Overview of the Application of Energy Consumption Forecast Models in Energy Efficiency Optimization

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Abstract: Energy consumption analysis, and energy demand forecasting and energy conservation effect evaluation based on such analysis are important bases for energy efficiency management. The wide application of AI machine learning methods in energy consumption forecasting not only expands the research route of energy consumption forecasting, but also provides a new perspective for energy efficiency optimization. The purpose of this article is to summarize the important applications of AI machine learning methods in the research of energy consumption forecasting -data-driven models and traditional forward models, and the comparison and application of the two types of models, and conclude the common application scenarios and technical routes of forecast models in the research of energy efficiency optimization so as to provide comprehensive model methods, application scenarios, forecast conditions and other multi-dimensional bases for energy consumption forecasting researchers. On this basis, the research questions and development needs in the research of energy consumption forecasting at the application and basic levels are raised herein.

1. Introduction
Building energy consumption analysis, and energy demand forecasting and energy conservation effect evaluation based on such analysis are important bases for energy efficiency management. For new buildings, accurate energy consumption evaluation in the preliminary design can optimize building and system design; for existing buildings, effective energy consumption analysis in the operation stage can optimize building operation management, and only by reasonably predicting energy consumption can building managers formulate suitable load management and energy-saving renovation plans, better tap the energy-saving potential, and improve the building energy efficiency.

With the widespread application of AI machine learning methods in building energy consumption forecasting, interdisciplinary methodology expands the research fields of building energy consumption forecasting, such as models, optimization and application of various data-driven methods, and also provides new perspectives for building energy efficiency analysis, such as comparison, combination and application of traditional energy consumption forecast models and AI algorithms. The purpose of this article is to summarize the important applications of AI machine learning methods in the research of energy consumption forecasting -data-driven models and traditional forward models, and the comparison and comprehensive application of the two types of models, so as to provide comprehensive model methods, application scenarios, forecast conditions and other multi-dimensional bases for energy consumption forecasting researchers.

Energy consumption analysis at different scales is conducted in different application scenarios, which means that the purpose and role of building load/energy consumption forecasting vary and depend on the time scale and spatial scale of the forecast object (energy consumption level). These
two dimensions directly determine the amount of effective information that can be obtained through the energy analysis of the current object. At the same time, the amount of effective information available and the requirements of application scenarios for forecasting accuracy determine the reasonable choice and model performance of forecasting methods.

Hahn[1] classified the building energy consumption forecasting into short-term forecasting (within one week), medium-term forecasting (one week to one year) and long-term forecasting (over one year). Based on the actual forecasting research, the time scales can be subdivided into one hour, one day, one month, one year, and one decade or above. At present, the spatial scale of energy consumption forecasting research is mainly based on stand-alone building and above. Figure 2 summarizes the application scenarios of energy consumption analysis and forecasting on different time scales and spatial scales (application level).

The amount of effective information available for energy consumption analysis at different scales and the accuracy requirements of application scenarios for forecast objects will affect the choice of forecasting methods and the effect of forecast models. The following section will focus on the building energy consumption forecasting methods and their application in building energy consumption forecasting at different scales to present an in-depth analysis of the current research status of building energy consumption forecasting.

2. Overview of energy consumption model
The mathematical model used to describe the building system consists of three parts[1]: input variables, including controllable variables and uncontrollable variables (such as meteorological parameters); system structure and characteristics, i.e., the physical description of the building system (such as the heat transfer characteristics of the building envelope and the characteristics of the air conditioning system); and output variable, i.e., the system's response to input variables, usually refers to energy consumption. After the input variables and the system are determined, the output variable (energy consumption) can be obtained. Building energy consumption forecasting methods can be divided into 2 categories according to their mathematical principles[2][3]: forward modeling methods based on physical meaning and data-driven methods based on AI algorithms. Forward modeling is to predict the output variable after the input variables, system structure and characteristics are determined, and to forecast and simulate building energy consumption by establishing physical models. At present,
forward modeling methods have been developed into a variety of building energy consumption simulation tools, including hourly energy simulation calculation engines such as DOE-2, BLAST, Energy Plus, ESP-r, and TRNSYS, and hourly energy simulation tools with mature user interfaces such as Design Builder, Energy-10, and eQUEST.

