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Electricity Load Forecast Emulation Research Based on the Multi-model Merit

Qingxin Zhang, Zhanbo Cui, Luping Wang and Yanki Zhou
School of Automation, Shenyang Aerospace University, Shenyang 110136, China
sauzhangqingxin@163.com, cui.zhanbo@163.com, 293529957@163.com, iamzhouyankai@163.com

Abstract

In order to overcome the problems which are difficult to be accurately predicted, such as voilent vibration, large amplitude, and pseudoperiod, we put forward a load-classification method and a model-selection method following a multi-model merit. The multi-model merit can be realized by the result of Network training, so we can forecast the load of iron and steel enterprises respectively. In this way, we can avoid the limitations of traditional load forecasting methods which simply depend on sample datas. In the framework of this model, to minimize the load forecast error is the target. On the one hand, it can be convenient to add new models into the framework, so as to improve the accuracy of the prediction, find more characteristics of the load, and better the model. On the other hand, based on the load data, we can also adaptively change the way the model is formed, so as to expand the applicability of prediction methods. By simulating different load management forecasting systems, we confirm that the effectiveness of the proposed method is verified.

A software package based on the methods presented in this paper for power systems scheduling is also completed. Some native steel generation corporations have already used the system.

Keywords: *Multi-model selection; Moving average; Linear regression; Neural network; Support vector regression*

1. Introduction

Electric load [1] is one of the primary energy of large-scale industrial production , at any time they want rational allocation of power resources, reduce energy loss, so they need to forecast electric load effectively. Prediction accuracy maintained each process of production operation. It often closely related to the safe operation of enterprise electrical equipment, power grid construction and economic operation [2]. The electric forecasting as an important basic work has been the development of several decades of history. Increasingly sophisticated computational methods have replaced the original methods that rely on operating person's experience to forecast. No matter any time we want rational allocation of power resources, reduce power losses, make the system highly informationization and real-time interactive [3]. For short-term daily load forecasting, aiming at short-term volatility of daily load electricity [4], large amplitude [5] and pseudo periodicity [6]. It is difficult to control the characteristics of the load sequence itself. The present methods include support vector machine (SVM)[7-8] linear regression, time series method[9-10] sliding smooth, the wavelet analysis method[11], fuzzy prediction, gray prediction method [12-14] and neural network[15-16]. No matter use what kind of network model, it related to using input and output samples. According to the

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error function, repeated iteration to determine parameters. Not only the initial weights and learning rate selection make a great impact on the accuracy of the network, but also it requires a lot of time for neural network training. In addition, to accurately predict load trends, we must analysis the volatility of the load and characteristics of the process effectively. In the industrial enterprises' load forecasting, because of the complexity of the prediction problem, which objectively calls for a multi-model prediction method for load forecasting. This requires Baosteel load forecasting framework to support multi-model predictions and can be adapted to increasing and expanding the model. At the same time it can automatically assembled or automatically merit for various models, and thus make the total load prediction. Therefore, in this system, this article proposed selecting-best Multi-model prediction framework of adaptive data quality.

2. Selecting-best Multi-model Prediction Framework of Adaptive Data Quality

2.1. Model space

The prediction problem that uses a regression method can be described as follows for solving the problem:

$$f : x \to y \tag{1}$$

In the formula (1), f is a regression function, can be selected as linear regression, neural network, support vector machine regression and so on. $\mathbf{x}$ is called independent variable, y is called response variable. Corresponding to the same y, we can choose different $\mathbf{x}$. This process is the process of selecting related factors, which is called feature selection problem in regression problems. Equally, y is similar to decomposable forecast goals of steel enterprises load, and y may have different meanings, such as furnace load, the total load and so on.

So, when using regression method to predict, all the models are in the model space as shown in the figure below.

