DOI: 10.3969/j.issn.1673-5188.2015.03.001
http:http://www.cnki.net/kcms/detail/34.1294.TN.20150909.1043.004.html,published online September 9, 2015

Theory Study and Application of the BP-ANN Method for Power Grid Short-Term Load Forecasting

Xia Hua[1], **Gang Zhang**[2], **Jiawei Yang**[3], **and Zhengyuan Li**[1]
(1. Gansu Electric Power Research Institute, State Grid Gansu Electric Power Company, Lanzhou 730050, China;
2. Institute of Water Resources and Hydro-Electric Engineering, Xi'an University of Technology Xi'an 710048, China;
3. College of International Communications, China Three Gorges University, Yichang 443000, China)

Abstract
Aiming at the low accuracy problem of power system short-term load forecasting by traditional methods, a back-propagation artificial neural network (BP-ANN) based method for short-term load forecasting is presented in this paper. The forecast points are related to prophase adjacent data as well as the periodical long-term historical load data. Then the short-term load forecasting model of Shanxi Power Grid (China) based on BP-ANN method and correlation analysis is established. The simulation model matches well with practical power system load, indicating the BP-ANN method is simple and with higher precision and practicality.

Keywords
BP-ANN; short-term load forecasting of power grid; multiscale entropy; correlation analysis

1 Introduction

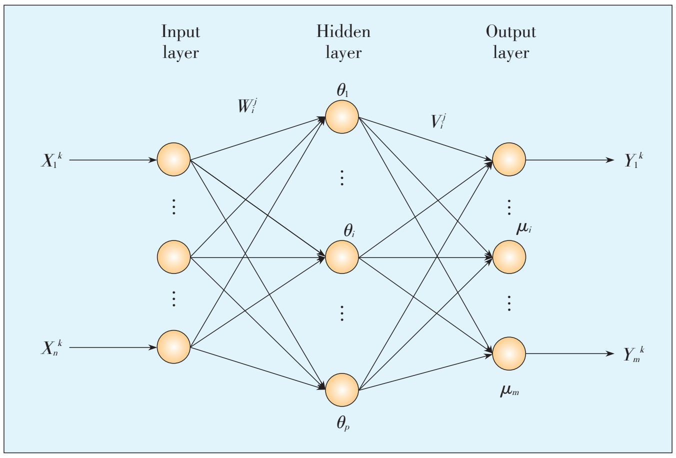
The short-term load forecasting is an important component of the power system generation projects, which supports the economic and stable power system operation [1]. Increasing the forecasting precision of power grid load has been a major concern all over the world. Recently, many short-term load forecasting methods have been studied, such as regression analysis method [2], exponential smoothing model [3], random time series model, grey forecasting model, support vector machine and its improved model [4]–[6], neural network and its improved model and combination forecasting model [7], [8]. Most of these methods can be divided into two types according to the utilized data, one takes the weather factors into account, while the other does not involve weather data. The two types both have advantages and apply to different situations. The type without weather impact mainly uses historical data, which has easy model and calculation, but the precision is relatively low. The other type includes weather and many impact factors, but most of these impact factors are predictive data, which introduce bigger errors in load forecasting model, not to mention that some weather factors are difficult to obtain. Therefore, it is significant to find a precise load forecasting method with few impact factors.

In this paper a back-propagation artificial neural network (BP-ANN) based load forecasting method is presented, to balance the problem of precision and impact factors. Firstly we pick historical load data and employ multiscale entropy analysis. Then we build the BP-ANN load forecasting model based on the screened historical data. The load forecasting model is applied to practical load prediction and compares with two literature forecasting methods, in order to verify its superiority and high precision.