When the input and output variables are known, data-driven models use statistical analysis methods to estimate the parameters of the building system based on these existing data to establish a mathematical description of the system. In the AI field, common data-driven models that are applied in building energy consumption forecasting include: regression models, time series models, and machine learning algorithm models (such as artificial neural network (ANN) and support vector machine (SVM)).

ASHARE has two classification methods for common building energy consumption forecast models: 1) Steady-state models/dynamic models: Steady-state models do not consider the short-term transient effects of variables. Such models are suitable for load/energy analysis on a daily and greater scale; and dynamic models consider the short-term transient effects of variables and are suitable for building load/system control, fault diagnosis, etc. on an hourly or smaller time scale. Dynamic models are usually more complex than steady-state models, and require more measurement data and detailed physical information of equipment and buildings to make adjustments; 2) Empirical models/grey models/verification simulation: Empirical models are mapping relationship models established between the measured energy consumption and its impact factors based on statistical methods, and are suitable for the energy conservation analysis of actual buildings in demand-side management, benchmark evaluation in energy conservation improvement, etc. Verification simulation is to determine more accurate input parameters based on the actual measured energy consumption of the existing physical model of the building, so that the output result is closer to the actual energy consumption of the building. This type of model can be used as a benchmark model in energy conservation improvement for comparison of improvement schemes, or as an optimization tool for energy conservation potential analysis of operational strategies. [2][4][5].

3. Data-driven models and their application
Data-driven energy consumption models are an interdisciplinary application of statistics, machine learning and other methods in the field of building energy consumption forecasting. The technical
route of this type of research is mainly to use data analysis methods to establish building energy consumption forecast models. Previous studies focused more on model methods and their forecasting performance and comparison. A great number of data-driven methods can build energy consumption forecast models independently or in combination with other methods, including forward modeling and optimization methods. However, there is currently a lack of generalization and summary based on the optimized application of building performance so that most researchers in the field of architecture can only choose forecast methods from the available research experience and the complexity of the model methods.

From the perspective of optimized application of building energy efficiency, how to apply data-driven methods to forecast building energy consumption depends on the time accuracy of their forecasting results.

1) Hourly forecast for the operation optimization of the energy system of stand-alone buildings. For example, the hourly load of the building/system is forecasted according to the measured operation data to optimize the control of the operation sequence of the energy system.

2) Daily forecast for the safe and economic operation of stand-alone buildings. For example, the load curve of the next day is forecasted according to the measured energy consumption data to achieve the demand forecast response.

3) Monthly forecast for the energy cost budget of stand-alone buildings. For example, the building load/energy consumption cycle trend curve is established according to the measured energy consumption data to predict the monthly energy cost taking into account weather and other influencing factors.

4) Yearly forecast for the analysis of energy conservation improvement of stand-alone buildings. For example, the energy consumption model of stand-alone buildings is verified according to the measured energy consumption data to compare the energy conservation effects of various improvement measures.

5) Yearly forecast for the design optimization and performance evaluation of a certain type of buildings. For example, the batch simulation calculation results of the model for a certain type of typical buildings are used as the training data of data-driven model to establish the statistical relationship between building design parameters and energy consumption to quickly evaluate and optimize the building design with the annual energy consumption as the target.

6) Long-term forecast for energy use decision of a certain type of buildings. There are two types of research routes for this scenario: direct forecasting and indirect forecasting. Direct forecasting is to establish a statistical relationship model between building energy consumption and long-term climate based on historical data. Weather parameters in climate change scenarios are used as input values of the model to directly predict future building energy consumption. Indirect forecasting is to separately establish typical building models and future weather parameter files in various development scenarios. Future weather parameters are used as input values of the verified typical model to predict long-term energy consumption changes through simulation. Indirect forecasting involves two parts of model application: the verification simulation of typical building models and the time series forecasting of future weather parameters.

3.1. Time series model

Building systems have huge inertia, so the building load/energy consumption at the next forecast moment is largely related to the value at the current moment. Therefore, considering a certain degree of randomness, the time series method can be used to establish an effective and accurate building energy consumption forecast model. It seems that this analysis method represents the spontaneous change of the dependent variable (building load/energy consumption) over time, while it actually reflects the comprehensive influence of various factors on the dependent variable (weather conditions and physical characteristics of buildings). When the time series method is used for forecasting, the past records selected should be as close as possible to the forecast moment, and the more detailed the past historical records are, the easier the study will be. Generally speaking, the monitoring data of
load/energy consumption are sampled and recorded at a certain time interval, while the requirement for the sampling time interval depends on the time accuracy of the forecast object.

