Research on short-term load forecasting based on feature similarity using PSO algorithm

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Abstract. In this paper, a short-term power load forecasting model based on feature similarity was proposed. The model can comprehensively consider the short-term load forecasting under the condition of multiple factors, such as meteorological information, holiday/workday information and other factors in a unified framework. Different values of the same characteristic have great influence on load forecasting. Therefore, hierarchical clustering algorithm is used to analyse the value of each feature dimension. Feature distance is used as feature mapping value to establish feature mapping relation table. Because different factors have different weights for load forecasting, a weighted feature similarity measurement strategy is designed. Taking the minimum residual sum of squares as the optimization objective, particle swarm optimization algorithm is used to solve the optimal characteristic weight. The validity of the model and the accuracy of load forecasting are verified by comparing the numerical simulation with the existing models.

1. Introduction
As the short-term power load forecasting has the characteristics of randomness, uncertainty and timeliness, it is of great significance to build an effective model to predict the change trend of power load in the future in a short time under different factors[1].

There are many factors affecting the power load, such as meteorological information (temperature, humidity, wind speed, air pressure, etc.), weather type (sunny, cloudy, rainy, snowing, etc.), holiday/working day, season (early, summer, autumn, winter), building type (Commerce, residents, industry, etc.)[2].

The classical load forecasting models include regression analysis[3], time series method[4], grey model[5], Kalman filter[6] and so on. When the historical load data is simple, the traditional forecasting methods have high accuracy. When the historical data set contains complex features, it is difficult to accurately describe the nonlinear relationship between multi factor features and load changes.

At present, many scholars use intelligent models represented by machine learning and artificial intelligence methods, such as genetic algorithm[7], particle swarm optimization algorithm[8], artificial neural network[9], support vector machine[10], fuzzy reasoning[11], etc., to build load forecasting models. Compared with traditional models, intelligent models have better robustness to disturbances and good description ability to nonlinear factors. Among them, the prediction model based on particle swarm...
optimization has been widely studied because of its high accuracy, fast convergence speed and few model parameters.

This paper classifies the trend of influence of attribute value on load into one category, and constructs a feature mapping value updating algorithm based on hierarchical clustering, which makes the attribute weight objectively reflect the influence of various factors on load and avoids the randomness brought by subjective evaluation. PSO algorithm is used to solve the weight coefficient of the optimal characteristic attribute, and the load to be predicted is the weighted average value of the historical load.

2. Feature similarity measurement strategy

The load from Monday to Friday (working day) is different from the load on Saturday, the influence trend of different temperature and season on the load is also different, and the load will fluctuate before and after holidays. At the same time, these factors restrict each other.

2.1. Weighted similarity measure of characteristic days

The distance $d_{ij}$ between characteristic days $i$ and $j$ can be expressed as follows:

$$d_{ij} = \sqrt{\sum_{k=1}^{m} \alpha_k (x^{ik} - x^{jk})^2}$$  \hspace{1cm} (1)

$$\sum_{k=1}^{m} \alpha_k = 1$$  \hspace{1cm} (2)

Where $k = 1, 2, \ldots, m$, $\alpha_k$ is the weight coefficient of the influencing factors of different characteristics. $x^{ik}$ and $x^{jk}$ represent the values of feature day $i$ and $j$ on the $k$-th feature respectively.

The similarity between characteristic days $i$ and $j$ is as follows:

$$S_{ij} = \frac{1}{1 + d_{ij}}$$  \hspace{1cm} (3)

Among them, the range of $S_{ij}$ is $[0, 1]$. The larger the value of $S_{ij}$ is, the smaller the distance $d_{ij}$ between feature days $i$ and $j$ is. That is to say, the smaller the feature distance is, the greater the similarity is.

This paper takes the RSS (residual sum of squares) of the predicted load value and the real historical data of the model as the optimization goal, and records it as $E_{RSS}$, as shown in equation (4).

$$E_{RSS} = \sum_{i=1}^{n} (L_i - \hat{L}_i)^2$$  \hspace{1cm} (4)

2.2. Feature mapping table

Due to the different dimensions of different features, in order to effectively compare the impact of different factors on the load. The data are normalized and the set D of characteristic factors is mapped to R. Different characteristic factors in R have different mapping values. As shown in Table 1, $r_{si}$ indicates the influence of different characteristic types on load weight.

