AN ANALYSIS OF ASSEMBLE PREDICTION MODELS FOR ENERGY USE IN BUILDINGS USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

Energy management requires predicting a facility's energy needs. Building energy prediction helps with commissioning, problem identification, and system diagnostics, saving energy overall. AI-based methods are popular due of their simplicity and precision. This research proposes a comprehensive assessment of AI-based building energy prediction systems using multiple linear regression, artificial neural networks, and support vector regression. This study will also examine ensemble prediction methods for building energy prediction. Ensemble models improve forecast accuracy. This paper discusses AI-based techniques' principles, applications, advantages, and drawbacks. AI-based building energy prediction research opportunities are also discussed.

INTRODUCTION

Oil and other non-renewable energy sources are scarce, causing a global energy crisis since the 21st century. Population growth and consumption have raised global energy demand in recent years. Building consumes 35% of global energy. Reducing building energy consumption dramatically reduces energy imports. The relevance of building energy management and conservation has brought attention to energy consumption prediction research during the past 20 years. Accurate building energy forecasts help us analyze energy efficiency, commission buildings, and diagnose building system issues. Academics have developed many building energy usage prediction methods since the 1990s.

Based on algorithms and models, these tools may be categorized as engineering, AI-based, or hybrid. Engineers use physical ideas to calculate building component thermal dynamics and energy behaviors. This "white-box" strategy is renowned for understanding the rationale. The AI-based methodology examines a building's energy usage without comprehending its links, making it a "black-box" approach. The hybrid methodology, known as the "grey method," combines the white-box and black-box techniques to address their drawbacks. Both white-box and grey-box techniques need building data to simulate the inner link and generate the energy model. Existing buildings may be difficult or impossible to collect this information. Creating a building energy model takes time and expert work, making it difficult to utilize. AI-based energy prediction systems anticipate building energy demand based on ambient variables and occupancy. Since input data is easy to collect and calculations are fast, many researchers use AI-based algorithms to anticipate building energy consumption. (Foucquier et al. 2013) summarizes white-box, black-box, and grey-box building energy forecast methods.

This study examines AI-based building energy demand prediction research. AI-based building energy prediction techniques investigate multiple linear regression, artificial neural networks, support vector regression, and ensemble prediction models. Paper layout: Section 2 discusses AI-based prediction models. Section 3 discusses AI-based prediction system basics, merits, cons, and future possibilities. Section 4 concludes.

ARTIFICIAL INTELLIGENCE BASED PREDICTION METHODS

AI-based prediction comprises four steps. Figure 1 depicts an AI-based prediction architecture. Historical input/output data is the initial step. Input data affect output data. Day types, occupancy, weather, and global heat loss coefficient are examples. Output data reflects building energy usage. Buildings use power, gas, chilled water, and hot water. The research's prediction time scale samples inputs and outcomes from years to minutes. Data must be preprocessed before training the prediction model. The model may not use the original data. In this step, data transformation, normalization, and interpolation improve data quality and reduce negative consequences. Data training is the third step. Empirical modeling requires training before use since it learns from past data. Model parameters determine this phase. Careful parameter selection may ensure model performance based on the researcher's methodologies. Performance indicators, training data, and input factors affect parameter selection. Test the model last. This step will test the trained model's prediction capabilities by adding testing data. RMSE and R2 measure performance.

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.

Multiple linear regression

Principle:

Multiple linear regression (MLR) is an approach for modeling the relationship between a dependent variable and several independent variables.

Applications:

Due to its simplicity, MLR models are used to anticipate building energy consumption. Catalina et al. (2008) predicted residential building monthly heating consumption using regression models. Regression models use the building form factor, building envelope U-value, window-to-floor area ratio, building time constant, and climate, which is a function of sol-air temperature and heating set-point. The proposed domestic heating demand forecasting methods are simple and effective. Catalina et al. (2013) reduced the MLR model's inputs to three: the building's 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 showed that the proposed technique may properly predict future building heat demand. Jacob et al. (2010) improved the regression model by adding the interior air temperature change rate as an independent variable. Their analysis shows adding acceptable independent factors may improve MLR's performance.

Advantages and limitations:

MLR's simplicity comes from not having to change settings. Since it doesn't need accurate structural data, this method is successful and cost-efficient. MLR cannot handle nonlinear difficulties, which is a major drawback. MLR has been demonstrated to accurately anticipate long-term building energy consumption, but its short-term accuracy is unclear.

