Available online www.jocpr.com

Journal of Chemical and Pharmaceutical Research, 2014, 6(7):2052-2060

Research Article

ISSN : 0975-7384
CODEN(USA) : JCPRC5

A research on IPO pricing model in China's growth enterprise market-based on analytic hierarchy process and BP Neural network

Wenxiu Tang and Xiaohua Zhou

School of Economics and Business Administration, Chongqing University, Chongqing, China

ABSTRACT

With the first batch of 28 companies listed on the China's Growth Enterprise Market (GEM) on October 30, 2009, high issue prices, high P/E and high over-raising capital, known as "Tri-highs" phenomena, have received intensive attention and suspicions from the very beginning of the GEM's establishment in China. The IPO pricing efficiency become the subject of concern again. In view of the existing problems of IPO pricing in China's GEM such as deviating from intrinsic value, high initial returns and from the point to improve pricing efficiency and effectiveness, this paper combines Analytic Hierarchy Process(AHP) with BP Neural Network to establish a new IPO pricing model. Firstly, we applies AHP to construct a comprehensive pricing assessment index system and screens the assessment indexes according to their weights. Then, we carries out example simulations with BP Neural Network model. The results indicate that the combination model of Analytic Hierarchy Process with BP Neural Network model is effective in fixing the prices of new issues in China's GEM.

Key words: IPO pricing, growth enterprise market, analytic hierarchy process, BP neural network

INTRODUCTION

The IPO pricing is a challenging problem because uncertainties are always involved in both product and stock markets. Artificial neural network, as a computing system containing many simple nonlinear computing units or nodes interconnected by links, can handle disorderly comprehensive information without requiring strong model assumptions, and also has good nonlinear approximation capability, strong self-learning and self-adaptive abilities. The neural network is a well-tested method for financial analysis on the stock market, pattern recognition and optimization. The nonlinear method of artificial intelligence in artificial neural network is widely used to predict stock price and to fix the price for options in financial markets. As for the application of neural network in IPO research, Robertson et.al(1998) constructed three models to predict the first-day return of an initial public offering and found that the neural network models perform well on both technology and non-technology offerings[1].

In fact, many researchers point out that the price of new issue shares in China's stock markets deviate from intrinsic value since the non-market pricing mechanism reduce the efficiency of IPO pricing. Therefore, multiple regulators start the market-oriented reform for the pricing mechanism. The inquiry system was introduced in 2004 in China's stock markets, in order to replace the "government pricing" with "market-based pricing"[2]. IPO inquiry system, however, does not fundamentally eliminate the phenomena of high initial returns and long-term weakness in China's stock markets. IPO pricing efficiency of China's stock market has been the focus of public and academic concern again.

The first batch of 28 companies listing on the Growth Enterprise Market (GEM) on October 30, 2009, marked the official opening of GEM, which is no doubt of great significance on the development of China's securities market. The introduction of the GEM is described as the "booster" and "incubator" for the high-tech, high-growth innovative companies, even if the actual situation is not satisfactory. "Tri-highs" phenomena (i.e., high issue prices, high P/E and high over-raising capital) have received intensive attention and suspicions from the very beginning of the GEM's establishment in China. The original purpose of the launch of GEM market in China is to meet the financing needs in the rapid development of small & medium sized enterprises and to make social scattered funds gathered in capital market. But the GEM is still an immature and emerging market, whose IPO pricing mechanism is not perfect, caused more serious IPO "Tri-highs" phenomenon than the main board market. Zhang & Yu(2012) calculated the inherent value of listed companies in GEM, and found that the IPO pricing was 50% more than the intrinsic value[3]. Guo & Wan(2011) used the residual income valuation model, stochastic frontier model and regression model to test the rationality of IPO issue price in China's GEM. Their result showed that IPO issue price in China GEM deviates from intrinsic value, existing price bubble, and the speculation behavior in secondary market is the main cause of IPO underpricing [4]. Therefore, the study of IPO pricing with Chinese GEM companies has a strong theoretical and practical significance to improve the efficiency of GEM IPO pricing, enhance the efficiency of small and medium enterprises' financing, and ameliorate the operating environment of Chinese capital market.

