INTEGRATION OF ARTIFICIAL NEURAL NETWORKS AND FUZZY DELPHI FOR STOCK MARKET FORECASTING

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ABSTRACT

The stock market, which has been investigated by various researchers, is a very complicated environment. So far, most of the research only concerned the quantitative factors, like index in open or volume, instead of qualitative factors, say political effect. However, the latter always plays a very important role in the stock market environment. Therefore, this research proposes an intelligent stock market forecasting system which considers the quantitative factors as well as the qualitative factors. Basically, the proposed system consists of (1) factors collection, (2) quantitative model (i.e., artificial neural network), (3) qualitative model (i.e., fuzzy Delphi), and (4) decision integration (i.e., artificial neural network). An example based on the Taiwan stock market is shown to evaluate the proposed intelligent system.

1. INTRODUCTION

The stock market is always one of the most popular investments due to its high profit. However, higher profit results in higher risk. Thus, a lot of research intended to develop an forecasting model in order to provide the investors an optimal prediction. Among the traditional research, most of the works employed the time series analysis techniques (i.e., mixed auto regression moving average (ARMA)) (Kendall 1990) as well as multiple regression models. However, most of them have their own constraints.

Recently, due to the increase of the computational speed, artificial neural networks (ANNs) have also been used in this area. ANN is a system which has been derived through the model of neurophysiology (Hertz 1991). (Baba 1992) applied modified error back-propagation (EBP) learning algorithm to predict the Japanese stock market. The network structure consists of fifteen input nodes and one output node representing the stock market tendency. Similar research can refer to (Jang 1993, Cheng 1994).

Though all the above mentioned research declared that their proposed models could accurately predict the stock market, they only concerned the quantitative factors instead of qualitative factors. It is doubtless since the quantitative factors are more convenient to process and obtained. However, in the reality, the non-quantitative factors sometimes are more important than the quantitative factors. Therefore, this paper intends to develop an intelligent stock market forecasting system based on both the factors to help the investors make the right decision. Basically, the proposed system consists of (1) factors collection, (2) quantitative model, (3) qualitative model, and (4) decision integration. In the first part, the system needs to collect all the possible factors, no matter quantitative or qualitative. Then the quantitative factors are fed into an ANN for prediction. But this is only for the general pattern of the stock market in the second part. Thus, the third part employs the modified fuzzy Delphi to decide the qualitative effect on the stock market. Finally, the above two values are integrated with time effect in order to provide the final decision. This paper consists of three more sections. Section two discusses the proposed system while the example results based on the Taiwan stock market are shown in section three. The conclusions and future study are explored in section four.

2. METHODOLOGY

This research intends to develop an intelligent stock market forecasting system (Figure 1) based on the view point of systems integration. Basically, the proposed system consists of four parts, factors collection, quantitative model, qualitative model, and decision integration. In the following, they will be discussed sequentially.

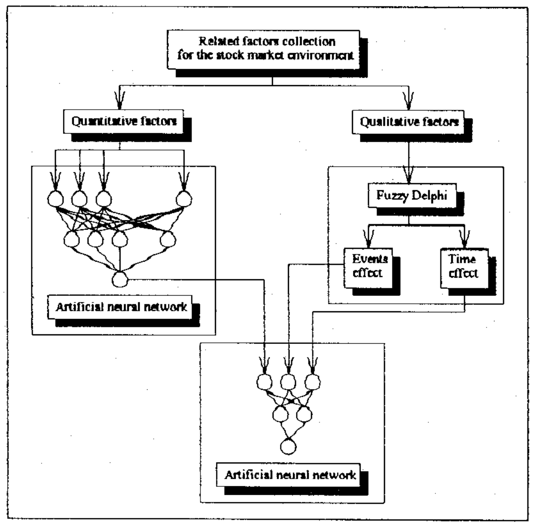

Figure 1. The structure of the forecasting system.

(1) Factors collection

In order to make a right decision, collecting the effective information regarding the forecasted object is very crucial. In this part, assume that the collected factors are good enough to support the forecasting model. It has been mentioned above that both the quantitative and non-quantitative factors are collected from the published journals and newspapers and the index data is provided by the stock company.

(2) Quantitative model (ANN)

Once the data has been collected in the first part, this part will employ the model-free method, ANN, instead of traditional statistics models to develop the relationship between the independent variables and dependent variable on the network connection weights. Among the different network structures and learning algorithms, this research selects the feedforward ANN with EBP learning algorithm since it can predict the continuous output and has been applied in a variety of areas, like control and pattern recognition (Lippmann 1987).

