Combination Forecasting Model of Daily Electricity Consumption in Summer Based on Daily Characteristic Meteorological Factors

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Abstract. Daily electricity consumption in summer is affected by numerous meteorological factors. In order to improve the accuracy of daily electricity consumption forecasting, a summer daily electricity consumption combination forecasting model based on daily characteristic meteorological factors is proposed in this paper. Firstly, the relationship between various meteorological indexes and daily electricity consumption is analysed considering the coupling effect and accumulative effect of meteorological factors on daily electricity consumption, and a single forecast model of daily electricity consumption is established. Then the meteorological mapping function is designed to evaluate the impact of each meteorological index on daily electricity consumption, and the weight of each single forecasting model is calculated. Finally, a combination forecasting model of daily electricity consumption in summer is established. The parameters of meteorological mapping function are optimized by adaptive training and virtual forecasting, and solved by genetic algorithm. Taking the daily electricity consumption in Chongqing in the summer of 2018 as an example, the results have shown that the proposed combination forecasting model can effectively improve the accuracy of daily electricity consumption forecasting.

1. Introduction
In recent years, with the development of social economy and the improvement of people's living standards, the ownership rate and utilization rate of air conditioners have increased significantly. In many large cities, the use of summer cooling equipment and winter heating equipment has led to a year-on-year increase in the proportion of electricity used by the tertiary industry and residents in urban electricity consumption [1]. Meteorological factors have become the main cause of high load and high electricity consumption. Therefore, in order to improve the accuracy and practicality of urban daily electricity consumption forecast, it is necessary to consider the influence of meteorological factors.

At present, there are relatively few studies on the electricity consumption forecasting considering meteorological factors in the field of load forecasting. In [2], Luo considered a lot of meteorological factors such as temperature, wind speed and precipitation, and established a city electricity
consumption prediction model, but ignored the influence of coupling effect generated by different meteorological factors. In [3], Zhong introduced the new meteorological indicator of effective temperature and analysed its relationship with electric load, but did not study the effect of multi-day accumulative effect of meteorological factors. In [4]-[5], authors studied the law of temperature accumulative effect on load and electricity consumption, and established a prediction model based on this law. However, the accumulative effect of meteorological factors also needs to include other meteorological indicators other than temperature.

This paper proposes a summer daily electricity consumption combination forecasting model based on daily characteristic meteorological factors. For the coupling effect and accumulative effect of meteorological factors, various meteorological indicators are used to describe them and the corresponding single-consumption model of electricity consumption is established. According to the meteorological mapping function of each meteorological indicator, the degree of influence on the electricity consumption is evaluated, the weight coefficient of each single prediction model is calculated, and the electricity consumption combination prediction model is established. For the optimal value of the meteorological mapping function parameters, adaptive training and virtual prediction methods are used to optimize them. This paper analyses the daily electricity consumption forecast of Chongqing in the summer of 2018 to verify the accuracy of the proposed model.

2. A single forecasting model considering daily characteristic meteorological factors

2.1. Decomposition of daily electricity consumption

A large number of studies have shown that time and meteorological are the main factors affecting daily electricity consumption in summer [6]. Based on this, it can be considered that the daily electricity consumption is composed of trend electricity and meteorological electricity.

\[ E = E_d + E_w + \varepsilon \]  

where \( E_d \) and \( E_w \) are trend electricity and meteorological electricity, respectively, and \( \varepsilon \) is the error. The trend electricity is determined by the time variable \( t \). The meteorological electricity is determined by the meteorological index vector \( \mathbf{w}=[w_1, w_2, \ldots, w_n]^T \) considering that the meteorological electricity may be affected by multiple meteorological indexes.

