Application of the Artifical Neural Network in predicting the direction of stock market index

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***Abstract*—In the business sector, it has always been a difficult task to predict the exact daily price of the stock market index; hence, there is a great deal of research being conducted regarding the prediction of the direction of stock price index movement. Many factors such as political events, general economic conditions, and traders' expectations may have an influence on the stock market index. There are numerous research studies that use indicators to forecast the direction of the stock market index. In this study, we applied two types of input variables to predict the direction of the daily stock market index. The main contribution of this study is the ability to predict the direction of the next day's price of the Japanese stock market index by using an optimized artificial neural network (ANN) model. To improve the prediction accuracy of the trend of the stock market index in the future, we optimize the ANN model using genetic algorithms (GA). We demonstrate and verify the predictability of stock price direction by using the hybrid GA-ANN model and then compare the performance with prior studies. Empirical results show that the Type 2 input variables can generate a higher forecast accuracy and that it is possible to enhance the performance of the optimized ANN model.**

Keywords—forecast; direction; indicator; artificial neural network (ANN); genetic algorithm (GA).

I. INTRODUCTION

The direction of the stock market index refers to the movement of the price index or the trend of fluctuation in the stock market index in the future. Predicting the direction is a practical issue that heavily influences a financial trader's decision to buy or sell an instrument. Accurate forecast of the trends of the stock index can help investors to acquire opportunities for gaining profit in the stock exchange. Hence, precise forecasting of the trends of the stock price index can be extremely advantageous for investors [1]. However, the behavior of stock markets depends on many qualitative factors such as political, economic, and natural factors, among many others. The stock markets are dynamic and exhibit wide variation, and the prediction of the stock market thus becomes a highly challenging task because of the highly non-linear nature and complex dimensionality [2, 3]. Forecasting of the financial index is characterized by data intensity, noise, non-stationarity, unstructured nature, high degree of uncertainty, and hidden relationships [4-6].

Previous studies have applied various models in forecasting the direction of the stock market index movement. Huang, et al. [7] forecasted stock market movement using support vector machines (SVM), and concluded that the model was good at predicting the direction. Kara, et al. [8] applied Artificial Neural Network (ANN) and SVM in predicting the direction of the Istanbul stock exchange. Their study proves that the two different models are both useful prediction tools, and ANN is significantly better than the SVM model. Şenol and Özturan [9] applied seven different prediction system models for predicting the direction of the stock market index in Turkey, concluding that ANN could be one of the most robust techniques for forecasting. The ANN model has been popularly claimed to be a useful technique for stock index prediction because of its ability to capture subtle functional relationships among the empirical data even though the underlying relationships are unknown or hard to describe [10, 11]. Application of ANN has become the most popular machine learning method, and it has been proven that such an approach can outperform most conventional methods [12-15]. In this study, we attempt to apply an ANN model to forecast the direction of the Japanese stock market index.

The most popular neural network training algorithm for financial forecasting is the back propagation (BP) algorithm, which is also a widely applied classical learning algorithm for neural networks [16-18]. The BP network has been widely used in the area of financial time series forecasting because of its broad applicability to many business problems and its preeminent learning ability [19]. However, many papers have reported that the ANN model, trained by the BP algorithm, has some limitations in forecasting, and it can easily converge to the regional (local) minimum because of the tremendous noise and complex dimensionality of the stock market data. In view of these limitations, genetic algorithms (GA) has been proposed to overcome the local convergence issue for nonlinear optimization problems. We attempt to determine the optimal set of weights and biases to enhance the accuracy of the ANN model by using GA.

The main objective of this study is to improve the prediction accuracy of the direction of stock price index movement by using the ANN model. In this study, we applied two types of input variables that have been widely used in previous studies to predict the direction of the daily stock market index. To improve the performance of these two sets of input variables, the Japanese stock market index is used as an illustrative example. In addition, we improve the prediction accuracy according to the optimization of the learning algorithm of the ANN model. The BP algorithm is a widely applied classical learning algorithm for neural networks.