The companies listed in GEM are small and medium sized enterprises with high growth. Compared with the main board IPO pricing, it is hard to find similar listed companies for reference for the short operating time of GEM. In addition, due to the initial enterprise life cycle stage the new issuing companies in, there is not enough historical operating data to carry on the forecast of future development accurately. Traditional methods such as free cash flow discounted, relative valuation and the economic added valuation techniques are no longer applicable to the GEM IPO pricing. Many scholars began to adopt the real option and neural network methods to fix the IPO prices. Taking advantage of AHP and BP neural network, this paper tries to resolve the nonlinear and dynamic mathematical problems of the IPO pricing and give reasonable prices of the new issues in China's GEM.

ANALYTIC HIERARCHY PROCESS AND BP NEURAL NETWORK

2.1. Analytic Hierarchy Process

AHP has been developed and applied to numerous areas since T. L. Saaty put forward it first in 1980[5]. AHP is an effective way to deal with importance grades with respect to many items. The decision problem is decomposed into a hierarchy of more easily comprehended sub-problems firstly. Once the hierarchy is built, the decision makers evaluate the factors systematically and compare them to one another in pairs. Among them, for the indexes in the same criteria layer, 1-9 proportional scaling method (shown in table1) is used to determine the relative weights of each index.Then, eigenvalue and vector are calculated according to comparison matrix.

Table 1. 1-9 Proportional scaling method

$a_{ij}=1$	u_i is as important as u_j
$a_{ij}=3$	u_i is a little more important than u_j
$a_{ij}=5$	u_i is obviously more important than u_j
$a_{ij}=7$	u_i is strongly more important than u_j
$a_{ij}=9$	u_i is extremely more important than u_j
2,4,6,8 are the medians of above judgement	

Consistency index (C.I.) is introduced to test whether the judgment matrix is consistency.

$$C.I.=\frac{\lambda_{\max}-n}{n-1} \qquad (1)$$

Table 2. The average random consistency index (R.I.)

n	1	2	3	4	5	6	7	8	9	10
R.I.	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Consistency Ratio is a comparison between Consistency Index and Random Consistency Index:

$$C.R.=\frac{C.I.}{R.I.} \qquad (2)$$

If the value of consistency ratio is smaller or equal to 10%, the inconsistency is acceptable. If the consistency ratio is greater than 10%, we need to revise the subjective judgment.

2.2. BP Neural Network

Statistical and valuation methods, such as discount cash flow model, economic value added model, comparable company analysis model, marketing returns model, real options valuation model and multiple factors pricing model, had been proposed to price the new issue stocks. Basically, these conventional methods rely on the restrictive assumptions on linear separability, multivariate normality, and independence of the variables. Unfortunately, many of the common models of forecasting methods violate these assumptions, and they may not completely reflect actual market conditions when they are applied to complex real world problems [6]. Seriously, these methods become more complex if relationships in the input/ output dataset are nonlinear [7]. Numerous factors that affect IPO pricing relate to each other and are not independent. They form a complex network of influence on IPO pricing. The correlation between influence factors, the subjective question of weight assignment, the difficulty of the quantitative calculation and the noise data of sample will affect the effectiveness of pricing methods. Artificial neural network has a good ability of fault tolerance and associative memory [8]. The interaction of input factors was considered into BP neural network and a comprehensive analysis was designed to deal with the influence factors' message. Therefore, it has been widely used to deal with complex nonlinear problems and get more reasonable final output. This paper analyzes the affecting factors of China's GEM IPO pricing from both internal and external aspects and applies Analytic Hierarchy Process and BP neural network to construct a China's GEM IPO pricing model, in order to improve the rationality and regulation of IPO pricing in China's GEM.

