems and their interactions with the environment to estimate energy use, i.e., energy consumption of individual building component or the entire building [4]. This method is referred to as the 'white-box' as the inner logic is known. Different from engineering approach, the AI-based method is referred to as the 'black-box' because it predicts energy use without knowing the internal relationship of the building and its individual components. The hybrid method, also known as the 'grey-box', integrates both white-box and black-box methods for the purpose of eliminating the limitations inherent in each method. Both white-box and grey-box methods require detailed building information to simulate the inner relations to estimate energy use and, therefore, are time-consuming and require tedious expert work for model development. For the study of existing buildings and their energy use, the use of these two methods becomes tedious as, if not impossible, it may be difficult to accurately gather specifications of building envelope and mechanical systems thus thwarting the widespread use of these methods for existing building stock. Whereas a detailed review of tools for building energy use prediction including the white-box, black-box, and grey-box methods is available in [3], this paper presents an in-depth review of the state-of-the-art AI-based methods for building energy prediction. Two prediction methods are studied and compared; they are single prediction methods that utilize one learning algorithm and ensemble prediction methods which integrate some of the single prediction methods to improve accuracy of prediction.

AI-based prediction method predicts building energy use according to its correlated variables such as environmental conditions, building characteristics, and occupancy status. Due to its prediction performance, AI-based methods have been widely applied in the domain of building energy use prediction. Previous studies have compared the AI-based methods with other prediction methods for building energy use. To give examples: Neto and Fiorelli [5] compared Artificial Neural Network (ANN) with EnergyPlus [6], a whole building energy estimation software, for predicting building energy use; Turhan et al. [7] compared Back Propagation Neural Network (BPNN) with KEP-IYTE-ESS [8], another energy simulation tool, for predicting the heating load of residential buildings; and more. These studies demonstrated the AI-based approaches, with advantages such as model simplicity, calculation speed, and learning capability when compared with the engineering and hybrid methods, is the most suitable method in energy use prediction of existing building stock. Because of their simple model structure and convenient data collection necessities, AI model development is rapid. To elaborate, the energy simulation engines such as EnergyPlus, although they can model complex systems, are comparatively slower than AI-based approaches owing to the sequential operations of the software structure, e.g., the space temperature is updated hourly using feedback from HVAC module. Furthermore, using time series data, AI-based models can be employed to predict future behavior of energy use whereas energy modeling software, as forward classical approach, offer energy estimation on a 15-min, hourly, monthly, or annual basis for the known structure. This leads to one of the significant advantages of AI-based models, in that, they require a small number of parameters that adequately represent the performance of the building, as a system when compared to a whole building energy simulation algorithms which require known structure and known parameters as they are subjected to input variables for estimation.

This paper provides a detailed literature review on the recent developments of AI-based building energy use prediction. The paper first investigates the current research trends of AI-based building energy use prediction. More specifically, this paper provides insight into a more recently applied approach for AI-based building energy prediction – the ensemble learning, which combines multiple AI-based models to improve prediction accuracy. After reviewing various AI-based models, this paper offers a detailed comparison between the conventional single prediction (i.e., using one AI-based model) and ensemble prediction models (i.e., using multiple AI-based models). Furthermore, using detailed discussion including principles, applications, and comparisons, this review paper offers the necessary constructs for successful ensemble model implementation. In a nutshell, this paper paves the way for greater understanding of the use of ensemble models for the prediction of building energy use.

The paper is organized as follows: Section 2 provides a review of current research trends of AI-based building energy use prediction. Section 3 discusses the principles, advantages, limitations, of different AI-based prediction models. Section 4 compares AI-based single and ensemble prediction methods and discusses the advantages, disadvantages, and future directions of AI-based building energy use prediction. Finally, conclusions are discussed in Section 5.

2. Current trends: AI-based building energy use prediction

To aid readers' understanding of current research trends of AI-based building energy use prediction as well as to reveal some of the common features used in research studies, we reviewed related journal articles published in recent six years (2011–2016). A total number of 35 representative journal articles were identified to comprehend the current research status and trends of AI-based building energy use prediction. The selection criteria for narrowing recent work included the building types, prediction approaches, energy output types predicted, time scale of the prediction, and input data types used for prediction. Table 1 compares the recent work in the field of AI-based approaches for building energy prediction using the criteria discussed earlier. The current research trends of AI-based building energy use prediction based on the investigation results of each aspect are discussed in the following part of this section.

2.1. Building type

For AI-based prediction, a validation process is always needed to test the prediction performance of the proposed prediction model. Based on the literature review, different types of buildings were used as the testbed to validate the prediction performance of the proposed prediction model. According to the functional usage, the tested buildings may be classified into four categories, e.g., commercial, residential, educational and research, and other building types. As shown in Fig. 1, the literature review performed in this paper indicates that the AI-based prediction models were largely used for energy prediction of the educational and research, and commercial building types, i.e., 42% and 33% respectively. These building types are most preferred for researchers to apply their AI-based prediction models particularly due to data availability and, potentially, easier access to the available data. Notably, although the residential buildings account for the largest proportion of building energy use [42], there are limited studies related to the application of AI-based approaches to predict energy use. Perhaps, this is due to the difficulty in data collection for residential buildings has adequately slowed the use of AI-based energy use prediction. Compared to educational and research buildings, residential buildings, particularly the single-family houses, are short of sensors and meters to collect occupancy and energy data, which are essential for AI-based prediction models. Even for large residential buildings such as apartment buildings, where adequate sensors may be available, it is hard, if not impossible, for researchers to collect the required data owing to privacy issues.

2.2. Prediction method

Various AI-based energy prediction models were proposed in the reviewed articles. According to the model structure and the number of prediction models used, these models may be classified into two categories: single and ensemble prediction models. Our study results show that the single prediction method is widely used for AI-based

Table 1
Previous work in AI- based building energy use prediction.

Year	Author	Building type				Prediction methods					Energy type			Prediction time scale				Input data type		
		Com[a]	Res[b]	E & R[c]	Other	MLR	ANN	SVR	Ens[d]	Others	BE[e]	H & C[f]	Other	Year	Day	Hour	Other	Met[g]	Occ[h]	Others
2011	Kwok et al. [9]	✓					✓						C			✓		✓	✓	
2011	Li et al. [10]			✓			✓			Grey Model	✓					✓		✓	✓	
2011	Escrivá-Escrivá et al. [11]			✓			✓				✓						15 min	✓		Calendar, day type
2012	Edwards et al. [12]		✓			✓	✓	✓			✓					✓		✓		Day type
2012	Yun et al. [13]	✓				✓							H[i]			✓		✓	✓	
2012	Leung et al. [14]			✓			✓						C[j]		✓	✓		✓	✓	Hour-type/day-type, pretreated air unit operation schedule
2013	Korolija et al. [15]	✓				✓						✓		✓					✓	Building, environment, and activity related parameters
2013	Sun et al. [16]	✓								Correlation Coefficient Algorithm			C			✓		✓		
2013	Li and Huang [17]	✓				✓	✓			ARMAX, RC network			C				Short Term	✓		Room temperature
2013	Catalina et al. [18]		✓			✓							H				Monthly			Global heat loss coefficient (G), the south equivalent surface (SES) and the temperature difference
2013	Roldán-Blay et al. [19]			✓			✓				✓					✓				Temperature, day type (working patterns)
2013	Borges et al. [20]			✓				✓			✓					✓				Day type
2013	Wu et al. [21]	✓				✓							Grid				1 week			Day type
2014	Lv et al. [22]				Zone					Dynamic Modeling	✓						15 Mins			
2014	Jetcheva et al. [23]		✓		Industrial		✓			SARIMA	✓				✓			✓		Historical energy consumption
2014	Fan et al. [24]	✓				✓	✓	✓	✓	GA	✓				✓			✓		
2014	Chou and Bui [25]				Simulated	✓	✓	✓	✓	CHAID, CART, DT		✓					Unknown			Building component characteristics
2014	Farzana et al. [26]		✓			✓	✓			Grey Model	✓			✓						
2014	Monfet et al. [27]	✓								CR	✓					✓		✓		
2014	Mena et al. [28]			✓			✓				✓						Minute	✓		
2014	Turhan et al. [7]		✓				✓						H				Unknown			Building characteristics
2015	Zhang et al. [29]			✓		✓	✓						Hot water		✓	✓		✓		
2015	Platon et al. [30]			✓			✓			CR	✓					✓		✓		HVAC component information
2015	Massana et al. [31]			✓		✓	✓	✓			✓					✓		✓	✓	Indoor data, calendar data
2015	Jung et al. [32]	✓						✓			✓				✓					Historical energy consumption
2015	Chitsaz et al. [33]			✓			✓				✓					✓				Historical energy consumption
2015	Li et al. [34]			✓			✓				✓					✓		✓	✓	
2015	Jovanovic et al. [35]			✓			✓		✓			✓			✓			✓		
2015	Chitsaz et al. [33]			✓			✓				✓					✓				Temperature, day type (seasonal pattern)
2016	Deb et al. [36]			✓			✓						C		✓			✓	✓	
2016	Zhao et al. [37]	✓					✓	✓		ARIMA	✓		Electricity			✓		✓		