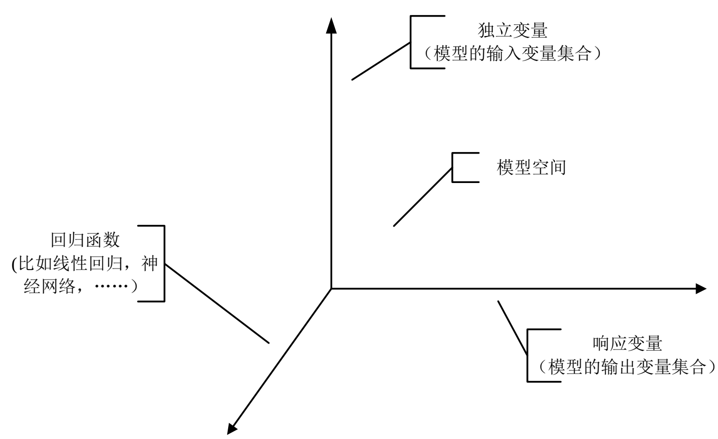

Figure 1. Schematic diagram of the model space

2.2 Combination of multi-model

Using the method of load classification and model classification shown in the above, the method of multi-model can be used to predict for the load of steel companies, it's basic idea is shown as follows:

Step1：Decompose the total load, using a variety of forecasting methods to establish predictive models for each load component.

Step2：By assembling flexibility each load component of different models, a variety of prediction scheme of total load are established. When some information is missing, it will lead to some models which need this information can not be used. So that the corresponding prediction scheme can't work, other prediction schemes which are nothing to do with those missing information can work properly and give prediction results.

Step3：In all prediction model which have been obtained, according to certain methods (such as using merit criteria named the previous day prediction effect best) the paper use selecting-best model, results fusion or artificial making prediction method to forecast the total load.

After establishing model according with the above way, the model needs to be combined to forecast the total load. The prediction value of the total load can be obtained through the following ways:

a. Aiming at the total load to forecast directly.

b. The prediction results of electric furnace +the prediction results of hot rolling +the prediction results of other load.

c. The prediction results of electric furnace +the prediction results of other load.

d. The prediction results of hot rolling +the prediction results of other load.

Taking into account the presence of a variety of models in model space, there are many ways to obtain the total load. For convenience, we assume that the number of combination scheme is N, the combination scheme set S_{all} which to obtain the total load is expressed as:

$$S_{all} = \{scheme_1 \quad scheme_2 \quad \cdots \quad scheme_n\}$$

When some information is missing, all the corresponding models or part of the models of some classification load of the information which we need can’t be predicted, thus the means to take advantage of the combination of the total load can not be used, either. But other models that do not use this information could be used to keep forecasting and the existing model of the combination of the total load can be used to forecast continually. It not only makes full use of forecasting information, but also improves the operability of the forecast. In the absence of predictive information, the combination scheme S_{active} of obtaining the total load becomes:

$$S_{active} = \{scheme_1, scheme_2, \cdots, scheme_m\}, m < n \text{, clearly, } S_{active} \in S_{all}$$

2.3 Frame design

Forecasting work can be divided into four parts, namely data processing, modeling warning, model updating and model predictions.

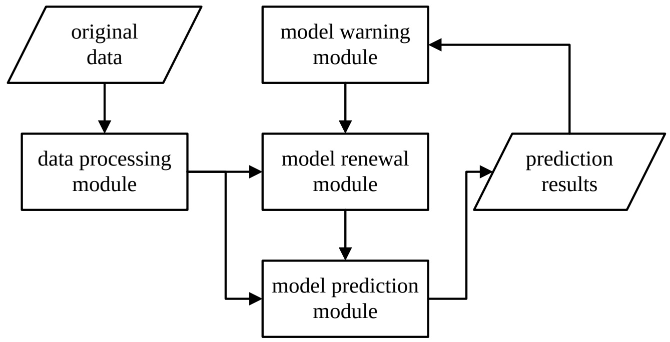

Figure 2. Forecasting system module diagram

The total schematic diagram is shown in Figure 2.

The data processing module is a part of data preprocessing, including deletion data completing, abnormal data correction and generating a processed log data on this basis for user reference system. Models warning module is to evaluate for the prediction effect of the model, so as to give model prompt signal model need to be updated. So that we can update the prediction model timely and prevent the situation that prediction error increases caused by model's long-term updating.

The standard of model warning can be set to two kinds:

(1) Set a prediction error limits. Once the error is out of the limit, system prompts the model needs to be updated;

(2) Checking the trend of prediction error. If the error sustained increases with the prediction time, system prompts to update the model.

