Research on Short-term Power Load Forecasting Method Based on Temperature Accumulation Effect Embedded in Time Series

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Abstract. Short-term power load forecasting is an important link in power grid dispatching, which has an important impact on unit combination, economic dispatching, optimal power flow, etc. As meteorological factors have great influence on load, the influence of meteorological factors should be considered reasonably in short-term load forecasting. The accuracy of short-term electric charge prediction results can help senior personnel of the power system to make accurate and feasible power operation methods. In order to ensure the safe and stable operation of power grid in various special periods and to ensure the economic benefits of related power enterprises to the greatest extent, it is imperative to establish a highly accurate prediction model. The accuracy of power load forecasting will directly affect the position of each power enterprise in the market. Based on the function of time series embedding, this paper analyzes the rule of cumulative effect on load. The correlation between temperature and load is greatly improved after considering the cumulative effect to deal with temperature correction.

1. Introduction
Short-term load forecasting is an important link in power grid dispatching, which has an important impact on unit combination, economic dispatching, optimal power flow, etc. Improving the accuracy of load forecasting is conducive to improving the utilization rate of power equipment and reducing the risk of power grid operation. Short-term load forecasting of power system usually refers to forecasting the power load index for one month, one week or one day in the future. It plays an important role in real-time control of power system and ensuring economic, safe and reliable operation of the system [2]. Short-term power load has strong nonlinear characteristics, and its changes are affected by many factors, and many factors cannot give the influence weight quantitatively [3]. The accuracy of short-term electric charge prediction results can help senior personnel of the power system to make accurate and feasible power operation methods. In order to ensure the safe and stable operation of power grid in various special periods, and to ensure the economic benefits of related power enterprises to the greatest extent [4]. There are many factors that affect the accuracy of load forecasting, including the change rule of load itself, the level of economic development in the region where it is located, the structure of electricity consumption, the level of electricity price, and climate change [5]. Different power load structures and climatic conditions in different regions lead to different load changes [6]. Therefore, the change in short-term load shows a certain degree of unpredictability, which is exactly the problem to be solved in the current short-term load forecast.
With the continuous development of the economy and the continuous improvement of people's living standards, high-power and high-energy-consuming appliances are becoming more and more popular, and the proportion of cooling and heating loads in the total electricity load is increasing. [7]. Among the many factors that affect load changes, meteorological factors are the main factors. Among the meteorological factors such as temperature, humidity and precipitation, the influence of temperature is the main factor. The change of power load is a non-linear function related to many factors. Because the traditional algorithms of load forecasting, such as the traditional time series method, cannot consider the non-linear influence of weather on the load, it is predicted in the face of sudden weather changes or sudden events. The error is large [8]. The short-term power load forecast is not only closely related to the average temperature of the day, but also has a great relationship with the temperature of the previous days [9]. The accuracy of power load forecasting will directly affect the position of each power company in the market, so it is imperative to establish a highly accurate forecasting model. In order to further improve the accuracy of load prediction, this paper combines the effect of time series embedding to analyze the influence of cumulative effects on load. The cumulative effect has different strengths in different situations. After considering the cumulative effect on the temperature, the correlation between temperature and load is greatly improved.

2. Typical Phenomenon of Cumulative Effect Affecting Load.

If a place is in high temperature for a long time, the load in this area will be at a higher level. In this case, even if the temperature drops, the degree of load reduction is not obvious, and may even rise instead of falling. There are many factors that affect short-term load. Due to the fact that relevant information is often not available before prediction and the degree of influence of some factors on load is very complex, it is unrealistic to consider all factors. Due to the uncertainty and locality of the change trend of humidity, wind force and rainfall, the impact on the total load in the area with large coverage area is uncertain on the whole [11]. Most of the current short-term load forecasting methods consider external factors such as meteorology and major political events, and the important influence of meteorological factors on short-term load forecasting has reached a consensus. Human senses have a process of adapting to temperature changes, which is the root cause of cumulative effect. The higher the proportion of air conditioning load, the more obvious the cumulative effect of air temperature, which is manifested as cumulative effect under the condition of continuous high temperature and cumulative effect under the condition of continuous low temperature. As the daily maximum load is not only affected by the daily maximum temperature, but also by other factors, such as holidays and week types. In this way, in the analysis process, the data on holidays and weekends must be eliminated first.

