

**A STUDY ON PREDICTION OF STOCK
MARKET INDEX AND PORTFOLIO
SELECTION**

by

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Abstract

In this thesis, we discuss investment strategies in the stock market. For professional investors, we provide the prediction of the stock market index. And for individual investors, a simple and effective investment strategy is introduced and applied.

Prediction of stock market index is an important task that has attracted significant attention in major financial markets around the world. As the most widely used market index for the Tokyo Stock Exchange, the Nikkei 225 index is a benchmark that is used to evaluate the Japanese economy. Hence, various methods have been proposed for its prediction. In recent years, artificial intelligence, especially the Artificial Neural Network (ANN), has been demonstrated to be effective in predicting the financial indices, while a number of efforts are made to improve the accuracy of prediction.

In this study, we apply the ANN model for prediction of the Nikkei 225 index. First, we forecast the return by using the monthly data of the Nikkei 225 index. In order to improve the prediction accuracy, we collect various indicators and use fuzzy surface technique to select the most effective input variables. Most of the indicators in the new set of input variables have not been examined in previous studies. Then, we apply the ANN model based on the back propagation (BP) learning algorithm to forecast the Nikkei 225 index. However, the BP algorithm has two significant drawbacks: i.e., slowness in convergence and inability to escape local optima. Hence, global search techniques, in particular, genetic algorithm (GA) and simulated annealing

(SA), are employed to overcome the shortcomings of the BP algorithm and improve the prediction accuracy of the ANN model. The empirical results show that the prediction accuracy of our study is improved by applying global search techniques in the ANN model.

In addition, we apply the GA-ANN hybrid model to forecast the direction of daily Nikkei 225 index. The empirical results suggest that the proposed method improves the accuracy for predicting stock market direction compared to the previous studies.

Moreover, for individual investors, we propose to apply the Dogs of the Dow investment strategy to the Japanese and Hong Kong stock markets. The effectiveness of this strategy is verified from a variety of perspectives.

Keywords: stock market index prediction; artificial neural network; fuzzy surface; genetic algorithm; simulated annealing; the Dogs of the Dow strategy

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List of Abbreviations

ANN.....	Artificial Neural Network
BP.....	Back Propagation
GA.....	Genetic Algorithm
SA.....	Simulated Annealing
MSE.....	Mean Square Error
BPNN.....	BP training algorithm for the ANN model
LR.....	Linear Regression
GABPNN.....	the hybrid GA and BP training algorithm used in the ANN model
SABPNN.....	the hybrid SA and BP training algorithm used in the ANN model
SVM.....	Support Vector Machines
DIJA.....	Dow Jones Industrial Average
HSI.....	the Hang Seng Index

Chapter 1 Introduction

1.1 Purpose of the Study

In the stock market, there are various types of investors who have their own characteristics, and it is essential to provide suitable investment strategy for each type of investors. Professional investors, such as institutional investors, normally have a high degree of knowledge about investing and prefer to conduct a short-term investment. On the contrary, most of the individual investors are not good at controlling professional investment skills, and they have limited time on the study of the movement of the stock market. Hence, long-term investment is suitable for the individual investors. In this thesis, we provide the professional investors with the prediction of the monthly and daily stock market index. We apply the models based on the Artificial Neural Network (ANN) for forecasting return and direction of the Nikkei 225 index. On the other hand, we propose a simple and effective long-term investment strategy which called the Dogs of the Dow strategy for the individual investors.

In the business and economic environment, it is very important to predict various kinds of financial variables to develop proper strategies and avoid the risk of potentially large losses. The forecast of a variety of economic indices has profound impact on the development of macro economy. Especially, in the case of stock markets, the task becomes more important because of the dynamic changes of the market behavior and immeasurable economic benefits. According to the prediction of stock market indices, risk manager and practitioners can realize whether their portfolio will decline in the future and they may want to sell it before it becomes depreciated. Therefore, the

research of predicting the future trends of financial indices is significant and necessary for people who are interested in the stock markets. However, the behavior of stock markets depends on many factors such as political, economic, natural factors and many others. The stock markets are dynamic and exhibit wide variation, and the prediction of stock market is a highly challenging task due to the highly nonlinear nature and complex dimensionality [20, 36].

ANN model that can map any nonlinear function without a prior assumption is proved to be effective in predicting financial indices by many researches [4, 10, 14, 15, 38]. Application of ANN has become the most popular machine learning method, and it has been proven that such an approach can outperform conventional methods [15, 40, 58, 62]. Although it is shown that ANN model is effective for solving nonlinear problems, many studies report that there are limitations in training the model when the amount of data is so large that it may not work well. Hence, scholars are focus on the optimization of learning algorithm of ANN model, and they propose various hybrid models to promote a high degree of the prediction accuracy. It should be noted that few studies have attempted to identify significant input variables. Some researchers select input variables of ANN model with no explanation, directly selecting adequate explanatory variables from previous studies which concluded that some variables were effective.

