Research on Electric Vehicle Charging Station Load Forecasting

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Abstract: In recent years, due to the pressure of energy crisis and environmental pollution, Electric Vehicle (EV) has gained opportunities for development. With the large-scale construction of charging station, the wide use of EV will cause the rapid growth of the power load in local areas. As the essential part of grid loads in the future, the charging station load forecasting, especially the short-term load forecasting, will play a very important role in production arrangement, economic dispatching, and safe operation of electric power system.

The traditional power load forecasting model is mainly based on the factor of weather (such as temperature and humidity). Compared with the traditional power load, the EV charging station load is more complicated and mutable. In view of present EV charging station load, the trend of charging station load curve is more closely related to the user action and the flexible factors of charging rather than weather. Taking the distinctive characteristics of EV charging station load into consideration, an approach to accommodate this change by establishing the suitable model for the charging station load forecasting is presented in this paper.

Based on the daily load data of Beijing Olympic Games EV Charging Station in 2010, this paper gives a brief introduction of characteristics of the charging station load and establishes three types of daily load forecasting model for EV charging station load, including BP neural network, RBF neural network and GM(1,1) model. The application of the models has been realized in MATLAB.

Keywords: EV charging station load forecasting, BP neural network, RBF neural network, GM(1,1) model

1 Introduction

With the global energy crisis and environmental pollution increased, Electric Vehicle (EV) has gained in opportunities for development in recent years, because it has many advantages, such as low energy consumption, less pollution and so on[1]. The development of EV relies on the foundation of infrastructures, such as charging station, which is one of the most important factors of exploiting market for EV [2]. With the large-scale construction of charging station, the wide use of electric vehicle will cause the rapid growth of the power load and cause peak power of electric power in local areas and some periods of time when all are charging [3]. Taking Beijing for instance, nowadays nearly more than 20,000 buses are running in the city, if we change all the traditional buses into electric vehicles, calculating with the same scale of energy consumption, the demand of power for EV charging station would account for about 3 percent of all power supply in Beijing [4]. As the essential part of grid loads in the future, the charging station load forecasting, especially the short-term load forecasting, plays a very important role in production arrangement, economic dispatching, and safe operation of electric power system [5]. Therefore, the accurate and appropriate load forecasting method for EV charging station will be the important guarantee for the planning and operation of the whole power system.

Compared with the traditional power load, the EV charging station load is more complicated and mutable based on the flexible user action. In view of present EV charging station load, different from the traditional power load, the trend of charging station load curve is more closely related to the user action rather than weather. The traditional power load forecasting method establishes model mainly based on the factor of weather (such as temperature and humidity), but the charging station load forecasting is more related to the user action and the flexible factor of charging. Then the different effect of relative factor determines the different load forecasting method for EV charging station load.

Based on the daily load data of Beijing Olympic Games EV Charging Station in 2010, this paper gives a brief introduction of characteristics of the charging station load and establishes three types of daily load forecasting model for EV charging station load, including BP neural network, RBF neural network and GM(1,1) model. The application of the models has been realized in MATLAB.

2 The characteristics of charging station load

A. The introduction of three charging modes

Based on the various demands of users, the modes of charging for EVs are mainly divided into three types, and the different modes of charging determines the different characteristics of charging station load. There are the following main charging

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modes with the development of EVs.

1) The fast charging mode

The fast charging station is usually set up alone the EV lines likes the petrol station used to the emergency charging for EV. In this charging mode, with the huge charging current, EV can charge to about above 90 percent of their battery capacity in a few minutes. Although this charging mode seriously impairs the quality of power supply system, it can greatly reduce the consumption of charging times and bring convenience to users. Because of the random charging action, the load of fast charging station distributes dispersedly in a day.

2) The normal charging mode

This mode of charging station is mainly applied in the residential areas where EV makes use of stopping time to charge with small current. According to the daily habits of user, the peak-load of normal charging station usually starts in off duty time and lasts to midnight. With the development of EV, the construction of the normal charging station in residential areas will be an important foundational work.

3) The quick change of battery mode

In this approach, the battery of EV which has run down will be replaced to charge in the certain charging station. This is an effective way to improve the weakness of short endurance of EV. With the quick change of battery mode, EV can renew energy at the special charging station in a short while. The exhausted batteries are charged as soon as they are changed from EV or charged together at a particular time at the charging station based on the different demands. Because of the convenient management, the quick change of battery mode has been applied to the buses operation in many cities, such as Beijing, Shanghai and Guangzhou.