According to the close relationship between daily maximum load and daily maximum temperature, a quadratic regression model between daily maximum load and daily maximum temperature can be initially established:

\[ L = at^2 + bt + c \]  

Where: \( L \) is the daily maximum load, MW; \( t \) is the daily maximum temperature, °C; \( a, b, \) and \( c \) are coefficients to be determined.

It can be seen from Fig. 1 that the daily maximum load and the daily maximum temperature change trends in summer are very similar, which indicates that temperature is one of the important factors affecting the load change. Some peaks or valleys of the two curves do not overlap in time series. The specific manifestation is that the load change lags behind the temperature change, which is the so-called cumulative temperature effect. The cumulative temperature effect refers to the phenomenon that the human senses have an adaptive process to temperature changes, and the daily load change to be predicted lags behind the temperature changes. In order to improve the fitting accuracy of the regression model, it is necessary to consider the cumulative effect of temperature.
Fig. 1 Curve of daily maximum temperature and daily maximum load of the power system

For provincial power grids in relatively large areas, the regional power grid has small capacity, the overall meteorological conditions and change trends are relatively consistent, the load composition is relatively simple, and the influence factors of power grid load by temperature are more obvious. Under the continuous high temperature or cool weather, when the temperature changes suddenly, the degree of load change is not obvious due to the influence of the temperature for several days before. Among the meteorological factors, the main factors that affect the load are temperature and climate [12]. The influence of temperature on load is not only related to random climatic factors such as sunshine, shade and rain, but also related to factors such as temperature level, rise, threshold value, specific time of change, duration of action, etc. Generally speaking, the occurrence of cumulative effect of temperature needs to meet the condition that the daily temperature to be predicted is in the temperature range where human body feels more sensitive.

3. Considering the Cumulative Effect of Time Series Embedding

3.1. Factors Affecting Cumulative Effect Intensity

The cumulative effect intensity is different under different conditions. Using temperature correction value to reflect cumulative effect can not only reflect the impact of cumulative effect on load, but also make full use of existing load forecasting methods. Research shows that when the average temperature is higher than 20℃, the temperature and load show a positive correlation. In other words, for central China, the influence of temperature and temperature accumulation on load can only be reflected in high temperature period. For example, Table 1 shows the correlation between daily summer load and temperature in a certain area.

| Temperature category | Maximum load | Minimum load |
|----------------------|--------------|--------------|
| Mean temperature of air | 0.775 | 0.763 |
| Maximum air temperature | 0.791 | 0.584 |
| Minimum air temperature | 0.736 | 0.536 |

There is a good correlation between the maximum load and the highest temperature in this area. Similarly, similar conclusions can be drawn from the analysis of the average temperature, the highest temperature and the lowest temperature. In order to explore the influence of temperature accumulation effect on daily load, the highest load and temperature data for several consecutive days in summer in this region were selected from historical data and Table 2 was formed.
Table 2 Summer daily load and temperature data in a certain area

| Date | Maximum load /MW | Minimum load /MW | Maximum temperature /℃ | Average temperature /℃ |
|------|------------------|------------------|-------------------------|------------------------|
| 8-1  | 631.5            | 402.8            | 34                      | 25                     |
| 8-2  | 692.8            | 496.5            | 36                      | 28                     |
| 8-3  | 721.7            | 507.9            | 38                      | 31                     |
| 8-4  | 711.6            | 522.8            | 38                      | 29                     |
| 8-5  | 748.9            | 547.3            | 37                      | 29                     |
| 8-6  | 732.3            | 556.2            | 38                      | 30                     |
| 8-7  | 685.7            | 537.7            | 38                      | 32                     |
| 8-8  | 722.8            | 541.5            | 37                      | 32                     |
| 8-9  | 736.7            | 505.2            | 37                      | 31                     |
| 8-10 | 547.1            | 388.6            | 28                      | 25                     |

