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Study on the Method of Enterprise Short-term Load Forecasting Considering Weather and Product Information

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Abstract

Short-term load forecast plays an important role in the safe and economic operation of power system. Its prediction accuracy affects the power system's security, profit and quality directly. And meteorological factor is one of the key factors that affect the accuracy of load forecasting. In this paper, we put forward enterprise electric load forecasting method combined with grey relational degree algorithm and multivariate linear regression forecasting method. The example shows that this method can get better prediction accuracy.

Keywords: *short-term load forecasting; power system operation; grey relational degree algorithm; multivariate linear regression*

1. Introduction

Power load forecasting is, satisfying a certain accuracy, to get the load value of a future time using a set of mathematical method processing the past and the future load system when considering some factors. Short-term load forecasting usually refers to the daily load forecasting for 24 hours or weekly load forecasting for 168 hours, which can provide real-time detection information of the system. Short-term forecasting is of great significance for the normal and safe operation of system. At the same time, due to its short time span, the influence of external factors is more obvious than the medium long term prediction, making the prediction more difficult. So the short-term forecasting has been the most active part in the field of load forecasting [1]. The current main methods for short-term prediction are as follows: load forecasting based on the autoregressive moving average model (ARMA model), load forecasting based on artificial neural network (ANN), load forecasting based on expert system, load forecasting based on the grey prediction model, load forecasting based on wavelet analysis and so on.

This paper mainly discusses the short-term load forecasting for industrial users. This paper is divided into three parts: the first part is a brief description of the load characteristics of industrial enterprises; the second part is to forecast industrial power load based on meteorological and product information; the third part conducts the simulation calculation for the prediction method.

2. Descriptive Analysis of Sample Load

It is the key to understand the load characteristic curve that understanding the main energy consumption sources and types such as industrial production equipment types.

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For large power consumption enterprises, its electrical characteristics are obviously different from large area, which makes the existing prediction techniques can not directly applied to the electricity load forecasting of large enterprises [2]. This paper selects typical winter day to collect total power load data. The sampling time is 24 hours. The obtained data is shown in Figure 1.

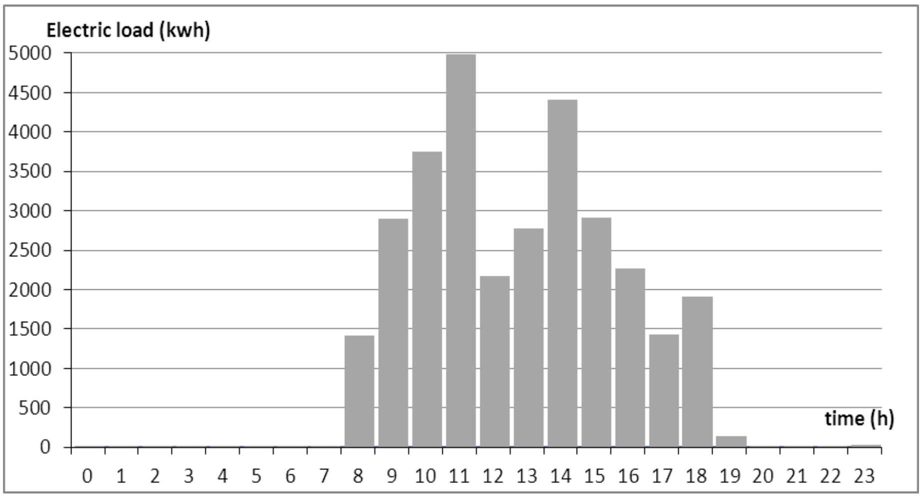

Figure 1. An Enterprise Typical Winter Electric Load Histogram

3. Study of Load Forecasting Method Based on Meteorological and Product Information

This paper firstly selects the data strongly associated with original data using the grey relational degree algorithm. Then make the original test data and its corresponding grey relational data into reconstruction and standardization. And take the normalized data as analytical samples of linear regression algorithm. Finally adopting the improved multiple linear regression based on meteorological and product information to forecast the industrial short-term power load. Fully considering the key factors' effect on the predicted results, this article builds the short-term load forecasting method based on meteorological and products information [3].

2.1. The Preprocessing of the Load Data with Grey Relational Algorithm

In consideration of the linear regression prediction algorithm can only describe the linear relationship, therefore we should firstly analyze and process the load data with grey relational algorithm to approach linear prediction model [4].