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However, it has significant drawbacks that need to be improved using other training algorithms. In this study, genetic algorithm (GA) is employed to improve the prediction accuracy of the ANN model and overcome the local convergence problem of the BP algorithm. The empirical results suggest that the proposed method improves the accuracy further for predicting stock market direction.

The remainder of this paper is organized as follows. Section 2 describes the ANN model trained by the BP algorithm, and the improvement using the GA. Then, we showcase two types of input variables that are used to forecast the direction, and the procedure of predicting the stock market direction in Section 3. Section 4 provides the experimental results. Finally, Section 5 presents the discussion and conclusion.

II. PREDICTION MODEL

A. Artificial neural network (ANN) model

Funahashi [20], Hornik, et al. [21] 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 in this study consists of an input layer, a hidden layer, and an output layer, each of which is connected to the other in the same sequence as listed here. The architecture of the ANN is shown in Fig. 1. The input layer corresponds to the input variables. We analyze two basic types of input variables for comparing the forecasting accuracy. The hidden layer is used for capturing the nonlinear relationships among variables. In this study, the output layer consists of only one neuron that represents the predicted direction of the daily stock market index.

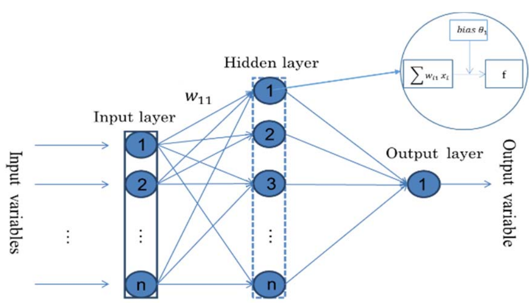

Fig. 1 The architecture of the back propagation neural network

B. Back propagation neural network

The BP algorithm is a widely applied classical learning algorithm for neural networks [17, 18]. As shown in Fig. 1, the BP process determines the weights for the connections among the nodes (e.g., W_{11} denotes the weight between Node 1 of the input layer and Node 1 of the hidden layer) and their biases (e.g., θ_1 denotes the bias of Node 1 in the hidden layer) on the basis of the training data. The network weights and biases are assigned initial values first, and the error between the predicted and actual output values is back-propagated via the network for updating the weights and biases repeatedly [22]. When the error is less than a specified value or when the termination criterion is satisfied, training is considered to be completed and the weights and bias values of the network are stored. Detailed descriptions of using the BP algorithm for training the ANN model can be found in Ref. [23].

Although researchers have commonly trained the ANN model by using the gradient technique of the BP algorithm, limitations of gradient search techniques are more apparent when ANNs are applied to complex nonlinear optimization problems [24]. The BP algorithm has two significant drawbacks, i.e., slowness in convergence and an inability to escape local optima [25]. In view of these limitations, global search techniques, such as GA, are proposed to overcome the local convergence problem for nonlinear optimization problems. In this study, we propose to apply the GA technique to optimize the weights and biases of the ANN model, and then predict the direction of the daily closing price movement of the stock market index.

C. Improvement using genetic algorithms (GA)

In this study, the GA algorithm is utilized to optimize the initial weights and bias of the ANN model. Subsequently, the ANN model is trained by the BP algorithm using the determined weights and bias values. Detailed descriptions of using the GA algorithm for optimizing the ANN model can be found in Ref. [26].

III. EXPERIMENTAL DESIGN

A. Data

The Nikkei 225 index is the most widely used market index for the Tokyo stock exchange. It includes 225 equally weighted stocks and has been calculated daily ever since 1950. In this study, we attempt to predict the direction of the daily Nikkei 225 index. The research data used in this study are technical indicators that are calculated from the daily price of the Nikkei 225 index. The total number of samples is 2190 trading days, from January 2007 to December 2015. The financial data used in this study is obtained from Yahoo Finance.