2 BP-ANN Basic Principles

BP network is one of the most commonly used neural network modes, which owns several advantages: 1) has simple structures and operability; 2) can realize any complicated nonlinear mapping since basically it is nonlinear mapping from input to output; 3) has self-study ability for further improvement and development. Based on these advantages of BP network, we employ the 3-layer BP network to dynamically evaluate the Muskingum model parameters. **Fig. 1** gives out the topological structure of the 3-layer BP network. We divide the 3-layer BP network into input layer, hidden layer and output layer, the point numbers of each layer are n, p, m, respectively. $W_i^{\,j}$ (i = 1, 2, ... , n; j = 1, 2, ... , p) represents the weight between the input layer and hidden layer, while $V_i^{\,j}$ (i = 1, 2, ... , p; j = 1, 2, ... , m) represents the weight between the hidden layer and output layer. The threshold values of the hidden and output layers are θ_i (i = 1, 2, ... , p) and μ_i (i = 1, 2, ... , m), respectively. The self-study processes of the BP network have been thoroughly discussed in literatures [1].

D:\EMAG\2015-08-47/VOL13\F3.VFT——4PPS/P1



▲**Figure 1. The structure of BP-ANN.**

According to the basic principles of BP-ANN method, the precondition of BP network forecasting is determining the input and hidden layers. As for the power load forecasting, i.e., use historical data to forecast the load of a future moment, the input layer plays the key role, since yet there is few effective method to determine the hidden layer parameters.

3 Multiscale Entropy of Load Data

3.1 Basic Principles of Multiscale Entropy

The entropy has been widely used to characterize the complexity of information, and is the measurement of the system randomness. The Kolmogorov-Sinai (KS) entropy can characterize the complexity of the signals by calculating the average generation rate of new information. The approximate entropy (ApEn) originates from KS entropy, and applies well in the complexity analysis of short-term time series. The sample entropy (sampEn) is the further modification of the ApEn.

3.1.1 Sample Entropy

The similar data comparison of the ApEn calculation contains the comparison with its own data part, which causes result errors. The sampEn is the precise value of the average natural logarithm of conditional probability, and avoids the comparison with its own data. Thus the sampEn calculation does not depend on the data length, showing better consistence than ApEn.

Set the initial time series as $x(1), x(2), \ldots, x(N)$, the sampEn of the series is calculated as follows:

1) Construct a m-dimension vector $X(i) = [x(i), x(i+1), \ldots, x(i+m-1)]$, $i = 1, 2, \ldots, N-m+1$;
2) Define the distance between $X(i)$ and $X(j)$ as $d[X(i), X(j)] = \max[\,|\,x(i+k)-x(j+k)\,|\,]$, $k = 0, 1, \ldots, m-1$;
3) Give the number of threshold values r and obtain the ratio $C_i^m(r) = [\textit{the number of all } d[X(i), X(j)]<r]/(N-m)$, $i = 1, 2, \ldots, N-m+1$;
4) Calculate the average value of $C_i^m(r)$ for all i, $C^m(r) = C_i^m(r)/(N-m+1)$, $i = 1, 2, \ldots, N-m+1$;
5) Add the dimension to $m+1$, then repeat processes 1-4 to get $C^{m+1}(r)$;
6) SampEn of this series sampEn$(m, r, N) = -\ln C_i^m(r)/C_i^m(r)$.

Apparently the values of m, r are very important to the sampEn results. Generally we choose $m = 2$, $r = 0.1$-$0.2\ SD$, where SD is the standard deviation of the initial data $x(i)$, $i = 1, 2, \cdots, N$, and the series length N is required to be larger than 1000.

3.1.2 Multiscale Entropy

The parameters of ApEn, sampEn are determined by the system step finite difference $(H_{n+1}-H_n)$, which is based on the single scale analysis and does not contain the system characters of high scale >1. The multiscale entropy analysis is calculated as following processes, in which τ is the scale index, when $\tau = 1$ the time series $y_j(\tau)$ is the initial time series.

Set the initial data as $\{x(1), x(2), \ldots, x(N)\}$, now we construct the coarse-graining series $\{y(\tau)\}$:

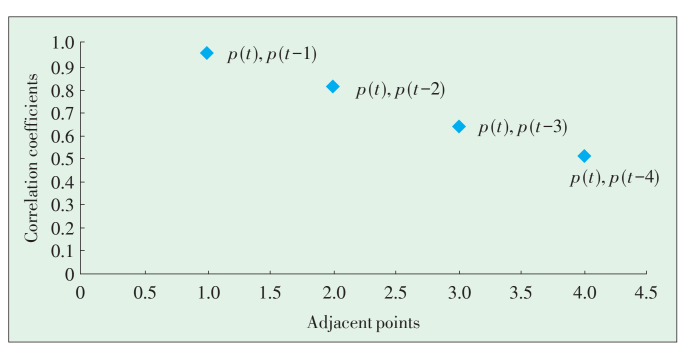
1) $y_j(\tau) = x(i)/\tau$, $i = (j-1)(\tau+1), \ldots, j\tau$, $j = 1, 2, \ldots, N/\tau$. The length of each time series equals the ratio of the initial time series length to scale index τ.
2) Calculate the sampEn of the coarse-grained series for different τ.