There are three main aspects that are required to be improved for ANN model. First, the selection of the input variables for ANN model. The data of stock market is commonly abundant and complex, and the model can easily reach regional minimum convergence without preprocessing of input variables. The selection of effective indicators that can be used to forecast the output variable of ANN model is significant

prior to modeling. Second, the setting of parameters of ANN model. Different combination of parameters which include the number of layers, hidden neurons, iterations and learning rate of ANN model may present quite different performance. The optimization and selection of the parameters should be discussed and concerned in the training procedure of ANN model. Third, the learning algorithm of ANN model. The back propagation (BP) algorithm is a widely applied classical learning algorithm for neural networks. However, the BP algorithm has significant drawbacks that need to be improved by other training algorithms.

The Nikkei 225 index is the most widely used market index of the Japanese stock market. In this study, first we forecast the return by using the monthly data of the Nikkei 225 index. The main contribution of this study is that we optimize the ANN model in the three aspects and then forecast the movement of the Nikkei 225 index. We conduct the experiments as follows: (1) To improve the effectiveness of prediction algorithms, we propose a new set of input variables for ANN models by fuzzy surfaces. To verify the prediction ability of the selected input variables, we predict the return of Nikkei 225 index by applying ANN model with BP learning algorithm. (2) We conduct numerical experiments for parameter settings of the network using the BP algorithm to determine the most appropriate parameters. (3) Global search techniques, such as genetic algorithm (GA) and simulated annealing (SA), are employed to improve the prediction accuracy of the ANN model and overcome the local convergence problem of the BP algorithm. It is observed through empirical experiments that the selected input variables are effective to predict the return of Nikkei 225 index. Hybrid approaches based on GA and SA improve prediction accuracy significantly and outperform the traditional BP training algorithm.

In addition, we utilize the GA-ANN hybrid model with daily data to forecast the direction of daily Nikkei 225 index. The empirical results suggest that the proposed method improves the accuracy for predicting stock market direction than previous studies.

Based on the accurate forecast of the future trend of the stock market index, investors can make effective investment strategy which outperforms the average level of the stock market. To provide the investors who are not good at investing with simple and effective strategies, we introduce the Dogs of the Dow investment strategy in this study. We apply the strategy to the Japanese and Hong Kong stock markets, and the effectiveness of it is verified from a variety of perspectives.

1.2 Structure of the Thesis

In this study, we use monthly data for forecasting the return of the Nikkei 225 index, meanwhile daily data for predicting the direction of next day's closing price of the Nikkei 225 index. We introduce a simple and effective investment strategy, the Dogs of the Dow strategy, and show the experimental results by applying the strategy in different Asian countries.

The structure of this thesis is shown in Fig.1. In Chapter 1, the aim and significance of the research, research methods and framework of this thesis are described.

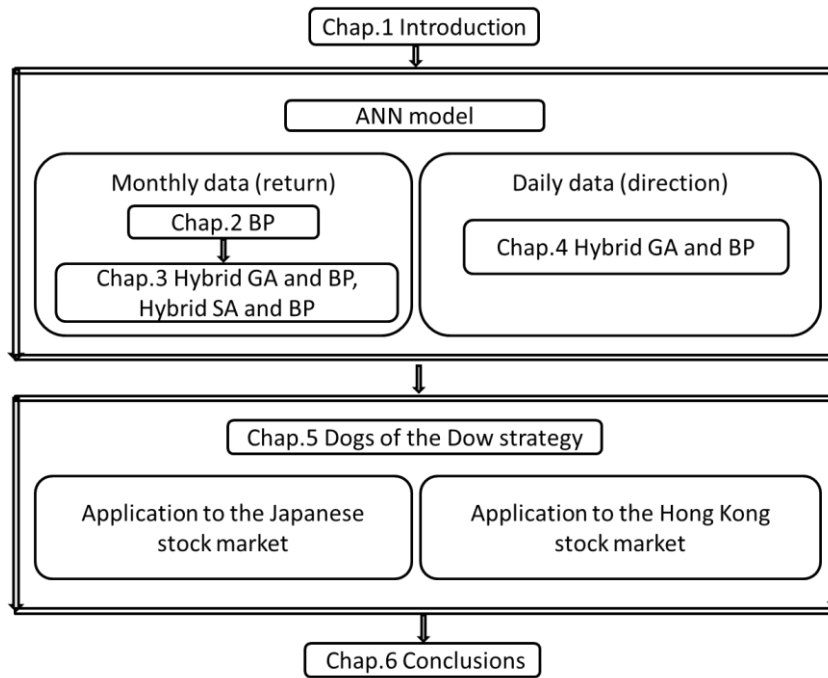


Fig. 1 Structure of this thesis

In Chapter 2, we collect 71 indicators that refer to different aspects of the Japanese stock market, and then we select 18 input variables by fuzzy surfaces. We use the monthly data of 18 good explanatory variables to predict the return of Nikkei 225 index, and then compare the prediction accuracy of different models. We found that the forecasting accuracy of ANN model based on BP algorithm is much more effective than the conventional linear regression.