Artificial neural networks

Principle:

ANNs are nonlinear statistical learning methods inspired by biological neural networks. It approximates random functions by representing complex input-output interactions. ANNs have three connected layers: input, hidden, and output. Each layer has several activated neurons. The three parameters used to build ANNs are the interconnection pattern between neurons in different layers, the learning procedure for updating the interconnection weights, and the activation function that converts a neuron's weighted input to its output activation.

Applications:

Over the last 20 years, ANNs have been used to predict building energy demands such cooling, heating, electricity, and overall energy consumption. Ben-Nakhi and Mahmoud (2004) predicted commercial building cooling demand using GRNN. A well-designed GRNN can predict a building's cooling requirement based on outside temperature, according to their study. Ekici and Aksoy (2009) predicted three buildings' heating energy demands using BPNN. BPNN predicted building heating needs accurately and reliably in their investigation. Yokoyama and colleagues estimated building cooling demand using BPNN to improve prediction performance. To discover model parameters, they introduced the "Modal Trimming Method" global optimization approach. Li and colleagues used neural networks and a hybrid Genetic Algorithm - Adaptive Network-based Fuzzy Inference System (GA-ANFIS) to predict building energy demand (Li et al. 2011). Mena et al. (2014) predicted bioclimatic building electricity usage using a short-term predictive neural network model. Platon et al. (2015) used an ANN model to predict the hourly electricity demand of an institutional building. ANN algorithms predicted building energy use fast and correctly in both studies. ANN has also been compared to AI-based prediction methods. Farzana et al. (2014) predict urban household energy consumption using regression and ANN. Zhang et al. (2015) also predicted HVAC hot water energy utilization using one ANN model and three regression models. ANNs outperformed regression for short-term predictions in both tests.

Advantages and limitations:

The primary benefit of the ANNs technique is its capacity to recognize complicated nonlinear relationships between inputs and outputs implicitly. It is feasible to use it for real-time monitoring because to this quality. The inability of the ANNs approach to establish a link between building physical characteristics and energy consumption restricts the model's capacity to fit when modifications have been made to building systems or components.

Support vector regression

Principle:

According to Basak, Pal, and Patranabis (2007), the foundation of SVR is the calculation of a linear regression function in a high-dimensional feature space using a nonlinear function to map the input data. Finding a function f(x) that has the least deviation from the objective yi that was really acquired for all training data while still being as flat as feasible is the aim of SVR. The choice of kernel function is crucial for the SVR model since it influences both the SVR's capacity for learning and its capacity for generalization.

Applications:

Dong and colleagues originally utilized SVR to estimate building energy usage in 2005 (Dong et al. 2005). Four tropical commercial buildings were randomly chosen as case studies, and their monthly energy consumption was estimated using local meteorological data including the monthly mean outdoor dry-bulb temperature, relative humidity, and global solar radiation. Less than 4% relative inaccuracy was found. Li and colleagues (2009) used SVR to predict office building cooling needs hourly. Weather data such dry bulb temperature, relative humidity, and solar radiation intensity projected hourly cooling needs. SVR may be a viable solution for building cooling demand forecasting. SVR and other AI-based building energy prediction methods have been studied. Li et al. (2009) tested SVR with many ANN models to predict the building's hourly cooling needs. Massana et al. (2015) predicted non-residential structural short-term load using SVR, MLR, and ANNs. Both findings suggest that SVR predicts building energy better than AI-based methods.

Advantages and limitations:

SVR's optimization approach uses structural risk reduction to minimize the upper limit of the general error, not only the training error (Foucquier et al. 2013). SVR balances prediction accuracy and computation speed better than MLR and ANNs. SVR can forecast accurately with the appropriate parameters. SVR's downside is kernel function determination. The kernel with the best SVR is unpredictable. Researchers must determine the kernel function using data and understanding.

Ensemble prediction models

Principle:

Ensemble learning is a new data mining method that overcomes the limitations of individual prediction algorithms. This technique produces a composite model from many prediction models, making it unique. This system uses many prediction approaches to reduce prediction mistakes.

Figure 2 depicts ensemble prediction model structure. An ensemble prediction model usually includes two stages. The first step creates basic models, followed by a second phase that uses combination techniques to obtain the final product. Fan et al. (2014) suggest two critical variables for ensemble model prediction. First, each base model's performance affects the ensemble model. Thus, foundation models should function as accurately as possible. Second, base model diversity greatly affects ensemble model performance. Uncorrelated base models reduce ensemble model error.

