User-Online Load Movement Forecasting for Social Network Site Based on BP Artificial Neural Network

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***Abstract*—A social network site is one social structure made up of a set of users including individuals or organizations, which plays a very import pole in the digital age. It has been one type of fashion online platform at providing services on facilitating the establishment of social networks or social relations among social members. Most social network sites provide web-based services and web-based means that allow users to interact over the internet to share individual experiences and spread information. Thus, the user-online load movement analysis is increasingly important for one social network site because of its significant effect on resource allocation, web traffic, maintenance management and economy of operations. Among the varying soft computational tools and algorithmic models available, the back-propagation artificial neural network (BP-ANN) model is one of the most commonly used and robust models. In this study, a typical BP-ANN with a single hidden layer is employed for forecasting the user-online load movement. Experimental results of the user-online load movement forecast at several social network sites show workability the proposed method.**

***Index Terms*—Social Network Site, User-online load, BP-ANN; Forecasting.**

I. INTRODUCTION

Social network sites (SNSs) have been a type of fashion online platform and website, which aims at providing services on facilitating the establishment of social networks or social relations among social members to share individual experiences. A social network site is usually composed of a representation of a number of members and each one represented by a profile with its social links. Thus, a social network site [1-4] is one social structure made up of a set of users including individuals or organizations. It plays a very import pole in the digital age as most social network sites provide web-based services [4] and web-based means for users that enable them to interact over the internet. Events, activities, personal ideals and interests are allowed to be shared and published within the social-network sites in a popular and convenient way, which has dramatically influenced and changed our normal daily lives [5]. It is observed that the interplay [6] by means of the digital interaction among individuals, organizations and social networks is mutually embedded and influenced. Since the first launch on the well-known recognizable network model called the "six degrees of separation" in 1997 [4, 7], social network sites (SNSs) have increasingly received the attention of both academic researcher and industrial engineers. Recently, the online social network sites have been a global phenomenon [7] that an enormous scale appears in the usage of online social network sites: growth of the Internet-users visiting online social network sites at least once a month is expected to increase from 41.0% in 2008 to over 65.0% in 2014 [7]. Thus, to forecast the user-online load movement is rapidly growing in its importance for one social-network site because of its close and relative effect on web traffic, resource allocation, maintenance management and economy of operations, which have received particular interesting from relative studies [8-15] and beyond [16-17], etc.

The daily user-online load movement, which may be influenced by various factors, is also time-series. Mathematic methods and technologies [18-20] mainly employed for time-series analysis include: spectral analysis, and classical time series analysis, and ccomputational intelligence, etc. The classical time-series analysis is a standard technique in statistics.

Among the varying soft computational models and tools available, the artificial neural networks (ANN) [21-25], especially the back-propagation artificial neural network (BP-ANN) is one of the most commonly used and robust models and reported with good performance. In this study, a typical BP-ANN with a single hidden layer is employed for forecasting the user-online load movement. The paper is organized as follows: In Section 2, based on the BP-ANN, a forecasting method for the user-online load movement is presented. In section 3, it presents our experimental results at several social network sites. Section 4 presents result analysis. Finally, Section 5 presents conclusion and our future study.

II. BP-ANN BASED USER-ONLINE LOAD MOVEMENT FORECASTING

Manuscript received Jan. 1, 2013; revised Apr. 25, 2013; accepted Apr. 28, 2013. Copyright credit, project number: 2013GK3090.
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doi:10.4304/jcp.8.12.3176-3183

An artificial neural network (ANN), also called a neural network, is a widely used mathematical model. An artificial neural network (ANN) is composed of an interconnected group of simple artificial neurons that also called nodes, neurodes, processing elements or units, are connected together to form a network with mimicking a biological neural network.

The ANN employs a connectionist approach to computation in processing information, which is used with algorithms designed to change the strength of the connections in the network to yield a desired signal flow. In most cases, an artificial neural network (ANN) can be seen as one adaptive system that alters its structural weights during a learning step. The ANN can be employed to model complex relationships between its inputs and outputs. Complex global behavior can also be determined by the connections between its processing elements and element parameters in the network. The typical structure of one completely connected ANN is composed of the input layer, the hidden layers and the output layer (Fig.1).