Model updating module is set by model of early warning information or manual, And system will update every model in the multiple model systems. According to the time of updating the model, system will update the model for the variety of loads (including load combinations). If data is not complete, the model exits option model. Thereby in the stage of updating the model, system will judge all the models and ultimately determine which model and the model parameters can be used.

When performing load forecasting, we will obtain relevant data according to the predicting time and the input parameters of the model that can be used. If the data is missing, we will remove the model from the model which can be used after updating .Finally obtaining the model which can be predicted.

In all the obtained models that can be predicted, according to a certain method (for example, using the combination form of best effect of recent forecast period), we use model selection, result fusion or artificial making prediction method to predict the total load.

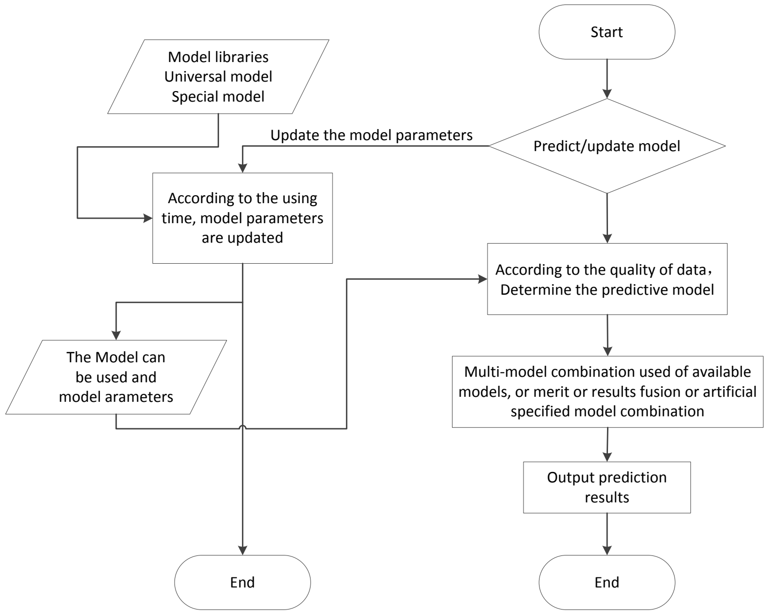

Figure 3. Schematic diagram of the overall framework of load forecasting

3. Multi-modeling and Simulation Analysis of Daily Load Forecasting

3.1 Combination of moving average and linear regression model

This is a composite model which is obtained by different moving average model weighting the day load forecasting values (linear regression). Here uses three moving average models. They are the first 14 days moving average, the first 7 days moving average and the first 3 days moving average. Model structure is shown as follows:

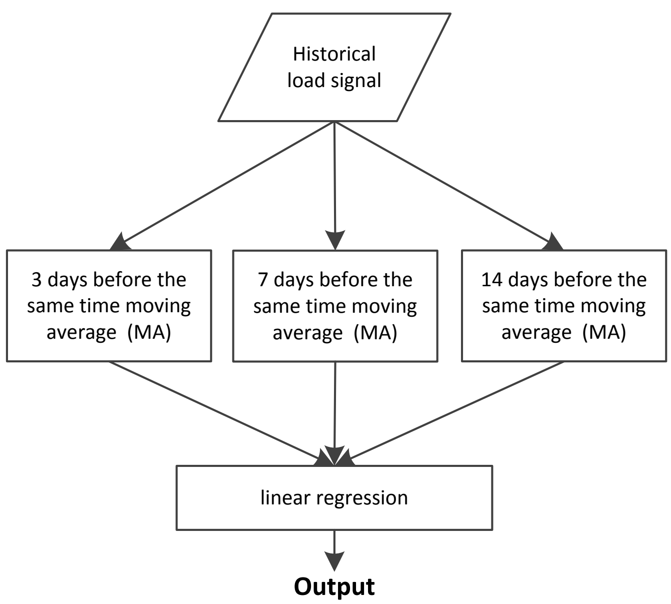

Figure 4. Combination of moving average and linear regression model structure diagram

Training samples used in the model is from 2012.09.16-2012.10.08, 288 point loads every day. Each prediction point uses the predicted value of three moving average models (moving average of the first 14 days, the first 7 days, and the first 3 days) in the same time on the day as input for linear regression. For example, in order to predict the load value at 0:05 on October 8, the input uses moving average at 0:05 on October 6, 5 and 4, from 0:05 on October 6 and 0:05 on October 5 to 0:05 on September 30, a total of seven times moving average. And so on, it plus the same moment at the first 14 days moving average historical load as input and get the integrated model output by linear regression.