BP algorithm is mainly divided into two stages: in the first stage, the input signal is transmitted forward to the hidden nodes, using activation function to calculate the actual output value of each unit; in the second stage, if the output layer fails to achieve the desired output value, the error between actual output and desired output will be calculated and transmitted step by step back to hidden and the input layers so as to adjust the weights and narrow the error. The process of neural network learning stops when the error satisfies requirements. As shown in Figure.1, the Back-propagation Neural Network is based on hierarchical structure, including an input layer, an output layer and one (or more) hidden layer [9-11].

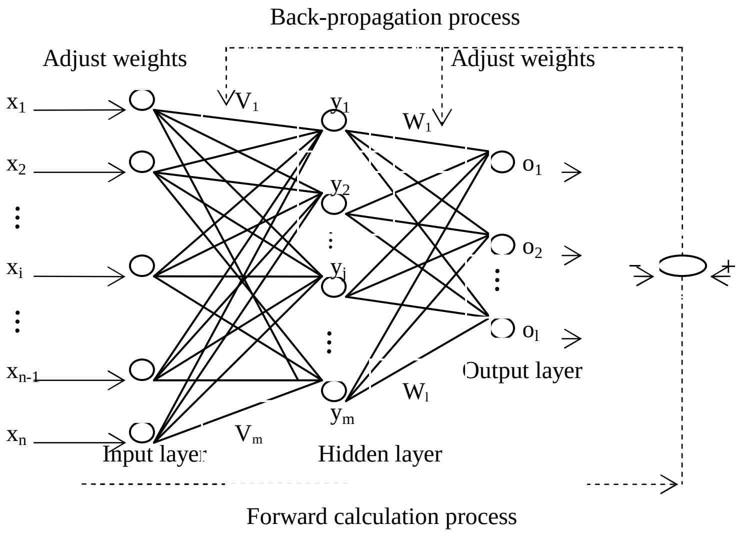

Figure 1. The structure of three-layer BP neural network

As shown in Figure.1, in a three-layer BP neural network, $X=(x_1,x_2,\cdots,x_i,\cdots,x_n)^T$ is the input vector; $Y=(y_1,y_2,\cdots,y_j,\cdots,y_m)^T$ is the output of the hidden layer; $O=(o_1,o_2,\cdots,o_k,\cdots,o_l)^T$ is the actual output of output layer and $D=(d_1,d_2,\cdots,d_k,\cdots,d_l)^T$ is the desired output vector. There are two weight matrices in a three-layer BP neural network: $V=(v_1,v_2,\cdots,v_j,\cdots,v_m)$ is the weight matrix between input layer and hidden layer; $W=(w_1,w_2,\cdots,w_k,\cdots,w_l)$ is the weight matrix between hidden layer and output layer. The outputs of all neurons in the hidden layer are calculated by the following calculations:

$$net_j=\sum_{i=0}^{n} v_{ij}x_i, \qquad j=1,2,\cdots m, \tag{3}$$

$$y_j=f(net_j), \qquad j=1,2,\cdots m. \tag{4}$$

Here net_j is the activation value of the j th node, y_j is the output of the hidden layer; $f(x)$ is called the activation function of a node, usually a sigmoid function as follows:

$$f(x)=\frac{1}{(1+e^{-x})} \tag{5}$$

The outputs of all neurons in the output layer are given as follows:

$$net_k=\sum_{i=0}^{m} w_{jk}y_j, \qquad k=1,2,\ldots l, \tag{6}$$

$$o_k=f(net_k), \qquad k=1,2,\ldots l. \tag{7}$$

Error appears when actual output and expected output turn out to be unequal. The neural network is to find the lowest error.