In Chapter 3, we improve the basic training algorithm by GA and SA. We optimize the weights and bias of the ANN model to predict the return of Nikkei 225 index. The experimental results show that hybrid approach of SA and BP overcome the weakness of basic BP algorithm. We synthesize the performance of prediction accuracy and running time, and consider that the hybrid GA and BP approach provides higher accuracy of future values than other prediction models.

In Chapter 4, we propose to apply two types of technical indicators to predict the

direction of next day's Nikkei 225 index. We train the two types of data by ANN model which was adjusted the weights and bias by GA algorithm. The experiments imply that input variables Type 2 can generate higher performance, and the probability for predicting the direction was 81.27%.

Chapter 5 shows the application of the Dogs of the Dow strategy to the Japanese and Hong Kong stock markets. It is shown that the effectiveness of this strategy is verified from a variety of perspectives.

In Chapter 6, the main results obtained in this thesis are summarized, and future research are described.

Chapter 2 Predicting the Return of the NIKKEI 225 Index by Using Artificial Neural Network (ANN)

2.1 Introduction

To revive the Japanese economy, the Japanese government has recently developed many significant economic strategies, and each strategy is closely related to the Japanese stock market. As the most widely used market index for the Tokyo Stock Exchange, the Nikkei 225 index, also known as the Nikkei average or simply Nikkei, is a benchmark that is used to evaluate the Japanese economy. Forecasting the stock return of the Nikkei 225 index is an important financial subject that has attracted significant attention in major financial markets around the world. The purpose of this chapter is to apply an artificial neural network (ANN) to forecast the return of the Nikkei 225 index.

It has been widely accepted by many studies that nonlinearity exists in financial markets and that an ANN can be used effectively to uncover this relationship [3, 4, 14, 35]. McCulloch and Pitts [41] created a computational model for neural networks based on mathematics and algorithms, and the application of ANNs to financial and investment decisions has been examined by researchers for many years. Compared to regression or the passive buy-and-hold strategy, Motiwalla and Wahab [45] found that ANN models are more successful in predicting returns. Enke and Thawornwong [14] used neural network models for level estimation and classification. They showed that the trading strategies guided by a neural network classification model can generate higher profits than any other model. Hodnett and Hsieh [22] utilized two ANN

learning rules to forecast the cross-section of global equity returns. Their findings support the use of ANNs for financial forecasting. Application of ANNs has become the most popular machine learning method, and it has been proven that such an approach can outperform conventional methods [15, 40, 58, 62].

In light of previous studies, it has been hypothesized that various technical indicators may be used as input variables in the construction of prediction models to forecast the return of a stock price index [7]. In most applications, input variables that have been proven effective by previous studies were used to predict stock market returns. Some effective indicators of stock price include lagged returns, interest rate value, foreign exchange rate, consumer price index, industrial production index, and deposit rate [14, 38]. In this chapter, we examine the indicators that were proven valid by prior studies and attempt to determine input variables that have not been previously used to predict stock market returns by assessing the ability of those indicators to predict a stock market index. We collect 71 input variables that cover financial and economic information of the Japanese stock market, most of which have not been examined in previous studies.

Although an ANN can be a very useful tool in the prediction of stock market returns, several studies have shown that ANNs have some limitations because stock market data contain a tremendous amount of noise, non-stationary characteristics, and complex dimensionality [5, 16, 29]. Therefore, we must perform data preprocessing prior to utilizing an ANN to predict stock market returns. This chapter attempt to implement fuzzy surfaces in the selection of optimal input variables. As a result, 18 valid explanatory variables are selected from the 71 input variables for experimentation.

As the most widely used algorithm for the ANN model, the back propagation (BP)

learning algorithm is applied in this chapter. We set the selected 18 effective variables as the input variables of ANN model, then train the model with BP algorithm. In order to verify the shortcomings of BP and the performance of various parameters, we conduct parameter setting experiments for ANN model with the BP training algorithm. According to numerous experiments, we find the characters of BP algorithm and the most appropriate combination of parameters. For the neural network model with BP algorithm, we compare linear regression model with it in the prediction ability of the stock market return. It is observed through empirical experiment that the ANN model performs well, and has a more effective ability than the conventional linear regression in forecasting the Japanese stock market. In addition, the prediction effect of the combination of 18 input variables is effective and can be therefore a good alternative for stock market returns prediction.

The remainder of this chapter is organized as follows. Section 2.2 describes the data, ANN model and the procedure of predicting the stock market return. Then, we apply fuzzy surfaces for selecting effective input variables in Section 2.3. Section 2.4 provides the numerical experiments of ANN model with BP algorithm and the findings of the characters of BP algorithm. We compare the linear regression model with ANN model based on BP algorithm, and show the experimental results in Section 2.5. Finally, Section 2.6 contains the discussion and conclusion. The data descriptions are given in Section 2.7.

