International Journal of Hybrid Information Technology
Vol.7, No.4 (2014), pp.201-212
http://dx.doi.org/10.14257/ijhit.2014.7.4.17

A Modified Wavelet Neutral Network Model for Measuring Goodwill

Han Dong Ping[1] and Bao Di[2]

[1]*School of management, Harbin Institute of Technology, Wei Hai, Shandong, China*
[2]*School of management, Harbin Institute of Technology, Harbin, Heilongjiang, China*
handongping@hit.edu.cn, baodi0824@163.com

Abstract

Recently years have witnessed the development of cultural enterprises. As one of the most valuable intangible assets, goodwill valuation for cultural enterprises has gained a lot of attention. An efficient method is to use Wavelet Neural Network (WNN) model for learning the predicted value of goodwill given a set of indicators. However, there are some issues of the basic WNN model. On one hand, the randomly determination of the initial state of the neural network leads to the possibility of converging to a local optimal point. To solve this problem, we propose to employ Genetic Algorithm (GA) for optimizing the initial parameters before model training. On the other hand, the training cost of basic WNN is typically big and its convergence speed is relatively slow. To accelerate the convergence speed, we introduce Levenberg-Marquardt (LM) algorithm for training. Besides, we conduct experiment to evaluate the performance of our proposed GA-LM-WNN algorithm.

Keywords: *Goodwill, Wavelet Neural Network*

1. Introduction

With the progression of economic globalization, industrial and academic research on cultural enterprises is increasing. As defined in [1], cultural industries refer to production activities of providing cultural products and other related products to the public, such as publishing and printing, arts and cultural services, social and human science research and community service, cultural information transfer service, entertainment, *etc*. After financial services, information technology, pharmaceuticals and biotechnology, and tourism, cultural industries are considered as the fifth largest economic sector [2] and have great achievements. For example, in 2000, cultural enterprises of Colombia contributed to the national GDP more than traditional industries such as restaurants and hotels [3]. In 2001, the value of cultural enterprises in China has increased to 1,364.9 billion Yuan, accounting for about 3% of the same period of GNP.

During the revolution of reforming cultural systems, great attentions have been paid to the valuation of intangible assets for cultural enterprises. As one of the most significant part, goodwill is defined as "the excess of the cost of the acquired company over the sum of the amounts assigned to identifiable assets acquired less liabilities assumed" [4]. For investors, it is transferable and depends on the profitability from continuous operations in future. That is to say, goodwill indeed brings excess financial benefits to companies. Therefore, it is necessary to evaluate the goodwill during the normal business period for the sake of maintaining and improving the commercial goodwill of enterprises.

As indicated in [5], as an unidentifiable intangible asset, goodwill is related to factors such as market penetration, distribution network, industrial relations and management. The measurement of goodwill aims to capture the excess value created by a company, and is

ISSN: 1738-9968 IJHIT

determined by many acquisition prices [6] and its financial statements. Suppose the indicators of goodwill can be obtained from domain experts, the process of measuring goodwill can be solved by an evaluation model.

The Wavelet Neural Network (WNN) is a hybrid of wavelet theory and Back Propagation (BP) neural network [7]. WNN is typically composed of a feed-forward neural network, with a hidden layer, and the activation functions are drawn from another normal wavelet family. One of the most popular applications for WNN is function estimation. Recently WNN has been widely applied to evaluation area due to its non-linear approximation ability and faster convergence speed than typical BP network. However, there remain some major shortcomings of WNN based evaluation model. For example, the convergence speed is still unsatisfactory, especially around the minimum point. Besides, it is likely to converge to local optimal point.

To solve above challenge, we propose a modified WNN model for measuring goodwill in this paper. Specifically, in order to avoid the local optimal issue, we employ Genetic Algorithm (GA) [8] to determine the initialization of parameters before model training. Then, we introduce Levenberg-Marquardt (LM) algorithm [9] to accelerate the speed of convergence. Moreover, we apply the modified WNN model to measure the goodwill values for cultural enterprises, and the experiment results show our algorithm exhibit better performance than other baselines.

The remain of this paper is organized as follows. Section 2 provides some related work. In Section 3, we present our LM-GA-WNN algorithm. Empirical experiments are conducted in Section 4. Finally, the paper is concluded in Section 5.