$$E=\frac{1}{2}(D-O)^2=\frac{1}{2}\sum_{k=1}^{l}(d_k-o_k)^2 \tag{8}$$

Where E is the error of output. To extend the calculation, we get equation as follow:

$$E=\frac{1}{2}\sum_{k=1}^{l}(d_k-f(net_k))^2=\frac{1}{2}\sum_{k=1}^{l}(d_k-f(\sum_{j=0}^{m}w_{jk}y_j))^2=\frac{1}{2}\sum_{k=1}^{l}\left\{d_k-f\left[\sum_{j=0}^{m}w_{jk}f(\sum_{i=0}^{n}v_{ij}x_i)\right]\right\}^2 \tag{9}$$

Output error E is a function of w_{jk} and v_{ij}. Thus, by correcting weights, the total error of neural network has been adjusted to satisfy the requirements. The steepest descent method, also known as the gradient descent method, used in BP neural network is a kind of optimization algorithm of differentiable function.

$$\Delta w_{jk}=-\eta\frac{\partial E}{\partial w_{jk}}, \qquad j=1,2,\ldots,m; \qquad k=1,2,\ldots,l \tag{10}$$

$$\Delta v_{ij}=-\eta\frac{\partial E}{\partial v_{ij}}, \qquad i=1,2,\ldots,n; \qquad j=1,2,\ldots,m \tag{11}$$

Where η is a constant, $\eta\in(0,1)$ is the learning rate. Combined E with above two equations, we get the weights adjustment calculation formula of BP learning algorithm as shown below:

$$\Delta w_{jk}=\eta(d_k-o_k)o_k(1-o_k)y_j \tag{12}$$

$$\Delta v_{ij}=\eta\left[\sum_{k=1}^{l}(d_k-o_k)o_k(1-o_k)\right]y_j(1-y_j)x_i \tag{13}$$

Above is the algorithm of BP neural network. All weights are assigned with random values initially, and then modified by the delta rule according to the learning samples [12-16].

Based on the analysis of the present status of IPO pricing in China's GEM, a model of IPO pricing with AHP-BPNN is introduced. The following steps (as shown in Figure. 2) are used to build a neural model capable of making IPO prices of China's GEM. Firstly, IPO pricing factors including financial and non-financial factors are pre-selected to construct the initial index system based on the experiential knowledge of authors. Then, AHP is implemented to calculate the index weights and accordingly screen the indexes in order to amend the index system and to enhance accuracy of IPO price making. Accordingly, three-layer BP Neural Network is established with sample data from GEM.