For a group of continuous daily electricity consumption and meteorological index historical data, the daily electricity consumption is decomposed into the trend electricity and the meteorological electricity according to the correlation between the electricity consumption and the meteorological indexes. The relationship between time and the trend electricity and that of meteorological electricity and meteorological indexes is established respectively. The detailed steps are as follows:

1) Dates are numbered according to the time sequence as \( 1, 2, \ldots, N_d \). \( N_d \) is the total number of days.

2) Calculate the correlation coefficient \( \rho \) between the daily electricity consumption and meteorological indexes [7].

\[ \rho = \frac{\sum_{i=1}^{n} (E_i - \bar{E})(w_{i,t} - \bar{w}_i)}{\sqrt{\sum_{i=1}^{n} (E_i - \bar{E})^2 \sum_{i=1}^{n} (w_{i,t} - \bar{w}_i)^2}} \]  

where \( E_i \) and \( w_{i,t} \) are the daily electricity consumption and the meteorological index \( i \) on day \( t \), respectively. \( \bar{E} \) and \( \bar{w}_i \) are the mean value of daily electricity consumption and that of the meteorological index \( i \), respectively.

3) Remove some days with high correlation between the daily electricity consumption and meteorological indexes until the correlation coefficient \( \rho \) is lower than the threshold \( z_\rho \). If \( \rho < 0 \), it will be removed from the day with the lowest meteorological index; otherwise, it will be removed from the day with the highest meteorological index. The days that are reserved constitute the set \( \Omega_1 \), and the days that are removed constitute the set \( \Omega_2 \).
4) Since the daily electricity consumption in the set $\Omega_1$ has a low correlation with meteorological indexes, the daily electricity consumption in $\Omega_2$ does not contain the meteorological electricity, that is, the daily electricity consumption is equal to the trend electricity. Regression analysis of trend electricity in $\Omega_1$ is carried out by using one dimensional linear linear model:

$$E_{d,t} = at + b$$

where $E_{d,t}$ is the trend electricity on day $t$. Constant coefficient $a$ and $b$ are calculated by parameter estimation.

5) Calculate the trend electricity in the set $\Omega_2$ according to the trend electricity regression model of (3), and calculate the meteorological electricity in $\Omega_2$.

$$E_{n,t} = E_t - E_{d,t}$$

where $E_{n,t}$ is the meteorological electricity on day $t$.

6) A variety of regression analysis models are used to model the variation of meteorological electricity. Each analysis model is as follows:

$$E_{w,t} = \sum_{i=1}^{k} \beta_i w_i + \alpha_1$$

$$E_{w,t} = \sum_{i=1}^{k} \chi_i w_i^2 + \sum_{i=1}^{k} \beta_i w_i + \alpha_2$$

$$E_{w,t} = \sum_{i=1}^{k} \delta_i w_i^3 + \sum_{i=1}^{k} \chi_i w_i^2 + \sum_{i=1}^{k} \beta_i w_i + \alpha_3$$

The different functional relationships between the meteorological electricity and the meteorological index $w$ are described by equations (5)-(7), and select the function with the best fitting effect as the final meteorological regression model of the meteorological electricity.

2.2. Single forecasting model of daily electricity consumption

There are many meteorological indexes describing meteorological conditions, such as: maximum temperature, minimum temperature, mean temperature, humidity, rainfall, wind speed, etc. In order to forecast daily electricity consumption more accurately, it is necessary to extract characteristic meteorological factors that have a great influence on daily electricity consumption. The temperature has the most significant impact on daily electricity consumption in summer. The correlation between humidity and daily electricity consumption is low. However, the coupling effect of humidity and temperature will strongly affect daily electricity consumption. The humidity-temperature index well reflects the coupling effect of humidity and temperature on daily electricity consumption, which is defined as [8]:

$$THI = Temp_c + \frac{1450.8(Temp_c + 235)}{4030 - (Temp_c + 235)\ln Hmd} - 43.4$$

where $Temp_c$ is the temperature in centigrade, which is the daily mean temperature; $Hmd$ is the percentage humidity.