2.2 Prediction Procedure

2.2.1 Data Description

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 since 1950. To predict the returns of the Nikkei 225 using an ANN, we collected 71 variables that include financial indicators and macroeconomic data. The entire data set covers the period from November 1993 to July 2013, providing a total of 237 months of observations. The data set is divided into two periods. The first period covers November 1993 to December 2007 (170 months), and the second period covers January 2008 to July 2013 (67 months). The first period, i.e., the in-sample data, is divided into training (70% of the period) and prediction (30% of the period) sets. The training data is used to determine model specifications and parameters, and the prediction set is reserved for evaluation and comparison of performances among the prediction models. The second period, i.e., the out-of-sample data, is reserved for testing the performances of the prediction models because this data is not utilized to develop the models.

2.2.2 Model Description

In the last few years, 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. McCulloch and Pitts [41] created a computational model for neural networks based on mathematics and algorithms. From then on, the study of applying ANN to financial and investment decision has been examined by researchers

for many years. The most interesting characteristic of ANN model is mimicking the human brain and nervous system to model non-linear processes from historical data. We can predict the stock return from the complexity data by using ANN, which do not contain prior standard formulas and have the ability to map the nonlinear relations between input variables and output variables. Various models have been used by researchers to forecast market value by using ANN, and ANN models train via the BP algorithm is one of the models which are most commonly studied now.

Funahashi [17], Hornik, Stinchcombe and White [23] 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, and each of which is connected to the other. The architecture of the ANN is shown in Fig. 2. 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 needs to be determined by repeated training. The output layer consists of only one neuron that represents the predicted value of the output variable.

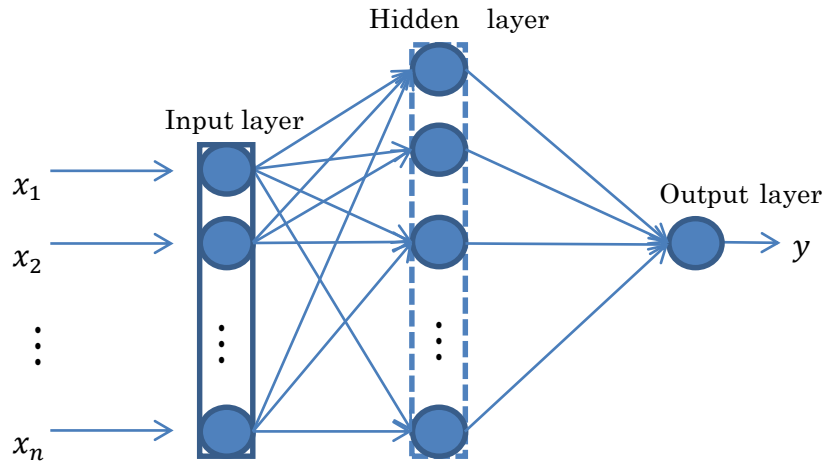


Fig. 2 Architecture of the three-layered ANN

2.2.3 Prediction Procedures

The architecture of our experimental process is shown in Fig. 3. First, we applied fuzzy surfaces to the selection of effective input variables prior to modeling. Then, we performed BP algorithm experiments 900 times to determine the most appropriate parameter combination for the ANN. We selected the best BP model for predicting the stock returns. Using the BP algorithm, we can obtain the optimized weights and biases of the network by repeated training. We also applied GA and SA to improve the ANN parameters (Chapter 3). We then trained the network using the BP algorithm with the improved weights and biases. Finally, we compared the experimental results of the three forecasting models (Section 3.4).

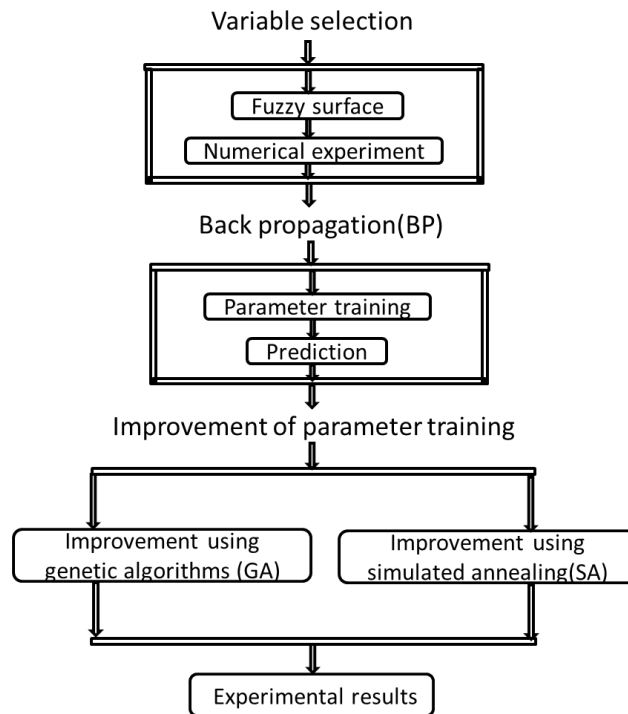


Fig. 3 Architecture of the experimental process

2.3 Variable Selection

2.3.1 Fuzzy Surfaces

In theory, a neural network based on nonlinear modeling techniques does not need to reduce the dimension of the input variables. However, the network can easily reach regional minimum convergence. In addition, with the development of the information age, data has become more complex and commonly requires preprocessing. Therefore, in practice, we must reduce the dimension of the input variables prior to modeling.