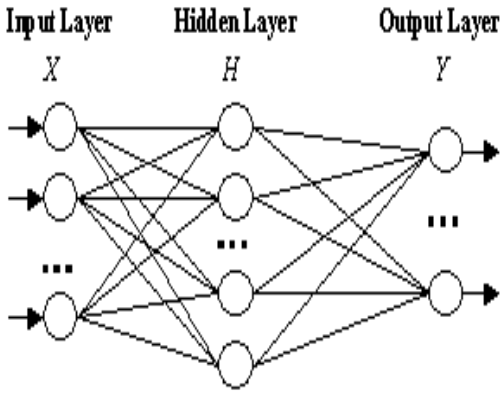

Figure 1. Typical structure of a 3-layer neural network

The famous BP-ANN employs the feed-forward back-propagation (BP) algorithm [23]. The term of "feed-forward" describes the processing flow in the neural network. In a feed-forward neural network, neurons (nodes) are only connected foreword. Connections in each layer of the neural network are linked to the next layer without connections backward. The term of "backpropagation" depicts the training type of the neural network that the backpropagation is a normal form used for the supervised training. That is, based on the given samples including the inputs and the desired outputs, the neural network compares the desired outputs against the actual outputs for the given inputs. Upon the error of the desired outputs and the actual outputs of the neural network, the backpropagation training algorithm then adjusts the weights of the layers in the network backwards from the output layer to the input layer, respectively. In this way, the artificial neural networks employing the backpropagation and feed-forward algorithms are called the BP-ANNs. The supervised training is similar to a child learning, but it is also unlikely that a child may recognize something after seeing them only once.However, many repetitions may usually be required for an artificial neural network in its training procedure. The best training procedure is also expected to be provided with a wide range of samples, which can present different and wide characteristics as much as possible.

Once the structure of an ANN is determined that the number of layers, and number of neurons (nodes) in each layer, has been selected, the connections' weights and thresholds in the network should be optimized as to minimize the error between its desired outputs and actual outputs. Its training algorithm is usually composed of the following steps.

- *Step 1*, selecting and perpetrating *training samples;*
- *Step 2, updating of the neuron connection weights by training;*
- *Step 3, repetition until convergence;*
- *Step4, the network is ready for simulation (working).*

In most practical problems, adopting one hidden layer is usually suggested [23] in building the ANN. Thus, to forecast the user-online load movement in the social-network site, we choose a typical BP-ANN with a single hidden layer. To determine number of neurons in the hidden layer is also one problem [23-24], which should be considered. Many rule-of-thumb methods for choosing the appropriate number of neurons to use in the hidden layers are introduced [23-25]. Among them, some simple rules may be considered [19]: the hidden neurons' number may (a) be in the range of the input layer size and the output layer size; (b) be two-thirds of the input layer size plus the output layer size; (c) be less than twice of the input layer size. Actually the selection of the structure of an ANN may come down to trial and error [23].

Each daily user-online load movement usually has 24 load values for 24 hours in each day. In each one-step forecast, we are to predict its next one at the successive time point in the future. After some testing, it is found that each using 12 previous ones to predict the next one seems to be a good choice. That is, in each step of forecasting the user-online load movement, we use its 12 previous load-value to predict its next one. Then 12 nodes and 1 node are selected in the input-layer and the output-layer, respectively. Considering the mentioned rules [23] for selecting the number of neurons in the hidden layers, we choose 15 hidden neurons in the hidden-layer. That is, the structure of the BP-ANN employed for forecasting the user-online load movement is: (12-15-1), that is, the network has 12 nodes in the input layer, 15 nodes in the hidden layer, and one node in the output layer.

III. Experimental Results

The presented BP-ANN model for forecasting the daily user-online load movement is applied to the following two social network sites (BBS.NJU.EDU.CN and BBS.WHNET.EDU.CN) in China.

A. Daily User-online Load Movement Forecasting for BBS.NJU.EDU.CN

10 daily user-online load movements from days of 2012-12-1 to 2012-12-10 at the social network site of **BBS.NJU.EDU.CN** are used for the user-online load movement forecast.

Table1 lists the first daily user-online load records on 2012-12-1 from 0:00 to 23:00.

TABLE I.
DAILY USER-ONLINE LOAD AT BBS.NJU.EDU.CN ON 2012-12-1

Time	User-Online	Time	User-Online
0:00	4827	12:00	4496
1:00	3289	13:00	4732
2:00	2094	14:00	4675
3:00	1712	15:00	4538
4:00	1575	16:00	4825
5:00	1490	17:00	4762
6:00	1462	18:00	4517
7:00	1602	19:00	4776
8:00	2193	20:00	5210
9:00	3231	21:00	5476
10:00	3940	22:00	5615
11:00	4308	23:00	5493

We take 60% of the 10 daily user-online data as the training data (the daily user-online data of days from 2012-12-1 to 2012-12-6, which include 240 hourly records) to build the BP-ANN, and then we use the rest 40% (the daily user-online data of days from 2012-12-7 to 2012-12-10) are used for forecast testing.

The user-online values are mapped into the range of [0, 1] in the forecast modeling by using the BP-ANN, and then the obtained results are returned by being re-mapped to normal values.The sigmoid activation function is employed in the input layer and the hidden layer, and the linear activation function is used in the output layer, and its learning rate η=0.2.