| Feature types | Description      | Value | Mapping value |
|---------------|------------------|-------|---------------|
| weather       | Sunny day        | 1     | $r_{si}$      |
| weather       | Rainstorm        | 2     | $r_{s2}$      |
| week          | Monday           | 1     | $r_{s1}$      |
| week          | Saturday         | 6     | $r_{s4}$      |
| ...           | ...              | ...   | ...           |

Table 1 mapping table of values of different feature types
3. Particle swarm optimization algorithm

Particle swarm optimization (PSO) algorithm is used to solve the optimal feature attribute weight \( \omega_k \). Suppose that in the m-dimensional search space, the population of particles can be expressed as \( X = (x_1, x_2, \ldots, x_n) \) and \( V = (v_1, v_2, \ldots, v_n) \). \( x_i \) represents the position of particle \( i \), \( v_i \) represents the speed of particle \( i \), and the formula for updating the speed and position of particle \( i \) is as follows:

\[
\begin{align*}
    v_i(t + 1) &= \omega v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (p_g - x_i(t)) \\
    x_i(t + 1) &= x_i(t) + v_i(t)
\end{align*}
\]  

(5)  

(6)

Where \( v_i(t) \) and \( x_i(t) \) represent the velocity and position of particle \( i \) at time \( t \). \( v_i(t) = [v_{i1}, v_{i2}, \ldots, v_{im}] \) and \( x_i(t) = [x_{i1}, x_{i2}, \ldots, x_{im}] \) represent the velocity and position vectors of particle \( i \) respectively. \( p_i \) represents the individual optimal position that the particle has searched, \( p_g \) represents the global optimal position that the particle has searched. \( \omega \) is the inertia weight coefficient of the particle. \( r_1 \) and \( r_2 \) represent random numbers in (0,1). \( c_1 \) and \( c_2 \) represent the individual learning factor and social learning factor of particles.

4. Numerical simulation

The validity and load forecasting accuracy of the proposed model are verified by comparing with standardized processing model and regression analysis model.

The load forecast value \( \hat{L}_i \) is the weighted average value of the historical data set, calculated according to the following formula, and the weighted coefficient is the normalized characteristic similar distance \( \tilde{S}_{01} \):

\[
\hat{L}_i = \sum_{l=1}^{n} \frac{S_{01} \cdot L_l}{\tilde{S}_{01} \cdot L_l}
\]

The comparison of the results of load forecasting curve and historical load curve of different models is shown in Figure 2. It can be seen that the accuracy of the PSO model proposed in this paper is better than the standardized processing model and regression analysis model. The prediction curve is close to the real historical load curve, and the prediction error is small.
Figure 2 load forecasting curve of different models

Figure 3 shows the comparison of relative error of load forecasting of different models. It can be seen that the prediction relative error of PSO model is smaller than that of other two models.

Figure 3 prediction relative error of different models

The simulation experiment forecasts 100 samples in the historical load data set, and calculates the average relative error of the three models. The statistics are shown in Table 2. The prediction accuracy of PSO model is the best, the average error is less than 2%, and the proportion of relative error less than 1% is 93.88%, while the normalized processing model and regression analysis model are 61.22% and 63.27%, respectively.

The standardized model needs to set the mapping relationship of eigenvalues manually, and the subjective factors are large. The PSO model uses the historical load data, according to the objective of minimizing the sum of the squares of the residuals. By solving the optimal characteristic attribute weighting coefficient, it can accurately describe the nonlinear effect of each characteristic on the load, so the model error is small.

Table 2 proportion of prediction error of different models (%)

| error (%) | PSO model | Standardized model | Regression analysis model |
|-----------|-----------|--------------------|--------------------------|
| <0.5%     | 73.47     | 55.1               | 59.18                    |
| <1%       | 93.88     | 61.22              | 63.27                    |
| <2%       | 100       | 75.51              | 71.43                    |
| <3%       | 100       | 100                | 81.63                    |
| ≥3%       | 0         | 0                  | 18.37                    |

5. Conclusion

In this paper, a short-term power load forecasting model based on feature similarity is proposed. The influence of many factors on load is considered in the model. Firstly, the hierarchical clustering algorithm is used to analyze the value of each feature dimension and establish the feature mapping table. Meanwhile, the weighted feature similarity measure strategy is designed, and the optimal feature weight is solved by particle swarm optimization algorithm. Compared with the existing models, the
PSO model proposed in this paper can effectively predict the short-term power load, and has a high prediction accuracy.

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