Predicting Direction of Individual Stock Price Movement Using a Hybrid Model

Cheng Li and Yu Song

***Abstract*—Predicting stock return or a stock index is an important financial subject which has attracted great popularity in major financial markets around the world. Scholars and investors tried to use many different kinds of algorithms to predict the stock market return. Various models have been used by researchers to forecast market value by using ANN (Artificial Neural Network). ANN model trained via back propagation algorithm is one of the models which are most commonly studied now. In this paper, a hybrid model is improved by testing the active function. To prove the applicability of the model, the improved model is applied to some individual stocks. Furthermore, an investment strategy is proposed based on the prediction results of individual stock.**

***Index Terms*—Artificial neural network, forecast, individual stocks, investment strategy.**

I. Introduction

The issuance and trading of stocks promoted the development of market economy. The stock market is a complex system with unstable nonlinear dynamic volatility. On the one hand, market trend is influenced by many factors, such as political situation, financial policy, company's performance, customer's expectations and so on. On the other hand, stock price is highly-nonlinear and instable [1], [2]. Therefore, predicting direction of stock price is an important financial subject which has attracted great popularity in major financial markets around the world.

Artificial Neural Network (ANN) is a powerful tool for nonlinear dynamic system predicting and modeling. It is considered to be possible to predict the stock market efficiently by using appropriate mathematical models. Using appropriate mathematical models, neural networks can predict the stock market efficiently. In practical application, 80%~90% of ANN models use error Back Propagation (BP) algorithm. However, in the process of finding the optimal solution, the neural network is apt to be stuck in a local optimal solution. To overcome these drawbacks, Qiu and Song proposed an ANN model to forecast direction of Nikkei 225 [3], [4]. The weighs and bias of this model are optimized by Genetic Algorithm (GA) to improve the above-mentioned drawbacks. Hence, this ANN model is also called a hybrid model.

For further research, we conduct some simulation experiments about changing active functions to improve original hybrid model. Then we apply the improved model on some individual stocks to predict the direction of stock market index. Furthermore, an investment strategy is proposed based on the prediction results of individual stock.

This paper is organized as follows. The second section introduces the previous studies. The back propagation algorithm and genetic algorithm are described briefly. The structure and parameters of artificial neural network are illustrated next. In Section III, we show the performance of different active function in improving original model and we apply the improved model to some individual stocks and get some good results. An investment strategy based on the results of prediction is described in Section IV. Finally, we summarize the results and their possible consequences for this paper in Section V.

II. Prediction Model and Parameters

A. Back Propagation Algorithm

The BP algorithm is a widely applied classical learning algorithm for neural networks [5]. In the BP algorithm, we enter the in-sample data, and then the algorithm adjusts the weights and bias of the network by repeated training in such a way that the error between the desired output and the actual output is reduced. When the error is less than a specified value or when termination criteria are satisfied, training is completed and the weights and bias of the network are saved.

First, the error between the actual value and the predicted value is calculated. Then the error generated by each layer of neural networks is diffused from the back to front. Next the weight and bias of the gradient are calculated. Then back propagate the errors and update of the weights and biases. Training stops when the value of the error function has become sufficiently small, or reached a prespecified number of epochs have expired.

B. Genetic Algorithm

As observed in the parameter setting experiments, there are two disadvantages in BP algorithm [6]. One is the result is apt to be trapped into local minima. Another one is when the result is close to convergence, the calculation speed will slow down. Note that these disadvantages have been verified by previous studies. To overcome these drawbacks, many studies prefer to use optimal global search techniques rather than gradient search techniques such as the BP algorithm, which is designed for local search. Many studies have used GA-based hybrid models to overcome the drawbacks of the BP approach [7], [8]. The results of these studies support the notion that GA can enhance the accuracy of ANN models and can reduce the time required for experiments [9].

We encoded all the weights and bias in a string and generated the initial population. Each solution generated by

Manuscript received September 20, 2018; revised January 10, 2019.
C. Li is with Graduate School of Engineering, Fukuoka Institute of Technology, Fukuoka, Japan (e-mail: 1chcheng1@163.com).
Y. Song is with Department of Systems Engineering, Fukuoka Institute of Technology, Fukuoka, Japan (e-mail: song@fit.ac.jp).

doi:10.18178/joebm.2019.7.2.582

GA is referred to as a chromosome (or individual). We evaluated each chromosome of the population using a fitness function that is based on MSE. Chromosomes with higher fitness values participate in reproduction and yield new strings by the GA (e.g., crossover and mutation). Thus, we obtain a new population. Through iterative progression, and after many generations, the population with the best fitness values can be found.

