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A Review of Load Forecasting of the Distributed Energy System

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Abstract. With the development of global intelligence industry and new energy systems, the role of load forecasting is increasingly prominent. This article reviews the research progress and applications of load forecasting technology. How to improve the accuracy and speed of load forecasting is the current research hotspot, and this paper comprehensively summarizes the influencing factors for the performance of load forecasting such as various input parameters and load forecasting models. Besides, this paper reviews evaluation indicators of load forecasting, three different sizes' buildings as typical cases. Finally, three research trends in this field are summed up: deep learning, predictive measurement, and combination with occupant behavior prediction.

1.Introduction

In the background of the energy Internet, the topology of the energy system tends to be diversified, and the matching of the supply and demand side is more demanding. The role of load forecasting is becoming more and more prominent. In order to ensure the stability of the energy system in operation, fast and accurate load forecasting is particularly attracting people's attention. The load forecasting technology commonly used in the present stage is based on the load forecasting factors and historical data, and the load forecasting model is established to get the load forecast value in a certain time period, and input to the operation and scheduling platform. The platform is adjusted according to the load forecasting results to optimize the system operation. This paper gives an overview of the classification and process of load forecasting, and then a comprehensive analysis of the work is done on how to improve the performance of load forecasting and how to improve the load forecasting factors and the improvement of the load forecasting model in the last few years. Besides, this paper reviews evaluation indicators of load forecasting, three different sizes' buildings as typical cases. Finally, three research trends in this field are summed up: deep learning, predictive measurement, and combination with occupant behavior prediction.



2. Load forecasting performance

How to improve the performance of load forecasting, such as precision, speed and stability, has become a hot spot in the research of load forecasting. The factors that affect the performance of load forecasting are reflected in many aspects. From the view of modeling, the proper selection of input parameters, models and algorithms have great influence on the performance of load forecasting. So Improving the load forecasting performance from the perspective of load forecasting parameters and load forecasting models are necessary. This paper emphasis on the intelligent load forecasting method, the typical model of which such as the artificial neural network and support vector machine are expounded in order to provide more ideas for the reader to improve the performance of load forecasting. Finally, a variety of load forecasting evaluation indicators are summarized.

2.1. Load influence factors

As the application body of energy system, the load time series of buildings is a multidimensional nonlinear complex variable. It is affected by its own attribute parameters, meteorological attribute parameters and operation attribute parameters. It has chaotic characteristics and is difficult to predict accurately. Therefore, in the research and practical application of load forecasting, all kinds of influence parameters contained in the time series should be considered comprehensively.

1) The property parameters of the building are the characteristic parameters of the building itself. In the study, the area, floor, window and wall ratio, orientation, window wall thermal performance, new wind volume and personnel density are commonly used in the study.

2) Weather parameters include outdoor temperature, humidity, solar radiation intensity, wind speed, rainfall and so on.

3) The operation parameters are closely related to the function of the building, including the working time of the building, the personnel density, the personnel activity, the human comfort and so on, which not only have certain periodicity, but also have great randomness.

2.2. Load forecasting model

In recent years, the research methods of building load forecasting have been developing continuously, and the research field has been deepened. The prediction modeling method is divided into the forward modeling method and the data-driven method based on whether the building physical model. The former is commonly used in new buildings, and the latter is often used in existing buildings. the forward modeling method is often used in the load forecasting of new building or air conditioning design stage, and it exposes many problems for the load forecast during the operation stage. For example, the workload of modeling is too large, the process is cumbersome, and a large number of parameters need to be input, and the professionalism of software is too strong. Except for simulation modeling, it is necessary to input a large number of influence parameters, and it is very difficult to obtain all parameters in practice. The method of data driving is to fit the mapping relationship between "input" and "output" by mining modeling to realize the accurate prediction of the load at a certain time in the future. This method is suitable for load forecasting in the running stage. It is simple in operation and has high prediction precision. It can be divided into three main categories: classical load forecasting models, traditional load forecasting models and load forecasting models. The representative algorithm of the three methods is shown in Table 1. For long-term load forecasting, the second, the third and the fifth one and so on are suitable. For medium-term load forecasting, the commonly used algorithms are the second, the third and the sixth one. As for short-term load forecasting and ultrashort-term load forecasting, intelligent forecasting method has obvious advantages and has become a research hotspot.