2. Related Work

Many prior efforts have been made on the valuation of goodwill. Standard SFAS 142 requires the estimation of goodwill to be conducted at the reporting unit level [10]. Beatty *et al*. (2006) [11] examined the initial adoption of SFAS 142. Watt [12] argued that the allocation of goodwill based on reporting units is open to considerable manipulation since goodwill stands for joint benefits for the firm. Jennings *et al*. [13] studied the effect of goodwill amortization and found it a significant indicator for the publicly traded companies. Shahwan *et al*. [14] suggested the positive relationship between the materiality of goodwill and identifiable intangible assets. By examining Australian GAAP from 1994 to 2003, Dahmash *et al.* [15] studied on the relevance and reliability on the value of intangible assets. Their results showed that goodwill is reliable while intangible assets are not, and the valuation of goodwill is generally under estimated. In order to more precisely valuating goodwill for companies, we propose to employ a WNN based model in this paper.

There exist many research on WNN applications. For example, Ghosh-Dastidar *et al.* [16] presented a wavelet-chaos-neural network for the classification of electroencephalograms. Bashir *et al.* [17] used WNN to forecast weather. Adeli *et al*. [18] proposed a dynamic fuzzy WNN model to identify structural systems. A model for freeway incident detection based on WNN was introduced in [19]. Chen *et al.* [22] proposed a local linear WNN to predict time series. Jiang *et al.*, [23] designed a dynamic WNN model for forecasting traffic flow. He *et al.* [24] applied WNN approach for fault diagnosis of analogue circuits. Different from existing works, we apply WNN based method to measure the goodwill of cultural enterprises, by combing GA and LM algorithm with basic WNN to avoid local optimal point and accelerate the speed of convergence.

3. Modeling

The basic idea of WNN is to construct a set of wavelet basis by scaling and translating the mother wavelet function, and feed them as the activation function of the hidden layer in a neural network. The evaluation process using WNN based models works as follows. Given the numerical information of determinants of the target object as input, the know value of evaluation from domain experts or experiences as output, and enough training samples, an adaptive training process is performed to learn the coefficients and weights of the model. Then evaluation on a new instance can be obtained based on the learned model.

The scaling and translating of mother wavelet function is achieved by consistent wavelet transformation:

$$W_f(a,b) = \int_{-\infty}^{\infty} f(t)h(a,b,t)dt \tag{1}$$

where $f(t) \in L^2(R)$, and $h(a,b,t) = |a|^{-\frac{1}{2}} h(\frac{t-b}{a})$ is called wavelet. $h(t)$ is mother wavelet function (or basic wavelet function), $|a|^{\frac{1}{2}}$ is the normalization factor, and a,b are scaling and translation coefficients respectively. The local structure of signal $h(t)$ is adjusted by the position and size of wavelet window (*i.e.*, parameters a,b).

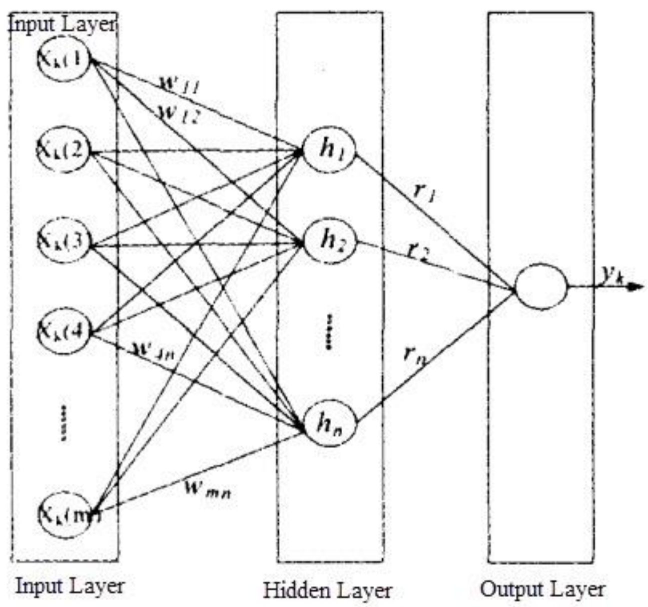

Figure 1. Model of 3-layer WNN

As illustrated in Figure 1, the output can be calculated as:

$$y_k = \sum_{j=1}^{n} r_j h\left(\frac{\sum_{i=0}^{m} w_{ij} x_k(i) - b_j}{a_j}\right) \tag{2}$$

where $x_k(i)$ is the normalized value of indicator i for instance k, w_{ij} is the weight from input layer to hidden layer, r_j is the weight from hidden layer to output layer, and a_j, b_j are scaling and translation coefficients respectively. $h(t)$ is defined as Morlet wavelet basis function:

$$h(t) = \cos(1.75t)\exp(-\frac{t^2}{2}), \tag{3}$$

and the structural of Morlet wavelet is shown in Figure 1.

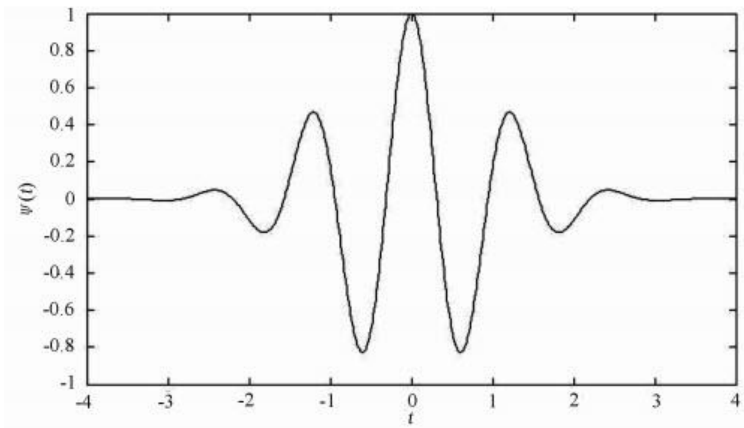

Figure 2. Morlet Mother Wavelet

Suppose d_k is known expected output of instance k, y_k is the calculated output of the model, and P is the number of training samples. Therefore, the coefficient of the network can be optimized by minimizing the following error function:

$$MSE = \frac{1}{2}\sum_{k=1}^{P}(y_k - d_k)^2 \tag{4}$$

Once the parameters of the network are learned, evaluation value of new instance can be calculated by feeding the indicator vector.

In order to accelerate the speed of convergence, we introduce Levenberg-Marquardt (LM) algorithm for optimizing Equation (4). Notate the parameters at iteration k as matrix $z_k = [w_{ik}, r_k, a_k, b_k]$, and the objective function can be presented as $F(z)$. The next iteration using Newton's method [20] can be represented as:

Algorithm 1 Levenberg-Marquardt (LM) algorithm

initialize $k = 0, \nu = 2, z = z_0$;
$A = J(z)^T J(z), g = J(z)^T v(z)$;
$found = (\|g\|_\infty \le \epsilon_1), \mu = \tau * max\{a_{ij}\}$;
while not $found$ and $k < k_{max}$ **do**
  $k = k + 1$;
  solve $(A + \mu I)h_{lm} = -g$;
  if $\|h_{lm}\| \le \epsilon_2(\|z\|) + \epsilon_2$ **then**
    $found =$ **true**
  else
    $z_{new} = z + h_{lm}$
    $\rho = (F(z) - F(z_{new}))/(L(0) - L(h_{lm}))$
    if $\rho > 0$ **then**
      $z = z_{new}$
      $A = J(z)^T J(z), g = J(z)^T v(z)$
      $found = (\|g\|_\infty \le \epsilon_1)$
      $\mu = \mu * max\{1/3, 1 - (2\rho - 1)^3\}, \tau = 2$
    else
      $\mu = \mu * \tau, \tau = 2 * \tau$
    end if
  end if
end while

Figure 3. Algorithm Description of LM

$$z_{k+1} = z_k - A_k^{-1} g_k \tag{5}$$

where $A_k = \nabla^2 F(z)|_{z=z_k}$ is a Hessian matrix, and $g_k = \nabla F(z)|_{z=z_k}$ is the gradient of the objective function.

