2012 International Conference on System Engineering and Modeling (ICSEM 2012)
IPCSIT vol. 34 (2012) © (2012) IACSIT Press, Singapore

Forecasting of Load Model Based On Typical Daily Load Profile and BP Neural Network

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Abstract. Load modeling is recognized as a difficult issue in field of power system digital simulation. The reliability of the simulation results depends on the veracity of the load model which will further affect power system planning and aid decision making. In order to increase the accuracy of the load model, the composite loads of power consuming-industries were classified by their industry attributes and the components of them were also analyzed in this paper. Then, the mathematical model of load composition is established on the basic of typical daily load profile and the identification algorithm developed by C language is used to identify the parameters of composite loads by choosing the data collected during the corresponding characteristic time period of the typical day. Based on the model vector machine theory and the parameters identified, the parameters of composite load model of power consuming-industries can be calculated by using the way of least square approximation. And the BP neural network was used to forecast the parameters of composite loads of power consuming-industries. Finally, an example shows the validity of the proposed scheme.

Keywords: load model forecasting; BP neural network; typical daily load profile; loads of power consuming-industries; model vector machine theory

1. Introduction

Load modeling, causing widespread concern in engineering and academic domain of power system, is of challenge and research value in the field of power system digital simulation and modeling[1-3]. Large-scale blackouts, such as the blackout of WSCC in 1996[4]etc, occurred in the past years need load models of high accuracy to simulate the practical running situations of power system at that very time which can provide experiences for further management and study.

The ways of load modeling can be classified into two categories: the statistical synthesis method and the overall measuring-identification method. The load model based on the statistical synthesis method is evident in physical significance and easy to understand. At the same time, through the analysis of the components of the load, the basic reasons that cause the characteristic differences of the composite loads can be studied. Reference[5] took advantage of fuzzy cluster methods to categorize generic loads and select the typical power consuming-industries, then the corresponding statistical synthesis load model is established. However, there are some literatures which use the overall measuring-identification method for load modeling. Volterra series model and artificial intelligence algorithm were adopted to study the quick on-line identification of percentage of dynamic load component respectively in Reference[6,7]. On the other hand, methods of load forecasting based on similar day theory, wavelet analysis and neural networks were proposed respectively in Reference[8-10]. Therefore, using the thought of load forecasting as the reference, the way of forecasting load mode is proposed by combining the powerful ability in nonlinear mapped of BP neural networks with the characteristic of composite loads of power consuming-industries. The composite loads of power consuming-industries were classified by their industry attributes and the components[11] of them were also analyzed in this paper firstly. And then the model of load composition is established on the basic of typical daily load profile. Based on the model vector machine theory and the parameters identified, the parameters of composite load model of power consuming-industries can be calculated by using the way of least square approximation. Then the parameters of composite loads of power consuming-industries can be calculated by using the least square approximation. Finally, the ideal prediction values will be obtained after the training of the BP neural networks. An example shows the validity of the proposed scheme.

2. Analysis Of Characteristic And Component Of Composite Loads Of Power Consuming-Industries

The classification of loads will have different results according to different classification criteria. Based on their industry attributes, The classification of loads can be divided into four categories: industrial loads, agricultural loads, commercial loads and loads of municipal government and households. The ratio of industrial loads is high and high percentage of inductive load set the industrial loads apart from the other three. The agricultural loads are consist of the loads of the vast rural areas which are highly affected by the climatic factors comparing with the industrial loads. Consist of lighting load, air conditioning load and utility equipment load of commercial department and covering a big area, the commercial loads are also affected by the climatic factors with its electricity consumption of is growing steady. The loads of municipal government and households, including the loads of residential area, utility department and government departments, are closely related to the daily life and work regulation of people with a upward trend year after year.

3. The Establishment Of The Mathematical Model Of Load Composition Based On Typical Daily Load Profile

3.1 The Division Of The Characteristic Time Period

As analyzed above, the establishment of the model of load composition should take the seasonal factor into consideration. However, the typical daily load profiles of different seasons have similar rules: two peak load time periods, a valley load time period and a flat time period in a day. Therefore, the division standard of the characteristic time period is given as follows: valley load time period——1:00~8:00, and 4:00~8:00 is the characteristic time period of valley load time period, peak load time period in morning——9:00~13:00, with 10:30~12:30 as the characteristic time period, flat time period——14:00~17:00, with the whole time period as the characteristic time period, and peak load time period in evening——18:00~24:00, with 20:00~22:00 as the characteristic time period.