The original data are normalized before being subjected to the ANN algorithm routine. The goal of linear scaling is to independently normalize each feature component to a specified range. It also ensures that the larger value input attributes do not overwhelm smaller value inputs, which in turn helps decrease prediction errors. We delayed one day for all the data to make the experiment more practical.

The prediction performance *Hit ratio* is evaluated using the following equation:

$$Hit\ ratio = \frac{1}{n}\sum_{i=1}^{n} P_i \ \ (i = 1,2,\cdots,n), \quad (3.1)$$

where P_i is the prediction result for the i^{th} trading day, which is defined by equation 3.2. The variable y_t denotes the actual value of the closing stock index for the i^{th} trading day, and $\hat{y}_t$ is the predicted value for the i^{th} trading day. The variable n denotes the number of test samples.

$$P_i = \begin{cases} 1, (y_{t+1} - y_t)(\hat{y}_{t+1} - \hat{y}_t) > 0, \\ 0, \text{otherwise.} \end{cases} \tag{3.2}$$

B. Input variables

In the light of previous studies, 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 [27]. Most financial managers and investors agree on the efficiency of technical indicators and exploit them as a signal for forecasting future trends. On the basis of the reviews of domain experts and prior studies, we summarized two sets of input variables as shown in Table 1 and 2 [9, 28, 29]. Technical indicators of the two types of input variables are usually used to predict the future trends, and they are derived from the real stock composite index. One of the aims of this study is to conduct the experiments by using the ANN model with two types of input variables, and then improve the performance of these two experiments.

TABLE 1 SELECTED TECHNICAL INDICATORS AND THEIR FORMULAS (TYPE 1).

Name of feature	**Formulas**
Type 1 input variables	
Stochastic %K	$(C_t - L_n)/(H_n - L_n)\times 100$,
Stochastic %D	$\sum_{i=0}^{n-1} \%K_{t-i}/n$,
Stochastic slow %D	$\sum_{i=0}^{n-1} \%D_{t-i}/n$,
Momentum	$C_t - C_{t-4}$,
ROC (rate of change)	$C_t/C_{(t-n)} \times 100$,
LW%R (Larry William's %R)	$(H_n - C_t)/(H_n - L_n)\times 100$,
A/O Oscillator (accumulation/distribution oscillator)	$(H_t - C_{t-1})/(H_t - L_t)$,
Disparity in 5 days	$C_t/MA_5 \times 100$,
Disparity in 10 days	$C_t/MA_{10} \times 100$,
OSCP (price oscillator)	$MA_5 - MA_{10}/MA_5$,
CCI (commodity channel index)	$(M_t - SM_t)/(0.015 \times D_t)$,
RSI (relative strength index)	$100 - 100/(1 + \frac{\sum_{i=0}^{n-1} Up_{t-i}}{\text{n}} / \frac{\sum_{i=0}^{n-1} Dw_{t-i}}{\text{n}})$

C_t is the closing price and L_t is the lowest price of the Nikkei 225 index at time *t*. L_n is the lowest low price of the Nikkei 225 index in the last *n* days, H_t is the highest price of the Nikkei 225 index at time *t*, H_n is the highest high price of the Nikkei 225 index in the last *n* days. MA_n is the moving average of the price value in the last *n* days: $MA_\text{n} = (\sum_{i=1}^{n} C_{t-i+1})/n$, $M_t = \frac{H_t+L_t+C_t}{3}$. $SM_t = (\sum_{i=1}^{n} M_{t-i+1})/n$, $D_t = (\sum_{i=1}^{n} |M_{t-i+1} - SM_t|)/n$. Up_t is the upward price change of the Nikkei 225 index at time *t* and Dw_t is the downward price change of the Nikkei 225 index at time *t*.

TABLE 2 SELECTED TECHNICAL INDICATORS AND THEIR FORMULAS (TYPE 2).