Suppose $F(z) = v(z)^T v(z)$, where $v(z)$ is the error vector. The gradient of objective function is:

$$\nabla F(z) = 2J^T(z)v(z) \tag{6}$$

where $J(z)$ is a Jacobian matrix:

$$J(z) = \begin{bmatrix} \frac{\partial v_1(z)}{\partial z_1} & \frac{\partial v_1(z)}{\partial z_2} & \cdots & \frac{\partial v_1(z)}{\partial z_n} \\ \frac{\partial v_2(z)}{\partial z_1} & \frac{\partial v_2(z)}{\partial z_2} & \cdots & \frac{\partial v_2(z)}{\partial z_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial v_N(z)}{\partial z_1} & \frac{\partial v_N(z)}{\partial z_2} & \cdots & \frac{\partial v_N(z)}{\partial z_n} \end{bmatrix}$$

Since Hessian matrix can be approximated as:

$$\nabla^2 F(z) \approx 2J^T(z)J(z) \tag{7}$$

Substitute Equations (6) and (7) into (5), we get:

$$z_{k+1} = z_k - \left[J(z)^T J(z) \right]^{-1} J(z)^T v(z) \tag{8}$$

Introduce unit matrix I , above equation can be rewritten as:

$$z_{k+1} = z_k - \left[J(z)^T J(z) + \mu_k I \right]^{-1} J(z)^T v(z) \tag{9}$$

When $\mu_k = 0$, the algorithm is simplified as Newton's Method. When μ_k gets bigger, it is similar to the gradient method with small step length. During the training iterations, if successful, decrease the value of μ_k to accelerate the learning; else, increase μ_k to slow down the learning for better point. In this way, LM algorithm assures the speed of convergence by compromising between the Newton's method and the descending gradient method. The pseudo code of LM is described in Algorithm 1.

Now we solve the convergence speed issue by leveraging LM algorithm during training iterations. However, local convergence problem still remains. Therefore, we introduce a global optimization algorithm to determine the initial status of the neural network, so that WNN can converge to a global point with minimum fitting error. In this work, we employ Genetic Algorithm (GA) to initialize the parameters. The processing flow of GA is illustrated as Figure 4, and the pseudocode of GA is described in Algorithm 2.

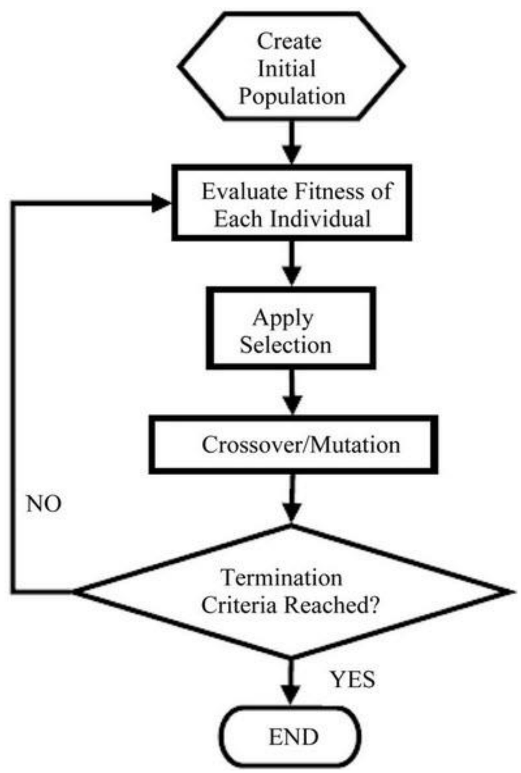

Figure 4. Processing Flow of GA

Algorithm 2 Genetic Algorithm (GA)

Input: population P;
Output: best fit individuals.

initialize $P(t = 0)$;
evaluate $P(t = 0)$;
while termination condition is not met **do**
    $P_p(t) = P(t).selectParents()$;
    $P_c(t) = reproduction(P_p)$;
    $mutate(P_c(t))$;
    $P(t+1) = buildNextGenerationFrom(P_c(t), P(t))$;
    $t = t + 1$;
end while
return best fit individuals

Figure 5. Algorithm Description of GA

The proposed GA-LM WNN algorithm is described as Algorithm 3. Specifically, in order to avoid local convergence, we employ Genetic Algorithm (GA) to optimize the initial parameters of WNN. Besides, we introduce Levenberg-Marquardt (LM) algorithm to accelerate the convergence speed. In summary, the training process of GA-LM WNN can be described as running GA first to determine proper initial state of neural network, and then optimizing using LM algorithm to minimize the fitting error.

