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A REVIEW OF ARTIFICIAL INTELLIGENCE BASED BUILDING ENERGY PREDICTION WITH A FOCUS ON ENSEMBLE PREDICTION MODELS

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ABSTRACT

Building energy usage prediction plays an important role in building energy management and conservation. Building energy prediction contributes significantly in global energy saving as it can help us to evaluate the building energy efficiency; to conduct building commissioning; and detect and diagnose building system faults. AI based methods are popular owing to its ease of use and high level of accuracy. This paper proposes a detailed review of AI based building energy prediction methods particularly, multiple linear regression, Artificial Neural Networks, and Support Vector Regression. In addition to the previously listed methods, this paper will focus on ensemble prediction models used for building energy prediction. Ensemble models improve the prediction accuracy by integrating several prediction models. The principles, applications, advantages, and limitations of these AI based methods are elaborated in this paper. Additionally, future directions of the research on AI based building energy prediction methods are discussed.

1 INTRODUCTION

Due to the shortage of oil and other non-renewable energy resources, the world has embarked on an indefinite energy crisis since the dawn of twenty-first century. Meanwhile, there has been an enormous increase in the global energy demand in recent years as a result of population growth and consumption. Building, as one of the biggest energy use sectors, accounts for nearly 35% of global energy usage. Any effort toward decreasing building energy use significantly reduces the reliance on global energy. Needless to say, the research of building energy usage prediction has attracted many researchers in the past twenty years because of the important role it plays in building energy management and conservation. Accurate building energy prediction will not only helps us evaluate our building energy efficiency, but also contributes to building commissioning and building system fault detection and diagnosis.

Many building energy usage prediction tools have been proposed by researchers since early 1990s. Based on applied algorithms and models, these tools can be further classified into three main categories: engineering, Artificial Intelligence (AI) based, and hybrid methods. The engineering method uses physical principles to calculate thermal dynamics and energy behaviors for each building component or on the whole building level. This method is also named as white-box method because of the inner logic is known. Different from engineering method, the AI based method is considered as a black-box method as it investigates building energy usage without knowing its internal relationships. While hybrid method is also known as grey method as it integrates both white-box and black-box methods for the purpose of eliminating the limitation of each method. Both the white-box and grey-box methods require detailed building information as their inputs in order to simulate the inner relation and build the energy model. However, it is difficult and sometimes impossible to acquire these information for existing buildings. What's more, to construct building energy model is time consuming and requiring tedious expert work, making it hard to be widely applied. AI-based building energy prediction methods predict building energy usage according to its correlated variables such as environmental conditions and occupancy status. Since the inputs information is easy to be acquired and the calculations are fast and efficient, AI based methods have been widely applied by many researchers in the domain of predicting building energy usage. An overview of building energy prediction tools including white-box, black-box, and grey-box methods has been given in (Foucquier et al. 2013).

This paper focuses on reviewing recent studies related to AI based building energy usage prediction methods. The AI based building energy prediction methods particularly; multiple linear regression, Artificial Neural Networks, Support Vector Regression, and ensemble prediction models are discussed in detail. The paper is organized as follows: section 2 provides a review of different AI based prediction models. Section 3 discusses the principles, advantages, limitations, and future directions of AI based prediction methods. And, the conclusion is drawn in section 4.