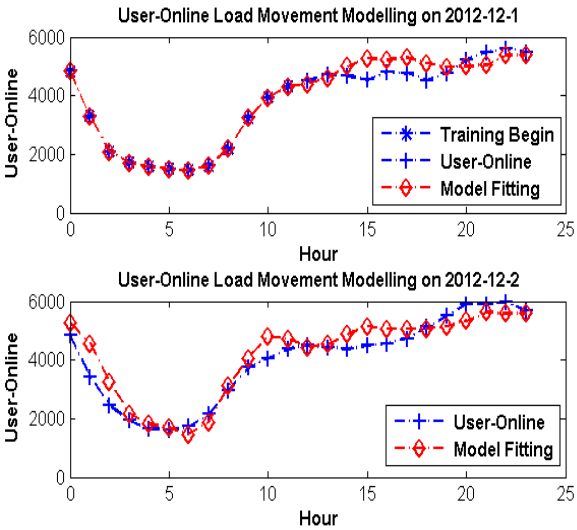

Figure 2. Model fitting results in the training for the daily user-online load movements (00:00-23:00) at the social network site of BBS.NJU.EDU.CN on 2012-12-1 and 2012-12-2, respectively.

By employing the BP-ANN model with its network structure of (12-15-1) (i.e., 12 nodes in the input layer, 15 nodes in the hidden layer, and 1 node in the output layer), model fitting results in the training of the BP-ANN model for the daily user-online load movements from 2012-12-1 to 2012-12-6 are plotted in Figures.2-4. The forecasting results for the daily user-online load movements from 2012-12-7 to 2012-12-10, are plotted in Figures.5-6, respectively.

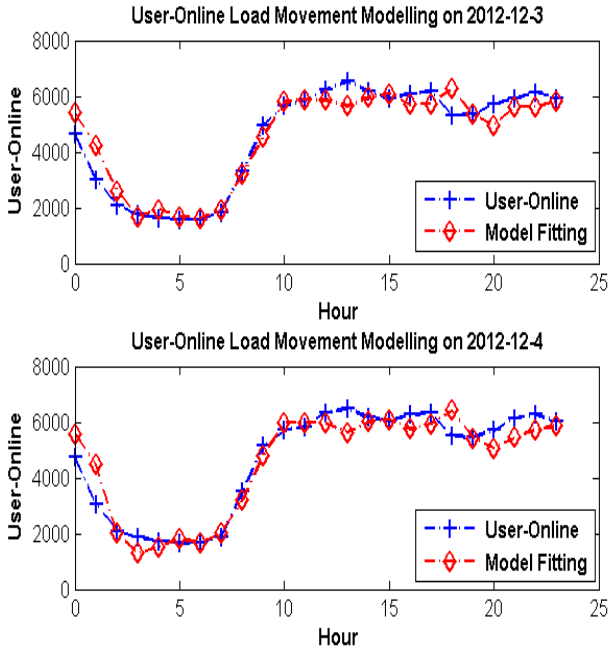

Figure 3. Model fitting results in the training for the daily user-online load movements (00:00-23:00) at the social network site of BBS.NJU.EDU.CN on 2012-12-3 and 2012-12-4, respectively.

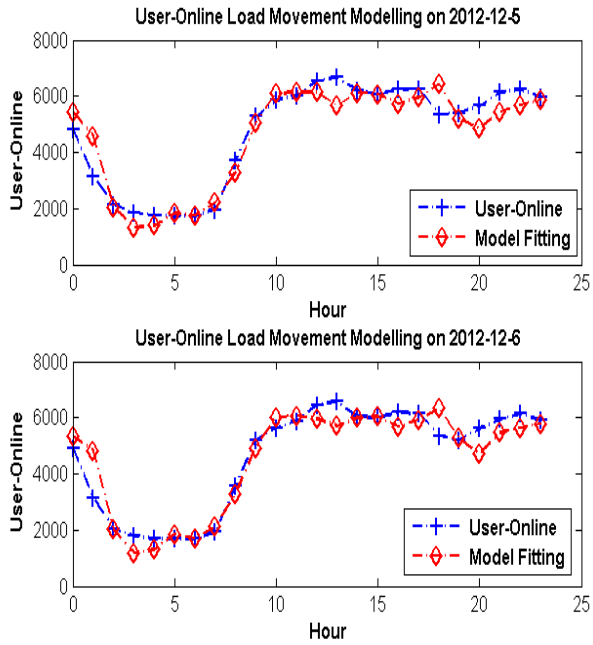

Figure 4. Model fitting results in the training for the daily user-online load movements (00:00-23:00) at the social network site of BBS.NJU.EDU.CN on 2012-12-5 and 2012-12-6, respectively.

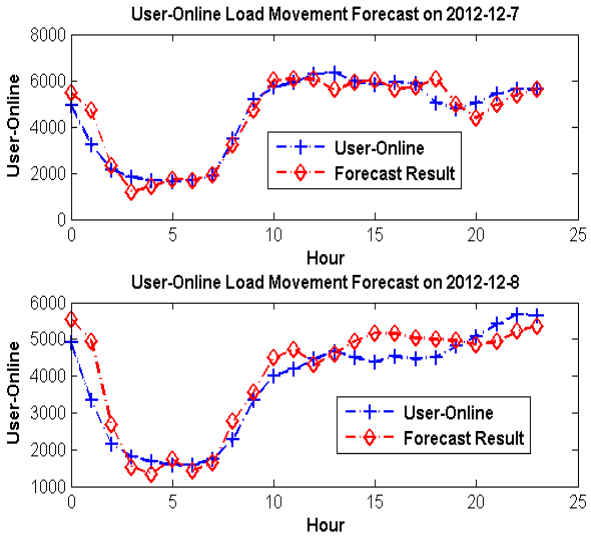

Figure 5. Forecast results for the daily user-online load movements (00:00-23:00) at the social network site of BBS.NJU.EDU.CN on 2012-12-7 and 2012-12-8, respectively..