The experimental results showed that GA based neural network saved a lot of time for the less number of iterations and faster convergence than BP algorithm. For these reasons, GA algorithm is utilized to optimize the initial weights and bias of the ANN model. Then, the ANN model is trained by the BP algorithm using the determined weights and bias.

C. The Design and Establishment of Experiment Model

By using the BP neural network, the primary prerequisite is that there are enough good typicality and high precision samples. To forecast the movement of some individual stocks by using ANN model, we collected the data from January 2008 to June 2018, including about 2400 trading days of sample data. The training data is used to determine model specifications and parameters, and the target data is reserved for evaluation and comparison of performances among the prediction models. The test data is used for testing accuracy of the ANN model. We show the data of Panasonic company as example in Fig. 1, which can illustrate the movement of Sony stock prices clearly. horizontal axis is the daily closing price of Panasonic stock. vertical axis is the data sequence.

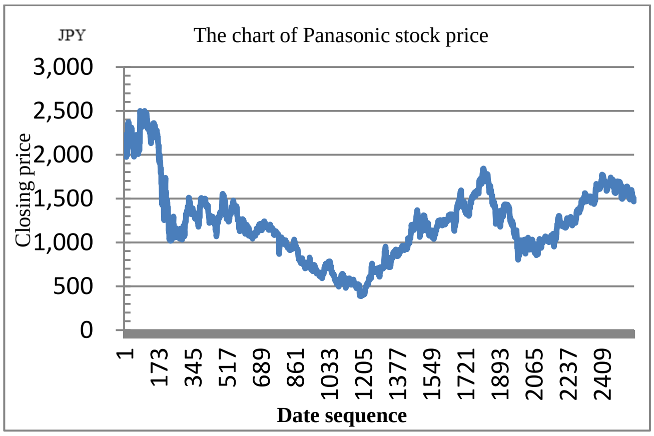

Fig. 1. The chart of Panasonic stock price.

In the light of previous researches, it is hypothesized that various technical indicators may be used as input variables in the construction of prediction models to forecast the direction of movement of the stock price index. K. Hornik, M. Stinchcombe and H. White [10] have shown that neural networks with sufficient complexity could approximate any unknown function to any degree of desired accuracy with only one hidden layer. Therefore, the ANN model is established by utilizing BP algorithm which is most commonly studied now. The Genetic algorithm is used to optimize the initial weights in order to overcome the disadvantages of BP algorithm. We reference this prior study [11] to select technical indicators as feature subsets.

The input layer corresponds to the input variables, with one node for each input variable. The hidden layer is used for capturing the nonlinear relationships among variables. Note that an appropriate number of neurons in the hidden layer needed to be determined by repeated training. The output layer consists of only one neuron that represents the predicted value of the output variable. In this study, we use OBV, MA_5, $BIAS_6$, $BIAS_6$, ASY_5, ASY_4, ASY_3, ASY_2, ASY_1 and the standardized closing value as input variables to predict the closing value of next period. The selected technical indicators' formulas and computational formulas are shown in Table I. The prediction model is consisted of an input layer, a hidden layer and an output layer. Hence, in this experiment, the numbers of input layer, output layer and hidden layer are 10, 1 and 20. The architecture of the ANN model is shown in Fig. 2.

TABLE I: SELECTED TECHNICAL INDICATORS

Name of indicator	Formulae
OBV	$OBV_t = OBV_{t-1} + \theta * V_t$,
MA_5	$MA_5 = (\sum_{i=1}^{5} C_{t-i+1})/5$,
$BIAS_6$	$BIAS_6 = \left(\frac{C_t - MA_6}{MA_6}\right) \times 100\%$,
PSY_{12}	$PSY_{12} = (A/12) \times 100\%$,
ASY_5	$ASY_5 = (\sum_{i=1}^{5} SY_{t-i+1})/5$,
ASY_4	$ASY_4 = (\sum_{i=1}^{4} SY_{t-i+1})/4$,
ASY_3	$ASY_3 = (\sum_{i=1}^{3} SY_{t-i+1})/3$,
ASY_2	$ASY_2 = (\sum_{i=1}^{2} SY_{t-i+1})/2$,
ASY_1	$ASY_1 = SY_{t-1}$,

