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Research in Residential Electricity Characteristics and Short-Term Load Forecasting

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Abstract

In this paper we make research in Residential short-term load forecasting. Different application scenes have different affecting factors of short-term load, so we should specifically analysis of factors that affect the load of the residential electricity. We use SPSS (Statistic Package for Social Science) to figure out the relationship between the daily load and temperature, weather conditions and other factors, finding the main factors among the impacting factors, and analyzing residential electricity consumption habits and load characteristics. Then, the paper introduces the common prediction methods. Combining with the above analysis to choose short-term load forecasting methods for residential users, we create automatic linear regression model and artificial neural network model to predict the future electricity load, calculating the residual between the predicted values and the actual values and mean square deviation of the values, and evaluating the accuracy of the load forecasting. The results prove that automatic linear regression model is effective in residential short-term electricity load forecasting.

Keywords: *residential electricity, short-term load forecasting, linear regression, artificial neural network*

1. Introduction

The power load forecasting begins by considering the known electricity historical data, the economic, social influence, climate and users' electricity habits. To make a reasonable electricity load forecasting of the future, we sum up all the influences above and make a suitable model. Short-term load forecasting is to predict the next period time (several hours, a day or several days) of load or its changing trends [1]. Forecast results depend on forecast date type (holidays, weekdays or weekends), temperature, and weather conditions etc. Its accuracy is important to scheduling, the optimal combination of the unit, economic dispatch and electricity market trading [2].

In the generation side of large power systems, including conventional hydropower, thermal power plants and pumped storage power station. Aiming to short-term load optimization, many experts and scholars propose different optimized algorithms, such as dynamic programming, genetic algorithm, short-term load optimization based on data storage [3]. On the demand side of the grid, load forecasting can reflect the entire consumption level of the grid, so it has an important significance to the development of power generation planning. To urban comprehensive short-term load forecasting with complex influencing factors, some authors present the methods that combined the relevant literature ingredients based on principal component analysis method with the BP neural network [4]. The principal component analysis method can reduce the dimensionality of the inputs data of BP neural network, making the model more effective. In the aspect of industrial electricity, the literature describes the commonly used artificial neural network, autoregressive model, gray model, illustrating how to improve the prediction accuracy and compensate for the prediction error by examples [5].

In recent years, electricity consumption is growing significantly, and the distance between peak load and valley load is increasing day by day and playing an important role in fueling [6]. Therefore, it needs more and more attention how to improve the prediction accuracy of the residential electricity consumption. However, most of the current short-term load forecasting and optimization methods are discussed for large industrial users or for a whole

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society or region [4, 5].The prediction system above is complex and is not suitable for residential power load forecasting.

In this paper, based on the analysis of load characteristics and influencing factors of community residents, we compare the short-term load forecasting methods and models, and then choose simple and effective methods for residential power consumption short-term load forecasting.

2. Residential Electricity Characteristics Analysis

2.1. Outline

With residential electricity consumption and the number of urban population continue rising, which causes great challenges to the grid power generation, transmission and distribution sector. The demand of residential electricity consumption load forecasting and electric management on the demand side is increasing urgently.

To Shanghai residential electricity consumption, for example, in the late nineties of the last century, the average power load growth rate is about 7%, and the rate of growth in consumption is around 5%. After 2000, with the development trend of the economy becoming better as well as some other climatic factors, the growth rate of power load and power rising rate are near to double-digit. The residential electricity proportion increased significantly, showing the features that peak-to-valley difference increases and living load proportion grows heavily than the electricity consumption proportion [7]. To this end, the residents load electricity forecasting and management compared with power management is even more important.

2.2. Temperature Influence on the Residential Electricity Load

According to the changing of load composition, residential electricity load can be divided into two parts, base load component and seasonal load component [8]. Base load component includes lighting, electric heaters, television sets, kitchen electrical equipment, refrigerators, washing machines etc. Seasonal load component is mainly caused by the air conditioning and heating. The transformation of the temperature influences human body comfort, and then the change of human body comfort influences electricity consumption. Under normal circumstances, when the room temperature is higher than 26°C or below 10°C, the electricity load will significantly changes with temperature changing. Among all of electricity equipment above, the air conditioning is most casual, and shares the most significant part in power load. During winter in southern China, people use air conditioning to heating and dehumidification, so electricity load increases by the temperature. In summer, generally north-south high-temperature air-conditioning load varies with temperature. In spring and autumn, outdoor temperature is suitable, and the turn-on time of temperature-regulating devices are shorter, so the impact of temperature on the load shows weakly.