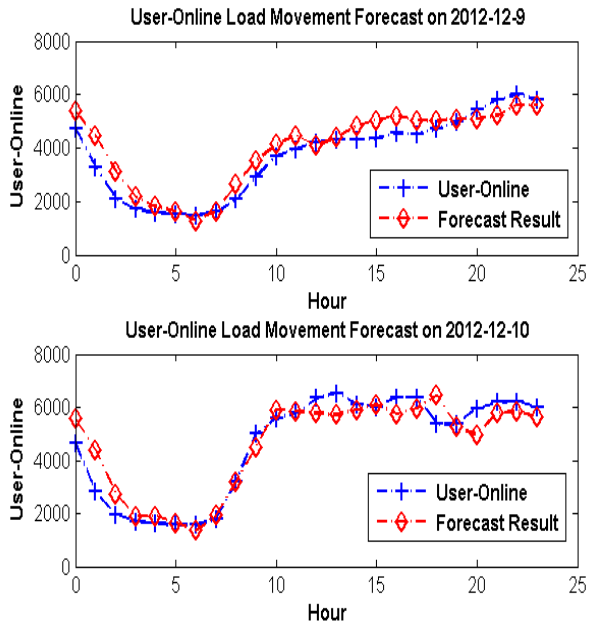

Figure 6. Forecast results for the daily user-online load movements (00:00-23:00) at the social network site of BBS.NJU.EDU.CN on 2012-12-9 and 2012-12-10, respectively.

In Figures.2-6, it is shown that the experimental results agree well with the actual user-online load movements at the social network site of BBS.NJU.EDU.CN .

B. Daily User-online Load Movement Forecast for BBS.WHNET.EDU.CN

In this section, we also use ten daily user-online load movements from the days of 2012-12-1 to 2012-12-10 at the social network site of BBS.WHNET.EDU.CN as the extra experimental data for forecasting the user-online load movement.

In Table2, we list its first daily user-online load records on 2012-12-1 from 0:00 to 23:00.

TABLE II.
DAILY USER-ONLINE LOAD AT BBS.WHNET.EDU.CN ON 2012-12-1

Time	User-Online	Time	User-Online
0:00	4827	12:00	4496
1:00	3289	13:00	4732
2:00	2094	14:00	4675
3:00	1712	15:00	4538
4:00	1575	16:00	4825
5:00	1490	17:00	4762
6:00	1462	18:00	4517
7:00	1602	19:00	4776
8:00	2193	20:00	5210
9:00	3231	21:00	5476
10:00	3940	22:00	5615
11:00	4308	23:00	5493

Under the similar setting condition that we use the sixty percent (60%) of the 10 daily user-online data with 240 hourly records at the social network site of BBS.WHNET.EDU.CN as the training data, i.e., the daily user-online data of days from 2012-12-1 to 2012-12-6 are taken as the training data to build the BP-ANN model. After training the BP-ANN model, we then use the rest 40% data (the daily user-online data of days from 2012-12-7 to 2012-12-10) for forecasting.

The user-online values are also mapped into the range of [0, 1] in the forecast modelling by using the BP-AANN, and then final results are returned by being re-mapped to normal values.

The sigmoid activation function is employed in the input layer and the hidden layer of the BP-ANN model, and the linear activation function is used in its output layer and its learning rate η=0.2.

By employing the BP-ANN model with its network structure of (12-15-1), that is, there are 12 nodes in the input layer, 15 nodes in the hidden layer, and 1 node in the output layer.

Model fitting results in the training of the BP-ANN model for the daily user-online load movements of the days of from 2012-12-1 to 2012-12-6 are plotted in Figures.7-9.

After training the BP-ANN model, the forecasting results for the daily user-online load movements of days from 2012-12-7 to 2012-12-10 at the social network site of BBS.WHNET.EDU.CN, are plotted in Figures.10-11, respectively.