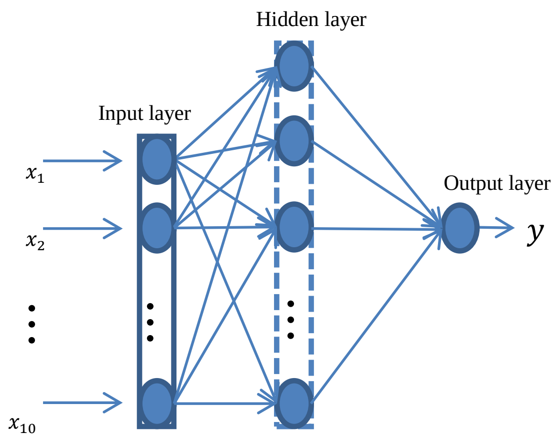

Fig. 2. Architecture of the ANN model.

Because the detailed value can't be predicted precisely, we use the value of next day to subtract the value of today to express the direction of individual stock price. If the result is positive, that means the stock is increasing. Otherwise, the stock is decreasing.

We select technical indicators as feature subsets by the review of prior researches. The research data used in this section are technical and fundamental indicators which are calculated by the daily price of the individual stocks index. The original data is normalized before being applied to the ANN experiments. We normalize the data as follows:

$$XN = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

X is a data point. XN is the normalized value of X, X_{min} is the minimum value of X, X_{max} is the maximum value of X. The goal of linear scaling is to independently normalize each feature component to the specified range. It also ensures that the larger value input attributes do not overwhelm smaller value inputs, and helps to reduce prediction errors [12].

After the data have been normalized, we encode all the weights and bias in a string and generate the initial population. Each solution generated in GA is called a chromosome (or an individual). The collection of chromosomes is called a population. Here each chromosome represents ANN with the certain set of weights and bias [13]. Next is training the ANN model with BP algorithm, and then evaluate each chromosome (individual) of the current population by a fitness function based on the MSE value. The value of the fitness function is inversely proportional to the error. The individuals with the higher fitness value are selected and pass on to the next generation directly. The new chromosomes are created by using enetic algorithms (e.g., crossover, mutation). The iterations will stop when reach the stop conditions.

The flow chart of the hybrid model is shown in Fig. 3.

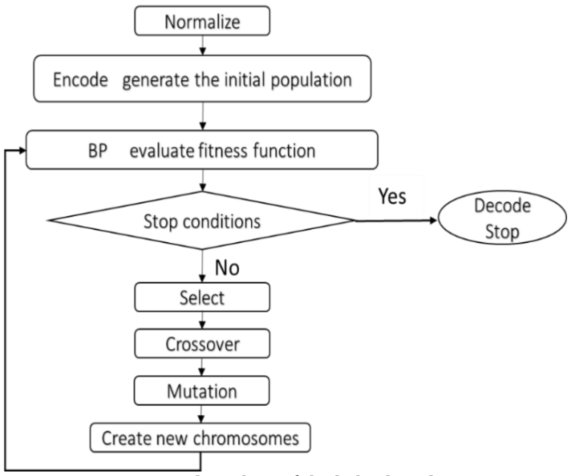

Fig. 3. Flow chart of the hybrid mode.

III. The Prediction of Individual Stocks

As mentioned before, first, we gather the experiment data from Yahoo! Finance website. Second, the original data is standardized before being applied to the ANN model. Because some values are too large and others are too small. By standardization, all of the value is limited in 0 to 1. Third, we select the training data (200 days) as input variables and select the testing data (30 days) as target data. When the neural network has been trained completed, we input the test data to test the performance of neural network models. We use value of today to minus value of the day before to see the stock market will increase or decrease. Hence the output variable can also represent the predicted direction of the daily stock market price. If predicted direction is same with true direction. That means we predict it correctly. Because the testing data is 30days, therefore the hit ratio is the times of predicting correctly divided by 30. Here, we present the results experiment in tables to read and understand data clearly.