The change of industrial electrical load is restricted by production management, weather factors and so on. So power load L can be expressed as:

$$L = L_p + L_w + L_r \tag{1}$$

Among them, L_p is the electricity load of production, correlating with the production plan of enterprise. L_w is the weather sensitive load, correlating with meteorological factors. L_r is the daily electricity load, basically remaining unchanged. So we build the load feature vector $F(\mathrm{i})$, i=1, 2, …, m, where i denotes as the i_{th} day selected by reference data, and m expresses that the number of historical references day is m. The feature vector of the i_{th} day is as follows:

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$$F(i) = \left[p_1(i), \ldots, p_{(n-2)}(i),\ p_t(i),\ p_{sr}(i) \right] \qquad (2)$$

Among them, （n-2） represents the number of sections required by industrial process affecting the production of electric load, $p_x(i)$ represents the production plan value of x_{th} section that affecting the load of L_p in i_{th} day, $P_t(i)$ is the average temperature of the i_{th} day, $P_{sr}(i)$ is the average irradiation intensity of the i_{th} day. In this paper we only consider temperature and irradiation intensity's influence on load.

Suppose feature vector for target day is as follows:

$$F_0 = \left[p_{10}, \cdots p_{(n-2)0},\ p_{t0},\ p_{sr0} \right] \qquad (3)$$

Here, taking F_0 as comparison vector, we can get F_i , i =1, 2…30, respectively by calculating feature vector of historical reference through the grey relational coefficient formula. And wo also obtain the correlation coefficient $\xi_i(q)$ between daily feature vector and the feature vector of target day, correlation coefficient of the q_{th} item between the i_{th} day and target day.

Suppose the index weight is as follows:

$$w = [w_1, \ldots, w_n] \qquad (4)$$

Use principal component analysis (PCA) to analyze the contribution value of each feature, then we can get each index weight [5]. First, we should normalize the data, and then get the weight of each feature vector w_k .

Normalize the data as follows:

$$p_{ij} = \frac{p_{ij} - \frac{1}{n}\sum_{i=1}^{n} p_{ij}}{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(p_{ij} - \frac{1}{n}\sum_{i=1}^{n} p_{ij}\right)^2}},\ i = 1, 2\ldots, n,\ j = 1, 2, \ldots, m \qquad (5)$$

Assuming n reference vectors' each parameter make its characteristic vector equation as follows:

$$\begin{aligned} P_1 &= p_{11}\lambda_1 + p_{12}\lambda_2 + \ldots + p_{1n}\lambda_n, \\ P_2 &= p_{12}\lambda_1 + p_{22}\lambda_2 + \ldots + p_{n2}\lambda_n, \\ &\ldots, \\ P_n &= p_{1n}\lambda_1 + p_{2n}\lambda_2 + \ldots + p_{nn}\lambda_n, \end{aligned} \qquad (6)$$

where $\lambda_1, \ldots, \lambda_n$ are the characteristic value. Then we can get the value of w_k with the following equation:

$$w_k = \frac{\lambda_k}{\sum_{i=1}^{n} \lambda_i} \qquad (7)$$

According to the weight coefficient of each evaluation criterion and corresponding grey relational coefficient, we obtained the grey weighted related degree between i_{th} day and target day. The calculation formula is as follows:

$$R_i = \sum_{k-1}^{n} w_i \xi_i(k) \tag{8}$$

Select the weighted degree of top n, named i=load1, …,loadn, which are the days with similar load. Calculate average load of similar day, where $q_{load1} \ldots q_{loadn}$ mean the load of similar days.

2.2. Multiple Linear Regression Analysis Model and Prediction

According to the eigenvectors of daily load obtained by grey relational degree algorithm, Fload1,⋯, Floadn, then we will establish the multivariate linear regression analysis model [6].

The mathematical relationship between daily load and the feature vector is:

$$\begin{cases} P_{dt} = l_0 + l_1 p_1 + l_2 p_2 + \ldots + l_n p_n + \varepsilon, \\ \varepsilon \sim N(0, \sigma^2). \end{cases} \tag{9}$$