At present, most studies use TSM to forecast urban energy consumption demand for the optimization of energy supply systems, such as power grid systems\[6\][7][8][9], urban natural gas pipeline networks\[10\], regional cooling and heating systems\[11\] and renewable energy supply systems in smart grids\[12\]. Although there are relatively few applications of TSM in energy consumption forecasting of stand-alone buildings, there are no shortage of successful cases. Some scholars introduced physical characteristics of buildings and personnel usage data into traditional TSMs, making TSMs more flexible when used for load/energy consumption analysis of stand-alone buildings. Newsham et al.\[13\] focused on the impact of personnel changes and introduced construction personnel data into the ARIMA model, improving the accuracy of the model. Zhou et al.\[14\] decomposed trend items, seasonal factors, and irregular factors based on the original series of energy consumption data; established a combined time series model for the seasonally adjusted trend cycle items, and introduced influencing factors that affect building energy consumption to perform physical regression fitting of seasonal factors and irregular factors; and finally combined the established time series model and the regression fitting model to obtain the ultimate building energy consumption forecast model. In addition, some studies combined traditional TSM methods with other data-driven models\[15\], physical models\[16\] or optimization methods \[8\]. In this type of studies, TSM models mainly describe the temporal characteristics of building energy consumption, while other data-driven models and physical models focus on simplifying the complex characteristics of building energy systems.

3.2. Machine learning models
As the most widely used AI models in the field of building energy consumption forecasting, artificial neural networks (ANNs) use known samples to build machine learning models, improve the parameter estimation process of traditional methods, and can effectively solve nonlinear and complex problems. An ANN is an arithmetic model composed of artificial neurons. An artificial neuron is obtained through the simulation and abstraction of a biological neuron, which is equivalent to a non-linear threshold device with multiple input values and a single output value. Different connection methods, weights, and excitation functions will generate different network output values. An ANN itself is usually an approximation of a certain algorithm or function in nature, while it can be an expression of a logic strategy. With the abilities of self-learning, contact storage and high-speed optimization ANN can realize parallel and distributed data processing.

Three aspects are mainly included in the description of an ANN model: neuron structure, neural node transfer function and learning algorithm. In practical applications, ANNs can be classified into multiple categories from different perspectives. From the perspective of network structure, they can be divided into forward network and feedback network; from the perspective of network performance, they can be divided into continuous and discrete, deterministic and random networks; from the perspective of learning methods, they can be divided into supervised learning networks and non-supervised learning networks; from the perspective of the nature of connection synapses, they can be divided into first-order linear association networks and high-order nonlinear networks. Among the various ANN models that have been continuously proposed and improved by many scholars, BP neural network (error backpropagation neural network) is most widely used in pattern recognition, adaptive control, image processing, language recognition, etc. The learning algorithm used by the BP model is a modification of the least mean square (LMS) algorithm. Its essence is to solve the LMS error, based on which the weights of the multilayer feedforward network are adjusted. In addition, several other commonly used ANNs include perceptron, Hopfield neural network, radial basis function network and competitive neural network.

In addition to ANN, support vector machine (SVM) is a machine learning method proposed by Vapnik and Cortes in 1995, based on the statistical learning theory. This theoretical system seeks to obtain the best results with limited information, provides a unified framework for solving the problem of learning with limited samples, and solves the problems of neural network structure selection and
local minima. Therefore, SVM shows obvious advantages in solving small sample, nonlinear and high-dimensional pattern recognition problems. SVM seeks an optimal classification hyperplane that meets the classification requirements by minimizing structural risks, so that the hyperplane can maximize the blank area on both sides of the hyperplane while ensuring the classification accuracy. In theory, SVM can achieve optimal classification of linearly separable data. Originally designed to solve classification problems, SVM has been successfully applied to many problems such as regression and pattern recognition, and gradually promoted in forecasting and comprehensive evaluation fields and disciplines, such as short-term traffic demand forecasting \[17\][18], power load forecasting \[19\][20][21], fault diagnosis, text recognition, handwritten font recognition, face image recognition, gene classification and time series forecasting. In the development process of the past 20 years, ANN/SVM models have been used to analyze building cooling and heating loads \[22\][23] and forecast energy consumption \[24\][25]. Of the two, ANN models require a larger amount of training data, so they are more used in short-term forecasts such as daily and hourly forecasts to avoid an overlong measurement interval.