(continued on next page)

Table 1 (*continued*)

Year	Author	Building type				Prediction methods					Energy type			Prediction time scale				Input data type		
		Com[a]	Res[b]	E & R[c]	Other	MLR	ANN	SVR	Ens[d]	Others	BE[e]	H & C[f]	Other	Year	Day	Hour	Other	Met[g]	Occ[h]	Others
2016	Shi et al. [38]	✓					✓				✓					✓		✓	✓	
2016	Naji et al. [39]		✓				✓			Genetic Programming		✓		✓						Building envelope parameters
2016	Chae et al. [40]	✓					✓				✓						15 Min	✓		Time indicator and operational condition
2016	Massana et al. [41]			✓				✓			✓		Electricity			✓			✓	

[a] Commercial buildings.
[b] Residential buildings.
[c] Educational & Research buildings.
[d] Ensemble model.
[e] Building electricity.
[f] Heating and Cooling.
[g] Meteorological.
[h] Occupancy.
[i] Heating.
[j] Cooling.

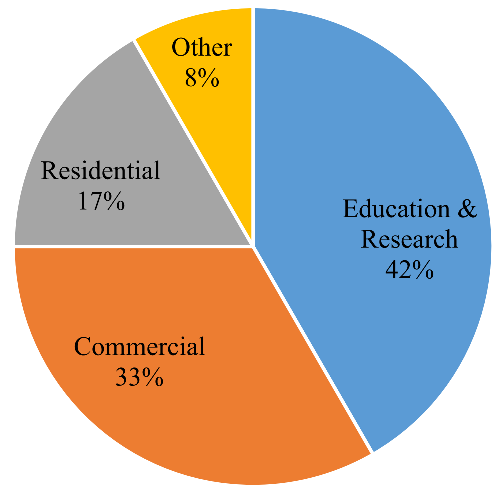

Fig. 1. The composition of building type.

building energy use prediction, i.e., 91% of all AI-based predictions used one prediction algorithm, while the studies on ensemble prediction method for building energy use prediction are limited (9%). This is due to the fact that the idea of single prediction method is deep-rooted, and the framework for applying it to building energy use prediction is well established. Whereas, the research on ensemble prediction method for building energy use prediction is still at the initial stage because of its complexity. Many research works such as the development of general implementation framework, the validation of model feasibility and superiority, and the test for computation efficiency, need to be undertaken before such ensemble models can be widely applied. It is to be noted that studies using ensemble models to predict building energy were not started until 2014; nevertheless, results of these studies demonstrated the superiority of ensemble models over single prediction models [24].

Furthermore, the prediction methods may be classified from the perspective of applied learning algorithms. In this paper, we classified the learning algorithms into four categories: regression, ANN, SVR, and all others. Few studies used multiple prediction algorithms and compared their robustness and ability for building energy use prediction [17,29]. Our review showed that the following percentages of types of learning algorithms applied to building energy use prediction: regression (26%), ANN (41%), SVR (12%), and all others (21%). ANN is the most widely used algorithm among these four categories. Various ANNs including, but are not limited to, MLP [9], BPNN [14,25], FFNN [12], and RBFN [35], were used in these recent studies. The ANNs were widely used because of their ease of implementation and reliable prediction performance. In the case of MLR, it has advantages in long-term building energy use prediction such as ease of use and computation simplicity. Only five studies were found to take advantage of SVR to predict building energy. However, SVR has shown its superiority in terms of prediction accuracy in building energy use prediction compared with other learning algorithms [25,31]. In addition, many other algorithms such as ARMAX [17], CHAID [25], and CR [27,30] were used for building energy use prediction.

2.3. Energy type

Based on the level of detail, the predicted energy may be classified into five categories namely, whole building energy/electricity, heating & cooling energy, heating energy, cooling energy, and all others. Fig. 2 illustrates the composition of different energy types. More than half of the studies focus on the prediction of whole building level energy use which reveals the overall energy performance of the building. The prediction of energy related to building heating and cooling combined relates to 35% of all the studies. This is because most studied buildings

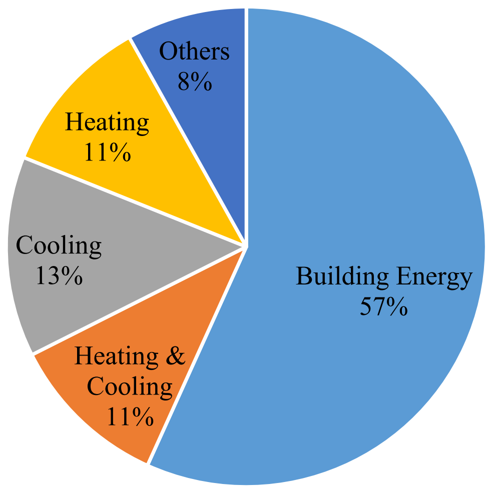

Fig. 2. The composition of energy type.

are either commercial or educational/research buildings whose heating and cooling energy usage accounts for a large proportion of overall building energy use. It is to be noted that some studies only chose heating [18] or cooling [9,14] energy as the outputs based on the climate zone and actual needs of their studies.

2.4. Prediction time scale

Prediction time scale represents the time resolution of the prediction which is often impacted by the sampling interval of sensors and the purpose of the research. Our review showed that various prediction time scales, e.g., minute-by-minute, hourly, daily, or annual, were chosen for building energy use prediction. Moreover, most of the studies chose only one prediction time scale, while multiple selections do exist in [31] and [14]. Fig. 3 shows the proportion each scale takes in the reviewed articles. Annual building energy use prediction is found only in eight percent of all studies. This may be due to the resolute focus on short-term prediction rather than long-term prediction. Almost half of the researchers selected hourly prediction as their preferred time scale, indicating that such scale is capable of satisfying the needs of current studies. In addition, researchers also chose minute-by-minute [28], 15 min [11,22], week [21], and month [18] as their time scales to predict building energy use.

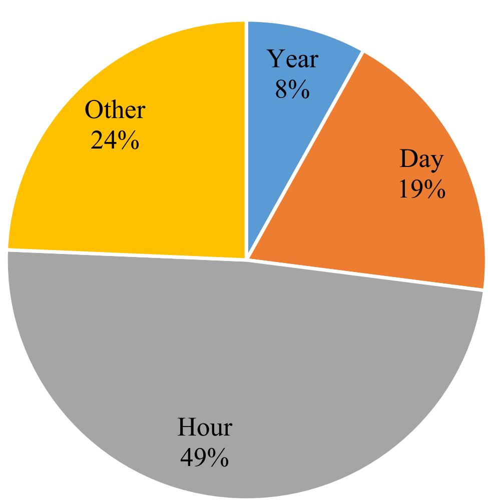

Fig. 3. The composition of prediction time scale.

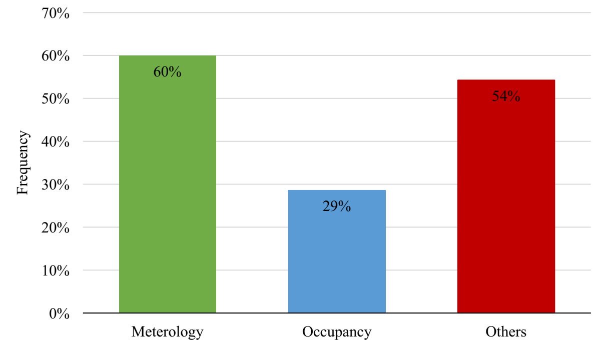

Fig. 4. The frequency of different types of input data used in the reviewed articles.