Table1. Typical load forecasting mode

Category	Designation	Description	Application
Classical load forecasting method	Regression analysis method	The theory is simple and the speed is fast. However, the requirement for comprehensiveness and accuracy of historical data is high. It is difficult to obtain reliable results in dealing with nonlinear complex problems.	[2]
	Time series method	The principle is simple and practical and effective, but it can only describe the linear model and has some limitations.	[3]
	Trend extrapolation	The research objects have strong dependence on the reasonable selection of trend models.	[5]
Conventional load forecasting forecasting	Calman filter method	Using the linear system state equation to reduce the noise and restore the real data, it has good results for the invalid data processing, but it is difficult to obtain the statistical characteristics of the noise in practice.	[4] [6]
	Grey forecasting method	The load data and statistics requirements are low, but only when the load data change rule is close to exponential type, can we achieve ideal results.	[7] [8]
Intelligent load forecasting prediction method	Artificial neural network method	It has strong nonlinear mapping ability and self learning ability.	[9]
	Support vector machine	It has strong nonlinear processing ability and fast convergence speed, but it has poor computational performance for large amounts of data.	[10]

Artificial neural networks (a typical model of which is showed in figure 1(a)) have strong ability to learn and generalize, and the related load forecasting methods have become the focus of research, especially in short-term and ultra-short term load forecasting. Support vector machine (SVM) plays an obvious advantage in the problem with small samples, multidimensional, nonlinear identification and prediction, whose structure is showed in figure 1(b) Although the traditional artificial neural network and support vector machines have strong nonlinear prediction ability, they also expose many deficiencies. With the emergence of big data, BP neural network and support vector machine will have many problems such as long iteration time, poor prediction accuracy and difficult model determination. At present, a large number of scholars have made many attempts to solve these shortcomings, and are trying to explore a more efficient and superior load forecasting model. The general practice summed up by the author includes:

- 1) On the basis of traditional algorithms, the parameters such as weights and thresholds are corrected;
- 2) secondly, intelligent algorithms, such as particle swarm optimization, artificial fish swarm algorithm, frog jumping algorithm, etc.
- 3) combined with the traditional methods such as decision tree, linear model, Bayesian theory, random forest and other traditional methods.

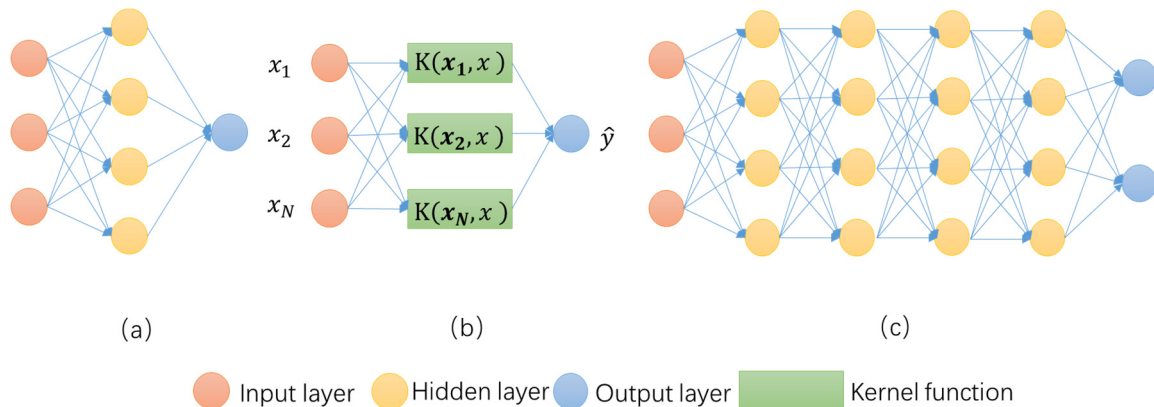


Figure 1. The structure of typical load forecasting models

(a) BP neural network structure (b) support vector machine structure (c) deep learning