In order to explore the instability of the ANN model, we have tried plenty of experiments about active functions. Based on the results of numerical experiments, the active function "logsig" is chosen as the best active function in this hybrid model. The best hit ratio is 86% in the Japanese stock market. It is 6% higher than the original model, where the active function is "Tansig/Logsig". The combination of active functions and results are shown in the Table II.

TABLE II: The Results of Different Active Function

Active function	Hit ratio	Feature
Tansig/Logsig	71.11%	Non-linear
Purelin/Purelin	51.22%	Linear
Logsig/Logsig	86.22%	Non-linear
Tansig / Tansig	62.77%	Non-linear
Logsig / Purelin	65.00%	Non-linear

After this experiment, we apply the improved model on some individual stocks. The procedures are same with the previous experiment. The results of individual stocks are shown in Table III.

TABLE III: The Predicted Results of Individual Stocks

Training period (200 days)	Testing period (30 days)	Hit ratio of Sony Corporation	Hit ratio of Panasonic Corporation	Hit ratio of Toyota Corporation
2008.1~	2008.10	86%	76%	73%
2008.12~	2009.8	83%	80%	71%
2010.4~	2011.3	59%	54%	54%
2012.2~	2012.12	78%	79%	79%
2014.9~	2015.6	79%	80%	76%
	Average ratio	79.6%	77.6%	70.6%

The first column is the training period and the second column is the testing period. The length of the two periods is same and continuous. The last three columns are the hit ratios of Sony corporation, Panasonic corporation and Toyota corporation respectively. They are 79.6%, 77.6% and 70.6%. There is an unusual phenomenon. When the testing period is 30 continuous days from 2011.3, all of three stocks' prediction results are not exceeding 60%. We analyzed about the phenomenon and ascribed reason to the great east Japan earthquake occurred in 2011.3. This result proves that this experiment model maybe lose efficacy when the incidents happened.

IV. The Profit and Investment Strategy

Stock investment strategy refers to methods of buying and selling stocks to avoid risk losses and gain maximum profitability. In this study, when the stock price is predicted to go down, we sell stocks at the opening price and buy at the closing price on the day. On the other hand, when the stock price is predicted to go up, we buy stocks at the opening price and sell at the closing price on the day. We use Table IV as an example to illustrate.

The first two columns are opening value and closing value of original data that we had collected from yahoo finance. The third column is output variable. Based on the prediction result, we can know the direction of the individual stocks. We use 1 to notate “the stock will increase”. We use -1 to notate “the stock will decrease”. If the stock will increase, we buy stocks at the opening value and sell stocks at the closing value. If the stock will decrease, we do a short selling, and cover the short at the closing value. The profit is the different value between opening price and closing price. The simulation results showed that investment strategy is effective to get profit in Panasonic case.

TABLE IV: THE EXAMPLE OF INVESTMENT STRATEGY

Open value (JPY)	Close value (JPY)	Actual direction	Predicted direction	Profit (JPY)
1131	1091			
1085	1034	-1	-1	51
1050	1049	1	1	-1
1064	1083	1	1	19
1092	1070	-1	1	-22
1089	1066	-1	1	-23
⋮				
1152	1190	1	1	38

There are eleven groups of prediction experiment of this stock. The profit result of Panasonic is shown in Tables V and VI. The testing periods are among January 2008 to June 2018. This table consists testing period, hit ratio, profit and return rate. When invest capital is JPY 500,000 in every testing period, the average profit and average return rate are JPY 79,463 and 15.9% respectively. The stock trading is daily trading and without considering the handling fee.

TABLE V: THE INVESTMENT RESULT OF PANASONIC

Period	2008.10	2009.8	2010.6	2010.11	2011.3
Hit ratio	72.3%	76.2%	82.2%	80.6%	53.9%
Profit (JPY)	80,015	85,252	77,489	87,384	72,297
Return rate	16.0%	17.1%	15.5%	17.5%	14.5%

TABLE VI: THE INVESTMENT RESULT OF PANASONIC

Period	2012.12	2013.10	2014.8	2015.6	2016.4	2017.1
Hit ratio	73.2%	72.3%	79.6%	65.9%	70.1%	81.0%
Profit (JPY)	72,581	105,236	30,378	72,468	126,951	64,050
Return rate	14.5%	21.0%	6.1%	14.5%	25.4%	12.8%

V. CONCLUSION

In this paper, we applied an artificial neural network for predicting the direction of some individual stocks. In order to improve the accuracy of the model, experiments were conducted to found out which active functions have a good performance to get a better hit ratio. In this experiment, the best performance of active functions of the hybrid model is “Logsig/Logsig”. The hit ratio is 6% higher than original model.