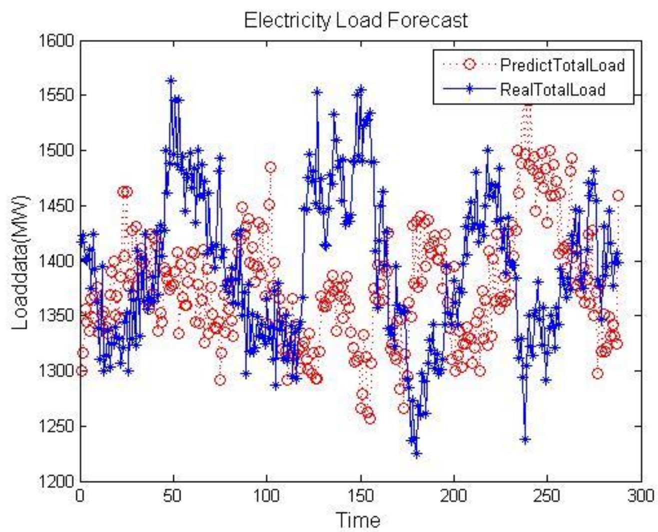

Figure 5. The actual load curve and the predicting curve on October 6, 2012

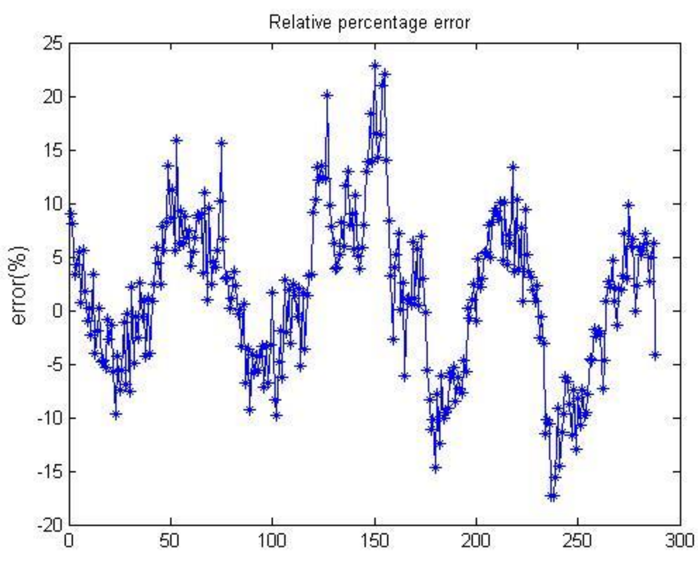

Figure 6. Relative percentage error maps on October 6, 2012

In the 288 points that day, the absolute average of relative prediction error is 7.62%. There are 256 points whose predicted value of the absolute value of the relative percentage error is less than 10%. In other words the day 88.88% points of absolute value of relative percent prediction error is less than 10%.

3.2 Artificial neural network [17]

Training samples used in the model are from 2012.09.16-2012.10.05, 288 point loads every day, each prediction point using the load value at the same time the day before and the load value that is projected total of 14 days forward at the same time as the input of the sample. For example, in order to predict the load value at 0:05 on October 8, the input using moving average at 0:05 on October 6, 0:05 on October 5, and by this analogy, until 0:05 on September 23, the total of 14 historical moments load values are used as input.

In the neural network training, 80% of the samples are training samples, and the remaining 20% are early stopping validation sample. After many experiments, the number of hidden nodes is12.

Model training sample set contains a total of 5760 samples, including:

training date range: 16/9/2012 to 5/10/2012.

train/validation ratio: 0.8

forecast date range: 6/10/2012 to 8/10/2012, a total of 864 points.