Table 2. Research status of load forecasting model improvement

Time	Author	Model	Time scale	Load category	Feature
2016	Wang Ning etc. [11]	Support vector machine regression combined model	Medium-long term	Cooling and heating load	Fine stability of prediction effect
2016	Ou Zhou etc. [12]	Fuzzy grey clustering and bp neural network based on wavelet decomposition	Short term	Electrical load	High precision
2017	Liu Jinrui [13]	Ga-bp neural network	Short term	Electrical load	Optimize connection weights to avoid falling into local optimization
2017	Chen Ya [14]	Artificial fish school algorithm -elman neural network	Short term	Electrical load	The initial weights and thresholds are optimized, and the training speed is fast and the accuracy is high
2017	Chen Yu etc. [15]	Particle swarm optimization - limit learning machine	Short term	Electrical load	High precision
2017	Chen etc. [16]	Cuckoo search algorithm -wavelet annes	Short term	Electrical load	Eliminate noise optimization parameters
2017	Sun Hairong etc. [17]	Secrpso-svm	Short term	Electrical load	Balance global and local search capabilities
2017	Huang Qingping etc. [18]	Fuzzy clustering and random forest	Short term	Electrical load	Ensure the consistency of input characteristic quantity, simplify model, high precision

2.3. Accuracy evaluation index

The prediction effect of load forecasting model is measured by relative error(RE), mean absolute error(MAE), mean square error(MSE), root mean square error (RMSE) , mean absolute percentage error(MAPE) and so on. The most commonly used indicators were MAE, MAPE and RMSE.

Table 3. Evaluation index expression and its description

Name	Expression	Description	Reference
Relative error	$e = \frac{L - \hat{L}}{L}$	Reflecting the deviation from the true value of the predicted value	[3]
Mean square error	$MSE = \frac{1}{n} \sum_{i=1}^n (L_i - \hat{L}_i)^2$	Because the deviation is absolute, there will be no positive and negative cancellation	[19]
Mean absolute error	$MAE = \frac{1}{n} \sum_{i=1}^n \left \hat{L}_i - L_i \right $	The average absolute error can better reflect the actual situation of the prediction error	[16]
Mean absolute percentile error	$MAPE = \frac{1}{n} \sum_{i=1}^n \left \frac{\hat{L}_i - L_i}{L_i} \right \times 100\%$	It is used to measure the prediction results of a model. When the value is less than 10, the prediction accuracy is high.	[16] [20]
Root mean square error	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\hat{L}_i - L_i \right)^2}$	Used to measure the deviation between the predicted value and the true value.	[16] [21]

3. Application Practice

Due to the development of intelligent buildings and smart grids, building to grid (BtG) integrated systems have become common. Because of the changes in energy topology of various new energy systems, it is urgent to combine construction with smart grid operation to meet the flexible demand for load control. Intelligent building can change its overall demand pattern to cope with the operation of distribution system, thereby contributing to the stability of power grid.

1) small buildings

As shown in Figure 2, the structure and load forecasting model of a building renewable energy system in Tianjin studied by our research group. The architectural model information comes from a physical building in Tianjin Binhai New Area, with a total area of 270 m², with a floor area of 90 m², and three-story family residential buildings. The energy system consists of three parts: supply side equipment, demand side equipment and control system. The supply side equipment consists of photovoltaic, wind power, battery and power. The demand side equipment is made up of building and electric vehicle rechargeable batteries. The cooling and heating load of the building system is supplied by an electrically driven air source heat pump. Besides, it also includes the electrical load of household appliances. The load forecasting process selects the BP neural network as the load forecasting model, and input the historical load, weather data and day type at its input end to get the load value of the day in the future, and then control the unit and equipment by the scheduling platform. The prediction process chooses MAPE as the evaluation index, and the result is 9%.