B. The analysis of present EV charging station daily load

With the development of the charging modes mentioned above, more and more EV charging stations are building extensively, especially the quick change of battery charging station. In this paper, the basis of data comes from the daily load data of Beijing Olympic Games EV Charging Station in 2010.

Beijing Olympic Games EV Charging Station is a quick change of battery charging station and it provides power to the No.84 buses. According to the running rules of the buses, the charging station load curve has the certain characteristics.

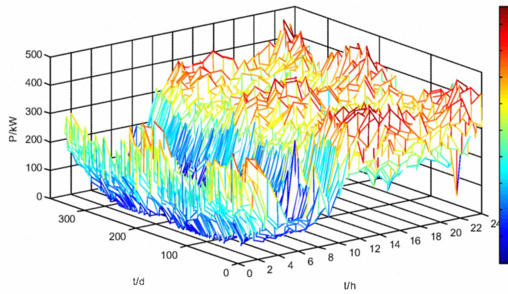

Figure 1 Daily load curves in a year

Figure 1 shows the daily load curves of Beijing Olympic Games EV Charging Station in 2010. It can be seen from the picture that the daily load curve is mutable and has the sensible peak and lower waves in a day. Besides, among all the annual daily load curves, the load of summer and winter is higher than spring and autumn. The reasons for this phenomenon are the consumption of cooling and heating load.

Analyzing the trend of above daily load curves, we find that the peak load usually center at four moments, including 11 am, 12 am, 22 pm and 23 pm. Therefore, we make an analysis of peak load at these four moments in particular. Figure 2 shows the distributions of peak load at four moments in a year. In the picture, the trend of peak load curves is same to the daily load curves in a year that the peak load of summer and winter are higher than spring and autumn. In addition, it reveals that there is a clear cycle of wave in the curve. Based on the day type in a week, the cycle of wave is changing in a primary periodicity of about 7days.

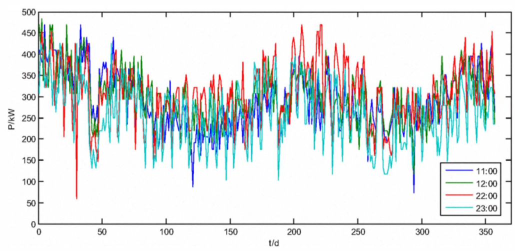

Figure 2 The peak load curves in a year

3 The establishment of forecasting models

Nowadays the existing power load forecasting has achieved a large number of researches and reached a high level of accuracy in common [6]. Similar to the existing power load forecasting method, the final purpose of EV charging station forecasting is accurate and useful. The researches in this paper are unfolded in the direction of reducing error between prediction data and actual data.

A. The selection of similar days

Because of the similar trend of daily load curves on similar days, choosing the similar days' loads as sample in the power load forecasting is an important way to reduce the error of result and this is also suitable to EV charging station load forecasting.

For a group data of daily loads whose length is 7n (n=1,2,3, • • •) days and the data begin on Monday and end on Sunday. Divided with the type of days that the mean of the similar days' daily loads is calculated as following equation (1):

$$P_{av} = \frac{1}{n}\frac{1}{24}\sum_{i=1}^{n}\sum_{t=1}^{24} P_{t-24} \quad (1)$$

Where n is the number of the similar days; P_{av} is the mean of n similar days' daily load; P_{t-24} is the load of t-th hour of similar days.

Standard deviation (STD) of the similar days' daily loads can be expressed as equation (2):

$$S = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(P_{avi} - P_{av})^2} \quad (2)$$

Where S is the standard deviation of the similar days' daily loads; P_{av} is the mean of n similar days' daily load; P_{avi} is the mean load of i-th day in similar days.

Table 1 Mean and std of the same day type in a year

Day type	Mean	Std
MON	208.15	36.84
TUE	216.39	37.12
WED	212.79	35.97
THU	211.45	38.31
FRI	210.70	37.71
SAT	191.75	34.19
SUN	191.17	33.79

In this paper, we choose the daily load data of Beijing Olympic Games EV Charging Station from January 4(Monday) to December 26(Sunday) in 2010. The group of daily loads contains 357 days and 51 weeks in total. Selecting the same type of days as the similar days, in accordance with above analysis method to daily loads, the final calculation results are presented in Table1.