Test results are as follows:

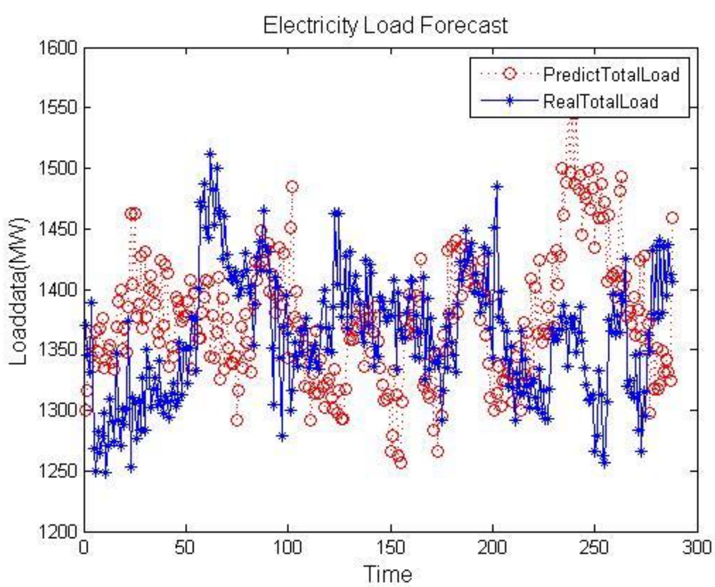

Figure 7. Load forecast on October 6, 2012

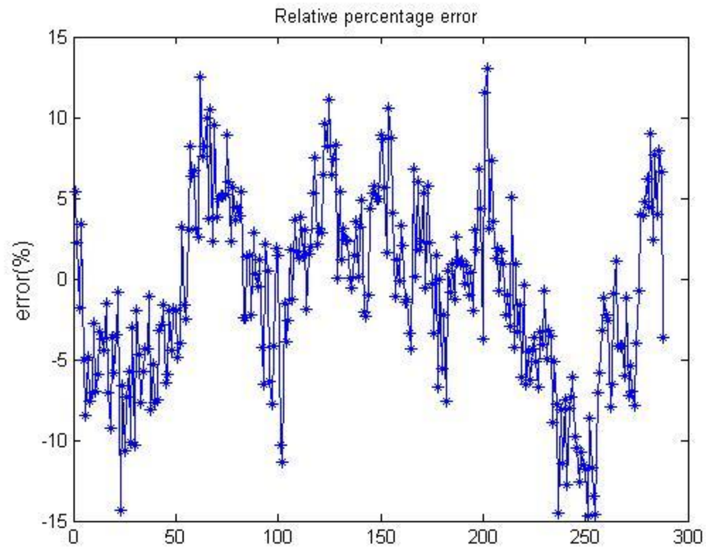

Figure 8. The total load distribution of relative prediction error on October 6, 2012 (The abscissa in the figure represent 5 minutes time point (one day 288), the vertical axis unit is %)

In the 288 points that day, the absolute average of relative prediction error is 9.87%. There are 244 points predicted value of the absolute value of the relative percentage error is less than10% (the number of points whose absolute value of relative error is less than 10% is 244). In other words the day 84.72% points of absolute value of relative percent prediction error is less than10%.

3.3 Support vector regression model

Support vector machine, using the SRM (Structural Risk Minimization) guidelines, at the time of minimizing the error of sample point, considering the Structural factors, the model fundamentally improves the generalization ability. Support vector machine (SVM) showing many unique advantages in tackling small sample, nonlinear and high dimensional pattern recognition problems, is a kind of prediction method which is worth studying. Its application in the electric power load forecasting has been more and more attention. The training sample data comes from Baogang' history records on every five minutes average total load from June 2012 to September 2012. Training set consists of 4000 random samples. Each sample includes 14 input variables and one output variable. We select parameter by genetic algorithm. In condition October 1 ~ 15, 2012, a total of 4896 samples will be predictive set, using the selected parameters of SVR model, to forecast the prediction set samples.