2 ARTIFICIAL INTELLIGENCE BASED PREDICTION METHODS

Typical AI based prediction method contains four main steps. Figure 1 shows the framework for AI based prediction method. The first step is to acquire historical input and output data. The input data are those aspects who impact or correlate with the output data. These aspects include, but are not limited to the following: exterior weather condition, occupants, global heat loss coefficient, and day types. The output data are those parameters represent building energy consumption. In real practice, building energy consumption are represented in terms of electricity consumption, gas consumption, chilled water consumption, and hot water consumption. The sampling periods of both inputs and outputs vary from year to minute according to the prediction time scale of the research. The next step is to preprocess the collected data into suitable format before they are used to train the prediction model. To some extent, the initial data may not able to be used directly to the model. Some data preprocessing techniques such as data transformation, data normalization, and data interpolation are applied in this step to improve data quality and reduce negative impact. Once the data are ready, the third step is to train the prediction model. Since the key concept of empirical modeling is learning from historical data, a training process is required to develop the model. This step is achieved by selecting appropriate parameters for the model. The type of parameters is determined by the algorithms selected by the researcher, while appropriate parameter selection can ensure the performance of the model. The parameter selection is impacted by the size of training data, the selection of input variables, and the performance indicators. The last step is testing the model. In this step, testing data will be loaded to the trained model to test the prediction performance of the model. Performance indicators such as RMSE, R^2 are used to evaluate the performance.

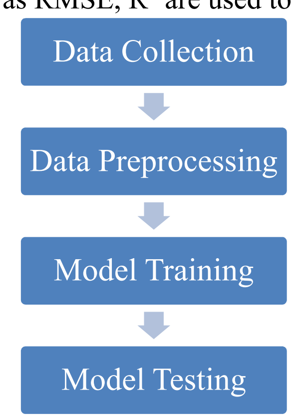

Figure 1. Framework for AI based prediction model.

The AI based prediction methods can be further classified into four types based on the learning algorithms used in the model. The following part of this section describes main techniques used for AI based prediction model.

2.1 Multiple linear regression

2.1.1 Principle:

Multiple linear regression (MLR) is an approach for modeling the relationship between a dependent variable and several independent variables. The basic model for MLR can be expressed by the following formula:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip} + \epsilon_i, \qquad i \in [1\!:\!n]$$

where X and Y are independent variables and dependent respectively. $(\beta_0, \beta_1, \dots, \beta_p)$ are parameters to be estimated, and ϵ_i is the i^{th} independent identically distributed normal error.

2.1.2 Applications:

Because of their ease of use, MLR models have been used to predict building energy loads. Catalina et al. (Catalina et al. 2008) developed regression models to predict monthly heating demand for residential buildings. The inputs for the regression models include the building shape factor, the building envelope U-value, the window to floor area ratio, the building time constant and the climate which is defined as function of the sol-air temperature and heating set-point. The proposed models showed promising features to be easy and efficient forecast tools for calculating heating demand of residential buildings. More recently, Catalina et al. (Catalina et al. 2013) simplified their MLR model by introducing only three inputs namely, the building global heat loss coefficient (G), the south equivalent surface (SES), and the difference between the indoor set point temperature and the sol-air temperature. Their results indicated that the proposed method can well predict future building heat demand. Jacob et al. (Jacobet al. 2010) improved the performance of regression model by introducing the rate of change of the indoor air temperature as an independent variable. Their research indicates that the performance of MLR can be improved by introducing appropriate independent variables.

2.1.3 Advantages and limitations:

The ease of use is considered as a main advantage of MLR method as no parameters need to be tuned. Meanwhile, since no detailed physical information of the building is required, this method is efficient and economical. However, MLR method shows a major limitation due to its inability to deal with nonlinear problems. What’s more, although previous research has proven MLR as an efficient tool to predict long-term building energy usage, whether it can be applied to short-term prediction successfully remains to be learned.

2.2 Artificial neural networks

2.2.1 Principle:

Artificial neural networks (ANNs) is a nonlinear statistical learning technique inspired by biological neural networks. It is used as a random function approximation tool as the complex relationships between inputs and outputs can be modelled. Typical ANN have three layers namely, the input layer, the hidden layer, and the output layer, which are interconnected. Each layer is made up of a number of interconnected neurons which has 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.