Comparing the mean and std of the seven types of days in a week, the mean and std of workdays are different from the mean and std of weekends. The mean and std of workdays are markedly higher than weekends'. Besides, there is a similarity among the mean and std of five-day workdays and the phenomenon is also fit to the two-day of weekends. Therefore, the pattern of choosing the same type of days as the similar days is more reasonable than choosing the continuous days as the similar days to EV charging station daily load forecasting.

In this paper, the selection of training databases is extracted from previous 70 days before the forecasting day. Considering the same characteristics of daily load in similar days, if the forecasting day is Monday or Saturday, choose the same type of days in the past weeks as the similar days. Differently if the forecasting day is others, the similar days consist of the day before forecasting day and the same type of days in the past weeks.

B. Forecasting models

The daily loads of EV charging station are complicated and non-liner and the traditional load forecasting algorithms such as linear time series and regression analysis hardly have the ability to simulate complex power load. Instead of the traditional load forecasting algorithms, the modern load forecasting algorithms are able to self-learn and perform non-linear modeling and adaptation [7]. In the paper, the BP neural network, RBF neural network and GM(1,1) model are established.

1) BP neural network

The BP neural network is one of the artificial neural networks which is widely using in load forecasting for electric power system. It has the characteristic of self-learning and consists of input layer, hidden layer and output layer. The three layers comprise individual processing units called neurons and each processing unit sums weighted inputs, and then applies a linear or non-linear function to the resulting sums to determine the outputs. Based on the error back-propagation algorithm, the prediction process will be continued until the output error of network is reduced to an acceptable level or the predetermined time of learning is achieved [5] [8].

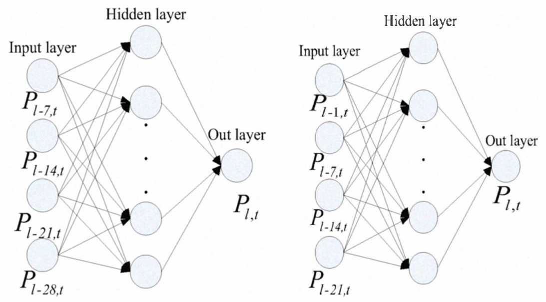

Figure 3 The structure of BP neural network based on the similar days

The structure of BP neural network plays a significant role in load forecasting which directly determines the performance of results. In order to avoid the redundancy of network and diminish the training time, we divide a day into 24 time points and establish 24 BP neural networks for each time point. Based on the selection of similar days, the structure of BP neural network is shown in figure3.

In the left-hand picture, the units of input layer is $P_{l-7,t}$, $P_{l-14,t}$, $P_{l-21,t}$, $P_{l-28,t}$ that are used to the forecasting day which is Monday or Saturday. In the right-hand picture, the units of input layer is $P_{l-1,t}$, $P_{l-7,t}$, $P_{l-14,t}$, $P_{l-21,t}$ that are used to the other circumstances. $P_{l-i,t}$ is the load at t-hour of the i (i =1,7,14,21,28) day before forecasting day. $P_{l,t}$ is the load at t hour on the forecasting day. Based on the experience formula, the number of hidden neurons is 2n+1 (n is the number of input neurons), so the number of hidden neurons is nine and the number of output neurons is one.

The historical data can't be directly used for the input of neural network, and we need to present a normalization to deal with daily loads data. The results of data are in [0, 1] by this normalization formula (3):

$$\overline{P}_t = \frac{P_t - P_{t\min}}{P_{t\max} - P_{t\min}} \quad (t=1,2,\cdots 24) \qquad (3)$$

In the formula, P , $P_{t\max}$ and $P_{t\min}$ respectively represents load data, maximum and minimum, and $\overline{P}_t$ is the normalized load data.

After the normalization of data, using the BP neural network toolbox of MATLAB, the transfer function of hidden layer and output layer respectively choose tansig and logsig. While the training function is trainbr which calculates with trainlm algorithm and self-define the regularization parameter with the Bayesian statistical method.