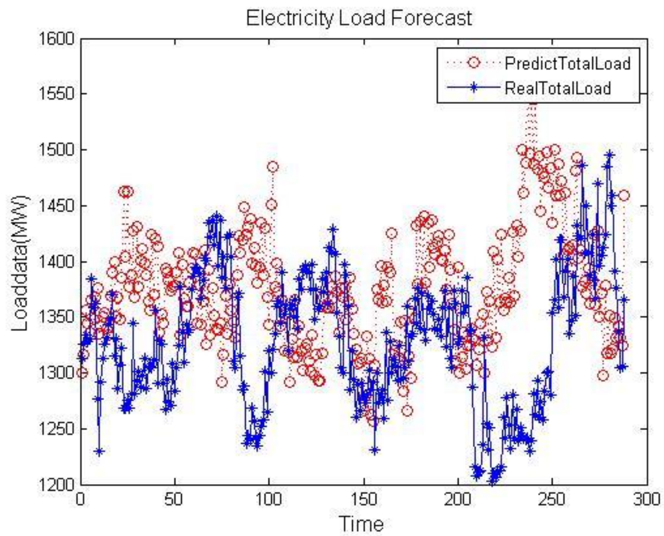

Figure 9. SVR load forecasting results and actual value comparison chart on October 2-4, 2012

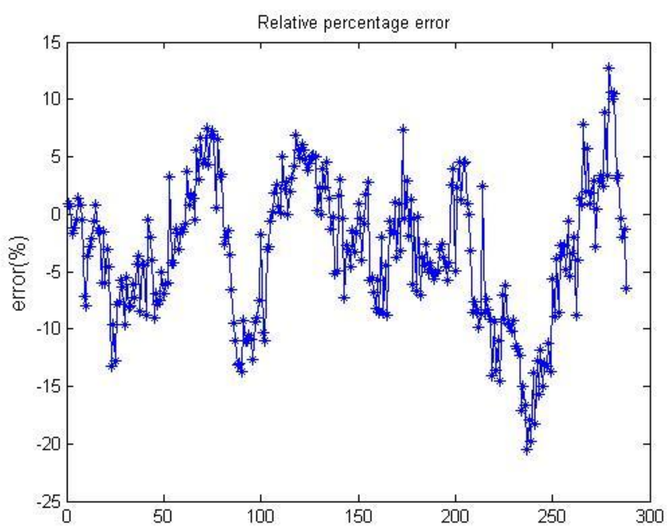

Figure 10. load forecasting error maps on October 2, 2012

In the 288 points on October 2, the absolute average of relative prediction error is 8.84%, which has 240 points predicted value of the absolute value of the relative percentage error is less than 10%.(the number of points whose absolute value of relative error is less than 10% is 240). In other words that is the day 83.33% points of absolute value of relative percent prediction error is less than 10%.

The total power load forecasting average error of these models for Baogang 2012 early October is about 7.7% -13.5%. In the 288 points per day, the proportion of the points whose predicted error is less than 10% is about 77% -88%. Power Load total average prediction error on late June 2012 in Baogang is about 8.74%-9.27% by using these models. In the 288 points per day, the proportion of the points whose predicted error is less than 5% is about 66% -72%.

4. Multi-model Selection

From the above analysis, there are a variety of schemes to get the system load forecast. This requires choosing the best prediction results in these results as the final output. In this way, the system prediction accuracy is further improved.

Merit criterion for results of scenarios predict is particularly important in this case. Through the research we found that load values of iron and steel enterprises in the adjacent time have greater relevance. Therefore, this article use the highest prediction accuracy of the prediction scheme in the recent forecast period as the prediction scheme in current forecast period by evaluating historical accuracy of prediction scheme. Specifically. The prediction system model, predicting the date specified load values at 288 points, while predicted interval with the specified start date n days before the day's load value, n is a positive integer. Since n days before the actual load value is already available, the previous n days by calculating the error indicator can be used as merit-based criteria. Through different ns' value, we can get different merit criteria.

The following example is to test the preferential effect of each selection criterion. The forecast period of examples is October 1, 2012 - October 15, 2012. Among them, the prediction of total load values are obtained by the programs listed in Table 1, a total of 12 schemes.