It should be noted that few studies have attempted to identify significant input variables. Some researchers have selected input variables with no explanation, and directly chose adequate explanatory variables from previous studies which concluded that some variables were effective by using the least squares method, stepwise

regression, or neural networks.

As there are many factors that affect stock market returns, the data in this chapter has a high degree of non-linear characteristic. Thus, we chose fuzzy curve analysis to select effective input variables for the ANN. Fuzzy curve analysis is based on the theory of fuzzy mathematics and does not require complicated mathematical modeling. First, we calculated the correlation between each input and output variable of the ANN. We then sorted all input variables according to importance. A relatively significant correlation exists between each input variable; thus, we excluded relevant variables by fuzzy surfaces and established a simple and optimal subset of input variables.

The simulation procedure are created by the following five steps:

Step 1: For each input variable x_i ($i = 1, 2, \dots, n$) and one output y , we have the M data points $(x_{i,k}, y_k)$, $k = 1, 2, \dots, M$.

Step 2: For each data point $(x_{i,k}, y_k)$, the fuzzy membership function is:

$$\mu_{i,k}(x_i) = \exp\left(-\left(\frac{x_{i,k}-x_i}{b}\right)^2\right). \quad (2.1)$$

$\mu_{i,k}$ is the input variable fuzzy membership function for x_i corresponding to the data point k . $\mu_{i,k}$ can be any fuzzy membership function, including triangle, trapezoidal, Gaussian, and others [39]. Here we choose Gaussians. We typically take b as 20% of the length of the input interval of x_i .

Step 3: Produce a fuzzy curve c_i for each input variable x_i using

$$c_i(x_i) = \frac{\sum_{k=1}^M y_k \times \mu_{i,k}(x_i)}{\sum_{k=1}^M \mu_{i,k}(x_i)}. \quad (2.2)$$

The function of the mean square error is:

$$MSE_{c_i} = \frac{1}{M} \sum_{k=1}^M (c_i(x_{i,k}) - y_k)^2. \quad (2.3)$$

MSE_{c_i} which is calculated by each fuzzy curve c_i and the original data is

used to choose significant input variables. Here we compute the fuzzy curves c_i for all input variables x_i , and then calculate the mean square error MSE_{c_i} for each fuzzy curve and rank the input variables by the value of MSE_{c_i} . The input variable with the smallest MSE_{c_i} is the most important variable for the relationship between this input and the output. On the contrary, the input with the largest MSE_{c_i} is the least important variable.

Step 4: A fuzzy surface $s_{i,j}$ is defined by

$$s_{i,j}(x_i, x_j) = \frac{\sum_{k=1}^M y_k \times \mu_{i,k}(x_i) \times \mu_{j,k}(x_j)}{\sum_{k=1}^M \mu_{i,k}(x_i) \times \mu_{j,k}(x_j)}, k = 1, 2, \dots, M. \quad (2.4)$$

Here x_i and x_j are the input variables. $s_{i,j}$ is a fuzzy surface for x_i and x_j .

A mean square error for the fuzzy surfaces is defined by

$$MSE_{s_{i,j}} = \frac{1}{M} \sum_{k=1}^M (s_{i,j}(x_{i,k}, x_{j,k}) - y_k)^2. \quad (2.5)$$

According to Step 3 we have found the most important input variable of x_i . Then the input variable x_j with the smallest $MSE_{s_{i,j}}$ is judged as the next most important input variable. The input variable with the largest $MSE_{s_{i,j}}$ is the most related to x_i , and we should eliminate it. In this chapter, we eliminate 10% of the inputs with the higher value of $MSE_{s_{i,j}}$.

Step 5: We select the important variables through Step 3 and Step 4 until all the variables are removed.

2.3.2 Numerical Experiment

We use the first period (November 1993 to December 2007; 170 months of observations) to select optimal input variables by using the fuzzy surface technique.

The data includes 71 input variables and one output variable. The experimental results are shown in Table 1.