Algorithm 3 GA-LM WNN algorithm

initialize parameter matrices $\mathbf{w}, \mathbf{r}, \mathbf{a}, \mathbf{b}$ using Algorithm 2;
input $\{x_k(i), d_k\}^P$ to compute output $y_k(i)$ and error e;
while $e \geq MSE$ **do**
    calculate matrix z_k by $\mathbf{w}, \mathbf{r}, \mathbf{a}, \mathbf{b}$;
    compute matrix $\mathbf{J}$;
    $\Delta z = -[\mathbf{J}^T(z)\mathbf{J} + \mu_k \mathbf{I}]^{-1}\mathbf{J}^T(z)v(z)$;
    $z_k = z_k + \Delta z$;
    calculate error e';
    if $e' < e$ **then**
        $\mu_{k+1} = \mu_k / \alpha$
        update parameters a, b, w_{ij}, r_j and $e = e'$
    else
        $\mu_{k+1} = \mu_k * \alpha$
    end if
end while

Figure 6. Algorithm Description of GA-LM WNN

4. Experiments

To accomplish the object of evaluating the goodwill value for cultural enterprises, we choose 15 companies from fortune 500 2012 in publishing and printing, Internet services and retailing, and entertainment fields. The cultural companies are described in Table 1. Data such as total assets, sales, total liabilities and income, are collected from the U.S. Securities and Exchange Commission (SEC) electronic database EDGAR. The expected goodwill values are determined by the average of five authoritative experts.

Table 1. Description of Selected Cultural Companies

Company	Fortune 500 rank	Revenues		Profits	
		$ millions	% change from 2010	$ millions	% change from 2010
Amazon.com	56	48,077.0	40.6	631.0	-45.2
Google	73	37,905.0	29.3	9,737.0	14.5
eBay	228	11,651.7	27.3	3,229.4	79.3
Liberty Interactive	230	11,624.0	5.8	912.0	-51.8
Yahoo	483	4,984.2	-21.2	1,048.8	-14.8
R.R. Donnelley & Sons	249	10,611.0	5.9	-122.6	-155.3
McGraw-Hill	384	6,336.0	2.7	911.0	10.0
Gannett	465	5,240.0	-4.2	458.7	-22.0
Walt Disney	66	40,893.0	7.4	4,807.0	21.3
News Corp.	91	33,405.0	1.9	2,739.0	7.9
Time Warner	103	28,974.0	7.8	2,886.0	11.9
Viacom	177	14,963.0	10.9	2,136.0	38.0
CBS	188	14,245.0	1.3	1,305.0	80.2
CC Media Holdings	394	6,161.4	5	-302.1	N/A
Live Nation Entertainment	450	5,384.0	6.3	-83.0	N/A

We use MATLAB to implement our GA-LM-WNN algorithm, and evaluate the performance compared to some other methods. The baseline algorithms are BP neural network, WNN and LM-BP. All the input and output values for indicators and expected goodwill are normalized to the range of [0, 1]. The input indicators are selected based on the determinants of goodwill measurement as indicated in [21].

Table 2. Goodwill Measuring Results Comparison

No.	Expected goodwill	BP		LM-BP		WNN		GA-LM-WNN	
		output	error	output	error	output	error	output	error
1	0.847	0.842	0.0061	0.844	0.0032	0.844	0.0031	0.846	0.0017
2	0.973	0.968	0.0053	0.969	0.0039	0.970	0.0028	0.972	0.0015
3	0.902	0.894	0.0089	0.896	0.0062	0.897	0.0058	0.898	0.0044
4	0.695	0.689	0.0082	0.691	0.0054	0.693	0.0031	0.693	0.0025