2.5. Input data type

Selecting highly correlated input data is crucial for AI-based building energy use prediction. Our literature review showed that researchers collected input data based on their knowledge of the prediction model and the availability of the data. Since the experimental condition varies in different studies, various input features have been selected to work as the input data for AI-based prediction models. Based on the type of input data, the authors classify them into three categories namely, the meteorological data, occupancy data, and all others. It should be noted that multiple types of data can be considered to conduct the prediction. Fig. 4 shows the frequency of different types of input data used in the reviewed articles. It can be seen that 60% of the articles used meteorological data to conduct their prediction. The meteorological data includes the information of outdoor temperature, humidity, wind speed, precipitation, and solar radiation, which can be collected from the local weather station. The occupants have significant impacts on building energy use, therefore, including occupancy information enhance the performance of AI-based prediction model. However, as shown in Fig. 4, only 29% of the reviewed articles utilized occupancy information to develop their prediction models. Most of the studies did not adopt occupancy information because it is hard to acquire quality data; for example, lack of occupancy sensors and other privacy concerns have led to data unavailability [23]. Researchers utilized occupancy indicators such as the time of day and day type, which could reveal the occupancy condition and pattern, to remedy the information lost from the omission of occupancy information in [11,12,14,40]. Moreover, more than half of the studies used all other input data to build their models. For example, the historical energy consumption data was used in [23,32], and [33], the indoor environmental information such as indoor temperature and indoor humidity were used in [31] and [17], some building characteristics data was used in [7] and [25], and information which reveals different working patterns or seasonal patterns such as hour type, day type, calendar day, and operation schedule was introduced in [11,12], and [14].

3. AI-based prediction models

AI-based prediction method consists of four main steps: data collection, data preprocessing, model training, and model testing. The first step is to acquire historical input and output data. The prediction accuracy of AI-based prediction model highly depends on the selection of input data. In general, most influential and highly correlated input data may bring better prediction results [43]. In the case of building energy use prediction, these aspects include but are not limited to, exterior weather conditions, occupants, global heat loss coefficient, and day types. The output data are those parameters that represent building energy use. In practice, building energy use data are represented in terms of electricity, gas, chilled water, and steam. The sampling frequencies of the utilized data vary from minute- to year-basis in accordance with the prediction time scale relevant to the investigation. Data preprocessing is performed on the collected data to organize them in a suitable format before they are used to train the AI-based prediction model. Data preprocessing techniques such as data transformation, data normalization, and data interpolation may be applied in this step to improve the data quality. The third step is to train the AI-based prediction model. Since the key concept of the AI-based prediction method is learning from historical data, a training process is required to develop the model. More specifically, the training process aims to select the most appropriate parameters that improve the prediction performance of the learning algorithm. Notably, the type of parameters varies between different learning algorithms. The parameter selections are impacted by various factors such as the size of training data, the selection of input variables, and the performance indicators [44]. The last step is to validate the prediction performance of the model by applying the testing data to the trained model. Performance indicators such as RMSE, MAPE, and coefficient of determination (R^2) are used to evaluate the performance.

Based on this framework, researchers applied different AI-based learning algorithms and prediction schemes to predict building energy. These applications may be further classified into two categories: single and ensemble prediction methods based on their prediction schemes. While the single prediction method uses one learning algorithm, the ensemble prediction method comprises of multiple prediction models and has a model integration process when outputting the data. The following section reviews these two major categories respectively in relation to building-related applications.

3.1. Single prediction method

The single prediction method refers to the prediction system which is formed based on one prediction algorithm. In this paper, the scope of single prediction method covers all available AI-based prediction models, i.e., MLR, ANN, and SVR. Consequently, this method may be subdivided into several types based on their applied learning algorithms. For this paper, we primarily focused on the algorithms that are employed in the field of AI-based building energy use prediction.

3.1.1. Multiple linear regression

Multiple linear regression is an approach to model the relationship between a dependent variable and several independent variables. Because of their ease of use, MLR models have been used to predict building energy loads. Catalina et al. [45] developed regression models to predict monthly heating demand for residential buildings. The inputs for the regression models include building shape factor, envelope U-value, window-to-floor area ratio, building time constant and climate which is defined as a function of sol-air temperature and heating set-point. These models were easy and efficient forecast tools for calculating heating demand of residential buildings. More recently, Catalina et al. [18] simplified their MLR model by introducing only three inputs namely, building global heat loss coefficient, south equivalent surface, and the difference between the indoor set point temperature and sol-air temperature. Their results indicated that the proposed method closely predicted future building heat demand. Jacob et al. [46] improved the performance of regression model by introducing the rate of change of the indoor air temperature as an independent variable. Their study indicated that the performance of MLR could be improved by introducing appropriate independent variables.

The ease of use is considered as the main advantage of MLR method because no parameters were to be tuned. However, MLR method has a major limitation - its inability to deal with nonlinear problems. Although previous studies have proven MLR as an efficient tool to predict long-term building energy use, whether it can be applied to short-term prediction successfully remains to be learned.

3.1.2. Artificial neural network

ANN is a nonlinear statistical learning technique inspired by biological neural networks. It is used as a random function approximation tool because the complex relationships between inputs and outputs can be modeled. Typical ANN has three layers namely, input, hidden, and output layers, which are interconnected. Each layer is made up of some interconnected neurons which have an activation function. Three types of parameters are typically used to define ANNs: the interconnection pattern between neurons of different layers; the learning process of updating the weights of the interconnection; and the activation function that converts a neuron's weighted input to its output activation [44].

In the past two decades, the ANN has been applied to predict various types of building energy use, such as the overall building energy consumption, cooling and heating loads, and electricity consumption. Ben-Nakhi and Mahmoud applied General Regression Neural Network (GRNN) to predict the cooling load for commercial buildings [47]. Their findings indicated that a well-designed GRNN could predict the cooling load of a building only based on external temperature. Ekici and Aksoy used Back Propagation Neural Network (BPNN) to predict the heating energy requirements of three different buildings [48]. Their research proved the reliability and accuracy of BPNN in the prediction of building heating loads. Yokoyama et al. used BPNN to predict the cooling demand of a building in which they introduced a global optimization method called “Modal Trimming Method” to identify the model parameters and improve the prediction performance [49]. Li et al. [10] used neural networks and a hybrid GA-ANFIS to predict building energy use. Mena et al. [28] developed a short-term predictive neural network model to predict the electricity demand of a bioclimatic building. Platon et al. [30] developed an ANN model to predict hourly electricity consumption of an institutional building. Recently, Chae et al. [40] combined ANN model with Bayesian regularization algorithm to predict sub-hourly electricity usage in commercial buildings. These studies showed that ANN models aid in the prediction of building energy consumption in a fast and accurate manner. Meanwhile, some researchers compared ANN with other AI-based prediction methods. Farzana et al. [26] used both regression and ANN method to predict annual urban residential buildings energy consumption. Similarly, Zhang et al. [29] applied three regression models and one ANN model to predict HVAC hot water energy consumption. Both studies indicated that ANNs could perform better than regression methods for short-term forecasting.

According to the reviews, the main advantage of ANN method is its ability to detect complex nonlinear relationships between the inputs and outputs implicitly. This characteristic makes it possible to be applied for real-time monitoring. However, ANN method fails to establish any interconnection relationship between building physical parameters and building energy use, which limits the model's fitting ability when changes are made to building components or systems.

3.1.3. Support vector regression

The concept of SVR derives from the computation of a linear regression function in a high dimensional feature space where the input data are mapped via a nonlinear function [50]. The goal of SVR is to find a function $f(x)$ that has at most ε deviation from the obtained target y_i for all the training data and at the same time is as flat as possible [44]. The selection of kernel function is important to SVR model because of the choice of kernel function affects the learning ability as well as the generalization ability of the SVR.

Dong et al. first applied SVR in the area of building energy consumption prediction in 2005 [51]. Four commercial buildings in the tropical region were randomly chosen as case studies to predict monthly energy use based on local weather data including monthly average outdoor dry-bulb temperature, relative humidity, and global solar radiation. The results showed a favorable relative error rate which is less than 4%. Similarly, Li and team used SVR to predict the hourly cooling load of an office building [52]. Weather condition information, such as the outdoor dry bulb temperature, relative humidity, and solar radiation intensity, were used as input parameters to predict hourly cooling loads. Their results demonstrated SVR as a promising alternative approach to predicting building cooling loads. Meanwhile, few researchers compared SVR with other AI-based prediction methods in building energy use prediction. Li et al. [53] compared SVR with several ANN models for predicting hourly cooling load in the building. Massana et al. [31] used SVR as well as MLR and ANNs to predict short-term load for non-residential buildings. Wang et al. compared SVR with BPNN, RBFNN, and GRNN for predicting hourly residential electricity use [54]. These studies showed that SVR improved building energy use prediction than other AI-based prediction methods. A detailed review on the applications of SVR and ANN for building electricity consumption prediction was discussed in [55].