3.2 Establishment Of The Mathematical Model Of Load Composition

The ratio of the loads of different power consuming-industries will change during different characteristic time periods which turn out to be nonlinear, time-varying and random on the whole. Therefore, the mathematical model of load composition was proposed as follows:

$$\sum_{i=1,j=1}^{m} k_{i,j} P(i,j) = \overline{P(j)} \tag{1}$$

The integer parameter $i(i=1,2,3,4)$ represents the four styles of the loads mentioned above; Similarly, the integer parameter $j(j=1,2,3,4)$ represents the four characteristic time periods mentioned above; $\overline{P(j)}$ represents the average value of loads of power consuming-industries during the characteristic time period of j in the corresponding season; $\sum_{i=1,j=1}^{m} k_{i,j} P(i,j)$ represents the total amount of power load of the i kind of power consuming-industries during the characteristic time period of j ;The integer parameter $k_{i,j}$ represents the season characteristic value of the i kind of the loads of power consuming-industries during the characteristic time period of j , and its specific values are in table 1.

Tabel1 values of time-varying variable $k_{i,j}$ under different circumstances

i	summer				winter				Spring&autumn			
j	1	2	3	4	1	2	3	4	1	2	3	4
1	1	0	0	0	1	0	0	0	1	0	0	0
2	1	0	1	0	1	1	1	0	1	1	1	0
3	1	1	1	0	1	0	1	0	1	0	1	0
4	1	0	1	1	1	0	1	1	1	0	1	1

3.3 Model Vector Machine Theory

According to the mathematical model of load composition related above, the proportion of loads of power consuming-industries at different characteristic time periods can be calculated. Therefore, the mathematical expression of model vector machine was proposed as follows:

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_m \end{bmatrix} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix} \tag{2}$$

For short, it can be expressed as follows:

$$AH = P \tag{3}$$

The element a_{ij} in matrix A represents the corresponding proportion of load of power consuming-industries h_i. However, every row vector h_i represents the model parameters of load of power consuming-industries to be obtained through calculation. The data of matrix A can be obtained by using the mathematical model of load composition. Matrix P represents the vector parameters of the model vector machine. And the data of Matrix P was obtained by using the real-time data of power grid with the optimizing of identification algorithm which was discussed in detail in the next section.

3. 4 The Parameters Identification Of The Composite Loads Model

As is known, the model of the composite load is consist of the dynamic model and static load model. And the three-order model of induction motor was used as the equivalent model of the dynamic model. The power function model is equivalent to the static load model. The identification of model parameters is an optimization problem with restrictive conditions. The parameter identified in this paper is as follows: $[p_v, q_v, R_s, X_s, X_m, R_r, X_r, H, A, B, K_m, b]$[1]. And parameter b represents the percentage of dynamic load component. The definition of it is: $b = P_s/(P_s + P_d)$. P_s and P_d represents the active power of dynamic load model and overall active power of composite load. The flow-process diagram of identification algorithm[2] was shown as above in Figure 1.