In addition to the coupling effect, it is necessary to consider the multi-day accumulative effect of meteorological factors on daily electricity consumption. In order to better quantify the accumulative effect of meteorological factors, a weighted humidity-temperature index is adopted by the US PJM market. There are two commonly used formulas, which are as follows [8]:

$$WTHI_{t-1} = (10THI_{t-1} + 4THI_{t-1} + THI_{t-2}) / 15$$

$$WTHI_{t-2} = (10THI_{t-1} + 5THI_{t-1} + 2THI_{t-2}) / 17$$

where $THI_{t-1}$, $THI_{t-1}$ and $THI_{t-2}$ are the humidity-temperature index of day $t$, yesterday $t-1$, and day before yesterday $t-2$, respectively.

According to the above analysis, five groups of characteristic meteorological factors can be extracted. For each group of characteristic meteorological factors, combined with the trend electricity regression model and the meteorological electricity regression model, five single daily electricity consumption
forecasting models can be established. The meteorological indexes used in each single forecasting model are as follows:

Single model 1: The lowest temperature \( \text{Temp}_{\text{min},t} \), the highest temperature \( \text{Temp}_{\text{max},t} \) and the mean temperature \( \text{Temp}_{\text{mean},t} \) of the day.

Single model 2: The lowest temperature \( \text{Temp}_{\text{min},t} \), the highest temperature \( \text{Temp}_{\text{max},t} \) and the mean temperature \( \text{Temp}_{\text{mean},t-1} \), the highest temperature \( \text{Temp}_{\text{max},t-1} \) and the mean temperature \( \text{Temp}_{\text{mean},t-1} \) on yesterday; The lowest temperature \( \text{Temp}_{\text{min},t-2} \), the highest temperature \( \text{Temp}_{\text{max},t-2} \) and the mean temperature \( \text{Temp}_{\text{mean},t-2} \) on the day before yesterday.

Single model 3: The humidity-temperature index \( \text{THI}_t \) of the day.

Single model 4: The weighted humidity-temperature index 1 \( W\text{THI}_{1,t} \) of the day.

Single model 5: The weighted humidity-temperature index 2 \( W\text{THI}_{2,t} \) of the day.

3. Combination forecasting model and meteorological mapping function

This section establishes a combination forecasting model of daily electricity consumption, combining the advantages of various single forecasting models [9]. The combination forecasting model can be expressed as follows:

\[
\hat{E}_{j+1} = \sum_{j=1}^{5} f_{j,t+1} \hat{E}_{j,t+1} 
\]

where \( \hat{E}_{j,t+1} \) is the forecast value of electricity consumption of the combination forecasting model in the future day \( t+c \); \( \hat{E}_{j,t+1} \) is the forecast value of electricity consumption of the single forecasting model \( j \) in the future day \( t+c \); \( f_{j,t+1} \) is the weight of the single forecasting model \( j \) in the future day \( t+c \).

When a single forecasting model is determined, the weight of a single forecasting model directly determines the accuracy of the combination forecasting model. It can be seen from the above modeling process that different single forecasting models consider different characteristic meteorological factors. It is not difficult to find that the weight of a single forecasting model actually reflects the degree of influence of the characteristic meteorological factor on daily electricity consumption. Therefore, it is necessary to evaluate the impact of various meteorological indexes on daily electricity consumption.

Since the dimension of each meteorological index is different, it is necessary to map each meteorological index accordingly. Considering that the meteorological indexes used in this paper are continuous variables, we map them by linear functions [10]. The meteorological mapping function of the meteorological index \( w_i \) can be expressed as follows:

\[
f(w_{ij}) = a_i w_{ij} + b_i
\]

where \( a_i \) and \( b_i \) are parameters of meteorological mapping function. In order to limit the range of meteorological index mapping values, \( 0 < a_i < 0.1 \) and \( 0 < b_i < 0.1 \) are specified.