Regarding the network structure, this research will consider one hidden layer as well as two hidden layers. For the proposed network, input layer with some neurons represents some effective quantitative factors. The hidden layer with some neurons is connected with the output layer with one neuron which represents the performed stock tendancy. Basically, the one-hidden-layer ANN can be written as follows:

Input layer:

$$O_{pi} = X_{pi}, \quad i = 1,2,\ldots,n_I, \tag{1}$$

Hidden layer:

$$O_{ph} = f(Net_{ph}), \quad h = 1,2,\ldots,n_H,$$

$$Net_{ph} = \sum_{i=1}^{n_I} W_{hi} \cdot O_{pi} + \Theta_h, \tag{2}$$

Output layer:

$$O_{pk} = f(Net_{pk}), \quad k = 1,2,\ldots,n_O,$$

$$Net_{pk} = \sum_{k=1}^{n_O} W_{kh} \cdot O_{ph} + \Theta_k, \tag{3}$$

The learning algorithm is based on the gradient search with minimizing the cost function defined as:

$$E = \frac{1}{2}\sum_p (T_p - O_p)^2 \tag{4}$$

where p is pattern number and T and O are the target and actual outputs, respectively. The updating rule for each connection weight is:

$$W_{kh}(t) = -\eta(\frac{-\partial E}{\partial W_{kh}}) + \alpha W_{kh}(t-1) \quad , \qquad (5)$$

where η is the training rate and α is the momentum.

(3) Qualitative model (Delphi method)

Delphi method was first founded by Dalkey in RAND Corporation. This approach has been widely applied in many management areas, like forecasting, public policy analysis, or project planning. However, the traditional Delphi method can not converge very well. Besides, high survey frequencies always result in high cost. Thus, Ishikawa (1993) utilized fuzzy sets theory in the Delphi method in order to solve the above two shortcomings. But the method proposed by (Ishikawa 1993) is not suitable for this research. Therefore, the procedures of the modified fuzzy Delphi method are as follows:

a. Divide the non-quantitative data collected from the first part into six dimensions (political, financial, economic, message, technical, international) in order to formulate the first questionnaire. Give some copies of the first questionnaire to the stock experts for the sake of elimination and grouping in order to formulate the second questionnaire.

b. Fuzzify the returned questionnaires from the stock market experts and determine the triangular shaped membership functions.

c. For each single questionnaire, calculate the average for each event by means of arithmetic average. Thereafter, use the following equations to obtain the final triangular shaped membership functions.

$$Min_i = Min(Min_{i,j}) \qquad (6)$$

$$Max_i = Max(Max_{i,j}) \qquad (7)$$

$$Mean_i = \sqrt[n]{\prod Mean_{i,j}} \qquad (8)$$

where $Min_{i,j}$, $Max_{i,j}$, and $Mean_{i,j}$ are the minimum, maximum, and mean values of ith event and jth sample, respectively and n is the total number of samples.

d. Put the information (Min, Max, Mean) obtained from the step three in the third questionnaire and give them to the stock experts. The main reason is to converge the membership functions.

e. Employ statistics mean-test and variance-test to decide whether the membership functions have converged or not. If not, continue the next questionnaire until converge.

f. After all the membership functions have converged, determine the fuzzy numbers for each dimension using:

$$Min_i = Min(Min_{i,j}) \text{ for all j} \qquad (9)$$

$$Max_i = Max(Max_{i,j}) \text{ for all j} \qquad (10)$$

$$Mean_i = \sqrt[n]{\prod Mean_{i,j}} \text{ for all j} \qquad (11)$$

where $Min_{i,j}$, $max_{i,j}$, and $mean_{i,j}$ are the minimum, maximum, and mean values of ith dimension and jth event, respectively and n is the number of events in each dimension.

g. Defuzzify the fuzzy numbers through the center of gravity.

Therefore, the results from the fuzzy Delphi represent the non-quantitative factor effects on the stock market.

(4) Decision integration

From the above two parts, quantitative and non-quantitative models, the general stock market tendency and special factors effects are obtained. In order to get the final result, these two are integrated with time effect through the other ANN. The investors can make a right decision based on the support of the proposed system.

3. MODEL EVALUATION

This section used the data collected from the Taiwan stock market in order to evaluate the proposed system. There are two reasons why to choose the Taiwan stock market. One is that it is an environment where the authors are familiar to and the other is that the Taiwan stock market is a kind of "light-tray" stock market. If the proposed system is able to provide the acceptable forecast, it will also be suitable for the other kinds of stock markets. Appendix lists all the considered factors after discussing with the stock market experts.