4. Model problems and analysis

4.1. Application level

The analysis of factors affecting building energy consumption at the beginning of the energy crisis in the 1990s made a breakthrough for the research of building energy consumption forecasting and energy efficiency optimization. There are not only macro-energy consumption influencing factors based on the entire city, but also micro-energy consumption influencing factors based on stand-alone buildings. Similar sensitivity analysis conclusions are relatively simple and often limited to some influencing factors. For example, the impact of other variable influencing variables on building energy consumption is studied for a certain area (fixed meteorological parameters) \[78\], or for a certain type of AC systems \[69\], or for fixed buildings (fixed weather parameters and system types) \[79\]. With the development of simulation tools and algorithm development technologies, most recent research on building energy consumption forecasting (such as the algorithm development, performance comparison and integrated application of various building energy consumption prediction models) directly follows the conclusions of the sensitivity analysis of building variables in the early years, and focuses on model methods.

The existing building energy consumption forecast models can be summarized as forward modeling and data-driven models. The modeling processes of the two types of models have higher requirements on basic data; this often leads to higher measurement and time costs. More critically, as basic theoretical support and application method guidance are generally lacking in the construction of existing energy management systems, accurate key and effective information can hardly be obtained, and massive redundant data monitoring has increased the difficulty of analysis on the contrary. Due to limited building and energy efficiency information, it is not easy to build an effective and usable analysis and forecast model that fits the actual building to support the optimization of building energy efficiency. At the same time, most of the existing studies focus on forecast methods and model comparisons, select forecast models or methods that researchers use skillfully, follow the variable selection and conclusions in previous studies, use established related variables to forecast energy consumption, and compare the forecasting accuracy and applicability of different model methods based on measured energy consumption data. In similar studies, variable selection fails to be combined with energy use analysis. Choosing established variables may miss key available variables with the characteristics of building energy consumption, and may also bring in variables with interference effects. Both may reduce the accuracy and timeliness of the forecast model, and the credibility of the empirical results.

4.2. Basic level

The analysis of model variables/features in building energy consumption forecasting research is a basic problem that does not match the mature development of various building energy consumption
forecast model methods. Accurate forecast of the two types of model methods depends on sufficient effective data. For forward modeling, the effective calculation depends on the user's professional knowledge and detailed input parameters. The lack or deviation of parameters will have a greater impact on the accuracy of the calculation results. Model variables are very important for data-driven models, especially for machine learning models. The number of variables and the effective information they represent will directly affect the accuracy, calculation speed, generalization ability, and other performance of the model. However, it is generally difficult to obtain complete basic data in the actual model building process. Although the whole industry has recognized the importance of basic data information, and various energy management platforms are emerging continuously, most of them focus on statistics such as operation and energy consumption data and development of systems such as architecture and interfaces, and lack of in-depth data insight, information mining, and analysis applications. The high-cost, low-availability and low-operability systems fail to effectively improve building data information management and relevant building energy efficiency optimization. This is not only a waste of research resources, while more importantly, such insufficient data is still hindering building performance evaluation, energy consumption forecasting, and energy-saving potential mining.

5. Conclusion

Energy demand forecasting and energy conservation evaluation are important contents of building energy efficiency management. Many factors have an impact on building energy consumption, determining the complexity of building energy consumption analysis and forecasting. Multiple analysis scales and application scenarios involved in building energy consumption forecasting are summarized herein. In different application scenarios, the role that building energy consumption forecasting can play is closely related to the time and space scale used in the forecasting, which depends on the amount of effective information available in the research. At the same time, the amount of effective information available and the requirements of application scenarios for forecasting accuracy determine the reasonable choice and model performance of forecasting methods.

Based on the insight that the modeling process of the existing two types of models has a higher requirement on effective basic data, the author proposes that considering the current situation where effective building data information is generally insufficient, in-depth exploration of the model variables in building energy consumption forecasting can help accurately forecast building energy consumption with limited data, while providing a more universal analysis basis for the performance comparison of existing model methods.

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