5	0.748	0.667	0.1080	0.741	0.0093	0.742	0.0079	0.744	0.0052
6	0.826	0.818	0.0091	0.820	0.0068	0.822	0.0045	0.823	0.0036
7	0.955	0.947	0.0088	0.950	0.0057	0.953	0.0025	0.953	0.0021
8	0.443	0.440	0.0063	0.441	0.0036	0.442	0.0012	0.443	0.0006
9	0.920	0.817	0.1125	0.911	0.0098	0.911	0.0094	0.913	0.0071
10	0.764	0.672	0.1201	0.688	0.1000	0.757	0.0097	0.757	0.0089
11	0.398	0.395	0.0064	0.397	0.0013	0.394	0.0090	0.398	0.0003
12	0.573	0.561	0.0204	0.562	0.0189	0.564	0.0164	0.567	0.0102
13	0.895	0.772	0.1374	0.886	0.0099	0.887	0.0093	0.888	0.0082
14	0.868	0.768	0.1155	0.859	0.0098	0.861	0.0085	0.862	0.0065
15	0.947	0.938	0.0099	0.941	0.0067	0.943	0.0046	0.945	0.0022

Table 2 gives the goodwill valuation results for 15 cultural companies. After multiple times of execution, we fix our model as 6 hidden layers and 1 output layer. The relative error is controlled below 0.005 after 1000 iterations for most companies. From the table, we can observe that our proposed GA-LM-WNN outperforms other algorithms. Besides, the fact that LM-BP is better than BP proves the employment of LM algorithm. Also, the fact that GA-LM-WNN outperforms LM-BP means that the optimized initialization based on GA algorithm leads to better performance.

Besides, in order to evaluate the speed of convergence, we also conduct experiment to evaluate the convergence curve of LM-BP, WNN and GA-LM-WNN. We can see that our GA-LM-WNN performs best. Also, benefit from the fast convergence characteristic of LM algorithm, LM-BP is better than the basic WNN algorithm. This result also confirms the shortcomings of WNN, *i.e.*, slow convergence speed.

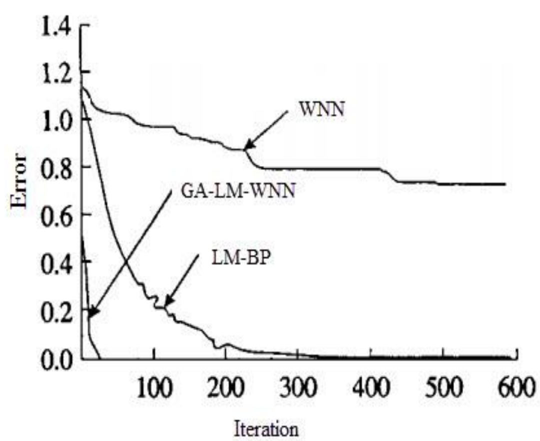

Figure 7. Convergence Curves for LM-BP and GA-LM-WNN Algorithms

5. Conclusion

In this paper, we propose a modified WNN model by combining GA and LM algorithm to avoid local optimal points and accelerate convergence speed. We also apply the modified algorithm to measure the goodwill value for cultural enterprise. Empirical results prove the efficiency of our method.