Firstly, the factors are divided into two categories, quantitative and non-quantitative, as mentioned above. Based on the literature survey results, twenty-five quantitative factors (Appendix) will be considered. Due to dynamical consideration, the factors with "*" whose previous (one-day before) values will also be included. Therefore, totally, there are forty-two input variables. Just like mentioned in section two, traditional research employed multiple regression models to find the relationship between the factors and the stock index. However, due to complexity of the model determination and linear constraint, most of them are not able to provide very acceptable results. Even time series analysis technique, ARMA, is applied, it also has the same problem. Thus, all the quantitative factors will be the inputs of the quantitative model, ANN. Since this research employs the feedforward ANN with EBP learning algorithm, all the quantitative factors should be normalized in [0, 1]. Forty two factors result in the number of the input nodes to be also forty two. The number of output nodes is one. But, this research will try to test two different outputs:

$$O_1 = (N_{t3} - N_{t0}) \tag{12}$$

$$O_2 = \frac{Max(N_{t0} \sim N_{t3}) - N_{t0}}{Max(N_{t0} \sim N_{t3}) - Min(N_{t0} \sim N_{t3})} \tag{13}$$

where N_{t0} and N_{t3} are the indexes of current day and three days after, respectively. Since the network can have more than one hidden layers, both one and two hidden layers are tested. In addition, since the number of hidden-layer nodes strongly affects the network performance, this paper will also make the sensitivity analysis for the number of hidden-layer nodes. For the above testing, the training rate and momentum are set to be 0.5 and 0.5, respectively. The network will not stop training until the 50,000 iterations. Table 1 shows the computational results, which imply that the best network is the one whose output is O_2. The network has only one hidden layer whose node number is sixty. The forecasting results are show in Figure 2. In here, such network is called the single ANN (SANN).

Table 1. Computational results for SANN.

	Output	Hidden layer	Node number	MSE
1	O_1	1	60	0.0035
2	O_2	1	50	0.1371
3	O_1	2	25	0.0035
4	O_2	2	60	0.1352

For the non-quantitative model, fuzzy Delphi method, the set up of questionnaire is based on the related references, like journals and newspaper. Basically, it consists of six dimensions as mentioned in section two. Consequently, tremendous amounts of events can be included. Thus, the authors spent plenty of time in the library in order to extract these events. Thereafter, use these events to formulate the first questionnaire and let the stock market experts make the ranking. Thus, we can obtain the second questionnaire. After three times of survey, the mean and variance tests show that the membership functions have converged. Therefore, this knowledge base will be integrated further with the SANN results shown in the above.

Intuitively, there is only one data which is the tendency of stock market from SANN result. But the fuzzy Delphi method at least provides six data which are political, economic, financial, message, international, and technical effects. However, the effects will also depend on how long it has been occurred. For this reason, the time levels for each dimension are also included for each dimension. Therefore, the network consists of thirteen input nodes which are connected to twenty-nine hidden nodes which are connected to twenty-nine hidden nodes which are connected to one output node after the sensitivity analysis. The MSE is equal to 0.037847 after 50,000 epoches of training. For such network, it is called the integration ANN (IANN). The forecasting results are shown in Figure 2.

It appears that if use only one ANN (SANN) to forecast the stock market, the results are acceptable, and the O_2 output provides the better result than O_1. The reason is that O_2 is more sensitive than O_1. However, through integration of ANN and fuzzy Delphi method, its performance is much better than the single ANN. The comparison of these two methods are shown in Table 2.

Table 2. The comparison of two different networks

Forecasting year	1994	
networks / Performance	SANN	IANN
MSE	0.1810	0.1175
Dominant rate of buying signal	12.37%	37.46%
Dominant rate of selling rate	22.97%	29.33%
Dominant rate	35.34%	66.78%
Transaction times	8	19
Effective transaction times	7	17
Ineffective transaction times	1	2
Rate of effective transaction times	87.5%	89.5%
Performance of buying and selling	2686.1	4523.5
Average return of per transaction	335.7	238.1
Average internal time of per transaction	13	5.5
Average keeping time of per transaction	22.4	9.4
Transaction cost	400	950
Net performance of buying and selling	2286.1	3573.5
The trade of stock index	+ 530.99	+ 530.99

The MSE value of IANN which is equal to 0.1175 is less than the value of SANN which is equal to 0.181. In addition, IANN performs better on the dominant rate of buying signal, the dominant rate of selling rate, and the dominant rate. The performance of buying and selling of SANN and IANN are 2686.1 and 4523.5, respectively. However, it is not feasible directly to use this performance to make the selection, since IANN has more transaction times which result in more transaction cost. After subtracting transaction cost from performance of buying and selling, the net performance of buying and selling for SANN and IANN are 2286.1 and 3573.5, respectively. Therefore, it is doubtless that IANN is better than SANN. Integration of ANN with fuzzy Delphi method really can improve the performance.