Instead of only minimizing the training error, the main advantage of SVR is its optimization process is based on the structural risk minimization principle which aims to minimize the upper bound of the general error consisting of the sum of the training error [3]. Another advantage is the fact that SVR provides a better balance between prediction accuracy and computation speed comparing with MLR and ANNs. High level of prediction accuracy can be achieved by SVR once parameters are appropriately selected. The limitation of SVR method is the determination of kernel function. There is no uniform standard for determining which kernel will result in the most accurate SVR. Researchers have to determine the kernel function based on the characteristics of the data as well as their own experience.

On one hand, AI-based prediction models have their own limitations and, the selection of an appropriate learning algorithm depends on the specific problem to be addressed. Currently, the selection process is carried out by the heuristic approach that requires adequate experience working with learning algorithms. On the other hand, the concept of ensemble learning, which cancels out the inherent limitations of single prediction models by combining multiple single prediction models in either a sequential or parallel manner, was proposed to overcome the limitation and to improve the prediction performance of single prediction method. Ensemble models, through their seamless linkages to multiple AI models, have exhibited higher accuracy in several research domains particularly in data classification [56], disease diagnosis [57], and weather forecast [58]. However, this approach is not prevalent in the building energy field, and this paper paves the way for bridging this gap by offering the theory, development, and applications of ensemble models to researchers in the field of building science.

3.2. Ensemble prediction method

3.2.1. Theory

Ensemble learning, as a more advanced data mining technique, was introduced in the early 1990s [59]. There are other terminologies found in the literature that denote the similar concept, i.e., fusion learning, aggregation, combination, integration, etc. In this paper, we use ensemble learning model to refer to all the learning algorithm integration methods. In machine learning, ensemble model is defined as an approach using multiple learning algorithms/models to obtain better predictive performance than that could be obtained from any of the constituent learning algorithms/models [60]. The concept of ensemble model is intuitively used in daily life where we consult multiple experts, weigh, and combine their views to make a more informed and optimized decision. Rather than a prediction algorithm, ensemble model works as a framework which aims to provide the best possible prediction performance by automatically managing the strengths and weaknesses of each base model, Fig. 5.

The data collection and preprocessing for ensemble model are similar to that of the single model. However, the major difference between these two types of models lies in the process of selecting and training the learning algorithms. Different from single prediction model which contains only one learning model, the ensemble model consists of multiple base models. The base models are developed by resampling, manipulation or randomization of the training data, learning algorithm, and learning parameters. Based on the selection of the base models, ensemble prediction models may be further classified into two types, namely, homogeneous and heterogeneous ensemble models. The homogeneous ensemble model uses the same base learner on different distributions of the training set, i.e., bagging and boosting [61]. This method works especially well for unstable learning algorithms, i.e., algorithms whose output undergoes major changes in response to small changes in the training data [62]. On the contrary, the heterogeneous ensemble model comprises of different learning models which are trained by the same data set. Ensemble models are implemented as per the following steps.

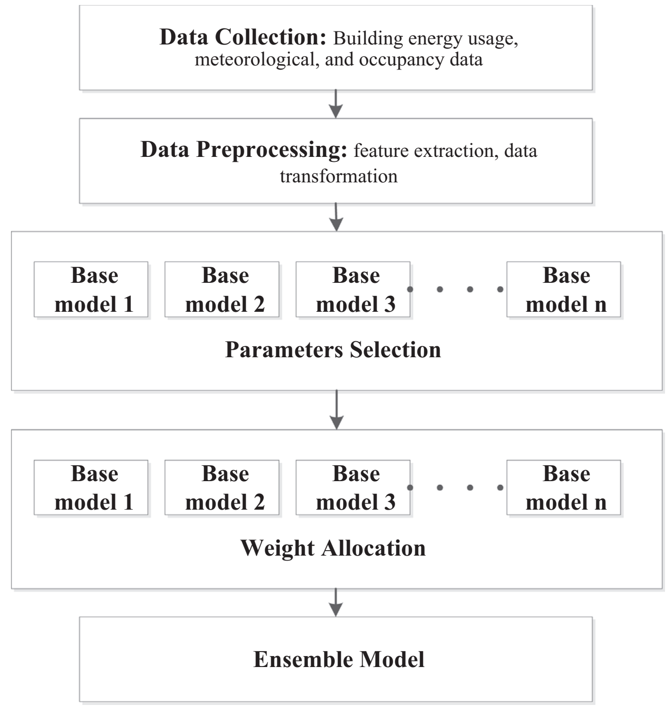

Fig. 5. Generic framework of an ensemble model.

Step 1: Input feature identification. The first step is the identification of required input features. In general, these features may include factors that affect building energy use such as environmental factors, building characteristics, and occupancy. However, to maintain a balance between computation simplicity and prediction accuracy, only those that are crucial for building energy use should be considered. It is to be noted that, for heterogeneous ensemble model, as different algorithms are used as base models, the identified parameters should be capable of establishing a universal dataset that may be used as the input for all algorithms.

Step 2: Data monitoring and preprocessing. In this step, both the identified input and output parameters should be monitored by adequate sensors. Examples of these sensors are the ambient sensors for environmental conditions, electricity, flow, and gas meters, chemical sensors for indoor conditions, and passive infrared sensors for occupancy. Instead of recording these sensors separately, a wireless sensor network which can monitor all the sensors and collecting the data collaboratively is preferable in the data monitoring process as it improves the efficiency of data acquisition. Data preprocessing may be required owing to missing data points, inaccurate data representation, and non-unified time interval issues. Taking appropriate measures to solve these problems in this step may reduce their impact in subsequent steps. The overall experiment can benefit from effective data preprocessing in both computation efficiency and prediction accuracy.

Step 3: Learning algorithm selection. This step is the major

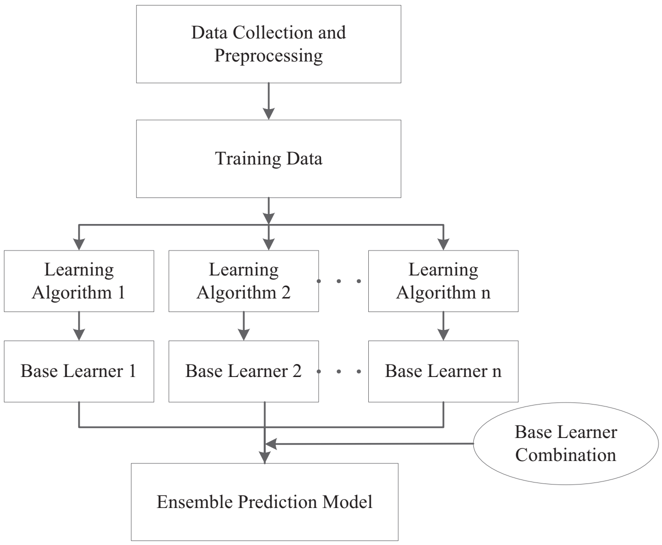

Fig. 6. Framework for heterogeneous ensemble model.