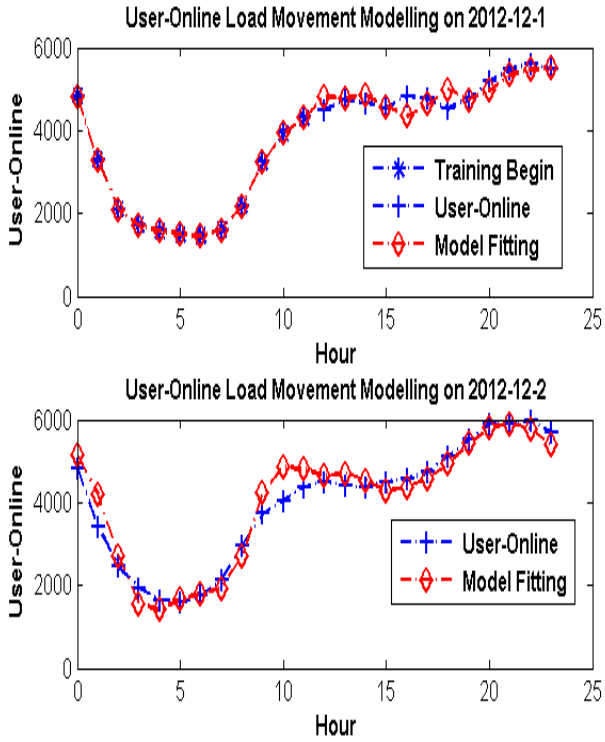

Figure 7. Model fitting results in the training for the daily user-online load movements (00:00-23:00) at the social network site of BBS.WHNET.EDU.CN on 2012-12-1 and 2012-12-2, respectively..

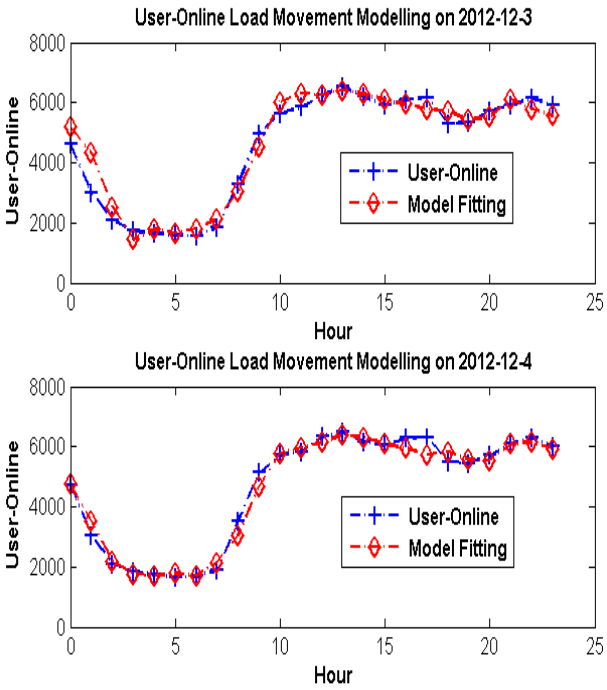

Figure 8. Model fitting results in the training for the daily user-online load movements (00:00-23:00) at the social network site of BBS.WHNET.EDU.CN on 2012-12-3 and 2012-12-4, respectively.

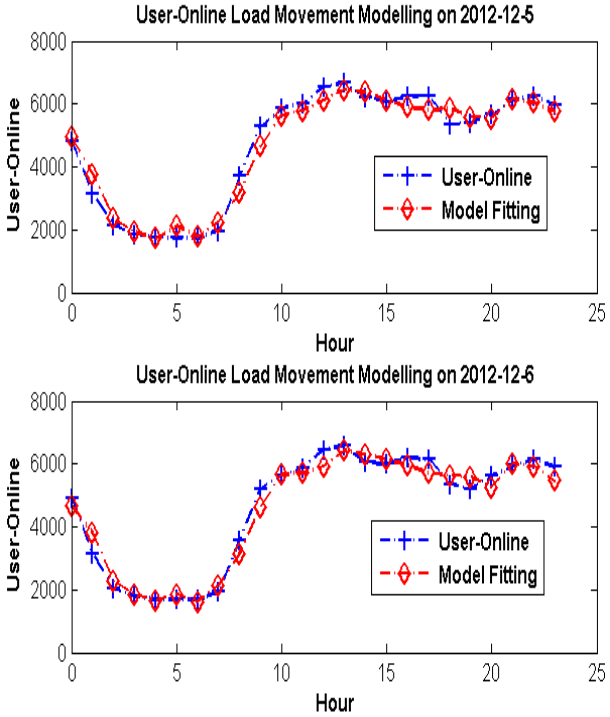

Figure 9. Model fitting results in the training for the daily user-online load movements (00:00-23:00) at the social network site of BBS.WHNET.EDU.CN on 2012-12-5 and 2012-12-6, respectively.