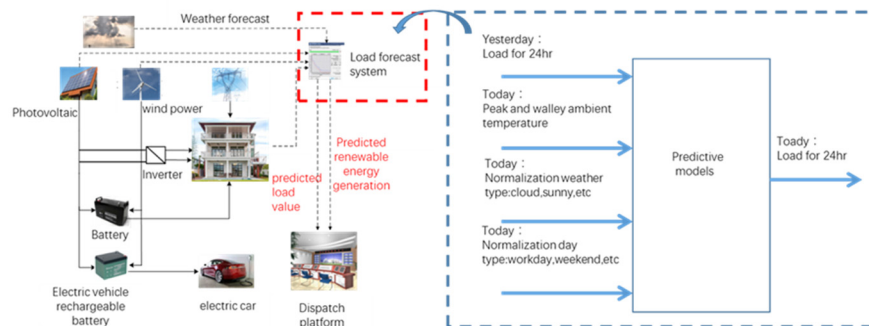


Figure 2. System and load forecasting model of an energy station in Tianjin

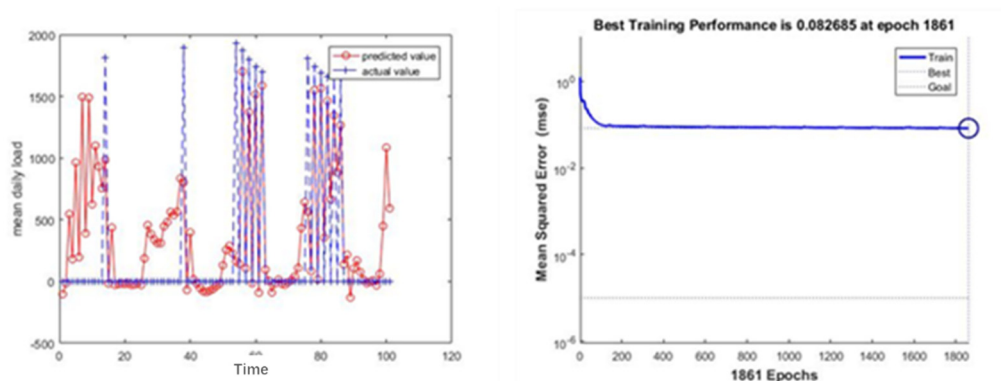


Figure 3. System and load forecasting model of an energy station in Tianjin

When one unit runs normally, the other is on standby. During the heating season, the HVAC system runs 24 hours a day. The result of load forecasting is shown in Figure 3.

2) Medium-sized buildings

The case is [22], a commercial office building in Tianjin. The building is composed of four floors and a ground floor. The total building area is 8677 square meters. The one or two floor of the building is the reception and exhibition hall, the three or four floor is the office area, the bottom is the restaurant and garage area. The office hours are from 9:00 to 18:00. The HVAC system is maintained and monitored through the building energy monitoring platform (BEMP). The heat source is two screw type ground source heat pump units. The amount of customized heat is 348.8 kilowatts. In daily operation. Building structure and load forecasting models are shown in figures 4 and 5.

The data used in the load forecasting model are hours of heat load, indoor and outdoor dry ball temperature, indoor and outdoor relative humidity, solar radiation and wind speed, population and lighting and office equipment consumption. The prediction process uses the multi-layer perceptron neural network (MLP) and support vector regression (SVR) to establish a short-term heating load and a super short-term heating load forecasting model to predict the heating load for the next 24 hours and the next 1 hours. The average relative error (MRE) of short-term heating load and ultra short term heating load prediction model is 10.7% and 6% respectively.



Figure 4. Building and meteorological station

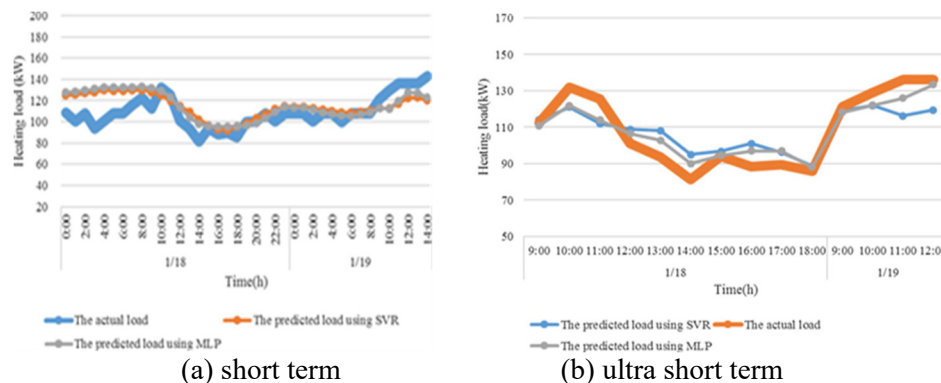


Figure 5. Load prediction results using MLP and SVR

3) Regional buildings

In the case of [23], a planned business district in Shanghai, it plans to use three energy stations to meet the load needs of the business district. The total building area of the business area is 3 million 120 thousand square meters. Among them, 1# energy station takes 960 thousand m^2 , and is divided into 3 phases, 2# energy station takes 830 thousand m^2 , 3# energy station takes 1 million 330 thousand m^2 . By analyzing the load leveling rate of different mixing degree, the configuration energy system can be used in an efficient interval, improving energy utilization rate, reducing energy consumption, and providing advice to planners for building group planning.