2.2.2 Applications:

In the past two decades, many studies have been carried out to predict various types of building energy use, such as cooling and heating loads, electricity consumption, and overall energy consumption by applying ANNs. Ben-Nakhi and Mahmoud applied General Regression Neural Network (GRNN) to predict the cooling load for commercial buildings (Ben-Nakhi and Mahmoud 2004). Their findings indicated that a well-designed GRNN is able to 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 (Ekici and Aksoy 2009). Their research proved the reliability and accuracy of BPNN in prediction of building heating loads. Yokoyama and team used BPNN to predict cooling demand of a building in which they introduced a global optimization method called "Modal Trimming Method" to identify the model parameters in order to improve the prediction performance (Yokoyama et al. 2009). Li and team used neural network and a hybrid Genetic Algorithm - Adaptive Network-based Fuzzy Inference System (GA-ANFIS) to predict building energy use (Li et al. 2011). Mena et al. (Mena et al. 2014) developed a short-term predictive neural network model to predict the electricity demand of a bioclimatic building. Similarly, Platon et al. (Platon et al. 2015) developed an ANN model to predict hourly electricity consumption of an institutional building. Both studies proved that ANN models can predict building energy consumption fast and accurate. Meanwhile, some researchers compared ANN with other AI based prediction methods. Farzana et al. (Farzana et al. 2014) used both regression and ANN method to predict annual urban residential buildings energy consumption. Similarly, Zhang et al. (Zhang et al. 2015) applied three regression models and one ANN model to predict HVAC hot water energy consumption. Both research indicated that ANNs can perform better than regression methods for short-term forecasting.

2.2.3 Advantages and limitations:

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

2.3 Support vector regression

2.3.1 Principle:

The idea of SVR is based on the computation of a linear regression function in a high dimensional feature space where the input data are mapped via a nonlinear function (Basak, Pal, & Patranabis, 2007). The goal of SVR is to find a function $f(x)$ that has at most ε deviation from the actually obtained target y_i for all the training data and at the same time is as flat as possible. 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.

2.3.2 Applications:

Dong and team first applied SVR in the area of building energy consumption prediction in 2005 (Dong et al. 2005). Four commercial buildings in tropical region were randomly chosen as case studies, and monthly energy use was predicted based on local weather data including monthly mean 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 hourly cooling load of an office building (Li et al. 2009). Weather condition information, such as out-door 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 predict building cooling loads. Meanwhile, some researchers compared SVR with other AI based prediction methods in building energy prediction. Li et al. (Li et al. 2009) compared SVR with several ANN models for predicting hourly cooling load in the building. Massana et al (Massana et al. 2015) used SVR ae well as MLR and ANNs to predict short term load for non-residential buildings. Both studies indicate that SVR has a better performance in building energy prediction than other AI based prediction methods.

2.3.3 Advantages and limitations:

Instead of only minimizing the training error, the main advantage of SVR is the 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 (Foucquier et al. 2013). 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.

2.4 Ensemble prediction models

2.4.1 Principle:

As each individual prediction algorithms may have their own limitations, a more advanced data mining technique, called ensemble learning, has been introduced by researchers recently. This method differs from any single prediction method as it develops a composite model which integrates different individual prediction models. Rather than a prediction algorithm, this method works as a framework which aims to reduce prediction errors by combining different prediction algorithms together.

Figure 2 shows the general framework for ensemble prediction models. The construction of ensemble prediction model generally contains two steps. The first step is to develop a number of base models, while the second step uses these base models to output the final result through certain combination schemes. To achieve satisfied prediction results for ensemble model, as mentioned by Fan et al. (Fan et al. 2014), two main considerations should be undertaken. Firstly, the performance of ensemble model is highly impacted by the performance of each base model. Therefore, the performance of each base model should be as accurate as possible. Secondly, the diversity of the base models has a significant impact on the performance of ensemble model. The error of base models can be cancelled out in the ensemble model if they are uncorrelated.