Table 1. prediction scheme list

Prediction scheme number	Prediction content
1	3 days moving average model to predict the total load
2	7 days moving average model to predict the total load
3	14 days moving average model to predict the total load
4	Linear regression model to predict the total load
5	Neural network model to predict the total load
6	Support vector machine model to predict the total load
7	3 days moving average model to predict the base-load + Furnace predictive value
8	7 days moving average model to predict the base-load + Furnace predictive value
9	14 days moving average model to predict the base-load + Furnace predictive value
10	Linear regression model to predict the base-load + Furnace predictive value
11	Neural network model to predict the base-load + Furnace predictive value
12	Support vector machine model to predict the base-load + Furnace predictive value

Table 2. lists the current selection criterion

Merit-based criteria	Content
1	Forecast load value 1 day ahead and the actual value of the MAPE
2	Forecast load value 2 days ahead and the actual value of the MAPE
3	Forecast load value 3 days ahead and the actual value of the MAPE

Table 3 lists merit-based program sequence based on the prediction results and performance evaluation. Among them, the performance evaluation using three indicators: the mean absolute percentage error (MAPE), mean absolute percentage error of the standard deviation, mean absolute percentage error of the maximum.

Table 3. Different merit-based criteria under the program sequence and performance prediction table

merit-based criteria	Merit-based program sequence	Performance Evaluation		
		MAPE(%)	The standard deviation of MAPE (%)	The maximum of MAPE (%)
1	9 9 12 11 1 10 10 11 11 6 9 8 8 11 10	3.30	1.07	5.8293
2	7 9 11 12 11 4 10 11 11 11 9 9 8 8 8	3.50	1.53	8.28
3	7 7 12 11 1 11 11 11 11 11 10 8 8 8 8	3.56	1.66	8.28

Table 4 shows that if one chooses the merit criterion 1 as the criterion he can obtain the best performance. At the same time, if one pays attention to the selected schemes which are mostly in scheme 7~12, he will see the large impact load electric separate modeling and other basic load accumulation scheme is superior to direct to the total load forecasting modeling scheme.

Here's comparison between optimized results of merit criterion 1 and actual optimal results. Table 4 lists the comparison and error comparison between scheme chosen by selection criteria every day and actual optimal solution.

Table 4. Error ratio comparison table between the prediction results based on the merit criterion and actual results of the optimal prediction scheme

	Criteria for selection		Actual optimal	
	scheme	MAPE(%)	scheme	MAPE(%)
October 1st	9	5.8293	12	3.1863
October 2nd	9	3.5097	11	2.5514
October 3rd	12	2.9061	11	2.2663
October 4th	11	2.1002	11	2.1002
October 5th	1	2.6805	10	2.5543
October 6th	10	2.6242	11	1.9392
October 7th	10	2.0959	11	1.8238
October 8th	11	3.1195	8	2.8781
October 9th	11	3.9945	9	2.4584
October 10th	6	2.4419	6	2.4419
October 11th	9	3.0344	8	2.3253
October 12th	8	2.6976	11	2.3711
October 13th	8	3.8993	10	2.726
October 14th	11	5.1778	12	2.6826
October 15th	10	3.425	8	3.2423

As can be seen from the table, during the 15 days, there is few points that the the scheme based on the merit-based criteria superpose with actual optimal scheme. There is a gap prediction error resulting in the two ways. The results show that the MAPE average value for prediction results of actual optimal scheme in15 days is 2.50%, while the MAPE average value for prediction results of preferred criterion in15 days is 3.30%. It is proved that there is research space in the problem of optimal fusion results prediction.

5. Conclusion

Among the large power users, because heavy industrial enterprise loads huge power, and it is a greater impact on the power grid, its prediction is particularly important. We mainly analyze load forecasting for the typical representative of heavy industry - steel enterprises. Since this is a new issues with the deepen reform of the electricity market and the emergence, this paper through studying the characteristics of electrical use in, deeply analyses electrical characteristics of the iron and steel enterprises in every power link, mainly makes a predictive model for main production processes of iron and steel enterprises with provided production information. As the load sequence is not a stationary time series, data quality is relatively poor and the load varied, we designed a variety of predictive models to adapt to different situations. And on the basis of these models we propose a kind of prediction problem for multi-model preferential framework, which has an adaptive data quality, multi-model automatic preferred and convenient model extensions and other characteristics. The framework has a promotional nature for the general types of load forecasting.