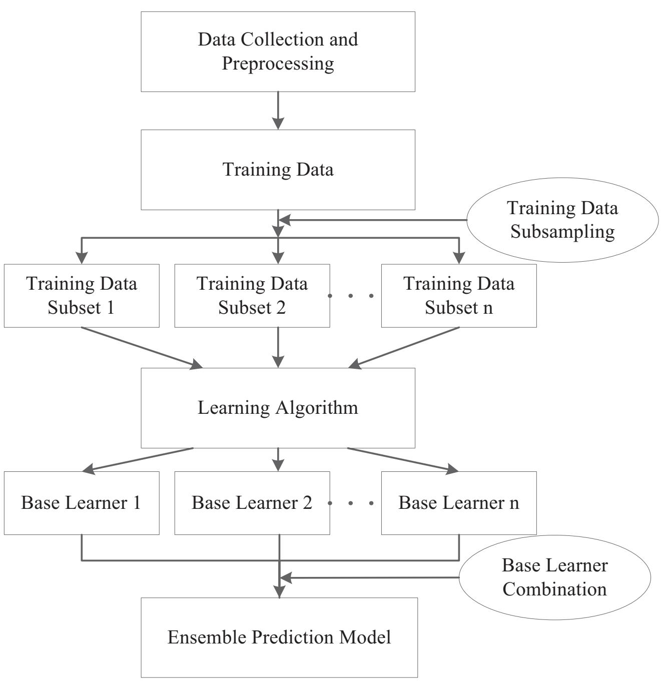

Fig. 7. Framework for homogeneous ensemble model.

difference between single and ensemble prediction models. Comparing with single prediction model which only use one learning algorithms to build the model, ensemble prediction model requires multiple learning algorithms to train its base models. Figs. 6 and 7 show heterogeneous and homogeneous ensemble model frameworks respectively. Based on the framework, it can be seen that the two types of ensemble models have different base model selection processes. The base models of homogeneous ensemble model derive from the same learning algorithm trained by different subsets of the training data. Hence, homogeneous ensemble model only needs to select one algorithm from the currently available machine learning techniques, which is similar to the algorithm selection process of the single prediction model. On the contrary, the heterogeneous ensemble model requires a collection of machine learning algorithms to work as its base models. As discussed in Fan et al. [23], the irrelevance between each base model can cancel out their individual errors, thus sufficient base models should be selected to enhance the diversity of the base models.

Step 4: Base model generation. Once the learning algorithms are selected, the next step is to train these base models. The training processes of homogeneous and heterogeneous ensemble models are different in the generation of the training subset. For homogeneous ensemble model, each base model shares the same learning algorithm while their training data are different. The training data for each base model is the subsets of the whole training data which are generated by data manipulation methods such as bagging and boosting. The training process for heterogeneous ensemble model is straightforward, that is, it uses the same training data to train each learning algorithm individually.

Step 5: Model integration. This step is to integrate all base models to output the final prediction results through certain combination schemes. For regression problems, minimizing the overall prediction error of the ensemble prediction model normally works as the objective function of the combination schemes. The weight of each base model is assigned based on its prediction accuracy, which means that the one with the least prediction errors may have the highest weight.

The generalization ability of an ensemble model is stronger than that of a single model. From the perspective of machine learning, Dietterich [22] identified reasons for effective ensemble model development, particularly (i) the training data may not provide sufficient information for choosing a single best learning algorithm; (ii) the learning algorithms may not be able to solve the difficult problems that we pose; and (iii) the hypothesis space being searched might not contain the true target function. Therefore, ensemble model becomes a favorable option as it provides a way of overcoming representational inadequacies in the hypothesis space.

3.2.2. Development and applications

Because of improved prediction accuracy compared to single prediction models, ensemble prediction method has become a favorable topic in recent years and has been applied to many fields successfully. The concept of ensemble learning was first proposed by Hansen and Salamon in 1990 to solve classification problems [59]. The authors used neural networks as base models to form the ensemble learning model. Each base model has its unique generalization error because they are trained by different subsets of the input data. Hansen and Salamon [24] argued that the collective decision produced by the ensemble model is less likely to be in error than the decision made by any of the individual models. Their research work supported this argument by showing that an ensemble of similar neural networks with a plurality consensus scheme performs better than a single neural network in data classification.

Owing to ensemble learning models' ability to improve the generalization ability of the learning system, several studies have been committed to the theoretical study of this area including data manipulation methods that can generate various training datasets. Breiman proposed a training data subsampling method, bagging, for manipulating the training data [63]. Similarly, another training data manipulation method, AdaBoost, was developed by Freund and Schepire in 1996 [64]. Meanwhile, methods for combining the base models were also developed to assist the ensemble model to output optimal results. For regression problems, Perrone and Cooper applied least squares regression to find weights that maximize the accuracy of ensemble model on the training data [65]. For classification problems, Ali and Pazzani proposed a method called likelihood combination in which they used the Naïve Bayes algorithm to learning weights for classifiers [66]. What's more, some researchers devoted to assisting users to select effective neural networks to form ensemble models [67]. Their research indicated that effective ensemble model might be built from a limited number of appropriate neural networks rather than including all available neural networks.

Along with the development of the theoretical study of ensemble learning model, researchers applied this technique to solve real-world problems. In the case of heterogeneous ensemble models to solve classification problems, Giacinto and Roli developed a neural network based ensemble model for image classification [68]. In this work, three neural networks, e.g., MLP, RBFNN, and PNN, were used to create the ensemble model. Results showed that the approach allowed users to design effective neural network ensemble classifiers. Later, this concept was used to assist scientists in the area of DNA microarray classification [56]. Multiple classification algorithms and integration schemes were used to develop ensemble models. More recently, Tuarob et al. [69] proposed a heterogeneous ensemble classifier that consisted of five different classification algorithms to solve health-related short text classification problem. A parameter sensitivity analysis was carried out to obtain the best possible features. Multiple model integration schemes such as multi-staging, reverse multi-staging, majority voting, and weighted probability averaging were used to combine the classification results of the base classifiers. The result indicated that the proposed ensemble classifier performs better than the single SVM classifier in the studied problem.

Homogeneous ensemble learning models were also used for classification. Tan and Gilbert proposed ensemble decision tree models for cancer classification [70] in which classification tasks on seven publicly available cancerous microarray data was performed. Results indicated that ensemble learning performs better than single decision tree in cancer classification. An SVM ensemble model developed by Kim et al. offered solution to multi-class classification problems [71]. In this work, two representative methods for selecting the training sample, namely, bagging and boosting were applied for training each SVM. Three combination techniques such as the majority voting, the LSE-based weighting, and the double-layer hierarchical combining were used to aggregate the individual SVMs. Three typical classification problems: data classification, handwritten digit recognition, and fraud detection were used to test the efficacy of the proposed ensemble model. Their results indicated that the ensemble model outperforms single SVM model in terms of classification accuracy. More recently, Kang et al. [57] proposed an efficient and effective ensemble of SVM for drug failure prediction. Results showed that the proposed method outperforms the conventional SVM ensembles in terms of classification accuracy.

Similarly, several studies focused on applying ensemble learning method to solve regression problems such as: accurate load prediction in power systems by Siwek et al. [72], in which the ensemble model showed a relative improvement of 13% in MAPE and 23% in MSE over the best single prediction model; Melin et al.'s [73] ANFIS ensemble models for time series prediction; Chou and Pham's work to predict the compressive strength of high-performance concrete (HPC) [74] that used six AI-based algorithms, namely, support vector machines, artificial neural networks, classification and regression trees, chi-squared automatic interaction detector, linear regression, and generalized linear were used to construct the ensemble models; Xu et al.'s [75] framework to predict the remaining useful life of an aircraft gas turbine engine in which three prognostics algorithms, namely, DSR, RNN, and SVM, were used as the base models to form the fusion prognostics tool; and Mendes-Moreira et al.'s [76] heterogeneous ensemble model to predict long-term travel time for public transportation using three algorithms, namely, random forest, projection pursuit regression, and SVM.

Even though ensemble learning methods have been successfully applied in the area of face recognition, medical diagnosis, and gene expression analysis since 2000 [77], their use in the area of building energy use prediction did not commence until 2014. Fan et al. [24] initially developed data mining based ensemble models to predict next day energy consumption and peak power command. In this work, eight prediction models including multiple linear regression, ARIMA, SVR, RF, MLP, BT, MARS, and kNN were used as base models. The weights associated with each base model were then determined by a GA with an objective function of minimizing the MAPE. The authors emphasized that ensemble models were able to take most of the advantages of the base models and achieve the most accurate results. Chou and Bui used AI models individually and in combination (as ensemble model) to predict residential building cooling load (CL) and heating load (HL) in building design stage [25]. Twelve building types simulated in Ecotect, an energy simulation software, were investigated in their research. All buildings have the same volume and the same materials but have different surface areas and dimensions. Activities in the buildings were assumed to be sedentary. Various data mining techniques, including SVR, ANN, classification and regression tree, chi-squared automatic interaction detector, general linear regression, and ensemble inference model were used for prediction. Eight building characteristics were used as the input to predict CL and HL. Comparison results indicated that the ensemble model (SVR+ANN) and SVR were the best models for predict CL and HL, respectively. Their research supported the feasibility of using ensemble model to facilitate early designs of energy conservative buildings. What's more, Jovanović et al. [40] used a neural network-based ensemble model for predicting daily heating energy consumption. Three artificial neural networks, i.e., FFNN, RBFNN, and ANFIS are used to build the ensemble model. Three different methods namely the simple average, weighted average, and median based averaging for combining ensemble models were used. Results showed that all proposed neural networks were able to predict heating consumption with great accuracy and that using ensemble achieves even better results.