2.3. Holidays Electrical Characteristics

China's major holidays include The Labor Day, National Day and Spring Festival. During the Labor Day and National Day Festival, the temperature is neither too hot nor too cold, and they're longer holidays. Many people choose to go out for party, tourism or other varieties of lifestyles, making the electricity load more dispersed. During the Spring Festival, the temperatures are low, and people visit friends and relatives to hold family gatherings, which makes the living electricity load heavier.

2.4. Life Habits

Community residential electricity consumption includes lighting, cooking, temperature regulation and so on. Smart metering can read each household's electricity consumption every 15 minutes, and even some meters can do real-time data reading. The wireless meter, read the load data and send it to the concentrator, and then they are sent to the background of the Electricity Authority. The data used in this article are electricity consumption values once an hour. The difference between adjacent data constitutes residents historical load sequences.

Figure 1 is a district of daily load curve. You can see the peak period concentrates in the 10:00 am-12:00 pm and 16:00 to 20:00. It has two peak periods at noon and night. During these periods people are cooking, watching TV, laundry and do other activities. It brings substantial growth of the load.

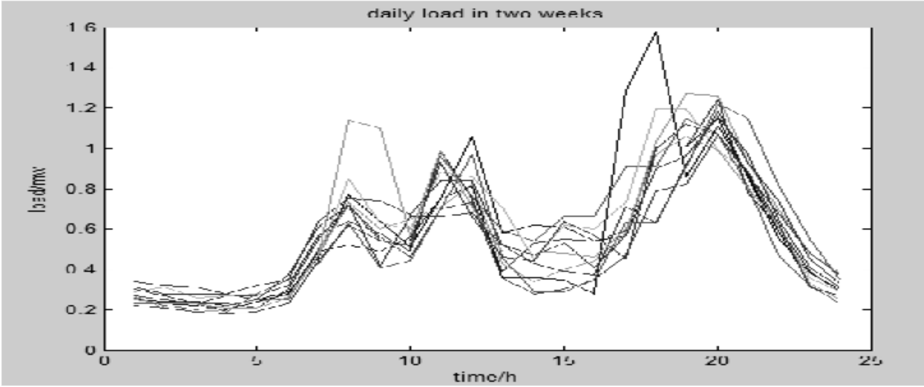

Figure 1. Daily Load Curve

In addition, the load level is also affected by working days/rest days, the weather conditions (sunny/rainy). Selecting the sample of March electricity consumption per day, together with the daily maximum temperature, minimum temperature, weather conditions (rainy or sunny), it analyzes the correlation of these factors by SPSS.

Daily consumption, daily maximum temperature, minimum temperature, rainy or sunny status Pearson correlation are shown in Figure 2. The daily consumption and daily maximum temperature Pearson correlation coefficient is 0.588, the daily minimum temperature correlation coefficient is 0.237, and the correlation coefficient of the weather conditions is 0.527.

Table 1. Correlations of Daily Consumption and Meteorological Factors

		Daily electricity load (L)	Maximum Temperature (MaxT)	Minimum temperature (MinT)	Sunny/rainy (SR)
Pearson correlation	L	1.000	-.237	-.588	-.527
	MaxT	-.237	1.000	.683	-.052
	MinT	-.588	.683	1.000	.581
	SR	-.527	-.052	.581	1.000
Sig.	L		.113	.000	.002
	MaxT	.113		.000	.397
	MinT	.000	.000		.001
	SR	.002	.397	.001	
N	L	28	28	28	28
	MaxT	28	28	28	28
	MinT	28	28	28	28
	SR	28	28	28	28

The importance of predictor variables Sort results are shown in Figure 3. The factors affect the electrical load in sequence is daily maximum temperature, weather conditions (rainy or sunny) and the daily minimum temperature.