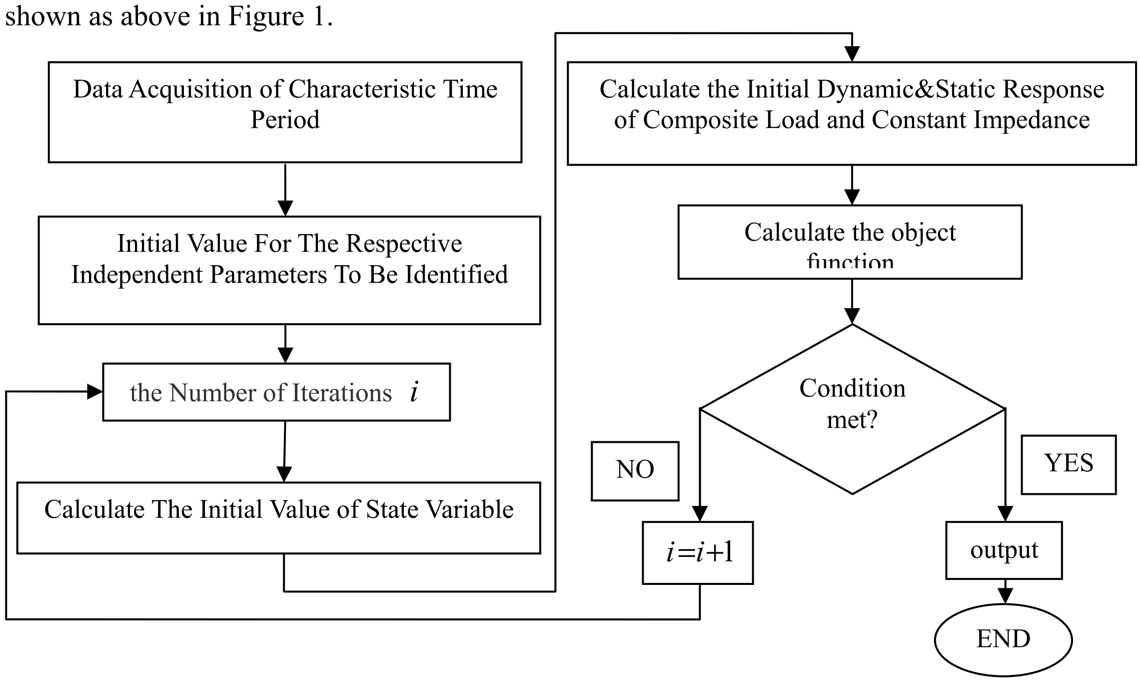

Fig1. The Operational Flow Chart of Parameter identification of Composite Load Model

[1] The meanings of the identified parameters ($p_v, q_v, R_s, X_s, X_m, R_r, X_r, H, A, B, K_m, b$)are as follows:
p_v and q_v represent the index of active and reactive power of power function model which is the equivalent model of the static load model, and the range of the both are form 0 to 1. The rest parameters are for the three-order model of induction motor representing the dynamic load model and the value of them are based on the per-unit value. R_s and X_s represent the inductance and resistance of the generator stator . X_m represents the excitation inductance. R_r and X_r represent the inductance and resistance of the generator rotor.
H represents inertial time constant of the equivalent generator. A and B represent the index of mechanical torque based on the square of the rotor speed and linearity with the rotor speed. K_m represents the initial ratio of induction motor. b represents the percentage of dynamic load component in the power system composite load.

[2] The identification algorithm was developed by C language and easy to use. Using the real time data collected at the corresponding characteristic time periods and typed in the prescribed format, the parameters of composite load can be identified.

4. Forecasting Of Load Model Of Power Consuming-Industried

4.1 Model Of BP Neural Network

Consisted of input layer with 12 nodes, hidden layer with 31 nodes and output layer with 22 nodes, and no feedback between the layers, the BP neural network model in this paper use the parameters of composite loads of power consuming-industries, percentage of dynamic load component in the power system composite load and weather factors as the data of the input layer. The expected results will be obtained through training. The model of BP neural network is formulated in MATLAB and part of the code is as follows:

net=newff(threshold,[31,12],{'tansig','logsig'},'trainlm');net.trainParam.epochs=1000;net.trainParam.goa 1=0.01;

4.2Case Study

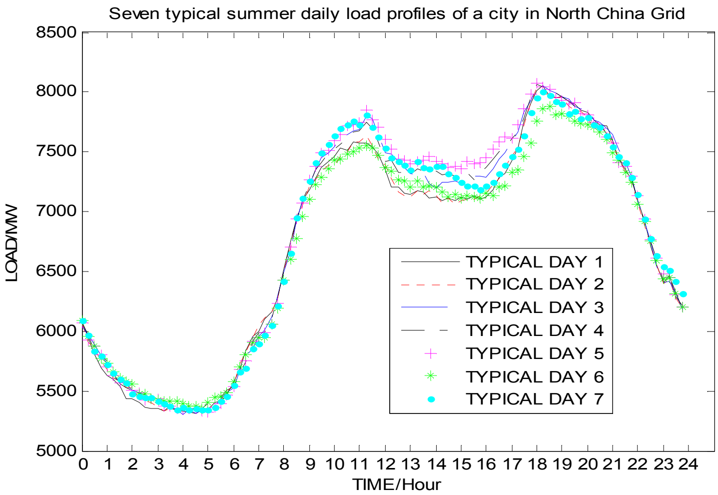

Fig2. Seven typical summer daily load profiles

As is shown in Figure 2, seven typical summer daily load data of were chosen as data for case study. According to the mathematical model of load composition, the parameters of composite load vary with time changing. The proportion of loads of power consuming-industries is shown in table 2 according to the mathematical model of load composition.

Tabel2 proportion of load of power consuming-industries

Load type / Typical day	industrial loads	agricultural loads	commercial loads	loads of municipal government and households
1	0.731	0.046	0.188	0.035
2	0.735	0.041	0.188	0.036
3	0.724	0.030	0.208	0.038
4	0.738	0.019	0.218	0.025
5	0.733	0.008	0.230	0.028
6	0.734	0.040	0.189	0.037
7	0.733	0.048	0.182	0.037

On the other hand, the characteristic time period chosen for identification of parameters is valley load time period of summer from typical day 1 to typical day 7. The identification result[3] of typical day 1is shown in table 3 by using the identification algorithm, and the analytical procedures and calculation to other typical days is the same.