Table 2 summarizes the applications of ensemble model reviewed in this paper. Based on our detailed review, it may be concluded that ensemble models have already been widely applied in many research fields. The research results indicated that this approach of combining multiple models performed better than any single prediction models for both classification and regression problems. For classification problems, both the homogeneous and heterogeneous ensemble model were used. While for regression problems, current research studies mainly focus on using heterogeneous ensemble model to optimize the prediction results. Notably, various integration schemes have been used by researchers to create the ensemble model, whereas majority voting is the most popular and widely used scheme for classification problems. However, there is no uniform integration scheme for regression problems. It can be seen from Table 2 that the choice of integration scheme for regression problems is diverse, while the ensemble prediction results have achieved improvements to some degree comparing with single prediction methods.

4. Discussion

4.1. Single vs. ensemble prediction models

Based on the review of previous research work, it can be concluded that the single prediction models have been widely used in the area of building energy use prediction for the past two decades, while implementation of the ensemble prediction models in this domain did not commence until 2014. Even though ensemble learning has shown remarkable achievements in many areas such as biotechnology [79], character recognition [80], disease diagnosis [81], and computer science [82], it took its first step in building energy use prediction only recently. The authors compared single and ensemble prediction models to aid readers' understanding of the minute differences between these two approaches in real world application.

While the advantages of the single prediction method are threefold: (1) reliability, (2) ease of implementation, (3) fast computation speed, the disadvantages include: limited prediction accuracy and reliability, particularly when compared to the ensemble prediction method; and that the users need to select a suitable learning algorithm for their problems as no one particular algorithm has dominated the others in predicting building energy use for all cases.

The advantage of the ensemble prediction method lies in its remarkably improved prediction accuracy and stability. Since it uses

Table 2
Summary of applications of ensemble model.

Research Field	Year	Author	Problem type		Ensemble type		Base model				Integration Scheme	Remarks
			Classification	Regression	Homogeneous	Heterogeneous	Regression	ANN	SVM	Others		
Image Classification	2001	Giacinto and Roli [68]	✓			✓		✓			MV	Purpose: To classify different agriculture areas from a set of multi-sensor remote-sensing images. Improvement: 6–10% improvement in classification accuracy against single algorithm.
Data Classification	2003	Kim et al. [71]	✓		✓				✓		MV, LSEW, DHC	Purpose: Handwritten digit recognition, fraud detection, and IRIS data classification. Improvement: 8–10% improvement in classification correction rates against single SVM.
Genomics	2006	Kim and Cho [56]	✓			✓		✓	✓	SOM, SASOM, DT, kNN	MV, WV	Purpose: DNA microarray classification. Improvement: 2–15% improvement of classification accuracy against single algorithm.
Biomedical Informatics	2014	Tuarob et al. [69]	✓			✓			✓	RF, BNB, MNB, RIPPER	MV, WPA, MS, RMS	Purpose: Health-related short text classification. Improvement: 18.61% and 46.62% improvement of F-Measure for small and large scale experiments respectively.
Disease Diagnosis	2015	Kang et al. [57]	✓		✓				✓		MV	Purpose: anti-diabetic drug failure prediction. Improvement: Up to 7% improvement of accuracy rate based on the bootstrap sample size.
Power System	2009	Siwek et al. [72]		✓		✓		✓			SA, WA, PCA filtering, and BSS	Purpose: Load prediction for power system. Improvement: 13% improvement of MAPE against single prediction algorithms.
Construction Material	2013	Chou and Pham [74]		✓		✓	✓	✓	✓	CART, CHAID, GENLIN	EN	Purpose: Prediction of concrete compressive strength. Improvement: 4.2–69.7% improvement in error rate against single prediction algorithms.
Aeronautical Technology	2014	Xu et al. [75]		✓		✓	✓	✓	✓		Comentropy Theory	Purpose: Prediction of aircraft engine remaining useful life. Improvement: 50% on average improvement in MAPE against single prediction algorithms.
Transportation	2015	Mendes-Moreira et al. [76]		✓		✓	✓		✓	RF	DS	Purpose: Long-term bus travel time prediction. Improvement: 8.2% improvement against single prediction algorithm.
Building Energy	2014	Fan et al. [24]		✓		✓	✓	✓	✓	RF, ARIMA, kNN	GA	Purpose: Prediction of daily energy consumption and peak power demand. Improvement: 50% on average improvement in MAPE against different single prediction algorithms.
	2014	Chou and Bui [78]		✓		✓		✓	✓		WA	Purpose: Modeling heating and cooling load Improvement: 4.9% improvement in RMSE against best single prediction algorithm in

(continued on next page)

Table 2 (*continued*)

Research Field	Year	Author	Problem type		Ensemble type		Base model				Integration Scheme	Remarks
			Classification	Regression	Homogeneous	Heterogeneous	Regression	ANN	SVM	Others		
												cooling load prediction
	2015	Jovanović et al. [35]		✓		✓		✓		ANFIS	SA, WA, MA	Purpose: Prediction of heating energy consumption. Improvement: 3–5% improvement in MAPE against different single prediction algorithms.

multiple base models to predict the results, the irrelevance among these base models will reduce the overall prediction error of the system. Similarly, as the prediction results are made based on the integration of the base models, it is unlikely that all the base models would fail to predict properly at the same time. Therefore, there is little chance for the ensemble prediction method to cause great errors. For heterogeneous ensemble model, another advantage is its universality. Different from single prediction method or homogeneous ensemble method which require the user to select the most appropriate learning algorithm, heterogeneous ensemble method omits this screening process. It actually works as a results optimization process which can be widely used as a framework to improve the prediction performance. However, comparing with single prediction method, ensemble prediction method requires more calculation time and high level of knowledge as it is the combination of different base models. Another drawback of the ensemble prediction method is the fact that its prediction performance highly depends on the selection of base models. In the previous studies, researchers selected base model based on their priori knowledge. There is a lack of approach to determine which base model should be considered and included in the ensemble model.

Table 3 compares ensemble prediction models with typical AI-based prediction algorithms. Needless to say, algorithm selection must be appropriate based on the problem to be solved. For example, MLR is more suitable than other methods in predicting long-term energy usage because of its ease of use and high computation speed. ANNs and SVR are more suitable for real-time monitoring because of their high level of prediction accuracy. For ensemble prediction methods, despite its improved prediction performance, the high level of knowledge and computation requirements have hindered its application in real practice. However, the computing capability has been greatly improved as the development of computer technology; we can foresee that the limitation of computation will not be an obstacle in the near future.

Table 3
Comparisons for AI-based building energy use prediction models (advantages are shown with "+" sign; disadvantages, with a "−" sign).

Characteristics	**MLR**	**ANNs**	**SVR**	**Ensemble model**
General	+Ease of use;	+Solve complex nonlinear problems;	+Good balance between prediction accuracy and calculation speed;	+Best prediction accuracy and stability;
	+Efficient and Economical;	+Good performance for short-term prediction;	+Few parameters need to be determined;	−High level of knowledge requirement;
	−Inability to deal with complex problems;	−Fails to interconnect building parameters with energy usage;	−The kernel function is crucial and difficult to be determined.	−Relatively low computation speed.
	−Hard to predict short-term energy usage.	−Many parameters need to be determined.		
Accuracy	Below average	Average	Good	Best
Computation speed	High speed	Medium speed	Medium speed	Low speed
Computation difficulty	Easy	Medium	Medium	Difficult
Energy sampling type	Long-term	Long-term; Short-term	Long-term; Short-term	Long-term (Daily energy usage)

4.2. Advantages and disadvantages of AI-based prediction methods

The followings summarize the advantages and disadvantages of AI-based prediction methods in the context of building energy use prediction.

4.2.1. Advantages

1. Compared with engineering methods, AI-based prediction method requires less detailed physical information of the building. There is no need for model developer to have high level of knowledge of the physical building parameters, which in return saves both time and cost for conducting the prediction;
2. The process of data acquisition and data loading is relatively convenient, which means the prediction model can be easy established;
3. Based on previous studies, AI-based prediction methods provide promising prediction accuracy once the model is well trained.