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References

[1] K. Moslehi and R. Kumar, “Smart Grid”, IEEE Transactions on, vol. 1, no. 1, **(2010).**
[2] Z. W. Shi and M. Han, “Control and Decision”, vol. 22, no. 3, **(2007).**
[3] W. Luan, D. Sharp and S. Lancashire, “Smart grid communication network capacity planning for power Utilities”, Transmission and Distribution Conference and Exposition, 2010 IEEE PES, Hydro, Canada, **(2010)** April 1-4.
[4] J. Lee, D. K. Jung, Y. Kim, Y. W. Lee and Y. M. Kim, „Network Operation and Management Symposium Workshop, 2010 IEEE, vol. 6, no. 17, **(2010).**
[5] P. E. Marken, J. J. Marczewski, R. D'Aquila, P. Hassink, J. H. Roedel and R. L. Bodo, “VFT – A Smart Transmission Technology That Is Compatible With the Existing and Future Grid”, IEEE Power Systems Conference and Exposition, Seattle, USA, **(2009)** March 15-18.
[6] F. Rahimi and A Ipakchi, “Overview of demand response under the smart grid and market Paradigms”, Open Access Technol. Int. Inc.(OATI), Minneapolls, Gaithersburg, USA, (**2010)** January 1-7;
[7] A. Akyüz-Daşcıoğlu, “Applied Mathematics and Computation”, vol. 217, no. 12, **(2011).**
[8] M. Y. Cho, J. C. Hwang and C. S. Chen, “Energy Management and Power Delivery”, vol. 1, no. 1 **(1995).**
[9] S. Fan, L. Chen and W. J. Lee, “Industry Application”, vol. 45, no. 4, **(2009).**
[10] D. H. Zhang, S. F. Jiang, „Electric power systems and Automation”, no. 2, **(2004).**
[11] Y. Chen, P. B. Luh, C. Guan, Y. Zhao, L. D.Michel, M. A. Coolbeth and S. J. Rourke”, Power Systems, vol. 25, no. 1, **(2010).**
[12] S. Sandeep and C. M. Verma, “load forecasting using fuzzy methods”, Power System Technology and IEEE Power India Conference, New Delhi, India**, (2008)** October 12-15.
[13] H. Y. Yu and F. L. Zhang, “Power System Technology”, vol. 31, no. 3, **(2007).**
[14] B. Y. Zheng and M. L. Song, “Application of grey regression model in power load forecasting”, Power Electronics and Intelligent Transportation System, the 2nd International Conference, Shenzhen, China**, (2009)** December 19-20.
[15] S. Fan, L. Chen and W. J. Lee, “Industry Application, vol. 45, no. 4, **(2009).**
[16] Y. Wang, X. Q. Ma and A. Liu, „Proceedings of the CSEE”, vol. 28, no. 14, **(2008).**
[17] P. J. Antsaklis, IEEE Control System Magazine, vol. 1, no. 2 **(1990).**

Authors

Qingxin Zhang

Professor at the Research Center of Information and Control, Shenyang Aerospace University. He received the PhD degree in Theory and New Technology of Electrical Engineering from Shenyang University of Technology in 2006, the People's Republic of China. He was a postdoctor at Key Laboratory of Industrial Informatics,Shenyang Institute of Automation,Chinese Academy of Sciences during 2011 to 2012. His research interest covers adaptive control, computer integrated manufacturing system, and computer control of industrial process.

Zhanbo Cui

Master candidate in control theory and control engineering at Shenyang Aerospace University. He received his bachelor degree from the Department of Automation, Shenyang Aerospace University in 2011. His research interest covers integrated production planning and scheduling problem, load forecast of power, system simulation modeling, intelligent optimization and application, and articial neural network.

Luping Wang

She received the bachelor degree from Shenyang Aerospace University, the People's Republic of China, in 2011. Since 2011, She has been with the College of Automation at Shenyang Aerospace University University. Her research interest covers computer integrated manufacturing system, and intelligent optimization and application.

Yankai Zhou

He received the bachelor degree from Langfan Teachers College, the People's Republic of China, in 2011. Since 2011, He has been with the Collage of Automation at Shenyang Aerospace University University. His research interest covers computer integrated manufacturing system, and Pattern Recognition.