Table 1 Identifying important input variables

	Identified input variable	Eliminated variables
Iteration 1	u_6	$u_{37}, u_{42}, u_{41}, u_{35}, u_{48}, u_{47}, u_{65}$
Iteration 2	u_{36}	$u_{38}, u_{51}, u_{19}, u_{43}, u_{34}, u_{32}$
Iteration 3	u_8	$u_{18}, u_{21}, u_{23}, u_{20}, u_{22}, u_{24}$
...
Iteration 17	u_{55}	u_{28}
Iteration 18	u_{56}	u_{11}

According to the simulation, the significant input variables were identified and ranked in order of importance: $u_6, u_{36}, u_8, u_{50}, u_{52}, u_{49}, u_7, u_{14}, u_{12}, u_{17}, u_{44}, u_{30}, u_{10}, u_{33}, u_{54}, u_{53}, u_{55}$, and u_{56} . The selected variables were renamed, and the meaning of each variable is shown in the Appendix (Section 2.7). The values of the input variables were preprocessed by normalizing within the range of 0 and 1 to minimize the effects of magnitude among the inputs and increase the effectiveness of the learning algorithm.

The output variable is the return of the Nikkei 225 index, which is computed as follows:

$$y_t = \frac{(P_t - P_{t-1})}{P_{t-1}}, \quad (2.6)$$

where P_t is the value of the index for Month t . Note that dividends are not considered in this chapter.

Among the selected input variables, we find that some variables, e.g., T-bill rate, has been proven effective and used frequently by previous studies. However, most input variables have not been previously examined; therefore, we verify the predicted effects of these variables in the following models. In addition, due to the lag associated with the publication of macroeconomic indicators, we applied a one-month time lag to certain data. We consider that using these variables in the forecasting models is similar to real-world practice.

2.4 Back Propagation Neural Network Training

2.4.1 Theory of Back Propagation Algorithm

The BP algorithm is a widely applied classical learning algorithm for neural networks [28, 56, 64]. 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.

Fig. 4 shows the illustration of an ANN processing unit, and the simple algorithm steps of BP algorithm are shown as follows:

Step 1: Initialize the connection weights w_{ij} , which is between i th neurons in the previous layer and Unit j . Random the value of the biases θ_j for each processing (hidden or output) Unit j .

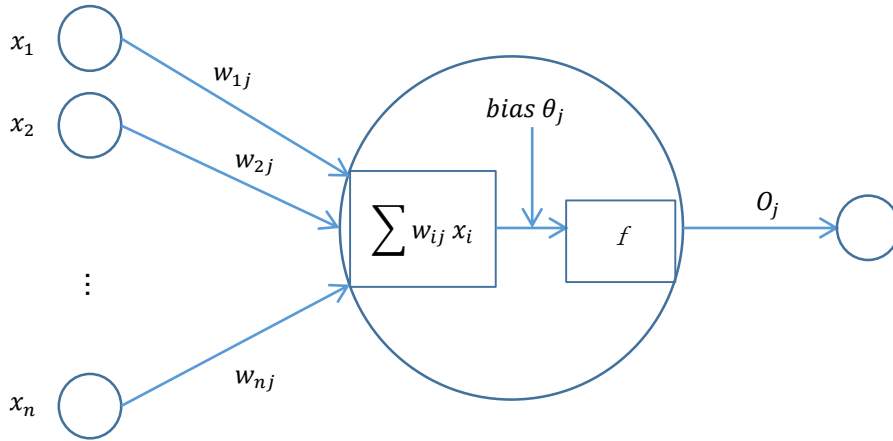


Fig. 4 Processing (hidden or output) Unit j

Step 2: Propagate the inputs forward.

Step 2-1: Compute the input I_j of Unit j with respect to the previous layer as follows:

$$I_j = \sum_{i=1}^n w_{ij} x_i + \theta_j. \quad (2.7)$$

In the formular, x_i is the output of i th neurons in the previous layer.

Step 2-2: Calculate the output O_j of each Unit j by using an activation function.

In this chapter, we use sigmoid function which is shown as follows:

$$O_j = \frac{1}{1+e^{-I_j}}. \quad (2.8)$$

Step 3: Back propagate the errors.

For each Unit j , the adjustable error is calculated as follows:

Step 3-1: If Node j is an output node, then

$$Err_j = O_j(1 - O_j)(T_j - O_j), \quad (2.9)$$

where O_j is the actual output of Unit j , and T_j is the true ouput based on the training sample.

Step 3-2: If Node j is an internal hidden node, then

$$Err_j = O_j(1 - O_j) \sum_k Err_k w_{jk}, \quad (2.10)$$

where w_{jk} is the connection weight from Unit j to Unit k in the next higher layer, and Err_k is the error of Unit k .

Step 4: Update of the weights and biases.

Step 4-1: For each weight w_{ij} in the network,

$$\Delta w_{ij} = l * Err_j O_i, \quad (2.11)$$

$$w_{ij} = w_{ij} + \Delta w_{ij}, \quad (2.12)$$

where Δw_{ij} is the change in weight w_{ij} . The variable l is the learning rate, a constant typically having a value between 0.0 and 1.0.

Step 4-2: For each bias θ_j in the network,

$$\Delta \theta_j = l * Err_j, \quad (2.13)$$

$$\theta_j = \theta_j + \Delta \theta_j, \quad (2.14)$$

where $\Delta \theta_j$ is the change in weight θ_j .