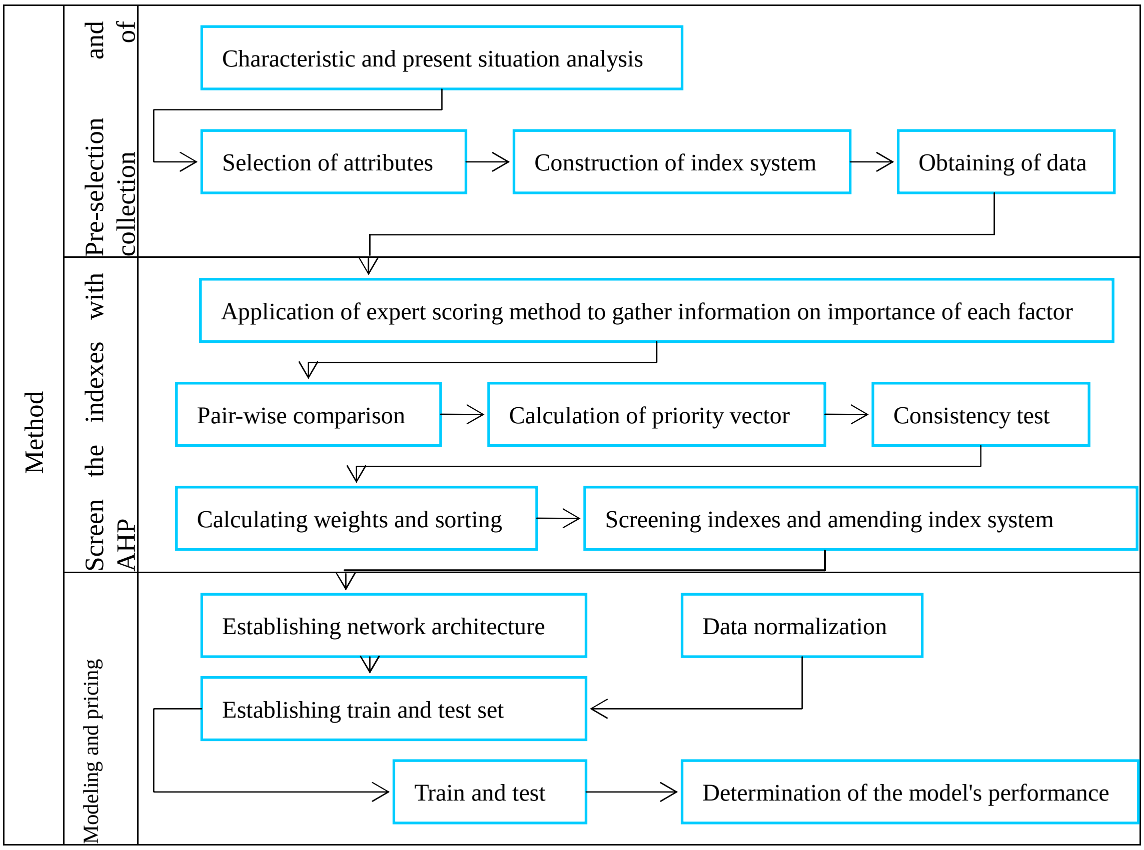

Figure.2. Process steps with AHP-BPNN in IPO pricing

FACTORS AND INDEX SYSTEM

The factors affecting stock price are often divided into two categories: financial indicators and non-financial indicators.

3.1 Financial indicators

Considering that the GEM is characterized by high growth, we put the financial factors into five categories as follows: financial fundamentals, debt paying ability, profitability, growth ability and operating ability.

Fundamentals
-total assets
-net assets value per share
-earnings per share
-accumulation fund per share
Debt paying ability
-debt asset ratio
-liquidity ratio
-cash to current debts ratio
-interest cover ratio
Profit and Earning ability
-return on equity
-return on total assets
-profit rate of sales
-surplus cash cover
Operating ability
-receivables turnover
-inventory turnover
-current assets turnover
-total assets turnover
Growth ability
-growth rate of sales

-growth rate of net profit
-growth rate of sales profit
-growth rate of total assets

Table 3 The judgment matrix and weights in financial index system

the criterion layer	Judge -ment matrix	The index layer	Comparison matrix	Membe-rship weights	Synthet-ic weights
C_1:fundam-entals	1	I_{11}:total assets	1 3 2 5	0.4759	0.1428
(0.30)	1	I_{12}:net assets value per share	1/3 1 1/2 2	0.1544	0.0463
	2	I_{13}:earnings per share	1/2 2 1 4	0.2884	0.0865
	2	I_{14}:accumulation fund per share	1/5 1/2 1/4 1	0.0813	0.0244
	3		C.R.=0.0078<0.1		
C_2:debt paying ability	1	I_{21}: debt asset ratio	1 3 5 5	0.3682	0.0957
(0.26)	1	I_{22}: liquidity ratio	1/3 1 2 2	0.3682	0.0957
	2	I_{23}: cash to current debts ratio	1/5 1/2 1 1	0.1930	0.0502
	1	I_{24}: interest cover ratio	1/5 1/2 1 1	0.0714	0.0184
	3		C.R.=0.0015<0.1		
C_3: profitabilit-y	1/2	I_{31}: return on equity	1 1 2 3	0.3507	0.0596
(0.17)	1/2	I_{32}: return on total asset	1 1 2 3	0.3507	0.0596
	1	I_{33}: profit ratio of sales	1/2 1/2 1 2	0.1893	0.0321
	1	I_{34}: surplus cash cover	1/3 1/3 1/2 1	0.1093	0.0186
	3		C.R.=0.0038<0.1		
C_4:	1/2	I_{41}:average sales growth rate	1 1/7 1/3 1/5	0.0569	0.0164
Growth	1	I_{42}:average net profit growth rate	7 1 5 3	0.5579	0.1605
ability	1	I_{43}:average sales profit growth rate	3 1/5 1 1/3	0.1218	0.0351
(0.18)	1	I_{44}:average total assets growth rate	5 1/3 3 1	0.2634	0.0757
	2		C.R.=0.043<0.1		
C_5: operating ability	1/3	I_{51}: receivable turnover	1 1 1 5	0.3152	0.0252
（0.08）	1/3	I_{52}: inventory turnover	1 1 1 5	0.2711	0.0218
	1/3	I_{53}: current assets turnover	1 1 1 3	0.3389	0.0271
	1/2	I_{54}: total assets turnover	1/5 1/5 1/3 1	0.0748	0.0059
	1		C.R.=0.0501<0.1		