2) *RBF neural network*

Radial Basis Function neural network (RBF) as one important branch of neural networks, has the best ability of approximation and the best overall performance. Compared to the BP neural network, the consumption of training time of RBF neural network is greatly diminished. Because of the advantages of the RBF neural network, it has been widely applied in nonlinear time series prediction [9].

RBF neural network is a three-layer forward network. The 1st is input layer. The 2nd is the hidden layer, and the number of unit depends on the described problem. The 3rd is output layer, which reacts to the role of input pattern. In this paper, using the RBF neural network toolbox of MATLAB, we establish an accurate RBF neural network with the function of 'newrbe'. The spread of training is 2 and the radial basis function is Gaussian function.

Based on the selection of similar days, figure 4 shows the structure of RBF neural network. In the left-hand picture, the units of input layer is $P_{l\text{-}7,t\_24}$, $P_{l\text{-}14,t\_24}$, $P_{l\text{-}21,t\_24}$, $P_{l\text{-}28,t\_24}$ that are used to the forecasting day which is Monday or Saturday. In the right-hand picture, the units of input layer is $P_{l\text{-}1,t\_24}$, $P_{l\text{-}7,t\_24}$, $P_{l\text{-}14,t\_24}$, $P_{l\text{-}21,t\_24}$ that are used to the other circumstances. $P_{l\text{-}i,t\_24}$ is the 24-hours daily load of the i (i =1,7,14,21,28) day before forecasting day. P_{l,t_24} is the 24-hours daily load on the forecasting day.

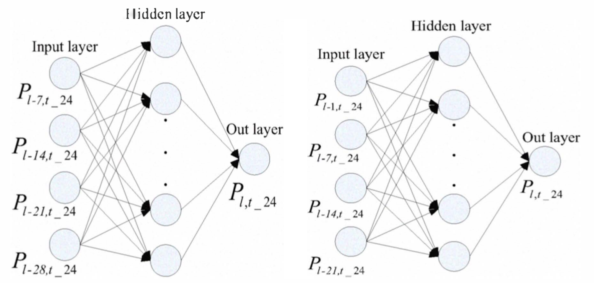

Figure 4 The structure of RBF neural network based on the similar days

Same to the BP neural network, the historical daily loads need to be made a normalization by the formula (3). Then through the prediction of above RBF neural network, the whole 24-hours load of forecasting day can be predicted.

3) *GM(1,1) model*

Grey model is the core of Grey System Theories which have been used widely in power load forecasting. GM (1, 1) model is the most common form of the Grey model, which is variable model consisting of first order differential equations. The grey forecasting model has three operations: (a) accumulated generation, (b) inverse accumulated generation, and (c) grey modeling. The detailed steps of establishing a common GM (1, 1) model are presented in [10].

In the paper, the daily load of the forecasting day is divided into 24 time points and the twenty-four GM (1, 1) models are established for each time point. Based on the selection of similar days, if the forecasting day is Monday or Saturday, choose the same type of days in the past ten weeks as the similar days. The load-series of similar days are $P_{l\text{-}i,t}$ (i =7, 14, $\cdots$, 70) ; In case of the forecasting day is others, the similar days consist of the day before forecasting day and the same type of days in the past nine weeks. The load-series of similar days are $P_{l\text{-}i,t}$ (i =1, 7, 14, $\cdots$, 63) , $P_{l\text{-}i,t}$ is the load at t-hour of the i day before forecasting day.

4 The realization of load forecasting

In order to verify the abilities of above daily load forecasting models, the simulation test of BP neural network, RBF neural network and GM(1, 1)model are performed in MATLAB. The procedures of forecasting models are illustrated in figure 5.