3.2 Load Analysis by Multiscale Entropy

Researchers generally use the adjacent data points before the predictive data point as the input data in the BP-ANN model for load forecasting [9], [10], because it is usually believed that the predictive points only relate to the changing trend of recent and adjacent data. In this paper we calculate the correlation coefficients of predictive points and adjacent points, which are illustrated in **Fig. 2** All data come from the daily load of Shanxi Grid in 2004.

Fig. 2. shows the changing trend of the predictive points and 4 adjacent points. The $p(t)$ represents the predictive load point value, and $p(t-1)$ represents the previous load point value before the predictive load point, and so on. Clearly, it is found that the correlation coefficients between predictive points and adjacent points gradually descend.

Then we utilize the multiscale entropy to evaluate the calcu-

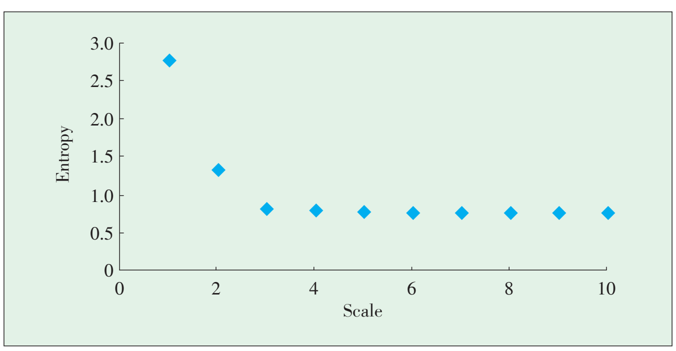


▲**Figure 2. Correlation coefficient of calculating point and adjacent point.**

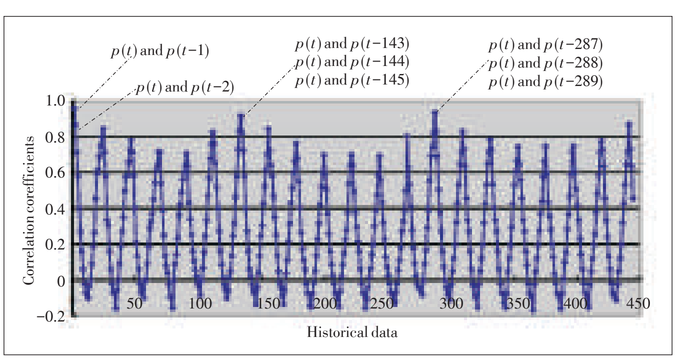
lation error introduced by adjacent data points in BP-ANN model. We pick the daily load data of Shanxi Grid (from 2003.1.1 to 2009.12.31) as the database, and calculate the entropy of load data through the above method in chapter 2.1, with parameters m = 3, r = 0.1 SD. The calculating results are demonstrated in **Fig. 3**. The entropy of load data decreases with the increment of scale index. Note that the entropy changes rapidly between scale 1 and scale 2, indicating that adjacent points introduce strong chaos. Combining with Fig. 2, it is clear that adjacent data points definitely affect the forecasting precision in BP-ANN load forecasting model. As a result, the forecasting model should be established based on nonadjacent data points to increase precision.