Applications:

Due to its high prediction accuracy, ensemble learning has become popular in various industries. Siwek et al. (2009) developed an ensemble neural network method to properly predict power system demand. The ensemble model beat the top prediction model by 13% MAPE and 23% MSE. Melin et al. (2012) also predicted time series using two ANFIS ensemble models. Their ensemble models beat many statistical and neural network models in predictions. Kang et al. (2015) proposed a successful SVM ensemble for medicine failure prediction. According to experiments, the proposed method beats SVM ensembles in classification accuracy.

Since 2000, ensemble learning has been applied successfully in face recognition, medical diagnosis, and gene expression analysis (Dietterich 2000), but research into utilizing it to estimate building energy demand began in 2014. Fan et al. (2014) developed data mining-based ensemble models to predict peak power demand and the next day's energy consumption. This work trained eight prediction models as ensemble models. Multiple linear regression, ARIMA, support vector regression, random forests, multi-layer perceptrons, boosting trees, multivariate adaptive regression splines, and k-nearest neighbors were among these models. To reduce MAPE, a genetic algorithm (GA) calculated base model weights. The ensemble models predicted better than individual models. The authors noted that ensemble models can take use of most base model features to get the most accurate findings. An ensemble neural network model by Jovanovi et al. (2015) predicted daily heating energy utilization. Three artificial neural networks—FFNN, RBFNN, and ANFIS—form the ensemble model. Three methods—basic, weighted, and median-based—were employed to merge ensemble models. All neural networks predicted heating usage, and using an ensemble improved results.

Advantages and limitations:

An ensemble model improves forecast stability and accuracy. This advantage has three causes. First, training data may prevent selecting the optimal model. However, merging many models may eliminate their shortcomings. Third, the desired function may not exist. Since ensemble models include numerous base models, they need more skill and computing time than single prediction approaches. Another concern is the ensemble model's prediction performance reliance on base models. Researchers picked the basis model from a previous study. The ensemble model lacks a base model selection technique. This method must also predict construction energy hourly.

DISCUSSION

According to study, each AI-based prediction strategy has benefits and downsides, so users must pick the optimal one to solve their problems. MLR's ease of use and fast computation speed make it better at long-term energy demand forecasting. ANNs and SVR are superior for real-time monitoring due to their prediction accuracy. Table 1 compares many AI-based building energy forecast algorithms to help consumers choose one.

AI-based building energy prediction has been compared to other methods. Neto and Fiorelli (2008) examined EnergyPlus and ANNs for building energy estimation. ANNs predicted energy use better than EnergyPlus. Turhan et al. (2014) also used KEP-IYTE-ESS to anticipate building heating demand using an ANN model. The ANN model outperformed energy simulation methods in building energy forecasting. This paper lists the pros and cons of AI-based prediction methods.

Advantages

The benefits of AI-based prediction models include the following:

• Unlike engineering approaches, AI-based prediction methods don't need in-depth physical knowledge about the building. The process of data acquisition and data loading is reasonably simple, so the prediction model can be easily established.

• According to prior research, AI based prediction methods offer encouraging prediction accuracy once the model is well trained.

• This in turn saves both time and cost for conducting the prediction.

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)

Disadvantages

The drawbacks of an AI-based prediction model are as follows:

1. There is no explicit relationship between the physical building parameters and model inputs, making it impossible to extrapolate building energy performance once the design or operation of the building has changed.
2. 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 validated against existing data.

Future directions

To integrate AI into real-world applications, the application must be streamlined. Selecting input variables helps standardize data collection tools. Early studies used heuristics to determine how much data to use to train the model. Training data size research is lacking. Few studies examined how building occupants affect energy forecasting. Occupancy parameters like number of people, type of people, and activity type affect building energy use. Occupancy information research can improve forecast accuracy.

CONCLUSIONS

This research evaluates ensemble models of AI-based building energy forecast methods. AI-based prediction models include multiple linear regression, artificial neural networks, support vector regression, and ensemble models. Their ideas and applications have been investigated. This research covers each model's pros and cons. AI-based prediction models have been extensively debated. Each AI prediction approach has pros and cons.

The ensemble model, which uses many methods, balances pros and cons. The ensemble model's diversity must be preserved by deciding on the foundation model and how many base models to use.

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