Step 5: Select the next pair of input patterns and then train the network repeatedly according to Step 2. Training stops when: all Δw_{ij} in the previous epoch were so small to below some specified threshold, or a prespecified number of epochs has expired.

2.4.2 Numerical Experiment

We used the in-sample data described in Section 2.2.1 for training the numerical experiments. To optimize the ANN learning algorithm, we conduct experiments of parameter settings for the network using the BP algorithm to determine the most appropriate parameters rather than choosing effective parameter values from a review of domain experts and prior research. The ANN parameters and their levels are summarized in Table 2. Ten levels of n , nine levels of mc , and ten levels of ep were

tested in the experiments. The larger the learning rate is, the greater is the adjustment amounts. It is noted that, as suggested in the literature, a small value of l (0.1) was selected. The momentum item of BP algorithm acts like a damper, which can restrain oscillations and improve the convergence property [49]. The addition of momentum stabilizes the descent path by preventing extreme changes in the gradient due to local anomalies. We obtained a different mean square error (MSE) value for each iteration when the ANN was trained by the same combination of parameters. Therefore, we ran the experiment once for each parameter combination.

Table 2 Tested ANN parameters and levels

Parameter	Meaning	Level(s)
n	The number of neurons in the hidden layer	10, 20, ... 100
ep	number of iterations	1000, 2000, ... 10000
mc	momentum constant	0.1, 0.2, ... 0.9
l	value of learning rate	0.1

The parameter setting experiments were performed with 900 parameter combinations. We selected the parameter combination that resulted in the best performance. Note that we used the MSE method to evaluate the performance of the ANN model:

$$MSE = \frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2, \quad (2.15)$$

where y_t denotes the actual return of the Nikkei 225 index, and \hat{y}_t is the predicted return.

Among the 900 parameter combinations, we found that the most appropriate

parameter combination was $n = 10$, $ep = 3000$, $mc = 0.4$, and $l = 0.1$. The *MSE* value of the best BP training algorithm for the ANN (i.e., BPNN) model was 0.0017. The average *MSE* value obtained from the 900 training experiments was 0.1219.

During the experiment, we observed the following characteristics.

- Calculation time increased with an increased number of neurons in the hidden layer; however, it was observed that the *MSE* value did not decrease gradually.
- Parameter combinations with relatively small *MSE* values always have relatively fewer neurons in the hidden layer. Note that the *MSE* value is relatively small when the number of neurons in the hidden layer ranges from 10–30.
- When the number of neurons in the hidden layer was large, the computer spent more time capturing nonlinear relationships among the variables. However, for many parameter combinations with a large number of neurons in the hidden layer, the experiment terminated in a short period of time. We speculate that the experiments achieved the best solution in the region of their starting point, which is the local minimum.
- Due to the complex nature and large volume of data, the time required to achieve convergence was significant; i.e., approximately one hour per parameter combination.

2.5 Empirical Results

2.5.1 Linear Regression Model

In order to verify the effectiveness of the ANN model with BP algorithm, we

conducted linear regression model to compare with it. In this chapter, we used the method of backwards for establishing the linear regression model. This method started with the full set of input variables, and then removed the variable which had the least contribution to the model from the last updated set. The final model was generated until there cannot delete any variables which significantly affect the model. The significant t-test was used as criteria of the significant input variables in the linear regression model. The remaining variables were thus used to predict the stock market returns. In this chapter we kept $x_2, x_3, x_8, x_9, x_{13}$ and x_{15} as the significant input variables in the regression model. The regression model has the following function:

$$R_t = 0.000000764 x_2 - 0.00003182 x_3 + 0.005506 x_8 + 0.004942 x_9 \\ - 0.002047x_{13} - 0.03664x_{15} + 1.095 + \varepsilon$$

Here ε is the error term, and follows the normal distribution. In this regression model, all the regression coefficients are significant and the F-statistic is 3.388 (p-value $0.004 < 0.05$), indicating that these forecasting variables can reflect the information of the stock market returns. The regression model shows that the changes of x_2, x_8 and x_9 have a positive effect on predictions of stock returns, whereas the effect of x_3, x_{13} and x_{15} on stock market return is negative.

2.5.2 Numerical Results

In this chapter, the models were tested on Windows 7 operating system, and we applied MATLAB R2011a by Math Works for operating all the experiments. Each of the models described in the previous is estimated and validated by the in-sample data. At this stage, the empirical evaluation for each model is based on the untouched

out-of-sample data which covers from January 2008 to July 2013 (67 months of observations). This is due to the fact that the superior in-sample performance does not always guarantee the validity of the forecasting accuracy.

With the formula of MSE above, the performance evaluation and the comparison of different models are calculated in Table 3.

Table 3 Error analyses of different forecasting models.

Models	LR	BPNN best	BPNN average level
MSE	12.7800	0.0044	0.1077

LR denotes the model of linear regression. Since 900 times of experiments on BP training had been executed in Section 2.4, here we chose the best ($n=10$, $ep=3000$, $mc=0.4$, $l=0.1$) parameter combination of BPNN (Back propagation neural network) model to compare with LR model. The average level of the performance of BP algorithm is also shown in Table 3.