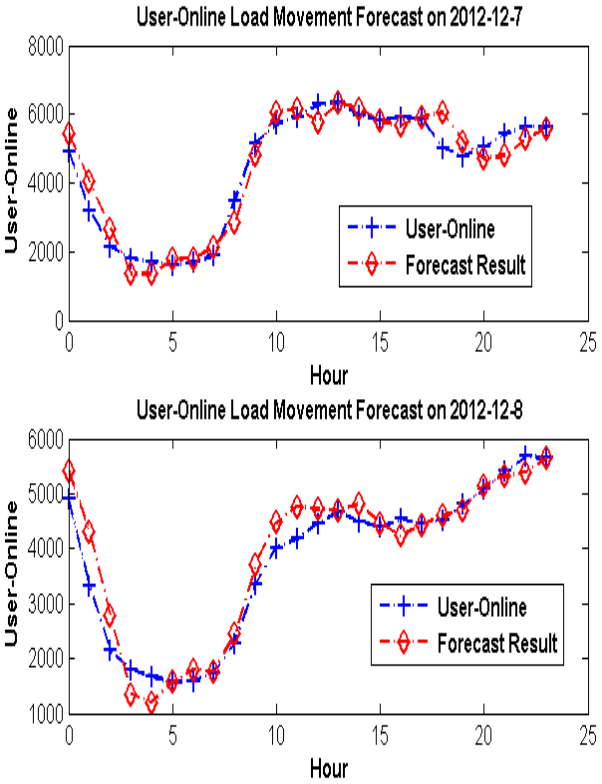

Figure 10. Forecast results for the daily user-online load movements (00:00-23:00) at the social network site of BBS.WHNET.EDU.CN on 2012-12-7 and 2012-12-8, respectively.

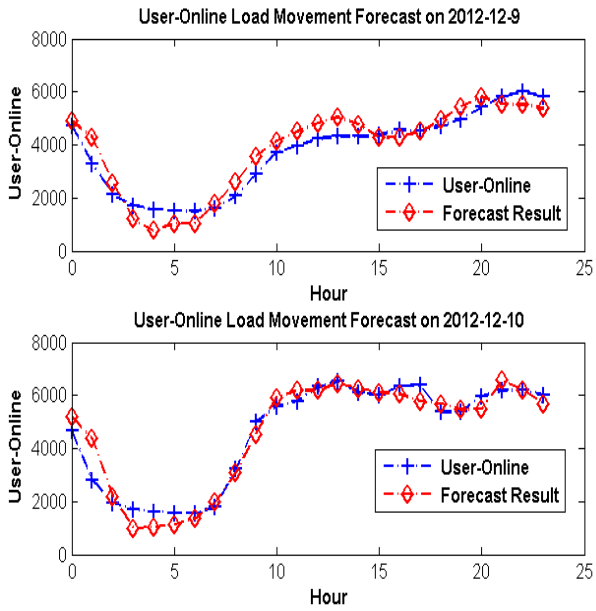

Figure 11. Forecast results for the daily user-online load movements (00:00-23:00) at the social network site of BBS.WHNET.EDU.CN on 2012-12-9 and 2012-12-10, respectively.

In Figures.7-11, it is shown that the experimental results agree well with the actual user-online load movements at the social network site of BBS.WHNET.EDU.CN.

IV. Result Analysis and Discussion

The presented BP-ANN model for forecasting the daily user-online load movement has been applied to the two social-network sites of BBS.NJU.EDU.CN and BBS.WHNET.EDU.CN in China. For each one of the daily forecast tasks, the BP-ANN model has been repeated 5 times to report its average performance.

To measure the obtained experimental results, the called correlation coefficient is employed, which is a classical measurement in measuring the strength and the direction of the linear relationship between two variables (the predicted results and their actual observation results). This measure can determine the degree to which the two variable's movements are associated.

Given N actual observation results: $\{X_1, X_2 ... X_i ... X_N\}$ and their predicted results $\{\hat{X}_1, \hat{X}_2 ... \hat{X}_i ... \hat{X}_N\}$, we have their means: $\bar{X}$ and $\hat{\bar{X}}$, respectively, and their standard deviations: S_X and $S_{\hat{X}}$, respectively.

Then, their covariance coefficient is defined by:

$$s_{X\hat{X}} = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \hat{X})(\hat{X}_i - \hat{\bar{X}}) \quad (1)$$

Accordingly, the definition of the correlation coefficient for the two variables (the predicted results and their actual observation results), denoted as *r*, is presented as follows:

$$r = \frac{S_{X\hat{X}}}{S_X S_{\hat{X}}} = \frac{\sum_{i=1}^{N}(X_i - \bar{X})(\hat{X}_i - \hat{\bar{X}})}{\sqrt{\sum_{i=1}^{N}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(\hat{X}_i - \hat{\bar{X}})^2}} \quad (2)$$

However, the correlation coefficient is one incomplete measure for prediction as a noticeable bias may exist between the two variables (the predicted results and their actual observation results) though one well correlation coefficient is measured on the results. In additional, the called Root Mean Square Error (RMSE) is usually to be further measured.

In mathematical statistics, the Root Mean Square Error (RMSE) (also called the Root Mean Square Deviation, RMSD), as a risk function, is a also commonly used method for measuring the difference between the values predicted by a model and the actual observation values that is to be modeled.

The RMSE of prediction results by one model with respect to their actual values, is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \hat{X}_i)^2}{N}} \quad (3)$$

Where X_i is the actual observation value and $\hat{X}_i$ is its modeled value.

With these above considerations, we see that the commonly used correlation coefficient is measurement of strength and direction of linear relationship between two variables, which determines the degree to which two variable's movements are associated. The RMSE (root-mean-square error, known as the standard error, σ) is a measurement of differences between the prediction results and their actual results, which is the most commonly and frequently used measurement on prediction accuracy. Thus, both the correlation coefficients and the RMSE are employed in our result analysis for the experimental results at the two social-network sites.