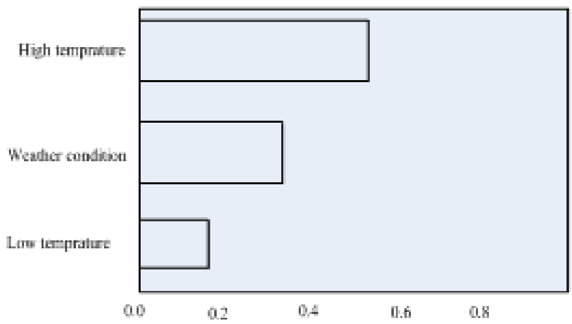

Figure 2. The Influence Factors in Sequence

During the power load forecasting, we can add or delete the input parameters based on the importance of influencing factors appropriately. It can optimize the network and reduce data redundancy.

3. Prediction Scheme Simulation Analysis

Residential electricity system is a small grid. The laws of electricity are obvious, and the power load is relatively stable. Considering the time and space complexity with accuracy requirements, we use linear regression analysis method and BP neural network method for load forecasting analysis and comparison.

In this paper, we take the March electricity load data in a residential district in Anhui Province as experimental samples. The raw data should be pre-processed, finding out the default data and making supplement to the data.

3.1. Linear Regression Model

Regression analysis is a method that predicts future data trends based on historical data variation. It requires less data, and the calculation speed is faster [9]. It is suitable for describing specific issues which sequence is stable and may achieve good results.

Power the load regression model forecasting techniques is based on the historical data of the load, and establishes mathematical analysis models to predict the future of the load. In this paper, two weeks load data before the forecasting day are inputted. Corresponding variable data from March 1 to 16 load sequence are the inputs $x_1, x_2, ..., x_{16}$. Regression model output for the 17th load sequence y .And March 17 actual load is the measured value x_{17} .

Then:

$$Y = a + b_1 x_1 + b_2 x_2 + ... + b_n x_n \tag{1}$$

$n = 16,\ a, b_1, b_2, ..., b_n$ are multiple regression parameters, it automatically determined by SPSS according to the load sequence.

Then the correlation on the predicted value and the actual measurement value is tested, and the correlation coefficient and the mean and variance parameters are calculated.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} E_i^{\ 2} = \frac{1}{n}\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{2}$$

The predicted value and the actual value of the linear regression model outputs are shown in Table 2. We calculate the correlation coefficient and the mean and variance parameters using Equation (2). The mean square error is 0.0016 and the root mean square error is 0.04.

Table 2. Comparison of the Actual Values and Predict Values using Linear Regression Model

Sequence	electrical data
3-17(actual value)	0.21 0.16 0.16 0.17 0.17 0.21 0.43 0.79 0.71 0.67 0.83 1.11 0.51 0.59 0.55 0.54 0.64 0.82 0.85 1.15 0.82 0.58 0.44 0.26
3-17(forecast results）	0.25 0.18 0.16 0.16 0.15 0.23 0.43 0.81 0.72 0.7 0.89 1.05 0.5 0.61 0.44 0.55 0.64 0.82 0.88 1.11 0.84 0.57 0.43 0.25

Analyzing the relative regularity of the load sequence, the impact of residential electricity load factor is relatively small, and the use of automatic linear regression model based on historical load value can get a better prediction result. The regression model will be saved as an XML file, and then we can predict other data by using this model file.

3.2. BP Neural Network Model

The artificial neural network can consider the non-linear characteristics of the load. The forward BP neural network is widely used in the electricity load forecast [10, 11].