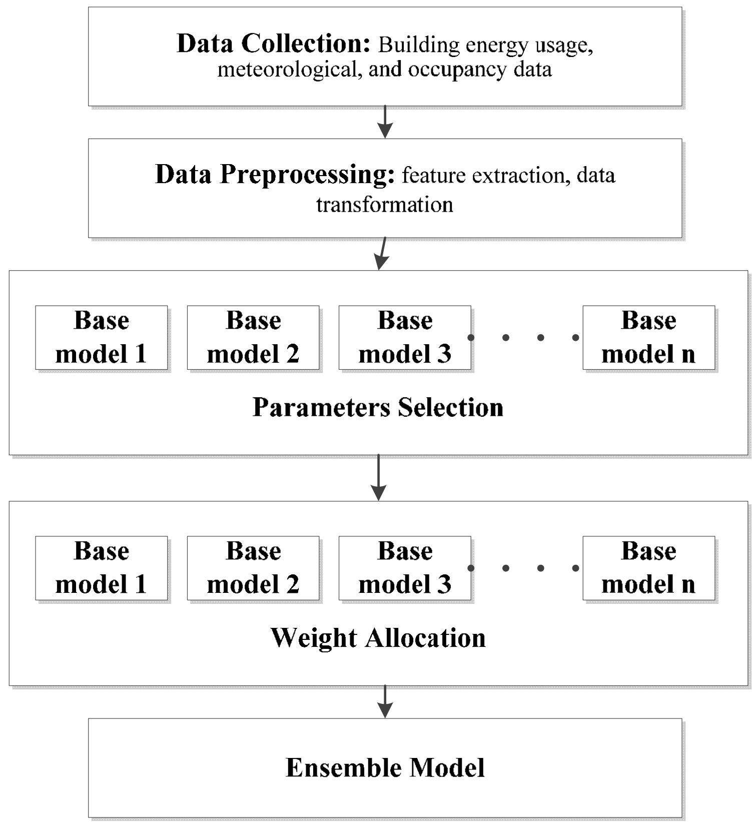

Figure 2. Framework for ensemble prediction model.

2.4.2 Applications:

Because of the high prediction accuracy, ensemble learning method has become a favorable topic in recent years and has already been applied to many fields successfully. For example, Siwek et al. (Siwek et al. 2009) developed an ensemble neural network approach for accurate load prediction in power systems. The ensemble model showed a relative improvement of 13% in MAPE and 23% in MSE over the best individual prediction model. Similarly, Melin et al. (Melin et al. 2012) used two different adaptive network based fuzzy inference system (ANFIS) ensemble models for time series prediction. The prediction results indicated that the performance obtained with their ensemble models overcomes several standard statistical approaches and neural network models. More recently, Kang et al. (Kang, et al. 2015) proposed an efficient and effective ensemble of SVM for drug failure prediction. Experiment results showed that the proposed method outperforms the conventional SVM ensembles in terms of classification accuracy.

Even though ensemble learning method has been successfully applied in the area of face recognition, medical diagnosis, and gene expression analysis since 2000 (Dietterich 2000), the research of applying it to the area of building energy prediction did not commence until 2014. Fan et al. (Fan et al. 2014) 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, autoregressive integrated moving average (ARIMA), support vector regression, random forests (RF), multi-layer perceptron (MLP), boosting tree (BT), multivariate adaptive regression splines (MARS), and k-nearest neighbors (KNN) were trained to work as base models for the ensemble models. The weights associated with each base model were then determined by genetic algorithm (GA) with an objective function of minimizing the MAPE. The result indicates that the prediction accuracy of the proposed ensemble models were higher than those of individual models. The authors emphasized that ensemble models were able to take most of the advantages of the base models to achieve the most accurate results. Similarly, Jovanović et al. (Jovanović et al. 2015) used a neural network- based ensemble model to predict daily heating energy consumption. Three artificial neural networks, i.e., feed forward neural network (FFNN), radial basis function neural network (RBFNN), and adaptive neuro-fuzzy interference system (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. The results showed that all proposed neural networks were able to predict heating consumption with great accuracy, and that using ensemble achieves even better results.