Ratios (percents) of RMSE (σ) to mean of actual user-online load values in the tasks of forecasting the user-online load movements are listed in Tables.3-4.

Correlation coefficients of the user-online load movements and their forecasting results are displayed in Table 5.

The experimental results of forecasting the user-online load movements show workability of the proposed method. In Tables.3-5, it is shown that with small errors, the forecast results agree well with their actual user-online movements, which indicates that the BP-ANN model yields satisfying results in tasks of forecasting the daily user-online load movements at the two social-network sites of BBS.NJU.EDU.CN and BBS.WHNET.EDU.CN in China.

TABLE III.
RATIOS (PERCENTS) OF *RMSE* TO MEAN OF ACTUAL USER-ONLINE LOAD IN THE FORECASTING TASKS AT BBS.NJU.EDU.CN

Daily User-online load Movement		Percent (RMSE/Mean)
Model Fitting In The Training	**2012-12-1**	**10.386%**
	2012-12-2	**11.307%**
	2012-12-3	**12.373%**
	2012-12-4	**11.798%**
	2012-12-5	**11.250%**
	2012-12-6	**11.583%**
Forecast	**2012-12-7**	**11.60%**
	2012-12-8	**12.42%**
	2012-12-9	**16.23%**
	2012-12-10	**14.60%**

TABLE IV.
RATIOS (PERCENTS) OF *RMSE* TO MEAN OF ACTUAL USER-ONLINE LOAD IN THE FORECASTING TASKS AT BBS.NJU.EDU.CN

Daily User-online load Movement		Percent (RMSE/Mean)
Model Fitting In The Training	**2012-12-1**	**9.152%**
	2012-12-2	**11.274%**
	2012-12-3	**10.452%**
	2012-12-4	**9.376%**
	2012-12-5	**9.745%**
	2012-12-6	**10.177%**
Forecast	**2012-12-7**	**10.187%**
	2012-12-8	**11.804%**
	2012-12-9	**13.597%**
	2012-12-10	**12.572%**

TABLE V.
CORRELATION COEFFICIENTS OF FORECAST ING RESULTS AND ACTUAL USER-ONLINE LOAD MOVEMENTS IN THE FORECASTING TASKS AT BBS.NJU.EDU.CN AND BBS.WHNET.EDU.CN

Daily forecast	BBS.NJ.EDU .CN	BBS.WHNET.E DU.CN
2012-12-7	0.9656	0.9456
2012-12-8	0.9173	0.9527
2012-12-9	0.9229	0.9594
2012-12-10	0.9566	0.9546

V. CONCLUSION AND FUTURE WORK

A social network site (SNS) is a popular online platform and web-server, which aims at providing services on facilitating the establishment of social networks or social relations among social members to share news, interests, activities, personal ideas or real-life valuable experiences. So, a social network site is usually composed of a representation of a number of members and each one represented by a profile with their social links. Usually, most social network sites provide web-based services for their members or users, which enable their users to interact over the Internet through emails or instant message tools to publish their shares within their individual cliques or networks in convenient ways.

Recently, the online social networks have been a global phenomenon [7] that an enormous scale appears in the use of the online social networks: the growth of the Internet-users visiting the online social networks at least once a month is expected to increase from 41.0% in 2008 to over 65.0% in 2014. Thus, the user-online load movement forecasting is increasingly vital for one social-network site for its increasingly important effect on web traffic, resource allocation, maintenance management and economic operations.

The user-online load movement is also a time series and may be influenced by the various factors. The ANN (artificial neural network), an emulation of the biological neural networks inspired by the biological neural systems, often also named as the neural network, is a popular mathematical model for a wide variety of many applications, such as engineering and scientific computing, prediction and problem solving, pattern recognition, etc. Among the varying soft computational tools and models available, the back-propagation artificial neural network (the BP-ANN) is one commonly used and robust model. In this study, addressing the user-online load movement forecasting for the social-network sites, we employ a typical BP-ANN model for predicting the user-online load movement and apply it to experiments.

The experimental results indicate workability of the proposed method. It is shown that the presented BP-ANN model yields satisfying experimental results in the tasks of forecasting the daily user-online load movements at the two social network sites of BBS.NJU.EDU.CN and BBS.WHNET.EDU.CN. Result analysis indicates that with small errors, the forecast results agree well with their actual user-online load movements.

Only the user-online load data itself (its previous data) is employed in the presented BP-ANN model, to further improve and investigate the presented forecast approach based on the BP-ANN model for forecasting the user-online load movements in the social-network sites, is still included in our future study.

ACKNOWLEDGMENT

The research was supported by Scientific Research Fund of Hunan Provincial Science and Technology Department (2013GK3090) and Scientific Research Fund of Hunan Provincial Education Department (09C399) and research fund of Hunan University of Science and Technology (E50811).

REFERENCES

[1] W. Stanley and F. Katherine, "Social Network Analysis in the Social and Behavioral Sciences," *Social Network Analysis: Methods and Applications*. Cambridge University Press. pp. 1-27, 1994.