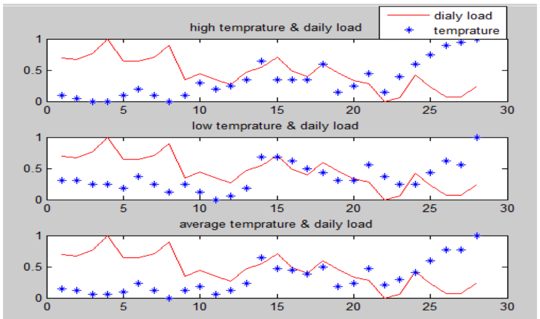

Figure 3. Daily Consumption and Temperature Curves

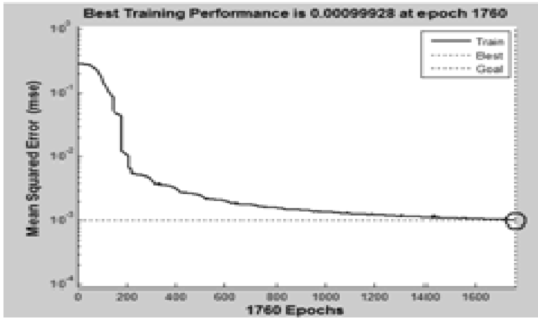

Figure 4. BP Network Training Performance

Neural network Artificial Neural Network (ANN) prediction technology, it can mimic the human brain to do the intelligent processing of non-linear, non-deterministic laws of adaptive function. In most cases, the temperature is taken as an important factor affects the short-term load, and other climatic factors are generally ignored, such as cloud cover, wind speed and load, in order to avoid network structure being too cumbersome [12]. Figure 5 is the daily consumption temperature curve in March 2012. The temperature on the daily load correlation is not obvious, and to simplify the artificial neural network model, it can be ignored.

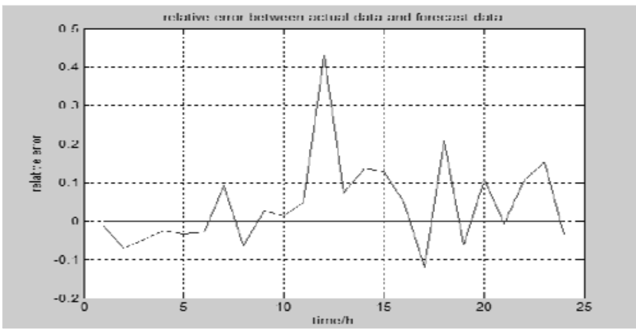

Figure 5. Test Sample Output Value of the Prediction Error Curve

In this paper, we construct a three layer BP neural networks, including input layer, hidden layer and output layer. We use the previous day's 24h historical load as inputs and select March 1 to March 16, 2012, 16 days' data as samples. The whole point load value as training inputs P, the whole point of time load values from March 2 to March 17 every 24h as the training outputs. Enter the number of input layer n1 equals 24, output layer m equals 24. According to the Kolmogorov theorem, the number of hidden layer neurons, scoping, try method to adjust, set the number of hidden layer neurons n2 equals 31. Till now we create a neural network. Set the maximum number of iterations for 2000, the target error for 0.05.The training function is traindgx Learning Algorithms which are gradient descent momentum method and adaptive learning rate. Training is completed setting up a test the vector P_test as March 17 24hours' historical load data as the network inputs. The target outputs Y are 24hours' load values on March 18. Figure 6 shows the performance of BP network training. The number of iterations epoch equals 1706 to achieve the requirements of network settings.

The test sample output and the actual value of the error curve are shown in Figure 7. It can be seen that the maximum error is about 0.3, and calculated mean square error MSE is 0.1202.

It can be seen from the analysis above, for district residents' short-term load forecasting, a simple linear regression analysis method can achieve more accuracy prediction results. In addition, linear regression analysis method is simpler than BP neural network, and easier to implement.

4. Summary

This paper analyzes the characteristics of residential electricity consumption, and uses economic analysis software SPSS to filter the factors that affect people in residential electricity load. The result shows that the daily maximum temperature and weather conditions (rainy or sunny) have larger correlation. Considering that the residential electricity load is relatively stable, influencing factors and other characteristics, we select the linear regression model and BP neural network model to do residential electricity short-term load forecasting. By comparing the disparity between the predicted values and the actual values, we find that using the regression model can achieve higher prediction accuracy than using BP neural network model. Therefore, we can use the regression model to make short-term residential electricity load forecasting.

Acknowledgements

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