4.2.2. Disadvantages

1. There is no explicit relation between the physical building parameters and model inputs, which makes it impossible to extrapolate building energy performance once the design and/or operation of the building has changed;
2. The AI-based method is hard to be applied in building design phase as it requires historical building performance data to train the prediction model;
3. AI-based prediction method requires extensive training data for model establishment and maintaining prediction quality;
4. The AI-based prediction model needs to be re-trained once changes are made to building envelope, system or operation.

4.3. Future directions

Based on the current research trends, the future research directions of AI-based building energy use prediction are summarized as follows.

1. To effectively employ AI-based methods in real practice, the application needs to be simplified. Previous studies used different types and numbers of input data to build their prediction model. Although most of the studies have received promising prediction results, it is difficult to widely apply any of them in real practice due to the lack of unified input data format. Therefore, both the type and the number of input variables should be determined to standardize the data collection instruments.
2. Previous studies used heuristic methods to determine how much data should be used to train the model. There is a lack of studies on identifying optimal training data size to shorten the training period.
3. There are only a few studies focus on the impact of occupants on building energy use prediction. In fact, occupancy factors such as the number of occupants, the types of occupants, and the types of activities play an important role in building energy use. The study of incorporating occupancy information into prediction model has a greater potential to improve the prediction performance.
4. There are only a few studies related to residential building energy use prediction. However, as discussed in this paper, residential buildings consume a larger portion of overall energy use of buildings in the U.S. More efforts should be devoted in residential building energy use prediction to improve the energy performance of buildings in this section.
5. There are only a few studies that focused on the application of homogenous ensemble model for building energy use prediction. Whether this method can be applied and improve the prediction performance needs to be justified.
6. And, finally, similar to the above, there are only a few studies related to the application of ensemble model for short term building energy use prediction. Whether the ensemble prediction method can be extended to the hourly based building energy use prediction still needs to be proven.

5. Conclusion

In this paper, we provided a thorough review of AI-based methods for building energy use prediction with a special focus on ensemble prediction methods. Current research trends of AI-based prediction methods are analyzed from five aspects, namely, the type of studied buildings, the methods used for prediction, the type of predicted energies, the time scale of the prediction, and the type of input data used for prediction. Two main categories of AI-based prediction methods, namely, the single prediction methods and the ensemble prediction methods are discussed and compared. The theory, application, and characteristics of three main types of single prediction methods (multiple linear regression, artificial neural networks, and support vector regression) and ensemble prediction methods were reviewed in this paper. A comparison between AI-based single and ensemble prediction methods is conducted to reveal their differences. An intensive discussion of advantages and disadvantages of AI-based prediction models including ensemble prediction is provided. Finally, future directions of the research on AI-based building energy use prediction are summarized.

References

[1] U.S. Energy Information Administration. How much energy is consumed in the world by each sector?, 7 January. [Online]. Available: ⟨http://www.eia.gov/tools/faqs/faq.cfm?Id=447&t=1⟩; 2015.
[2] Li X, Wen J. Review of building energy modeling for control and operation. Renew Sustain Energy Rev 2014;37:517–37.
[3] Foucquier A, Robert S, Suard F, Stéphan L, Jay A. State of the art in building modelling and energy performances prediction: a review. Renew Sustain Energy Rev 2013;23:272–88.
[4] Zhao H-x, Magoules F. A review on the prediction of building energy consumption. Renew Sustain Energy Rev 2012:3586–92.
[5] Neto AH, Fiorelli FAS. Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. Energy Build 2008;40:2169–76.
[6] National Renewable Energy Laboratory, "EnergyPlus," National Renewable Energy Laboratory, Online Available: https://energyplus.net/. [Accessed 15.07.15]
[7] Turhan C, Kazanasmaz T, Uygun IE, Ekmen KE, Akkurt GG. Comparative study of a building energy performance software (KEP-IYTE-ESS) and ANN-based building heat load estimation. Energy Build 2014;85:115–25.
[8] KEP-SDM . Dwelling energy performance-standard assessment procedure. Izmir: Chambers of Mechanical Engineers; 2008.
[9] Kwok SS, Yuen RK, Lee EW. An intelligent approach to assessing the effect of building occupancy on building cooling load prediction. Build Environ 2011;46(8):1681–90.
[10] Li K, Su H, Chu J. Forecasting building energy consumption using neural networks and hybrid neuro-fuzzy system: a comparative study. Energy Build 2011;43(10):2893–9.
[11] Escrivá-Escrivá G, Álvarez-Bel C, Roldán-Blay C, Alcázar-Ortega M. New artificial neural network prediction method for electrical consumption forecasting based on building end-uses. Energy Build 2011;43(11):3112–9.
[12] Edwards RE, New J, Parker LE. Predicting future hourly residential electrical consumption: a machine learning case study. Energy Build 2012:591–603.
[13] Yun K, Luck R, Mago PJ, Cho H. Building hourly thermal load prediction using an indexed ARX model. Energy Build 2012;54:225–33.
[14] Leung M, Tse NC, Lai L, Chow T. The use of occupancy space electrical power demand in building cooling load prediction. Energy Build 2012;55:151–63.
[15] Korolijaa I, Zhang Y, Marjanovic-Halburd L, Hanby VI. Regression models for predicting UK office building energy consumption from heating and cooling demands. Energy Build 2013;59:214–27.
[16] Sun Y, Wang S, Xiao F. Development and validation of a simplified online cooling load prediction strategy for a super high-rise building in Hong Kong. Energy Convers Manag 2013;68:20–7.
[17] Li Z, Huang G. Re-evaluation of building cooling load prediction models for use in humid subtropical area. Energy Build 2013;62:442–9.
[18] Catalina T, Iordache V, Caracaleanu B. Multiple regression model for fast prediction of the heating energy demand. Energy Build 2013;57:302–12.
[19] Roldán-Blay C, Escrivá-Escrivá G, Álvarez-Bel C, Roldán-Porta C, Rodríguez-García J. Upgrade of an artificial neural network prediction method for electrical consumption forecasting using an hourly temperature curve model. Energy Build 2013;60:38–46.