[2] K. Lewis, J. Kaufman, M. Gonzalez, A. Wimmer and N. Christakis, "Tastes, ties, and time: A new social network dataset using Facebook.com," *Social Networks*, vol.30, no.4, pp.330-342, 2008.

[3] G. Robin, T. Snijders, P. Wang, M. Hancock and P. Pattison, "Recent developments in exponential random graph (p*) models for social networks," *Social Networks*, vol.29, no.2, pp.192–215, 2007.

[4] D.M. Boyd and N.B. Ellison, "Social network sites: definition, history, and scholarship," *Journal of Computer-Mediated Communication*, vol.13,no.1, pp.210–230, 2007.

[5] R.C. Yeh, Y.-C. Lin, K.-H. Tseng, P. Chung, S.-J. Lou and Y.-C. Chen, "Why do people stick to play social network sites? An extension of expectation-confirmation model with perceived interpersonal values and playfulness perspectives," *Studies in Computational Intelligence*. vol.457, pp.37-46, 2013.

[6] R. Agarwal, A.K. Gupta and R. Kraut. "The interplay between digital and social networks," *Information Systems Research*, vol.19, no.3, pp. 243–252, 2008.

[7] J.L. Heidemann, M. Klier and F. Probst, "Online social networks: A survey of a global phenomenon," *Computer Networks*. vol.56, no.18, pp.3866–3878, 2012.

[8] E.D. Kolaczyk, *Statistical Analysis of Network Data: Methods and Models.* Springer, New York, 2009.

[9] S. Piramuthu, "On learning to predict Web traffic," *Decision Support Systems,* vol.35, pp. 213-229, 2003.

[10] A. Aussem and F. Murtagh, "Web traffic demand forecasting using wavelet-based multiscale decomposition," *International Journal of Intelligent Systems*, vol.16, no.2, pp.215-236, 2001.

[11] J. Li and A. W. Moore,"Forecasting Web Page Views: Methods and Observations," *Journal of Machine Learning Research*, no.9, pp.2217-2250, 2008.

[12] K. Papagiannaki, N. Taft, Z.-L. Zhang, and C. Diot, "Long-term forecasting of Internet backbone traffic," *IEEE Trans. Neural Networks*, vol.16, no.5, pp.1110-1124, 2005.

[13] K.a Xu, J.b. Li and Y.c. Song, "Identifying valuable customers on social networking sites for profit maximization," *Expert Systems with Applications,* vol.39, no.17, 1 pp.13009-13018, 2012.

[14] P. Wu and S.K. Li, "Social Network Analysis Layout Algorithm under Ontology Model," *Journal of Software*, vol.6, no.7, pp.1321-1328, 2011.

[15] X.T. Han and L. Niu, "Word of Mouth Propagation in Online Social Networks," *Journal of Networks*, Vol.7, No.10, pp.1670-1676, 2012.

[16] L.A. Adamic and E. Adar.," Friends and neighbors on the web," *Social Networks*, vol.25, no.3, pp. 211–230, 2003.

[17] L.R. Men, W.H.S. Tsai,"How companies cultivate relationships with publics on social network sites: Evidence from China and the United States," *Public Relations Review*, vol.38, no.5, pp.723-730, 2012.

[18] StatSoft, Inc, *Electronic Statistics Textbook.* Tulsa, OK: StatSoft. WEB: http://www.statsoft.com/textbook, 2012.

[19] C. Chatfield, *The Analysis of Time Series*. Chapman & Hall/CRC, New York, 2004.

[20] S. Chatterjee, A. Hadi and B. Price, *Simple Linear Regression. Ch. 2 in Regression Analysis by Example (3rd edition)*. New York: Wiley, pp. 21-50, 2000.

[21] S.F. Ding, X.Z. Xu, H. Zhu, J. Wang and F.X. Jin, "Studies on Optimization Algorithms for Some Artificial Neural Networks Based on Genetic Algorithm (GA),"*Journal of Computers*, vol.6, no.5, pp.939-946, 2011.

[22] M. Xue, "A Novel Water Quality Assessment Method Based on Combination BP Neural Network Model and Fuzzy System," *Journal of Computers*, vol.8, no.6, pp.1587-1593, 2013.

[23] J. Heaton, *Introduction to Neural Networks with Java. Chapter5: Understanding Back Propagation,* pp.125-154, Heaton Research, Inc., 2005.

[24] R. Sikora, T. Chady, P. Baniukiewicz, M. Caryk and B. Piekarczyk, The Choice of Optimal Structure of Artificial Neural Network Classifier Intended for Classification of Welding Flaws. REVIEW OF PROGRESS IN QUANTITATIVE NONDESTRUCTIVE EVALUATION, VOLUME 29. *AIP Conference Proceedings*, Vol.1211, pp. 631-638, 2010.

[25] J. Dobes, L. Posisil and V. Panko,"Selecting an optimal structure of artificial neural networks for characterizing RF semiconductor devices," *IEEE International Midwest Symposium on Circuits and Systems* (*MWSCAS*), 1-4 Aug, 2010, pp.1206-1209 2010.

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