As shown in table3, the paper applies AHP to calculate the weights of all financial factors on the basis of scoring method and pair-wise comparison. To simplify the inputs of BP network, we exclude the indexes whose weights are less than 0.020, including interest cover ratio, surplus cash cover, average sales growth rate and total assets turnover. The exclusion guarantee the contribution rate of the cumulative weight of the remaining 16 indexes is more than 90%, which will not affect the degree of pricing assessment.

3.2 Non-financial indicators

Non-financial factors refer to the elements independent of the enterprise's normal operation, but reflect its endogenous sustained profitability indirectly, such as market interest rate, unexpected events, policy guidance, product market expectations, industry competition, market volatility, stock issuance scale and underwriters' reputation etc. Non-financial factors may have uncertain, nonlinear influences on the pricing process. According to the existing literature research, this paper chooses the following factors: index returns, underwriter reputation, lottery rate and issuing scale.

(1) Index returns
In general, investors can accept higher IPO price in a prosperous capital market, on the other hand, investors only accept lower new issue price in the decline of the stock market [17]. Due to imperfect of China's GEM composite index, the Shenzhen composite index returns (SRET) are used to measure the market sentiment instead. Considering IPO price is generally fixed in the two weeks before the IPO date, we include Shenzhen composite index returns during a 30 trading interval from 35 trading days before and 5 trading days before the IPO date into our model.

(2) Underwriter's reputation
Underwriters' reputation plays an important role in the IPO underwriting process. Reputation is the important basic to security underwriters' function of "information producer" and "certifying agency"[18]. Reputation stands for the underwriters' behavior features in the past. Investors have more confidence in the message revealed by higher reputation underwriters. We use underwriter ranking as our proxy for underwriter reputation.

(3) Issuing Scale
Generally, the greater issue scale, the greater potential risk of failure. Companies listed in China's main board are divided into large cap stock issuance, mid-cap and small-cap by the boundaries of 100 million and 500 million. However, companies listed on China's GEM are small and medium sized enterprises with high growth and mainly belong to energy, health care, information industries. Firms with large issuing scale are subject to more strict

verification of the government and regulators, thus the IPO price is often reduced to a lower level by underwriters and issuers [19]. It is consistent with "small company effect" in China's stock markets that small-cap stocks have higher returns than large-cap stocks.

(4) Lottery Rate
The price for new issue was determined by taking into account the market demand factors. If the aggregate demand in the book-building process was great, the offer price could be increased. Conversely, if there is little demand for the new issue, underwriter and issuer shall lower the offer price in order to ensure the success of IPO. It is the essence of the inquiry system. So, Lottery rate is selected to measure the market demand in this paper.