Though it looks that the results of IANN is pretty good, the performance still can be improved. For example, this paper used the center of gravity to combine the fuzzy numbers from six dimensions. The reason is that it is easy instead of the best to implement. Thus, it is feasible to try the other alternatives. In addition, recurrent ANN is very suitable to the time series data. It appears to be very promising to replace the ANN with time series data.

4. CONCLUSIONS

This paper has shown that the proposed intelligent stock market forecasting system is able to handle both the quantitative and non-quantitative factors. In the future, we will try to apply the fuzzy neural network (Kuo 1996) to replace the fuzzy Delphi method in order to obtain the more accurate results since fuzzy neural network is capable of learning.

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Appendix

1. Average Volume*
2. Rate of volume change*
3. Four Days Moving Average
4. Nine Days Moving Average
5. Eighteen Days Moving Average
6. MACD*
7. MACD (DIF) *
8. Six Days RSI*
9. Twelve Days RSI*
10. Nine Days "K" Value*
11. Nine Days "D" Value*
12. TAPI*
13. Three Days BISA*
14. Six Days BISA*
15. "Three - Six" Days BISA*
16. Fourteen Days "+"DI*
17. Fourteen Days "-"DI*
18. Fourteen Days ADX*
19. Momentum*
20. OBV*
21. Three Days ADI
22. Six Days ADI
23. D. J. I. A.
24. Nikkai Index
25. Hensen Index

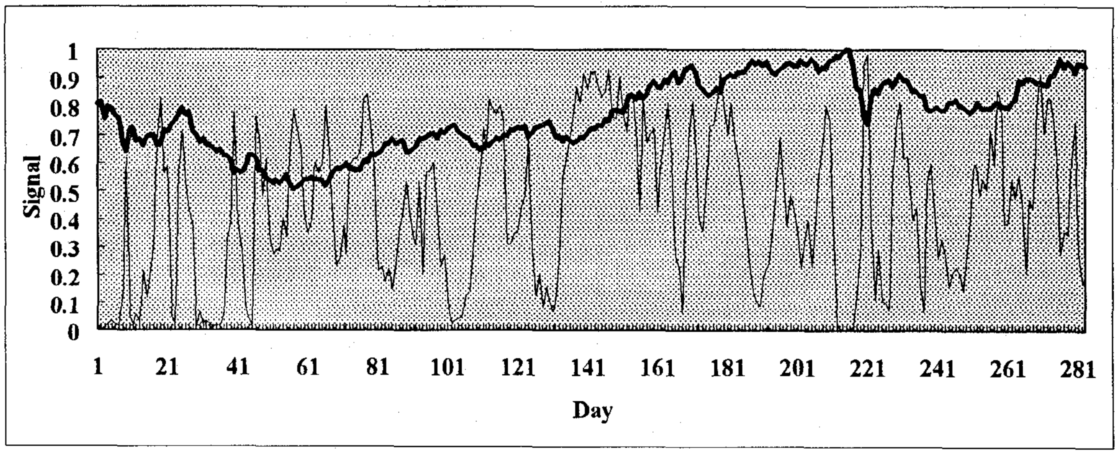

Figure 2. The forecasting results of using single ANN.

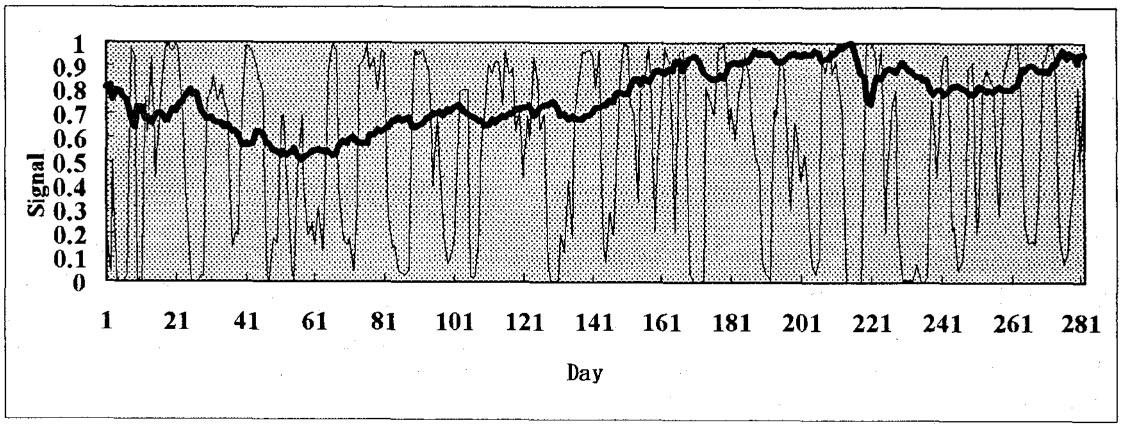

Figure 3. The forecasting results of using integration ANN.