Table3 Parameter identification of Composite Load Model(typical day 1 at valley load time period)

p_v	q_v	R_s	X_s	X_m	R_r	X_r	H	A	B	K_m	b
1.959	1.955	0.036	0.272	2.135	0.025	0.143	2.203	0.193	0.346	0.579	0.658
1.975	1.969	0.041	0.295	1.994	0.030	0.213	2.472	0.186	0.289	0.731	0.633

[3] The identification result of each typical day at different characteristic time period will be different. And seven time point was chosen in the valley load time period to indentify the parameters. Form typical day 2 to typical day 7, the process of parameters identification is the same.

1.928	1.942	0.035	0.227	2.435	0.031	0.214	2.449	0.215	0.325	0.624	0.648
1.959	1.962	0.041	0.286	2.145	0.021	0.221	2.607	0.201	0.323	0.566	0.618
1.868	1.882	0.028	0.239	3.036	0.019	0.177	2.424	0.224	0.654	0.202	0.621
1.879	1.965	0.027	0.196	1.966	0.012	0.116	2.631	0.180	0.455	0.474	0.608
1.937	1.976	0.027	0.277	2.246	0.024	0.106	2.619	0.150	0.749	0.261	0.615

So the matrix H is calculated through mathematical expression (6) by using the way of the least square approximation, the results is shown as follows:

$$H=\begin{bmatrix} 1.963 & 1.983 & 0.035 & 0.247 & 2.155 & 0.071 & 0.437 & 2.380 & 0.193 & 0.286 & 0.590 & 0.739 \\ 1.901 & 1.979 & 0.037 & 0.264 & 2.624 & 0.035 & 0.397 & 2.112 & 0.228 & 0.372 & 0.494 & 0.640 \\ 1.951 & 1.920 & 0.036 & 0.254 & 2.180 & 0.060 & 0.320 & 2.069 & 0.226 & 0.357 & 0.511 & 0.375 \\ 1.983 & 1.958 & 0.040 & 0.273 & 2.134 & 0.031 & 0.697 & 2.556 & 0.294 & 0.283 & 0.553 & 0.512 \end{bmatrix}$$

So the parameters of the four kinds of loads were calculated, from typical day 2 to typical day 7, which is the same by choosing the corresponding characteristic time period. Due to partial data of load parameters exceed the threshold restrictions of transfer function connecting hidden layers of BP neural network. Normalized data processing techniques are used. Finally, the forecasting result and error of load model based on BP neural network and typical load profile is shown in figure3.

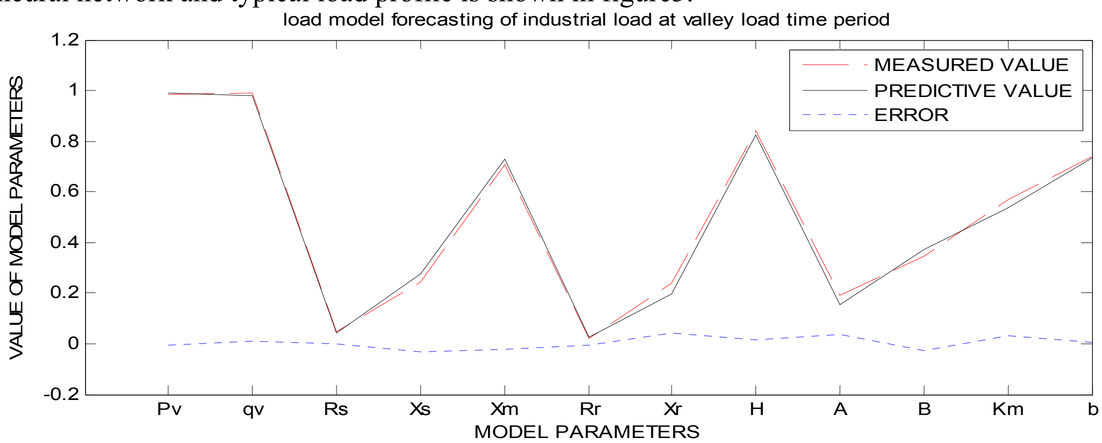

Fig3.load model forecasting of industrial load at valley load time period

5. Conclusion

Load modeling is recognized as a difficult issue in field of power system digital simulation which needs to consider many factors such as time-varying, non-linear complexity and diversity of loads. The corresponding characteristic time period of typical day 1 to typical day 7were chosen to identify the parameters is to reduce the bad effect of time-varying characteristic of loads. The powerful ability in nonlinear mapped of BP neural networks was used to reduce to error of forecasting. The results show the validity of the proposed scheme which can provide accurate load model for the power system stability simulation and analysis and reference for reasonable arrangement of the scheduling and evaluation for the coming day.

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