Name of feature	**Formulas**
Type 2 input variables	
OBV	$OBV_t = OBV_{t-1} + \Theta * V_t$,
MA_5	$MA_5 = (\sum_{i=1}^{5} C_{t-i+1})/5$,
BIAS_6	$\text{BIAS}_6 = \left(\frac{C_t - MA_6}{MA_6}\right) \times 100\%$,
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	$ASY_1 = SY_{t-1}$,

V_t is the volume of trade of the Nikkei 225 index at time t, $\Theta = \begin{cases} +1, C_t \geq C_{t-1} \\ -1, C_t < C_{t-1} \end{cases}$. PSY_n is the ratio of the number of rising periods over the *n* day period. Variable *A* is number of rising days in the last *n* days. SY_t represents the return of the Nikkei 225 index at time *t*, $SY_t = (\ln C_t - \ln C_{t-1}) \times 100$. ASY_n is the average return in the last *n* days.

C. Prediction process

After we finish the work of collecting the real stock composite index data and calculating the two types of input variables that we will compare in the following process, we plug in the data into the optimized ANN model to forecast the future direction of the stock market. We conduct the prediction process as follows: First, we calculate all the indicators for the two types of input variables. Then, we normalize the data to decrease the experimental errors. Before we enter the data into the ANN model, we optimize all the weights and biases of the ANN model using the GA algorithm. After that, we apply two types of indicators for predicting the direction of next day's movement by the GA-ANN hybrid model. After we finish all the experiments, the performance among the two types of input variable sets is compared with prior reports.

IV. EXPERIMENTAL RESULTS

Before we conduct the experiments, the hybrid model requires a number of parameters that can influence the performance of the model, and these parameters are described here in Table 3.

TABLE 3 DESCRIPTION OF PARAMETERS THAT ARE USED IN THE HYBRID MODEL.

Variable	**Value**	**Definition**
n	20	number of neurons in the hidden layer of the ANN model
ep	3000	number of iterations for the hybrid model
mc	0.4	momentum constant of the ANN model
l	0.1	value of learning rate of the ANN model
pcro	0.9	crossover rate of the GA-ANN model
pmut	0.3	mutation rate of the GA-ANN model
popu	100	Initial population number of the GA-ANN model

First, we conducted experiments based on the initial parameter setting, which is mentioned in Table 3. Then, we tested the performance of the two types of indicators by changing the different parameter combinations of the GA-ANN hybrid model. Table 4 shows the various performance of each type of input variables. The *hit ratio* denotes the percentage of trials when the predicted direction was correct.

A. Comparison of the performances between the two types of input variables in continuous testing period

TABLE 4 COMPARISON OF THE HIT RATIO BETWEEN THE TWO TYPES OF INPUT VARIABLES.（TRAINING PERIOD IS 100 DAYS）

Training period	**Testing period**	**Active function**	**Hit ratio for Type 1**	**Hit ratio for Type 2**
2010.9.22-2011.2.21 (100 days)	2011.2.22-2011.4.6 (30 days)	Tansig (1st layer) Logsig (2nd layer)	77.11%	68.67%
2010.9.22-2011.2.21 (100 days)	2011.2.22-2011.4.6 (30 days)	Purelin (1st layer) Purelin (2nd layer)	63.22%	51.22%
2010.9.22-2011.2.21 (100 days)	2011.2.22-2011.4.6 (30 days)	Logsig (1st layer) Logsig (2nd layer)	76.11%	75.44%

From Table 4, the hit ratio that we have observed for two types of indicators are various when we choose different active function in each layer. We set the same training period and testing period for the two types of indicators, and change the active function to validate the influence. We found that the best hit ratio for forecasting the direction correctly by applying Type 1 input variables is 77.11% and 75.44% for Type 2 input variables. The Type 1 indicators always has higher performance than Type 2 in different conditions. Next, we expand the training period to 200 days, and then compare the performance between the two types of indicators.