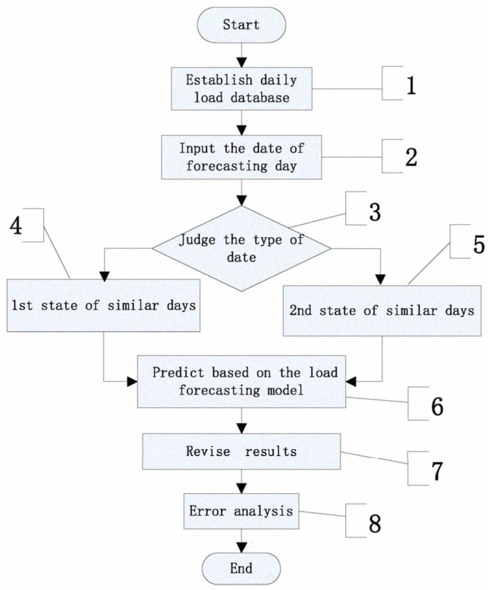

Figure 5 The forecasting procedures of models

Step 1. To form a database with Beijing Olympic Games EV Charging Station daily loads in 2010. The database begins Monday , January 4 and ends Sunday. The group of daily loads contains 357 days and 51 weeks in total.
Step 2. Determine the value of S in the program, that is to say to define the date of forecasting day.
Step 3. Judge the date of forecasting day whether the test day is Monday /Saturday or other circumstances.
Step 4. If the forecasting day is Monday or Saturday, the 1st state of similar days means choosing the same type of days in the past weeks as the similar days.
Step 5. If the forecasting day is others, the 2nd state of similar days means choosing the day before forecasting day and the same type of days in the past weeks as the similar days.
Step 6. Make use of BP neural network, RBF neural network and GM（1, 1）model to predict and get the daily load curve of forecasting day.
Step 7. Based on the user action and the flexible factors of charging, revise the daily load curve. Make sure the reasonable deviation between predictable load and actual load curve.
Step 8. Make the analysis of error with the relative error.

After the forecasting models are established, they need to be tested, and then we can decide whether they are available. The following is the simulation and analysis of the models.

A. S=155, the value of S determines the forecast day is Monday, June 7. Using the 1st state of similar days, the predictable result sees in figure 6.

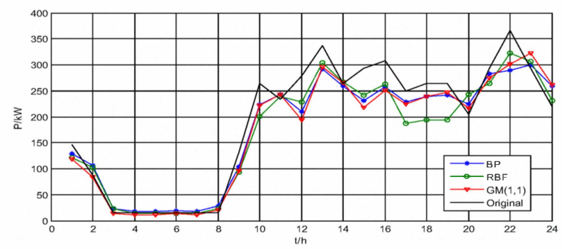

Figure 6 The comparison of forecasting results among BP neural network, RBF neural network and GM(1,1)

Comparing the results of three forecasting models, we find that there are different accuracies of BP neural network, RBF neural network and GM(1, 1) model at the different times in a day. The relative error of above forecasting models show in figure 7.

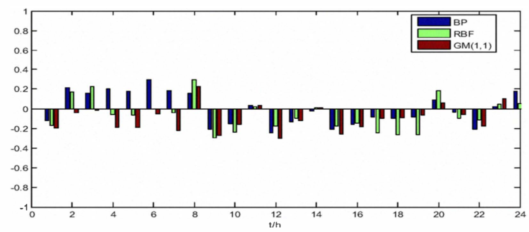

Figure 7 The relative error of BP neural network, RBF neural network and GM(1,1)

B. S=255, the value of S determines the forecast day is Wednesday, September15. Using the 2nd state of similar days, the predictable result sees in figure 8.

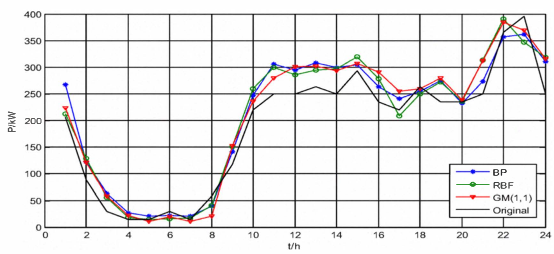

Figure 8 The comparison of forecasting results among BP neural network, RBF neural network and GM(1,1)

The relative error of forecasting models show in figure9.

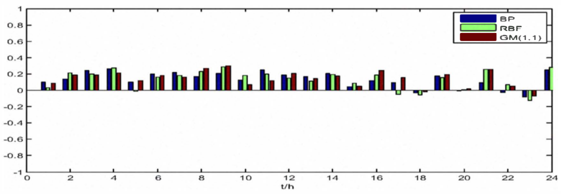

Figure 9 The relative error of BP neural network, RBF neural network and GM(1,1)

It is can been seen from the figure 7 and figure 9 that the error of BP neural network, RBF neural network and GM(1, 1) have the similar trend with the times in a day. There are greater errors between 1 am and 8 am, because the load of EV Charging Station is very small and a slight fluctuation of historical daily loads will causes big error of predictable results. In fact, EV have stopped charging after one o'clock, so the load at this time is rather low and can been neglected.