According to the mapping values of various meteorological indexes, the degree of influence of meteorological indexes on daily electricity consumption can be obtained:

\[
r_{ij} = \frac{w_{ij}}{\sum_{i=1}^{N_e} f(w_{ij})}
\]

where \( N_e \) is the number of meteorological indexes used for five single forecasting models, with a value of 12.

The calculation formulas of weight of each single forecasting model are as follows:

\[
f_{1,t+1} = f_{\text{Temp}_{\text{min},t+1}} + f_{\text{Temp}_{\text{max},t+1}} + f_{\text{Temp}_{\text{mean},t+1}}
\]

\[
f_{2,t+1} = \sum_{k=2}^{12} r_{\text{Temp}_{\text{min},t+k}} + r_{\text{Temp}_{\text{max},t+k}} + r_{\text{Temp}_{\text{mean},t+k}}
\]
The electricity consumption of day \( t \) is decomposed using the decomposition method of daily electricity consumption mentioned in Section 2.1. The parameters of the trend forecasting model are calculated by the parameter estimation method.

2) Based on the input data of time and meteorological indexes of day \( t \) day \( t+1 \), the electricity consumption of day \( t \) day \( t+1 \) is forecasted by each single forecasting model. The forecasting value of single forecasting model \( j \) is denoted as \( \hat{E}_{j,t} \) \((1 \leq k \leq F_c)\).

3) Two types of chromosomes are generated, one represents the primary coefficient \( A \) of the meteorological mapping function, and the other represents the constant coefficient \( B \) of the meteorological mapping function. The initial population is formed by several chromosomes.

4) Decoding the information of all chromosomes in the population and obtaining the parameters of meteorological mapping function and the influence coefficients of meteorological indexes, thereby obtaining the weight coefficient \( f_{j,k} \) \((1 \leq k \leq F_c)\) of the single forecasting model \( j \), and calculating the fitness value of each chromosome. The fitness function is set to (20).

\[
\text{fitness} = \sum_{k=1}^{F_c} \frac{\sum_{j=1}^{F_c} f_{j,k} \hat{E}_{j,k} - E_{t,k}}{E_{t,k}}
\]

5) Generate new paternal population by selecting, crossing and mutating on chromosomes of the existing population.

6) Determine whether the maximum number of iterations is reached. If it is reached, the calculation is stopped and the result is output to obtain the optimal value of the parameters of the meteorological mapping function; otherwise, turn to step 4).

5. Case studies
In order to verify the effect of the combined forecasting model, the electricity consumption data of Chongqing in the summer of 2018 was selected for analysis. This paper selects August 22\textsuperscript{th} 2018 to August 28\textsuperscript{th} 2018 as the forecast date, and predicts the daily electricity consumption during the week.
In order to effectively decompose electricity consumption, estimate parameters and optimize parameters, you should select as much historical data as possible. This paper uses electricity consumption and meteorological data from May 1st 2018 to August 21st 2018 as historical data. The correlation coefficient threshold $z_p$ is set to 0.2.

Table 1 shows the predicted values of various predictive models and the relative errors between predicted value and actual value. As it can be seen from Table 1, the combined prediction model is superior to each single prediction model, and can more accurately predict the daily electricity consumption. Especially for the electricity consumption on August 22nd, the relative error of the combined forecast is only 0.30%, and the prediction accuracy is significantly higher than the single prediction. Among the five single prediction models, the overall prediction of single model 2 is the best, and the prediction of single model 3 is good on some days. These reflect that temperature and humidity-temperature index are important meteorological factors affecting electricity consumption.