TABLE 5 COMPARISON OF THE HIT RATIO BETWEEN THE TWO TYPES OF INPUT VARIABLES. （TRAINING PERIOD IS 200 DAYS）

Training period	**Testing period**	**Active function**	**Hit ratio for Type 1**	**Hit ratio for Type 2**
2013.12.24-2014.10.14 (200 days)	2014.10.15-2014.11.28 (30 days)	Tansig (1st layer) Logsig (2nd layer)	63.56%	63.78%
2013.12.24-2014.10.14 (200 days)	2014.10.15-2014.11.28 (30 days)	Logsig (1st layer) Logsig (2nd layer)	61.78%	89.22%

After we expand the training period for two types, we found that Type 2 generate higher performance than Type 1 in various conditions. The best hit ratio for forecasting the direction correctly by applying Type 1 input variables is 63.56% and 89.22% for Type 2 input variables. Next, we set the training period as 100 days for Type1, and 200 days for Type2.

B. Comparison of the performances between the two types of input variables in discontinuous testing period

TABLE 6 REAL PERIOD FOR EACH TESTING PERIOD

Testing period number	Real period
Testing period 1	2007.11.9-2007.12.25 (30 days)
Testing period 2	2008.9.3-2008.10.20 (30 days)
Testing period 3	2009.2.4-2009.3.19 (30 days)
Testing period 4	2009.11.30-2010.1.15 (30 days)
Testing period 5	2010.9.22-2010.11.8 (30 days)
Testing period 6	2011.7.20-2011.8.31 (30 days)
Testing period 7	2012.10.3-2012.11.15 (30 days)
Testing period 8	2013.12.24-2014. 2.6 (30 days)
Testing period 9	2014.10.15-2014.11.28 (30 days)
Testing period 10	2015.8.10-2015.9.24 (30 days)

Table 6 shows the real period for each testing period.

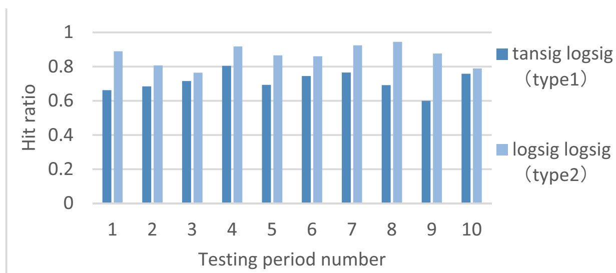

Fig. 2 Comparison of the hit ratio between the two types of input variables.

In this section, we train the hybrid ANN model in a long period for Type 2, which is from 2007.1.24 to 2007.11.8 (200 days). To compare the performance with Type 2, we train the hybrid ANN model from 2007.1.24 to 2007.6.19 (100 days). Then, we predict the direction of ten discontinuous testing periods, and compare the performance of the two types of input variables based on choosing the same testing periods. From Fig.2, both of the two types of indicators are successful in predicting the discontinuous time period. The average hit ratio for Type 1 and Type 2 are 71.19% and 86.39%, respectively. Type 2 performed better than Type 1 in each testing period (each testing period includes 30 days). Hence, we conclude that Type 2 input variables are more effective in predicting the direction of closing price of Nikkei 225 index than the Type 1 input variables when the testing period is discontinuous.

V. CONCLUSION

In this study, we applied two types of technical indicators to predict the direction of next day's Nikkei 225 index movement. We adjusted the weights and biases of the ANN model using the GA algorithm and then tested the performance of the GA-ANN hybrid model by applying these two types of input variables and comparing the predictions with actual data. The experiments revealed that Type 2 input variables can provide better performance and the hit ratio for predicting the direction is 86.39%.

However, the prediction performance of this study may be improved further in three means. The first method is to combine the two types of input indicators, or test a subset of these variables. In addition, we can include a few other variables that may affect the prediction performance. Second, optimal methods other than the GA may also be utilized to adjust the parameters of ANN model. We may even use models based on probabilistic neural networks for predicting the movement of the stock index. Lastly, we could even propose an investment strategy (portfolio) based on the prediction outcomes of this study for future research, practical use and further validation.

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