To start with the charging of EV after 7 am, due to the random running factors of electric buses, the charging load curve is changeable on different days. The most obvious phenomenon is the error of peak-load at the peak charging time is bigger than other times. According to this case, the reason is that the user action and the charging factor of forecasting day are different from the sample days. Take an example of *B*. Because the forecasting day is September 15 in autumn and the similar days of the day is previous 70 days before the forecasting day. Therefore, because of the sample days is in Summer and the load at noon is greater than others due to the load-consumption of air conditioning, so the greater load of similar days draw greater results of prediction than actual load.

In practice, it is need to revise the predictable load curve based on the actual charging conditions on the forecasting day. The impact factors of EV charging station including traffic information, weather, operational rules, etc. All of them are greatly influence the daily load curve of EV charging station and it is essential to revise the predictable results based on the relative impact factors.

A phenomenon has been found that the impact factors of forecasting day are very similar to the previous days of forecasting day in the past one week. Therefore, considering the similar impact factors of similar days, establishing the relationship between predictable daily load curve and impact factors, through some certain revise methods, just like the membership grade (RMG) theory, we can greatly diminish the predictable error of the forecasting day.

5 Conclusion

With the purpose of research on EV charging station load forecasting, this paper establishes three types of daily load forecasting model for EV charging station load, including BP neural network, RBF neural network and GM(1,1) model. Based on the daily load data of Beijing Olympic Games EV Charging Station in 2010, three load forecasting models are briefly introduced and the realizations of them in MATLAB are presented in the paper. To diminish the error of predictable results, it is essential to make the revisions according to the impact factors of the forecasting day.

The research on EV charging station load forecasting is the new secular trend, with the large-scale construction of charging station, it will play an important role in local electric grid dispatching automation.

1 Zhang Yu, Minghong Zhang, Jianning Yang, "Design of Energy Management Systems for Mobile Power Station of Electric Vehicles", IEEE International Conference on Information Management, Innovation Management and Industrial Engineering (ICIII) , Zibo, China, 26-27 Dec 2009, pp.250-253

2 Yunyan Wang, Jingxin Li, Jiuchun Jiang, Liyong Niu, "Management information system of charging station for electric vehicle (EV) ", International Conference on Electrical Machines and Systems (ICEMS) , Nanjing,China,27-29 Sep 2005,pp.857-860

3 Wang Zhenpo, Liu Peng, "Analysis on Storage Power of Electric Vehicle Charging Station", Power and Energy Engineering Conference (APPEEC), Chengdu, China, 28-31 March 2010,pp.1-4

4 WANG Zhen-po, SUN Feng-chun, Lin Cheng, Forecasting and Simulation of the Distribution Capacity of E-Bus Charge Station[J], Transactions of Beijing Institute of Technology,2006,26(12):1061-1064

5 WANG Hongbin, CHANG Wei-li, "Load Forecasting For Electrical Power System Based On BP Neural Network", Education Technology and Computer Science (ETCS) ,Wuhan, China, 7-8 March 2009,pp.702-705

6 Li Xiao-cong, Wang Le, Li Qiu-wen, Wang Ke, "The Short-Term Load Forecasting Based on Grey Theory and RBF Neural Network ", Power and Energy Engineering Conference (APPEEC), Wuhan,China25-28 March 2011,pp.1-4

7 Ning Lu, Jianzhong Zhou, "Particle Swarm Optimization-Based RBF Neural Network Load Forecasting Model", Computer Research and Development (ICCRD), Shanghai,China,11-13 March 2011,pp.465-468

8 ZHANG Caiqing, LIN Ming, TANG Mingyang, "BP Neural Network Optimized with PSO Algorithm for Daily Load Forecasting", Information Management, Innovation Management and Industrial Engineering(ICIII), Taipei, China,19-21 Dec. 2008 ,pp.82 – 85

9 Yang Zhangang, Che Yanbo,Cheng, K.W.E., "Genetic Algorithm-Based RBF Neural Network Load Forecasting Model", in Power Engineering Society General Meeting, 2007. IEEE