4 Building BP-ANN Model for Short-Term Load Forecasting

Start from the correlation coefficients discussed above, we set up the BP-ANN model for short-term load forecasting. Firstly we pick the most relevant load data series with the predictive data series, as the input of the BP-ANN model. The correlation coefficients between the predictive point $p(t)$ and historical data is illustrated in **Fig. 4**. We find that the predictive load point $p(t)$ not only shows strong correlation with the adjacent two load points $p(t-1)$ and $p(t-2)$, also periodically correlates to long-term historical data. Thus these periodically correlated historical data can also be used to build the forecasting model as well. We choose 8 historical data points with the strongest correlation with $p(t)$ in Fig. 4 as the input of neural network. The parameter of hidden layer is 4, and the output is the predictive load data $p(t)$ of next hour. As a result, we build the 8-4-1 BP-ANN load forecasting model, which is schematically shown in **Fig. 5**.



▲**Figure 3. Entropy of load data under different scale.**

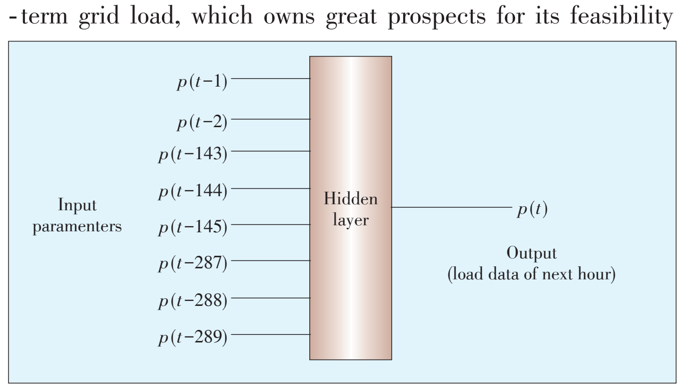


▲**Figure 4. Correlation coefficient of prediction set and history set.**

5 Application Examples of Shanxi Grid

Shanxi Grid mainly serves Shanxi Province and includes both hydropower and thermal power. The short-term load forecasting is of great significance for Shanxi Grid, which directly determines the operation mode of hydropower and thermal power. In this paper we use 24 short-term load data points from the year of 2003 to 2008 as the database, and employ the presented BP-ANN model for prediction. The results are verified with the load data of 2009. Also, we use the methods of literatures [10], (named as Method 1 and Method 2, respectively) to obtain predictive results, and compare the results of three methods through mean absolute error, error quadratic sum, and average relative error. The results are shown in **Table 1**. The result of the presented BP-ANN method in this paper has the lowest errors for all three evaluation index, which indicates its superiority and high precision.

The presented BP-ANN method applies well to the short-term load forecasting of Shanxi Grid for its operability and stability. We predict one day load of Shanxi Grid in 2009 through the BP-ANN method, and give out the result in **Fig. 6**. We find that the predictive load data is in good accordance with the observed load data. The highly matched results imply that the simple presented BP-ANN method is with high precision and practical for short-term load forecasting in Shanxi Grid. This method opens another simple and accurate way to forecast short-term grid load, which owns great prospects for its feasibility

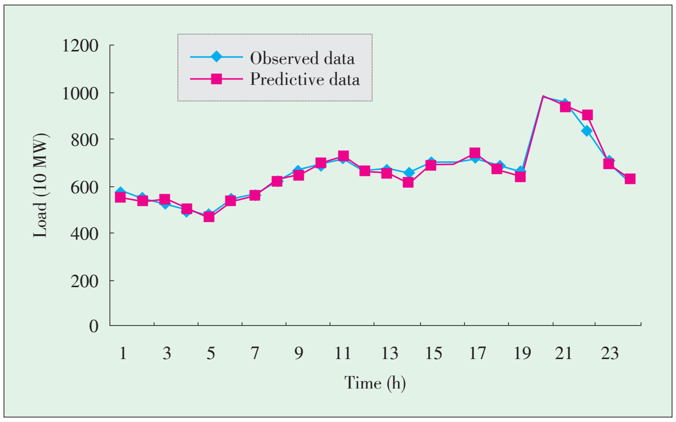


▲**Figure 5. BP-ANN model for load prediction.**

▼**Table 1. Comparison of 3 prediction methods**

Evaluation index	Mean absolute error (10 MW)	Error quadratic sum (10 MW^2)	Average relative error (%)
Method 1	0.12	4280	0.21
Method 2	0.08	3750	0.17
Presented BP-ANN method	0.03	2270	0.11

D:\EMAG\2015-08-47\VOL13\F3.VFT——4PPS/P3



▲**Figure 6. Load prediction result of 2009.**

and precision.