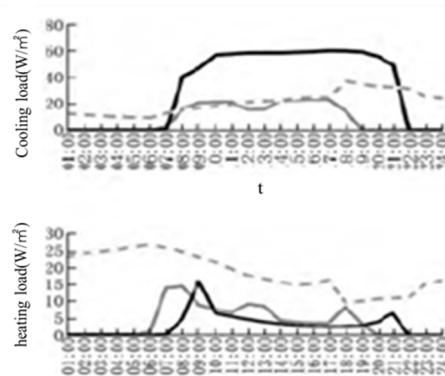


Figure 6. Average heating and cooling load in heating period and cooling period

According to the urban planning information, the related building energy conservation design standards and standards and field investigation, the typical model of different functional buildings is set up, and the load of the single building is obtained, and then the load of the regional building group is expanded. Using software simulation and scenario analysis to predict the load of regional buildings. Taking 1# energy station as an example, through scenario analysis, the 3 types of office buildings, shopping malls and hotels in the planning documents are allocated. The leveling of load of mixed functional buildings is analyzed, and the best proportion of office buildings, shopping malls and hotel buildings in business district is 0.5, 0.1 and 0.4 respectively. The load forecast diagram is shown in Figure 6.

4. Frontier

4.1. Deep learning

At present, most load forecasting models focus on the shallow learning level. With the increasing trend of data, the scale of the model, and the increasing accuracy and complexity of the model, the mapping ability and generalization performance of the shallow learning model are very limited. The depth learning model has been successfully applied to the fields of speech recognition and image

processing because of its good expressiveness, robustness and generalization, and it also plays a role in the field of prediction.

4.2. Predictive measurement

The deployment of load forecasting technology is dependent on the collection, integration of a large number of monitoring data, network analysis and data mining. With the extensive use of intelligent, digital, networked sensors and measuring instruments, massive heterogeneous data have been produced. For example, sensors such as temperature and humidity which can monitor meteorological data in real time, while smart meters provide a large amount of load data for data mining. Therefore, how to improve the performance of predictive instrumentation to obtain more accurate and effective data is very important for load forecasting.

4.3. Random behavior

When carrying out load forecasting, the randomness and uncertainty of indoor personnel behavior pose a great challenge to the prediction accuracy. At present, there are two kinds of research on indoor personnel behavior at home and abroad: office workers and housing personnel. The research on the random behavior of building energy can be divided into personnel movement behavior and personnel energy use behavior. The person's movement behavior refers to what room in which people are in, and the behavior of personnel energy use is to study how the indoor person use all kinds of equipment [24]. For the cold and hot load of the residential building, the mode of air conditioning, the ventilation mode in the room and the heating mode of the indoor personnel and equipment are the main factors affecting the load. Many typical behavior characteristics such as lighting, switch windows, office equipment, sunshade and louver are selected for the study of office personnel behavior. In order to obtain a more accurate and comprehensive model of personnel behavior, the practice adopted at home and abroad is to collect and extract the measured data, then use statistical methods to analyze the behavior patterns of people, and then establish the behavior model based on the measured data.

5. Conclusion

In this paper, the influence parameters, modeling methods, international typical cases and the trend of frontier research in the frontier of load forecasting are summarized and analyzed, and the following conclusions are drawn:

- 1) Load forecasting has become a very important link in a new type of power supply and distribution system. Its precision directly affects the matching and stability of the two sides of supply and demand. How to improve the precision of load forecasting has become the focus and hot spot of research.
- 2) It is very important to improve its performance, especially the precision. It can be based on the influence factors of load forecasting, load forecasting model and so on. The commonly used evaluation indexes are MAE, MAPE and RMSE.
- 3) In order to improve the performance of load forecasting, based on the above two aspects (influence parameters and models), the trend of the frontier includes: Improve the performance of smart sensors to improve the accuracy of input parameters. The load forecasting model is optimized by deep learning and indoor personnel behavior model.

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