**Table 1.** Comparison of predicted value and actual value of electricity consumption in both August 22nd 2018 and August 28th 2018 in Chongqing

| Date | Actual Electricity Consumption (GWh) | Predicted Electricity Consumption (GWh) | /Relative Error (%) |
|------|------------------------------------|----------------------------------------|---------------------|
|      | Model 1               | Model 2               | Model 3               | Model 4               | Model 5               | Combined Model        |
| 08/22| 306.16                | 275.20/-10.11        | 310.82/1.52           | 274.32/-10.40        | 284.98/-6.92          | 290.88/-4.99          | 307.09/0.30          |
| 08/23| 285.13                | 278.66/-2.27         | 293.88/3.07           | 281.16/-1.39         | 275.90/-3.24          | 278.65/-2.27          | 291.09/2.09          |
| 08/24| 298.79                | 290.64/-2.73         | 283.89/-4.99          | 292.05/-2.26         | 283.56/-5.10          | 282.92/-5.31          | 286.09/-4.25         |
| 08/25| 303.90                | 306.48/0.85          | 294.57/-3.07          | 300.20/-1.22         | 294.19/-3.19          | 293.86/-3.30          | 294.52/-3.09         |
| 08/26| 300.82                | 307.73/2.30          | 309.18/2.78           | 296.70/-1.37         | 294.81/-2.00          | 295.85/-1.65          | 306.88/2.01          |
| 08/27| 332.33                | 322.97/-2.82         | 323.58/-2.63          | 308.61/-7.14         | 303.57/-8.65          | 304.11/-8.49          | 320.31/-3.62         |
| 08/28| 332.38                | 339.33/2.09          | 339.51/2.15           | 326.43/-1.79         | 320.26/-3.65          | 319.71/-3.81          | 336.28/1.17          |

In order to further compare the various prediction models, Table 2 gives average values and maximum values of the relative error absolute values of the respective prediction models. The average value and maximum value reflect the accuracy and the stability of the forecast, respectively. It is not difficult to find that the average value and maximum value of the relative error of the combined prediction model are 2.36% and 4.25%, respectively, which are the lowest. This proves the correctness of the combined prediction method proposed in this paper. The weight coefficient obtained by the meteorological mapping function can be used to avoid weaknesses and combine the advantages of each single prediction well. In addition, the prediction advantage of single model 2 is more obvious than the other single predictions, which indicates that the accumulative effect of temperature has a huge impact on electricity consumption.

**Table 2.** Comparison of the relative error absolute value between predicted value and actual value of each prediction model

| Type of Relative Error Absolute Value (%) | Single Model 1 | Single Model 2 | Single Model 3 | Single Model 4 | Single Model 5 | Combined Model |
|-----------------------------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Average Value                           | 3.31           | 2.89           | 3.65           | 4.68           | 4.26           | 2.36           |
| Maximum Value                           | 10.11          | 4.99           | 10.40          | 6.92           | 8.49           | 4.25           |

The correlation threshold affects the decomposition of daily electricity consumption, resulting in different prediction accuracy. The results are shown in Table 3. Choosing the appropriate correlation threshold will facilitate the improvement of prediction accuracy.

**Table 3.** Comparison of combined prediction accuracy under different correlation thresholds

| Correlation Coefficient Threshold $z_p$ | Average Value of Relative Error Absolute Value (%) |
|----------------------------------------|-----------------------------------------------|
| 0.15                                   | 5.13                                          |
| 0.20                                   | 2.36                                          |
| 0.25                                   | 2.61                                          |
| 0.30                                   | 3.33                                          |
6. Conclusions
This paper proposes a combined forecasting model of daily electricity consumption, and synthesizes the effect of meteorological factors. The combined forecasting model considers the effects of multiple meteorological indicators, coupling effect, and cumulative effect. Moreover, this paper designs the meteorological mapping function. The mapping value of meteorological indicators describes the influence degree of meteorological indicators on electricity consumption, and determines the weight coefficient of single prediction model, thus the influence of various meteorological indicators is effectively combined. The example calculation proves that the combined forecasting model can greatly improve the accuracy of power consumption forecasting, and it can provide guidance for power system planning, grid operation and transaction management.

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