6 Conclusion

This paper presents a simple and accurate BP-ANN method for the short-term load forecasting. We use the multiscale entropy to analyze the load data. The BP-ANN model using adjacent data points greatly affect forecasting precision. And the predictive load data not only shows strong correlation with the adjacent load data, also with periodic long-term data points. Therefore, we employ adjacent data correlation method to screen the input layer parameters of BP-ANN model, and establish the short-term load forecasting BP-ANN method. We apply the model and method to the short-term load forecasting of Shanxi Grid, and compare it with other two forecasting methods in previous literatures. The predictive results of the presented BP-ANN method owns the lowest average relative error 0.11% among three methods, and matches very well with the observed load data, which indicates the extremely high precision. Thus this method serves as a simple and feasible approach to realize precise short-term grid load forecasting.

References

[1] I. Drezga and S. Rahman, "Short-term load forecasting with local ANN predictors," *IEEE Transaction Power System*, vol. 14, no. 3, pp. 844–850, 2002. doi: 10.1109/59.780894.

[2] CH Hsien, "Grey neural network and its application to short term load forecasting problem," *IEICE Transaction Information System*, no. 3, pp. 897–902, 2002.

[3] X. Yao, M. Fischer, and G. Brown, "Neural network ensembles and their application to traf fi c fl ow rediction in telecommunications networks," *International Joint Conference on Neural Networks*, Washington, USA, 2001, pp. 693–698.

[4] L. C. Ying and M. C. Pan, "Using adaptive network based fuzzy inference system to forecast regional electricity loads," *Energy Conversion and Management*, vol. 49, no. 2, pp. 205–211, 2008.

[5] P. J. Santos, A. G. Martins, and A. J. Pires, "Designing the input vector to ANN-based models for short-term load forecast in electricity distribution systems," *Electrical Power and Energy Systems*, vol. 29, no. 4, pp. 338–347, 2007.

[6] S. M. Pincus, "Approximate entropy as a measure of system complexity," *Proceedings of the National Academy of Sciences*, vol. 1, no. 8, pp. 2297–2301, 1991.

[7] S. M. Pincus, "Approximate entropy as a complexity measure," *Chaos*, vol. 5, no. 1, pp. 110–117, 1995.

[8] J. S. Richman, and J. R. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy ," *American Journal of Physiolog Heart*, vol. 1, no. 23, pp. 2039–2040, 2000.

[9] H. S. Hippert, C. E. Pereira, and S. R. Castro, "Neural networks for short-term load forecasting: a review and evaluation," *IEEE Transaction Power System*, vol. 16, no. 4, pp. 44–45, 2001. doi: 10.1109/59.910780.

[10] I. Dreaga, and S. Rhaman, "Input variable selection for ANN-based short-term load forecasting," *IEEE Transaction Power System*, vol. 13, no. 11, pp. 1238–1344, 1998. doi: 10.1109/59.736244.

Manuscript received: 2015-04-13

Biographies

Xia Hua (kevinxhua@163.com) received the bachelor degree in physics from Shanghai Jiao Tong University in 2009. He received his PhD degree in semiconductor physics from the Department of Physics and Astronomy, Shanghai Jiao Tong University from the Department of Physics and Astronomy, Shanghai Jiao Tong University in 2014. He is currently working in the Gansu Electric Power Research Institute, Lanzhou, China. His research interest focuses on new energy and photovoltaic systems.

Gang Zhang (zhanggang3463003@xaut.edu.cn) received his PhD degree in water resources and hydrology from Xi′an University of Technology in 2013. He is currently working in the Institute of Water Resources and Hydro-electric Engineering, Xi′an University of Technology. His research interest focuses on new energy and power saving.

Jiawei Yang is currently pursuing the bachelor's degree in Electrical Engineering and automation. His current interests include smart grid systems.

Zhengyuan Li is currently working in the Gansu Electric Power Research Institute, Lanzhou, China. His research interest focuses on power system protection.

D:\EMAG\2015-08-47/VOL13\F3.VFT——4PPS/P4