Among them l_0, l_1,⋯, l_n, σ^2 are unknown parameters and irrelevant to the eigenvectors, l_0, l_1,⋯, l_n are known as the regression coefficients. Then plugging the eigenvectors into the formulas,

$$F = \begin{bmatrix} 1 & p_1(load1) & p_2(load1) & \ldots & p_{n-2}(load1) & p_t(load1) & p_{sr}(load1) \\ & & & \ldots & & & \\ 1 & p_1(loadn) & p_2(loadn) & \ldots & p_{n-2}(loadn) & p_t(loadn) & p_{sr}(loadn) \end{bmatrix}$$

$$P_{dt} = \begin{bmatrix} p_{dt}(load1) \\ \ldots \\ p_{dt}(loadn) \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \ldots \\ \varepsilon_n \end{bmatrix}, \quad l = \begin{bmatrix} l_0 \\ \vdots \\ l_n \end{bmatrix} \tag{10}$$

We can get the equation set:

$$\begin{cases} P_{dt} = Fl + \varepsilon, \\ \varepsilon \sim N(0, \sigma^2 E_n) \end{cases} \tag{11}$$

Among them E_n is N order unit matrix.

We can get regression coefficient $\hat{l}$ which makes error sum of squares of ε minimum using the least square method that is $P_{dt} = F\hat{l}$. Plugging the eigenvectors of target day $F_0^r = [p_1(0), p_2(0), \ldots, p_{n-2}(0), p_t(0), p_{sr}(0)]$ into the formulas, then we can get the daily average load $P_d = F_0\hat{l}$ of target day.

When we get the daily average load, we build grey relational matrix whose eigenvectors are based on production plan information, weather information and daily load, and get some, noted as i=load1,,⋯, loadm. Then we take 24 hours as time period, corresponding to t=0,1, ⋯ ,23, and build 24 linear regression forecasting models, corresponding to forecasting value of historical most similar days' corresponding history values[7].

$$\hat{F} = [F_1, F_2, \ldots, F_{24}]^T, \hat{P} = [P_1, P_2, \ldots, P_{24}] \tag{9}$$

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Among them,

$$F_i = \begin{bmatrix} 1 & p_1^i(load1) & p_2^i(load1) & \dots & p_{n-2}^i(load1) & p_T^i(load1) & p_{sr}^i(load1) \\ & & & \dots & & & \\ 1 & p_1^i(loadm) & p_2^i(loadm) & \dots & p_{n-2}^i(loadm) & p_T^i(loadm) & p_{sr}^i(loadm) \end{bmatrix}$$

$$P_i = \begin{bmatrix} p_{dt}^i(load1) \\ \dots \\ p_{dt}^i(loadm) \end{bmatrix}, \quad \varepsilon_i = \begin{bmatrix} \varepsilon_1^i \\ \dots \\ \varepsilon_m^i \end{bmatrix}, \quad l_i = \begin{bmatrix} l_0^i \\ \vdots \\ l_m^i \end{bmatrix} \tag{10}$$

Calculation process is the same as solving the daily average power load, so no longer expatiatory.

Corresponding to the 24 hours' load forecasting results of target day, revising the forecasted daily average power load, then we can get the load curve solution of target day.

$$\hat{p}_t^i = \frac{24 P_d}{\sum_{k=1}^{24} p_t^k} p_t^i \tag{11}$$

Among them, $\hat{p}_t^i$ is the correction value of the forecasted daily average power load at time t on the load curve, p_t^i is the predictive value of regression analysis at time t on the load curve.

3. Analysis of Examples

Aiming at our research object, the enterprise of data source, eigenvectors built for power load forecasting include 5 kinds of production information and 2 kinds of meteorological information, which are temperature and irradiation intensity. Take number of history day m=15, number of production planning section is 5, evaluation criterion n=7, that is yield of 1# section, yield of 2# section, yield of 3# section, yield of4# section, yield of 5# section, the average temperature of the day, the average irradiation intensity of the day, resolution ratio ρ =0.5. Get the history data of the enterprise on January 1 to January 15, including production output of the day ,average temperature ,average irradiation intensity and average daily electricity load, they are shown in Table 1. This is the data foundation of the simulation calculation.

Table 1. History Day's Basic Electrical Load Data Table

evaluation criterion	yield of 1#	yield of 2#	yield of 3#	yield of 4#	yield of 5#	daily mean temperature (℃)	daily mean irradiation intensity (wh/m^2)	average daily electricity load ($kw·h$)
i=1	5	23	41	12	62	-15	127	100
i=2	6	29	18	9	55	-14	129	92
i=3	8	22	39	15	22	-12	98	84
i=4	4	21	42	8	65	-16	98	92
i=5	3	25	35	12	59	-17	105	92
i=6	4	35	38	12	60	-14	108	99
i=7	8	20	40	11	28	-8	111	81
i=8	5	24	42	14	62	-10	62	90
i=9	2	22	21	11	35	-15	78	68