As indicated above, forecasting accuracy of the hybrid model with new pair of active functions outperforms the one that is trained by original active functions. By utilizing improved model, the hit ratio of Sony corporation and Panasonic corporation and Toyota corporation are 79.6%, 77.6% and 70.6% respectively. Based on the prediction results, we proposed an investment strategy. Numerical tests showed that the investment strategy is effective for more investment profit with less investment risk. To get a better neural network structure, we need to fine tune neural network artificially. It is a very laborious and time-consuming work. We propose to utilize CNN (Convolutional Neural Network), RNN (Recurrent Neural Network) or some others variations of neural networks to continue our research in the future work.

REFERENCES

[1] E. Guresen, G. Kayakutlu, and T. U. Daim, "Using artificial neural network models in stock market index prediction," *Expert Systems with Applications*, vol. 38, pp. 10389-10397, 2011.

[2] T. Lee and C. Chiu, "Neural network forecasting of an opening cash price index," *International Journal of Systems Science*, vol. 33, pp. 229-237, 2002.

[3] M. Qiu and Y. Song, "Predicting the direction of stock market index movement using an optimized artificial neural network model," *PloS One*, vol. 11, no. 5, p. e0155133, 2016.

[4] M. Qiu, Y. Song, and F. Akagi, "Application of artificial neural network for the prediction of stock market returns: The case of the Japanese stock market," *Chaos, Solitons & Fractals*, vol. 85, pp. 1-7, 2016.

[5] T. Jo, "VTG schemes for using back propagation for multivariate time series prediction," *Applied Soft Computing*, vol. 13, no. 5, pp. 2692-2702, 2013.

[6] K. Kim and I. Han, "Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index," *Expert Systems with Applications*, vol. 19, no. 2, pp. 125-132, 2000.

[7] D. J. Montana and L. Davis, "Training feedforward neural networks using genetic algorithms," *International Joint Conference on Artificial Intelligence*, vol. 89, pp. 762-767, 1989.

[8] B. B. Nair, S. G. Sai, A. Naveen, A. Lakshmi, G. Venkatesh, and V. Mohandas, "A GA-artificial neural network hybrid system for financial time series forecasting," *Information Technology and Mobile Communication Springer*, pp. 499-506, 2011.

[9] K. Jadav and M. Panchal, "Optimizing weights of artificial neural networks using genetic algorithms," *International Journal of Advanced Research in Computer Science and Electronics Engineering*, vol. 1, no. 10, pp. 47-51, 2012.

[10] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural Networks*, vol. 2, no. 5, pp. 359-366, 1989.

[11] G. Armano, M. Marchesi, and A. Murru, "A hybrid genetic-neural architecture for stock indexes forecasting," *Information Sciences*, vol. 170, no. 1, pp. 3-33, 2005.

[12] M. A. I. Khan, "Financial volatility forecasting by nonlinear support vector machine heterogeneous autoregressive model: evidence from Nikkei 225 stock index," *International Journal of Economics and Finance*, vol. 3, no. 4, pp. 138-150, 2014.

[13] Y. Lee, S. Oh, and M. Kim, “The effect of initial weights on premature saturation in back propagation learning,” *International Joint Conference on Neural Networks*, vol. 1, pp. 765-770, 1991.

Cheng Li was born in China. He earned his bachelor's degree in Qingdao University of Science and Technology, China and he got his master degree in Fukuoka Institute of Technology, Japan. Currently he is a Ph.D student at Graduate School of Engineering in Fukuoka Institute of Technology.

Yu Song was born in China. He earned his Ph.D. at Tohoku University, Japan. Currently he is a professor at Department of Systems Engineering, Fukuoka Institute of Technology, Fukuoka, Japan. His research interests include financial engineering, queueing theory and other operations research techniques. Prof. Song is a senior member of IEDRC.