[20] Borges CE, Penya YK, Fern´andez I, Prieto J, Bretos O. Assessing tolerance-based robust short-term load forecasting in buildings. Energies 2013;6(4):2110–29.
[21] Wu J, Wang J, Lu H, Dong Y, Lu X. Short term load forecasting technique based on the seasonal exponential adjustment method and the regression model. Energy Convers Manag 2013;70:1–9.
[22] Lv X, Lu T, Kibert CJ, Viljanen M. A novel dynamic modeling approach for predicting building energy performance. Appl Energy 2014;114:91–103.
[23] Jetcheva JG, Majidpour M, Chen W-P. Neural network model ensembles for building-level electricity load forecasts. Energy Build 2014;84:214–23.
[24] Fan C, Xiao F, Wang S. Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques. Appl Energy 2014;127:1–10.
[25] Chou J-S, Bui D-K. Modeling heating and cooling loads by artificial intelligence for energy-efficient building design. Energy Build 2014:437–47.
[26] Farzana S, Liu M, Baldwin A, Hossain MU. Multi-model prediction and simulation of residential building energy in urban areas of Chongqing, South West China. Energy Build 2014;81:161–9.
[27] Monfet D, Corsi M, Choiniere D, Arkhipova E. Development of an energy prediction tool for commercial buildings using case-based reasoning. Energy Build 2014;81:152–60.
[28] Mena R, Rodríguez F, Castilla M, Arahal M. A prediction model based on neural networks for the energy consumption of a bioclimatic building. Energy Build 2014;82:142–55.
[29] Zhang Y, O'Neill Z, Dong B, Augenbroe G. Comparisons of inverse modeling approaches for predicting building energy performance. Build Environ 2015;86:177–90.
[30] Platon R, Dehkordi VR, Martel J. Hourly prediction of a building's electricity consumption using case-based reasoning, artificial neural networks and principal component analysis. Energy Build 2015;92:10–8.
[31] Massana J, Pous C, Burgas L, Melendez J, Colomer J. Short-term load forecasting in a non-residential building contrasting models and attributes. Energy Build 2015;92:322–30.
[32] Jung HC, Kim JS, Heo H. Prediction of building energy consumption using an improved realcoded genetic algorithm based least squares support vector machine approach. Energy Build 2015;90:76–84.
[33] Chitsaz H, Shaker H, Zareipour H, Wood D, Amjady N. Short-term electricity load forecasting of buildings in microgrids. Energy Build 2015;99:50–60.
[34] Li K, Hu C, Liu G, Xue W. Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis. Energy Build 2015;108:106–13.
[35] Jovanović RŽ, Sretenović AA, Živković BD. Ensemble of various neural networks for prediction of heating energy consumption. Energy Build 2015.
[36] Deb C, Eang LS, Yang J, Santamouris M. Forecasting diurnal cooling energy load for institutional buildings using Artificial Neural Networks. Energy Build 2016;121:284–97.
[37] Zhao D, Zhong M, Zhang X, Su X. Energy consumption predicting model of VRV (Variable refrigerant volume) system in office buildings based on data mining. Energy 2016;102:660–8.
[38] Shi G, Liu D, Wei Q. Energy consumption prediction of office buildings based on echo state networks. Neurocomputing 2016.
[39] Naji S, Keivani A, Shamshirband S, Alengaram UJ, Jumaat MZ, Mansor Z, Lee M. Estimating building energy consumption using extreme learning machine method. Energy 2016;97:506–16.
[40] Chae YT, Horesh R, Hwang Y, Lee YM. Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings. Energy Build 2016;111:184–94.
[41] Massana J, Pous C, Burgas L, Melendez J, Colomer J. Short-term load forecasting for non-residential buildings contrasting artificial occupancy attributes. Energy Build 2016;130:519–31.
[42] Perez-Lombard L, Ortiz J, Pout C. A review on buildings energy consumption information. Energy Build 2008;40:394–8.
[43] Raza MQ, Khosravi A. A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. Renew Sustain Energy Rev 2015;50:1352–72.
[44] Wang Z, Srinivasan RS. A review of artificial intelligence based building energy prediction with a focus on ensemble prediction models. In: Proceedings of the 2015 winter simulation conference, Los Angeles; 2015.
[45] Catalina T, Virgone J, Blanco E. Development and validation of regression models to predict monthly heating demand for residential buildings. Energy Build 2008;40(10):1825–32.
[46] Jacob D, Dietz S, Komhard S, Neumann C, Herkel S. Black-box models for fault detection and performance monitoring of buildings. J Build Perform Simul 2010;3(1):53–62.
[47] Ben-Nakhi AE, Mahmoud MA. Cooling load prediction for buildings using general regression neural networks. Energy Convers Manag 2004;45:2127–41.
[48] Ekici BB, Aksoy TU. Prediction of building energy consumption by using artificial neural networks. Adv Eng Softw 2009;40:356–62.
[49] Yokoyama R, Wakui T, Satake R. Prediction of energy demands using neural network with model identification by global optimization. Energy Convers Manag 2009;50:319–27.
[50] Basak D, Pal S, Patranabis DC. Support vector regression. Neural Inf Process – Lett Rev 2007;11:203–24.
[51] Dong B, Cao C, Lee SE. Applying support vector machines to predict building energy consumption in tropical region. Energy Build 2005:545–53.
[52] Li Q, Meng Q, Cai J, Yoshino H, Mochida A. Applying support vector machine to predict hourly cooling load in the building [October]. Appl Energy 2009;86(10):2249–56, [October].
[53] Li Q, Meng Q, Cai J, Yoshino H, Mochida A. Predicting hourly cooling load in the building: a comparison of support vector machine and different artificial neural networks [January]. Energy Convers Manag 2009;50(1):90–6, [January].
[54] Wang Z, Srinivasan RS, Shi J. Artificial Intelligent Models for Improved Prediction of Residential Space Heating. J Energy Eng 2016.
[55] Ahmad A, Hassan M, Abdullah M, Rahman H, Hussin F, Abdullah H, Saidur R. A review on applications of ANN and SVM for building electrical energy consumption forecasting. Renew Sustain Energy Rev 2014;33:102–9.
[56] Kim K-J, Cho S-B. Ensemble classifiers based on correlation analysis for DNA microarray classification. Neurocomputing 2006;70:187–99.
[57] Kang S, Kang P, Ko T, Cho S, Rhee S-j, Yu K-S. An efficient and effective ensemble of support vector machines for anti-diabetic drug failure prediction. Expert Syst Appl 2015;42(9):4265–73.
[58] Parker WS. Predicting weather and climate: uncertainty, ensembles and probability. Stud Hist Philos Sci Part B: Stud Hist Philos Mod Phys 2010;41(3):263–72.
[59] Hansen LK, Salamon P. Neural network ensembles. IEEE Trans Pattern Anal Mach Intell 1990;12:993–1001.
[60] Opitz D, Maclin R. Popular ensemble methods: an empirical study. J Artif Intell Res 1999:169–98.
[61] Reid S. A Rev Heterog Ensemble Methods 2007.
[62] Dietterich T. Machine learning research: four current direction. AI Mag 1997;18(4):97–136.
[63] Breiman L. Bagging predictors. Mach Learn 1996;24(2):123–40.
[64] Freund Y, Schapire RE. Experiments with a New Boosting Algorithm. In: Proceedings of the thirteenth international conference on machine learning, Bari; 1996.
[65] Perrone MP, Cooper LN. When networks disagree: Ensemble methods for hybrid neural networks. In: Mammone, RJ (Ed.), Neural networks for speech and image processing; 1993
[66] Ali KM, Pazzani MJ. Error reduction through learning multiple descriptions. Mach Learn 1996:173–202.
[67] Zhou Z-H, Wu J, Tang W. Ensembling neural networks: many could be better than all. Artif Intell 2002:239–63.
[68] Giacinto G, Roli F. Design of effective neural network ensembles for image classification purposes. Image Vis Comput 2001;19:699–707.
[69] Tuarob S, Tucker CS, Salathe M, Ramd N. An ensemble heterogeneous classification methodology for discovering health-related knowledge in social media messages. J Biomed Inform 2014;49:255–68.
[70] Tan AC, Gilbert D. Ensemble machine learning on gene expression data for cancer classification. In: Proceedings of New Zealand bioinformatics conference: Te Papa; 2003
[71] Kim H-C, Pang S, Je H-M, Kim D, Bang SY. Constructing support vector machine ensemble. Pattern Recognit 2003;36:2757–67.
[72] Siwek K, Osowski S, Szupiluk R. Ensemble Neural Network Approach for Accurate Load Forecasting in a Power System. Int J Appl Math Comput Sci 2009;19(2):303–15.
[73] Melin P, Soto J, Castillo O, Soria J. A new approach for time series prediction using ensembles of ANFIS models. Expert Syst Appl 2012;39(3):3494–506.
[74] Chou J-S, Pham A-D. Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength. Constr Build Mater 2013;49:554–63.
[75] Xu J, Wang Y, Xu L. PHM-Oriented Integrated Fusion Prognostics for Aircraft Engines Based on Sensor Data. IEEE Sens J 2014;14:1124–32.
[76] Mendes-Moreira J, Jorge AM, Sousa JF d, Soares C. Improving the accuracy of long-term travel time prediction using heterogeneous ensembles. Neurocomputing 2015;150:428–39.
[77] Dietterich TG. Ensemble methods in machine learning. In: Proceedings of the first international workshop on multiple classifier systems, Cagliari; 2000.
[78] Chou J-S, Bui D-K. Modeling heating and cooling loads by artificial intelligence for energy-efficient building design. Energy Build 2014:437–47.
[79] Whalen S, Pandey G. A comparative analysis of ensemble classifiers: case studies in genomics. In: Proceedings of the 13th IEEE International Conference on Data Mining; 2013. pp. 807–816.
[80] Rahman A, Verma B. Effect of ensemble classifier composition on offline cursive character recognition. Inf Process Manag 2013;49(4):852–64.
[81] Vinay K, Rao A, Kumar GH. Computerized analysis of classification of lung nodules and comparison between homogeneous and heterogeneous ensemble of classifier model In: Proceedings of the third national conference on computer vision, pattern recognition, image processing and graphics (NCVPRIPG), Hubli; 2011.
[82] Hu Y, Feng B, Mo X, Zhang X, Ngai E, Fan M, Liu M. Cost-sensitive and ensemble-based prediction model for outsourced software project risk prediction. Decis Support Syst 2015:11–23.