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i=10	7	33	33	13	49	-11	81	93
i=11	5	32	29	4	57	-10	95	84
i=12	6	25	36	8	52	-7	102	84
i=13	7	21	19	10	46	-9	110	81
i=14	9	27	26	18	61	-13	93	104
i=15	5	30	31	13	53	-11	74	87
i=16	7	32	28	5	55	-16	95	92

The information of enterprise production plan and meteorological information of 16_{th} day to be forecasted can be expressed as the feature vector F_0 :

$$F_0 = \left[P_{10}, \cdots, P_{(n-2)0}, P_{t0}, P_{sr0} \right] = [7,32,28,5,55,-16,95,92] \tag{12}$$

Normalize the basic data, and then solve each index weight. The results are shown as Table 2.

Table 2. The Result of Each Index Weight

evaluation criterion	$P_1(i)$	$P_2(i)$	$P_3(i)$	$P_4(i)$	$P_5(i)$	$P_t(i)$	$P_{sr}(i)$
i=1	0.428571	0.2	0.958333	0.571429	0.930233	0.8	0.970149
i=2	0.571429	0.6	0	0.357143	0.767442	0.7	1
i=3	0.857143	0.133333	0.875	0.785714	0	0.5	0.537313
i=4	0.285714	0.066667	1	0.285714	1	0.9	0.537313
i=5	0.142857	0.333333	0.708333	0.571429	0.860465	1	0.641791
i=6	0.285714	1	0.833333	0.571429	0.883721	0.7	0.686567
i=7	0.857143	0	0.916667	0.5	0.139535	0.1	0.731343
i=8	0.428571	0.266667	1	0.714286	0.930233	0.3	0
i=9	0	0.133333	0.125	0.5	0.302326	0.8	0.238806
i=10	0.714286	0.866667	0.625	0.642857	0.627907	0.4	0.283582
i=11	0.428571	0.8	0.458333	0	0.813953	0.3	0.492537
i=12	0.571429	0.333333	0.75	0.285714	0.697674	0	0.597015
i=13	0.714286	0.066667	0.041667	0.428571	0.55814	0.2	0.716418
i=14	1	0.466667	0.333333	1	0.906977	0.6	0.462687
i=15	0.428571	0.666667	0.541667	0.642857	0.72093	0.4	0.179104
RESULT	**0.277529**	**0.191173**	**0.172453**	**0.144835**	**0.131965**	**0.065413**	**0.016632**

Then we can get the weight of each feature vector w_k .

$$w = [w_1, \ldots, w_7] = [0.277529\ 0.191173\ 0.172453\ 0.144835\ 0.131965\ 0.065413\ 0.016632] \tag{13}$$

According to the weight coefficient of each evaluation criterion and corresponding grey relational coefficient, we obtained the grey weighted related degree between i_{th} day and target day. The results are shown as Table 3.

Table 3. The Result of Grey Weighted Related Degree

evaluation criterion	$P_1(i)$	$P_2(i)$	$P_3(i)$	$P_4(i)$	$P_5(i)$	$P_t(i)$	$P_{sr}(i)$	RESULT
i=1	0.6190	0.4362	0.4615	0.4815	0.7404	0.8228	0.4929	0.56426
i=2	0.7647	0.6989	0.5270	0.6190	1.0000	0.6989	0.4778	0.71202
i=3	0.7647	0.4105	0.5032	0.3939	0.3769	0.5372	0.9120	0.5346
i=4	0.5200	0.3877	0.4432	0.6842	0.6663	1.0000	0.9120	0.56246
i=5	0.4483	0.4987	0.6142	0.4815	0.8331	0.8228	0.7567	0.57175
i=6	0.5200	0.6989	0.5270	0.4815	0.7997	0.6989	0.7053	0.60154

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i=7	0.7647	0.3672	0.4815	0.5200	0.4251	0.3672	0.6603	0.53188
i=8	0.6190	0.4654	0.4432	0.4194	0.7404	0.4362	0.4852	0.53225
i=9	0.3939	0.4105	0.6142	0.5200	0.4996	0.8228	0.6466	0.49954
i=10	1.0000	0.8744	0.6903	0.4483	0.7689	0.4815	0.6896	0.7731
i=11	0.6190	1.0000	0.9176	0.8667	0.9089	0.4362	1.0000	0.81187
i=12	0.7647	0.4987	0.5821	0.6842	0.8694	0.3403	0.8163	0.65761
i=13	1.0000	0.3877	0.5532	0.5652	0.6893	0.3988	0.6747	0.65717
i=14	0.6190	0.5821	0.8478	0.3333	0.7689	0.6075	0.9396	0.63441
i=15	0.6190	0.7769	0.7879	0.4483	0.9089	0.4815	0.5970	0.6825

As Table 3 shown, the n top weighted degree days are loadn=11,10,2,15,13,14,6 , and the similarity of these similar day are 81.6%, 77.6%, 70.3%, 67.7%, 65.9%, 63.5%, 60.0%, 56.7%, 56.4%. The data obtained meet the reference requirement of target day.