IPO PRICING MODEL BASED ON AHP-BPNN

4.1. The structure of AHP-BPNN

Three-layer network is adopted in this paper. We select and screen the variables to construct the GEM IPO pricing index system. The pricing assessment index system including 20 variables could serve as the inputs of AHP-BPNN, as shown in Table4.

Table 4. The inputs of AHP-BPNN

C_1 fundamentals	I_{11}:total assets I_{12}:net assets value per share I_{13}: earnings per share I_{14}:accumulation fund per share	C_4 growth ability	I_{42}:average net profit growth rate I_{43}:average sales profit growth rate I_{44}:average total assets growth rate
C_2 debt paying ability	I_{21}: debt asset ratio I_{22}: liquidity ratio I_{23}: cash to current debts ratio	C_5 operating ability	I_{51}: receivable turnover I_{52}: inventory turnover I_{53}: current assets turnover
C_3 profitability	I_{31}: return on equity I_{32}: return on total asset I_{33}: profit ratio of sales	Non-financial factors	index returns underwriter's reputation issuing scale lottery rate

Lei(2003), Zhao(2008) put forward the idea of constructing neural network to price the new issue, but without empirical research for further support. The key of designing output layer is to choose an appropriate variable for "target-price". But so far there is no definition of reasonable price for IPO. Huang(2008) point out that the successful price is the highest acceptable price which ensure the success of the issue. Based on the actual situation, it is inappropriate to take the first day opening/closing price as the reasonable price. For the purpose of narrowing the gap between IPO price and first day opening price, we adopt the method of Huang(2012) and take the average value of IPO price and the first opening price is selected as the expected output of the pricing model [20-22].

The selection of hidden layer generally is often decided on experience. One hidden layer is selected to construct network when the problem is not very complex and the number of neurons in hidden layer is decided by the following formula:

$$\frac{m+n}{2} \le k \le \frac{m+n}{2} + 10 \tag{14}$$

Where m is the number of neuron in input layer, n is the number of neuron in output layer, k is the number of neuron in hidden layer. We choose one hidden layer in out pricing model and get the number of neuron $k \in [10, 20]$ in hidden layer with formula (14). The precise k is determined through debugging and comparing in the training. The ANP-BPNN model of China's GEM IPO pricing is implemented through the neural network toolbox of MATLAB 2013a. Twenty-five samples are used to train the network. In the training process, the parameters set are adjusted continuously until the error satisfies the requirements.

4.2. Simulating and testing

Different industries have different potential profitability. Expectations of investors on companies' value vary among firms with different growth abilities in different industries. Considering new shares' pricing of the same industry has greater similarity, firms of electronic information technology industry with the important characteristic of innovation, are selected as a representative of new issues of GEM in this paper. Thirty new issues listed from Oct. 2009 to Jun. 2010 are involved. The first 25 samples are used to train the network and the last 5 samples are taken as a test set.

There are twenty nodes in input layer and one node in output layer. The data is normalized before training and the following parameters are applied in the model: performance goal 0.001, training epochs 1000. We set the number of nodes in hidden layer from 10 to 20 and train the network with calling program. After debugging and comparing, fourteen nodes of the hidden layer are determined due to the least mean square error it has .

Table 5. The comparison of running results and expected results

Stock code	Expectation price	Normalized data of expected price	Output data	Error
300073	54.79	0.3589	0.3631	1.17%
300074	89	0.6746	0.7165	6.21%
300075	64.5	0.4485	0.4811	7.27%
300076	70	0.4993	0.4999	0.12%
300077	124.25	1.0000	0.8348	16.52%

After running the program, we obtain the following output: Y_1=0.3631, Y_2=0.7165, Y_3=0.4811, Y_4=0.4999, Y_5=0.8348, as shown in Table 5. Considering the situation of China's GEM, we hold that error below 10% is acceptable. So, we accept the results for the average error is 6.258% which verifies the validity of the model. From the results, we also find that the bigger the expectation data, the greater the error, which is coincide with the research results of Huang(2012).