2.4.3 Advantages and limitations:

The main advantage of ensemble model is the improvement of both prediction accuracy and stability. There are three reasons to explain such superiority. Firstly, the training data may not be sufficient enough to select the best single model. On the second hand, the integration of different models can eliminate the imperfection in each individual model. Thirdly, the true target function may not exist in the real practice. However, comparing with other single prediction method, ensemble model requires more calculation time and high level of knowledge as it is the combination of different base models. Another drawback of the ensemble model is the fact that its prediction performance highly depends on the selection of base models. In the previous research, 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. What's more, whether this method can be extended to the hourly based building energy prediction still needs to be proven.

3 DISCUSSION

According to previous analysis, each type of AI based prediction method has its own advantages and disadvantages, thus people have to choose appropriate method to solve their problems. 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. While ANNs and SVR are more suitable for real time monitoring because of their high level of prediction accuracy. In order to help people understand each prediction model and select the appropriate one, a comparison between different AI based building energy prediction models is shown in table 1.

Moreover, some studies have been conducted to compare AI based prediction methods with other methods in building energy prediction. For example, Neto and Fiorelli compared ANNs with EnergyPlus for predicting building energy use (Neto & Fiorelli 2008). The results showed that both models are capable of building energy consumption prediction, while ANNs provide a slightly better prediction result than EnergyPlus. What's more, Turhan et al. (Turhan et al. 2014) compared ANN model with an energy simulation software called KEP-IYTE-ESS to predict buildings heating load. Their study suggested ANN model as a simpler and more efficient building energy prediction tool when comparing with energy simulation software. Based on these research, the advantages and disadvantages of AI based prediction methods are summarized below.

3.1 Advantages

The advantages of AI based prediction model include:

1. Comparing with engineering methods, no detailed physical information of the building is required for AI based prediction methods. 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 research, AI based prediction methods provide promising prediction accuracy once the model is well trained.

Table 1. Comparisons for AI based building energy prediction models (advantages are shown with "+" sign; disadvantages, with a "-" sign).

	MLR	**ANNs**	**SVR**	**Ensemble model**
General	+Ease of use; +Efficient and Economical; -Inability to deal with complex problems; -Hard to predict short-term energy usage.	+Solve complex nonlinear problems; +Good performance for short-term prediction; -Fails to interconnect building parameters with energy usage; -Many parameters need to be determined.	+Good balance between prediction accuracy and calculation speed; +Few parameters need to be determined; -Kernel function is crucial and difficult to be determined.	+Best prediction accuracy and stability; -High level of knowledge requirement; -Relatively low computation speed.
Accuracy	Below average	Average	Good	Better
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)

3.2 Disadvantages

The disadvantages of AI based prediction model can be summarized as follows:

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 or operation of the building has changed;
2. The model cannot be applied in the design phase as the model requires historical building performance data;
3. AI based prediction methods require extensive training data for model establishment and maintaining prediction quality;
4. The model needs to be re-trained once changes are made to building envelope, system or operation.

3.3 Future directions

In order to effectively integrate AI based methods into real practice, the application needs to be simplified. Both the type and the number of input variables should be determined in order to standardize the data collection instruments. What's more, previous researches used heuristic methods to determine how much data should be used to train the model. There is a lack of research to identify optimal training data size in order to shorten the training period. Moreover, very few researches focused on the impact of occupants on building energy 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 usage. The study of incorporating occupancy information into prediction model has a greater potential to improve the prediction performance.

4 CONCLUSIONS

In this paper, we provide a review of AI based building energy prediction methods with a special focus on ensemble models. The principles and applications of four main types of AI based prediction models including multiple linear regression, artificial neural networks, support vector regression, and ensemble model have been reviewed. The advantages and limitations of each type of model are also discussed in this paper. An intensive discussion of advantages and disadvantages of AI based prediction model has been carried out. Each AI based prediction techniques has its own advantages and limitations. The ensemble model which integrates different techniques together is able to take over the advantages and cancel out the limitations. However, problems like which technique should be selected as the base model and how many base models should be used to maintain the diversity of the ensemble model need to be solved in the future.

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