With equation (9) ~ (11), we can get regression coefficient $\hat{l}$ result and $P_{dt} = F\hat{l}$ as follow:

$$F = \begin{bmatrix} 1 & 6 & 29 & 18 & 9 & 55 & -15 & 127 \\ 1 & 7 & 33 & 33 & 13 & 49 & -11 & 81 \\ 1 & 5 & 32 & 29 & 4 & 57 & -10 & 95 \\ 1 & 6 & 25 & 36 & 8 & 52 & -7 & 102 \\ 1 & 7 & 21 & 19 & 10 & 46 & -9 & 110 \\ 1 & 9 & 27 & 26 & 18 & 61 & -13 & 93 \\ 1 & 5 & 30 & 31 & 13 & 53 & -11 & 74 \\ 1 & 4 & 35 & 38 & 12 & 60 & -14 & 108 \end{bmatrix}, P_{dt} = \begin{bmatrix} 997 \\ 926 \\ 841 \\ 842 \\ 808 \\ 1039 \\ 871 \\ 988 \end{bmatrix} \tag{14}$$

$$\hat{l} = [3.2108\ 21.031\ 5.1653\ 3.0124\ 7.8258\ 4.2641\ -8.0623\ 1.3175] \tag{15}$$

$$P_d = F_0\hat{l} = \hat{l}_0 + \hat{l}_1 p_1 + \hat{l}_2 p_2 + \hat{l}_3 p_3 + \hat{l}_4 p_4 + \hat{l}_5 p_5 + \hat{l}_6 p_t + \hat{l}_7 p_{sr} = 1307.308 \tag{16}$$

The daily average load $P_d = F_0\hat{l}$ of target day is 924.6676kWh, the actual load date is 916 kWh, the relative error is 0.0946%, the quadratic sum of residual error is 6.268, and the regression sum of squares is 432.435. This means random error effects much less on the accuracy of the result than P_i .

To establish the prediction model of the forecasting day, this article takes 9:00 am as example to simulate. Therefore we will use these data of 9:00 at similar days to calculate the load of 9:00 at target day. The Simulation results of grey correlation coefficient when t=9 are shown in Table 4.

Table 4. Simulation Results of Grey Correlation Coefficient when t=9

t=9	i=1	i=2	i=3	i=4	i=5	i=6	i=7	
RESULT	0.557198	0.703023	0.545977	0.563745	0.56655	0.600125	0.537931	
	i=8	i=9	i=10	i=11	i=12	i=13	i=14	i=15
RESULT	0.528112	0.497836	0.77637	0.81626	0.658261	0.658574	0.635358	0.676862

Using the grey correlation equation and the results in table 4, we can get the top 9 days most similar with t=9, they are load m=11, 10, 2, 15, 13, 14, 6, 5, 4. Applying the forecasting results when t=9 to the equation (9) ~ (10), we can calculate the load of 9:00at target day. Similarly, we can also forecast load of 24 hours at target day. The Simulation results of Electrical load forecasting results are shown in Table 5.