CONCLUSION

IPO pricing is one of the most basic and important theme relative to the profit of the issuing firm and investors in the stocks offerings plan, and it also affect the stocks' real performance after coming into the stock market. If the offering price is too low, it is difficult to satisfy the capital demand of issuing firm and may injure the original shareholders' profits. On the other hand, if the offering price is too high, it will enlarge the underwriters' issue risk and investors' investment risk. Based on the analysis of the current situation of IPO pricing in China's GEM and the characteristics of the capital market and companies, we obtain the IPO pricing factors of the GEM from both financial and non-financial aspects. Both theoretical and empirical findings suggest that combining different methods can improve the efficiency and effectiveness of making price of new issues. This paper presents an AHP-BPNN model for IPO pricing by combining Analytic Hierarchy Process with BP Neural Network. In the AHP-BPNN IPO pricing model, AHP is used to filter out the unrelated variables and keep only those variables, which have significant weights to the IPO price. Then a comprehensive and clear index system based on AHP was constructed and taken as the input variables of BP Neural Network. In order to improve the normativeness of GEM IPO pricing in China, reasonable IPO price was defined and calculated as the expected output of the network based on the current situation of China's GEM. After training and testing, the result we have obtained shows that the combination model of Analytic Hierarchy Process with BP Neural Network model (AHP-BPNN) is effective in pricing new issues in China's GEM.

REFERENCES

[1] SJ Robertson; BL Golden; GC Runger; EA Wasil. *Neurocomputing*, **1998**, 18(1), 165-182.
[2] SW Huang; GP Hu. *Journal of Changchun University of Science and Technology (Social Sciences Edition).* **2012**,25(7),92-95.
[3] JF Zhang; J Yu. *Journal of Shenyang University(Social Science)*. **2012**,14(6),20-22.
[4] HX Guo; WD Fang.*China Soft Science*.**2011**,9,156-166.
[5] H Jiang; JH Ruan. *Journal of networks*, **2010**,4(5).
[6] B Luo; WJ Huang; S Yang. *Journal of Chongqing University (Natural Science Edition)*, 2005. 28(2),137-140.
[7] HX Lin . *Journal of Minjiang University*, **2004**,. 25(2),72-75.
[8] XH Tan; YP Bai. *Economist*, **2009**,12, 93-95.
[9] SL Yu; XC Qi. *Journal of Tsinghua University (Science & Technology)*, 2011,51(12), 1917-1920.
[10] YANG Gelan; Yue WU; Huixia JIN. *Journal of Computational Information Systems*, **2012**, 8(10): 4315-4322.
[11] L Han;R Li;HL Zhu. *Chinese Society of agricultural machinery*.**2011**,42(7), 109 -115.
[12] HY Shen; ZX Wang; CYGao. *Journal of Tianjin University of Technology*. **2008**, 24(5),13 -15.
[13] K Hornik; M Stinchcombe; H White. *Neural Networks*, **1989**.2(5), 359-366.
[14] JF Cui; JX Qi; SD Yang. *Journal of Central South University (Science and Technology)*, **2009**,40(1), 190-194.
[15] RG Ibbotson..*Journal of Financial Economics*, **1975**,2,235-272.
[16] P Anna;I Vong; N Zhao. *Applied Financial Economies*, **2008**, 18:1539-1547.
[17] MK Henry; YV Hui. *Pacific- Basin Finance Journal*, **1998**, 6(5), 453-474.
[18] XZ Steven; AS David. *Financial Management*, **2008**, 36(2), l- 20.
[19] WW Huang. *South China University of Technology* **2012**.
[20] G Yang; X Xu; G Yang; J Zhang. *Models and Applications*, **2010**, 517-524.

[21] GL Yang; Q He; XJ Deng. *International Journal of Advancements in Computing Technology(IJACT)*, **2011**,3(10), 266 - 273.
[22] ML Zhao. *Lanzhou Academic Journal*.**2010**, 7,77-80.