References

[1] "Cultural and Related Industries Classification", National Bureau of Statistics, **(2004)**, pp. 24.
[2] Cultural Strategy Group, "Creative South Africa: A strategy for Realising the Potential of the Cultural Industries", Unpublished Report for the Department of Arts, Culture, Science and Technology, Pretoria **(1998)**.
[3] Recognizing Culture: A series of briefing papers on culture and development", Comedia, **(2001)**.
[4] Accounting Principles Board, "Opinion No. 16: Business Combinations", AICPA, **(1970)**.
[5] G. Malcolm, "Goodwill Discontent: The Meshing of Australian and International Accounting Policy." Australian Accounting Review, vol. 5, no. 9, (1995), pp. 3-16.
[6] W. K. Chauvin,and M. Hirschey, "Goodwill, Profitability, and the Market Value of the Firm." Journal of Accounting and Public Policy, vol.13, no. 2, **(1994)**, pp. 159-180.
[7] Q. Zhang and A. Benveniste. "Wavelet Networks", Neural Networks, IEEE Transactions", vol. 3, no. 6, **(1992)**, pp. 889-898.
[8] D. E. Goldberg, "Genetic Algorithms in Search, Optimization, and Machine Learning", Reading Menlo Park: Addison-Wesley, **(1989)**.
[9] A. A. Suratgar, M. B. Tavakoli and A. Hoseinabadi, "Modified Levenberg–Marquardt Method for Neural Networks Training", World Acad Sci Eng Technol, vol. 6, **(2005)**, pp. 46-48.
[10] C. Chen, M. Kohlbeck and T. Warfield, "Goodwill Valuation Effects of the Initial Adoption of SFAS 142", SSRN 534484, **(2004)**.
[11] A. Beatty and J. Weber, "Accounting Discretion in Fair Value Estimates: An Examination of SFAS 142 Goodwill Impairments", Journal of Accounting Research vol. 44, no. 2, **(2006)**, pp. 257-288.
[12] R. L. Watts, "Conservatism in Accounting Part I: Explanations and Implications", Accounting Horizons, vol. 17, no. 3, **(2003)**, pp. 207-221.
[13] R. Jennings, M. LeClere and R. B. Thompson, "Goodwill Amortization and the Usefulness of Earnings", Financial Analysts Journal, **(2001)**, pp. 20-28.
[14] Y. Shahwan, "The Australian Market Perception of Goodwill and Identifiable Intangibles", Journal of Applied Business Research(JABR) vol. 20, **(2011)**, pp. 4.
[15] F. N. Dahmash, R. B. Durand, and J. Watson, "The Value Relevance and Reliability of Reported Goodwill and Identifiable Intangible Assets", The British Accounting Review, vol. 41, no. 2, **(2009)**, pp. 120-137.
[16] G.-D. Samanwoy, H. Adeli, and N. Dadmehr, "Mixed-band Wavelet-chaos-neural network Methodology for Epilepsy and Epileptic Seizure Detection", Biomedical Engineering, vol. 54, no. 9, **(2007)**, pp. 1545-1551.
[17] B. Zidan, and M. E. El-Hawary, "Short Term Load Forecasting by Using Wavelet Neural Networks", Electrical and Computer Engineering, vol. 1, **(2000)**.
[18] A. Hojjat and X. Jiang, "Dynamic Fuzzy Wavelet Neural Network Model for Structural System Identification", Journal of Structural Engineering, vol. 132, no. 1, **(2006)**, pp. 102-111.
[19] G.-D. Samanwoy and H. Adeli, "Wavelet - Clustering - Neural Network Model for Freeway Incident Detection", Computer - Aided Civil and Infrastructure Engineering, vol. 18, no. 5, **(2003)**, pp. 325-338.
[20] Q. Liqun and J. Sun, "A Nonsmooth Version of Newton's Method", Mathematical Programming, vol. 58, no. 1-3, **(1993)**, pp. 353-367.
[21] H. Carla, and P. J. Hughes, "Leading Indicators of Goodwill Impairment", Journal of Accounting, Auditing & Finance vol. 21, no. 3, **(2006)**, pp. 223-265.
[22] C. Yuehui, B. Yang, and J. Dong, "Time-series Prediction Using a Local Linear Wavelet Neural Network", Neurocomputing vol. 69, no. 4, **(2006)**, pp. 449-465.
[23] J. Xiaomo, and H. Adeli, "Dynamic Wavelet Neural Network Model for Traffic Flow Forecasting." Journal of Transportation Engineering, vol. 131, no.10, **(2005)**, pp. 771-779.
[24] H. Yi-gang, Y.-H. Tan and Y.-C. Sun, "Wavelet Neural Network Approach for Fault Diagnosis of Analogue Circuits", IEE Proceedings-Circuits, Devices and Systems, vol. 151, no. 4, **(2004)**, pp. 379-384.

Authors

Han Dong Ping, she got a Bachelor of Accounting Degree (1990) in Dongbei College of Finance & Economics, then a Master's degree in Thermal engineering in Harbin Institute of Technology (1994), and a Doctoral of Accounting Degree (2002) in Harbin Institute of Technology. She studied first at Hong Kong University of Science &Technology in 1997, and then enrolled at Finland Lappeenranta

Industrial Technology University in 1998. She was a teacher in College of Management, a graduate and doctoral tutor in Harbin Institute of Technology between 1987 and 2005. In 2005, she worked as a Deputy Division Chief in finance department and the dean of School of Economics and Management in Weihai at the Harbin Institute of Technology in 2012.

Bao Di, she received the Master of Management in Public Administration (2010) from Yanshan University. Now she is majoring in PhD of Management in management Department from Harbin Institute of Technology University. Her current research interests include different aspects of Valuating Goodwill of Cultural enterprises Using Wavelet Neural Network.