Table 5. Electrical Load Forecasting Results

Time t(h)	Forecasted Value (kwh)	Revised Forecasted Value (kwh)	Actual Value (kwh)	Relative Error (%)	Revised Relative Error (%)	Absolute Error (kwh)
0	1.6928	1.6713	1	19.8848	18.3646	0.2593
1	1.6928	1.6713	1	19.8848	18.3646	0.2593
2	1.6928	1.6713	1	19.8848	18.3646	0.2593
3	1.6928	1.6713	1	19.8848	18.3646	0.2593
4	1.6928	1.6713	1	19.8848	18.3646	0.2593
5	3.3856	3.3427	3	19.8848	18.3646	0.5186
6	1.6928	1.6713	1	19.8848	18.3646	0.2593
7	3.3856	3.3427	3	12.8533	11.4223	0.3427
8	85.9942	84.9038	89	-3.0153	-4.2451	3.7640
9	201.1046	198.5545	209	-3.7405	-4.9611	10.3648
10	222.6032	219.7804	226	-1.3978	-2.6482	5.9785
11	181.8067	179.5013	185	-1.9516	-3.1949	5.9241
12	177.7440	175.4901	175	1.4186	0.1325	0.2322
13	241.3933	238.3323	224	7.6086	6.2440	14.0069
14	247.6566	244.5162	230	7.8641	6.4963	14.9155
15	250.5344	247.3575	240	4.4065	3.0825	7.3969
16	150.9978	149.0830	156	-3.1774	-4.4052	6.8701
17	93.4426	92.2576	92	1.3423	0.0573	0.0528
18	180.4525	178.1642	186	-3.0953	-4.3241	8.0523
19	180.9603	178.6656	180	0.6177	-0.6582	1.1838
20	1.5235	1.5042	1	7.8963	6.5281	0.0922
21	3.3856	3.3427	3	19.8848	18.3646	0.5186
22	3.3856	3.3427	3	19.8848	18.3646	0.5186
23	2.6238	2.5906	2	15.1157	13.6560	0.3113

Through the predicted result, we can obtain data contrast curve of actual and forecasted data, which is shown in Figure 2.

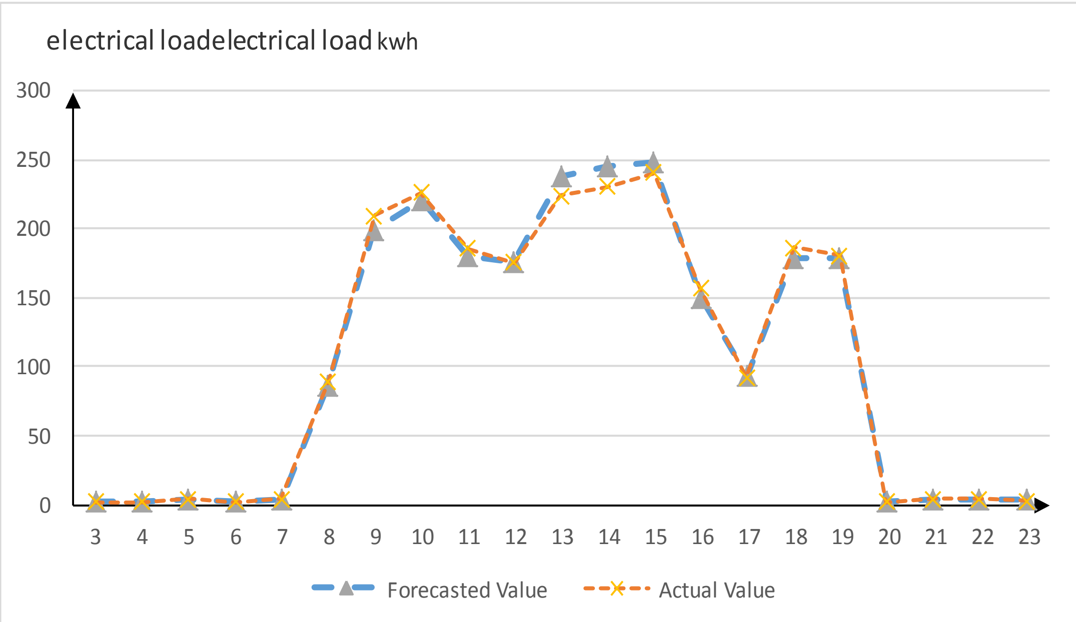

Figure 2. Forecasting Load Curve Vs Actual Load Curve

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The simulation result shows that the forecasting daily average load before correction is 22425.368kWh, after correction is 22141kWh, the actual daily average load is 22412kWh and the average relative error is 13.07%. During the working hours, the maximum value of the relative error is 7.86%, the minimum value of the relative error is 0.62%, and the average value of the relative error is 3.3%. During the off-working hours, the average value of the relative error is 19.9%, but the maximum value of absolute error is 5.18kWh, but the minimum value of absolute error is 0.922kWh, the average value of the absolute error is 4.53kWh, so it can achieve better prediction for energy using of target day.

4. Conclusion

In this paper, we find the more similar historical date as the basic data of load forecasting through Grey Relational analysis (GRA).Then we use multiple linear regression algorithm, and forecast the enterprise short-term power load based on the meteorological factors and product information. The simulation results show that this method is of better accuracy.

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