In the short-term dispatching, due to the randomness and uncontrollable nature of power, it will cause the increase of the system's rotational reserve capacity and the change of the conventional unit start-up and stop strategy after the power is connected to the network, which may lead to the increase of the operation cost of the power system. The algorithm evolution curve is shown in Fig. 2.

Fig. 2 Algorithm evolution curve

The intensity of temperature accumulation effect is not only affected by the temperature of the day to be predicted, but also closely related to the difference between the temperature of the day to be predicted and the temperature of the previous N days. The greater the temperature difference, the greater the cumulative effect of the temperature in the previous N days on the day to be predicted. Time series decomposition model is widely used in short-term load forecasting of power system. Through a large number of data comparison, time series decomposition model improves the accuracy of load forecasting model to the greatest extent by dividing periodic components and non-periodic components. Time series method takes time as independent variable and the predicted target as dependent variable to establish an appropriate mathematical model. When using this method to predict, it is generally necessary to use a lot of historical data, so that the corresponding mathematical model can accurately reflect the change trend of things. In actual load forecasting, it is often encountered that the error increases due to incomplete training samples or obvious load trend. The time series decomposition model can reflect the multiple factors affecting the load value and reduce the actual error value of load forecasting.

3.2. Temperature Correction Method Considering Cumulative Effect

The historical data of power load is an ordered set sampled and recorded at certain time intervals, so it is a time series. It is difficult to change samples in real time for real-time training, because the number of samples used to train neural networks is usually large due to the inclusion of various patterns, and it takes a long time to train.
The cumulative effect can be considered according to the following formula to modify the daily temperature to be predicted:

\[
T' = (1-k)T_0 + kT_i - \sum_{i=0}^{P} k^{i+1}(T_i - T_{i+1})
\]

Where: \( T' \) is the maximum temperature correction value of the day to be predicted after considering the cumulative effect; \( T_0 \) is the highest temperature on the day to be predicted; \( T_i \) is the true value of the temperature \( i \) days before the day to be predicted; \( K \) is the cumulative effect coefficient; \( P = \min(n,3), n \) is the number of consecutive days when daily maximum temperature is higher than 28°C.

The power load time series forecasting technology is to try to establish a mathematical model of time series according to the historical data of load. On the one hand, the model is used to describe the regularity of the time series change process of power load, on the other hand, the mathematical expression of load forecasting is established on the basis of the model to forecast the future load. Most load forecasting problems are nonlinear programming problems, and the solution is to solve the maximum and minimum values of multivariate nonlinear functions in mathematical functions.

4. Summary
Meteorological factors are important factors that affect the accuracy of summer load forecasting, especially the temperature. An in-depth analysis of the relationship between load and temperature is of great significance to improve the accuracy of load forecasting. Short-term load forecasting under high temperature in summer is still a difficulty in the whole load forecasting work. The long-lasting meteorological characteristics determine that it is not enough to consider only the meteorological factors on that day. Theoretical and practical applications show that no single power load forecasting method can be applied to all occasions. Considering that the power system is a multi factor system, combined with the analysis of relevant factors, we can try to mine the historical data and find out the leading factors that affect the prediction accuracy. In this paper, the rule of cumulative effect on load change in summer high temperature season is studied. It is found that the intensity of cumulative effect is different under different conditions. With the improvement of technology and service of meteorological department, it is possible to obtain the meteorological information in time. If we can use these more accurate meteorological information, the short-term and ultra short-term load forecasting work will be further developed and improved.

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