In the Table 3, the smaller the criteria is shown, the better is the prediction effect. From Table 3, we can see that LR model has the largest value of MSE . The value of MSE for the average level of BPNN model is 0.1077. The best model which we found from the large number of experiments performs well and the value of MSE is 0.0044. We conclude that the prediction ability of the BPNN model is much more effective than the performance of the linear regression model. From the performance of the experiments, we also find that even though the 18 effective input variables has not been examined, the prediction effect is effective. The combination of 18 effective input variables can be therefore a good alternative for stock market returns prediction.

2.6 Conclusion

In this chapter, in order to search more new effective input variables, which are used to predict the return of Nikkei 225 index, we collected 71 variables that refer to different aspects of the Japanese stock market. And then we selected new combination of input variables of 18 good explanatory variables by fuzzy surfaces and utilized the combination to predict the return. We used the monthly data of 18 good explanatory variables to predict the return of Nikkei 225 index, and then compared the ability of the prediction for different models. We found that the forecasting accuracy of ANN based on BP algorithm was much more effective than the conventional linear regression. In addition, the prediction effect of the combination of 18 input variables is effective, and we may apply it for other stock markets for the future research.

2.7 Appendix: Input Variables

Input variables	Meaning
x_1	Average Amounts Outstanding of Monetary Base
x_2	Banknotes in circulation of average amounts outstanding of monetary base
x_3	Coins in circulation of average amounts outstanding of monetary base
x_4	Uncollateralized overnight of call rates at the end of month
x_5	Yen spot rate at the end of month of Tokyo market
x_6	Yen central rate at the end of month of Tokyo market
x_7	Yen lowest in the month of Tokyo market
x_8	Percent changes from the previous year in average amounts outstanding of

	money stock
x_9	Percentage changes in average amounts outstanding from the previous year of loans and discounts for total of major and regional banks
x_{10}	Loans and discounts of regional banks
x_{11}	Import price index of all commodities
x_{12}	Real exports
x_{13}	Real imports
x_{14}	Indices of industrial production
x_{15}	1-year T-bill rate
x_{16}	2-year T-bill rate
x_{17}	3-year T-bill rate
x_{18}	4-year T-bill rate

Chapter 3 Improvement of Training Algorithms

3.1 Introduction

In Chapter 2, we applied BP algorithm to train the neural network by conducting a large number of experiments. The BP algorithm is a widely applied classical learning algorithm for neural networks. Wong, Bodnovich and Selvi [65] found that most of the studies that had used ANNs relied on gradient techniques for network training, typically some variation of the BP algorithm. Although, researchers have commonly trained ANNs using the gradient technique of the BP algorithm, limitations of gradient search techniques emerge when ANNs are applied to complex nonlinear optimization problems [53]. The BP algorithm has two significant drawbacks; i.e., slowness in convergence and an inability to escape local optima [37]. In view of these limitations, global search techniques, such as genetic algorithms (GA) and simulated annealing (SA), have been proposed to overcome the local convergence problem for nonlinear optimization problems.

This chapter attempt to determine the optimal set of initial weights and biases to enhance the accuracy of ANN model by using GA and SA. The experimental results show that hybrid approaches based on GA and SA improve the prediction accuracy of the return of the Nikkei 225 index and outperform the BP training algorithm. In addition, the effect on prediction of the combined 18 input variables is effective and can therefore be a good alternative for predicting stock market returns.

The remainder of this chapter is organized as follows. Section 3.2 describes the GA, and we apply the algorithm for improving the predictive ability of ANN model.

Then, we improve the ANN model by using SA in Section 3.3. Section 3.4 provides the numerical experiments of ANN model improved by GA and SA. Finally, Section 3.5 contains the discussion and conclusion.

3.2 Improvement Using Genetic Algorithms (GA)

As observed in the parameter setting experiments, we find that the BP algorithm has two drawbacks; i.e., trapping into local minima and slow convergence. Note that these drawbacks have been verified by previous studies. To overcome these problems, many studies prefer to utilize 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 [32, 43, 46]. 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 [27].

Chang and Lin [26] proposed an auto-tuning method for the fuzzy neural network by GA, and showed that the characteristic of the proposed system was to obtain the minimal and the optimal structure of a fuzzy model. Marwan and Mat [6] used GA to find the optimal set of initial weights to enhance the accuracy of artificial neural networks. And their study of using simple GA has been proved to be effective for improving the prediction accuracy of ANN. Subhra and Jehadeesan [48] compared standard BP algorithm with GA based on BP algorithm on the prediction of parameters in Nuclear Reactor Sbusystems. 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. In this chapter, 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.

We encoded all the weights and bias in a string and generated the initial population. Each solution generated by GA is referred to as a chromosome (or individual) [27]. The collection of chromosomes is called a population. Here, each chromosome represents an ANN with a certain set of weights and bias. 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.

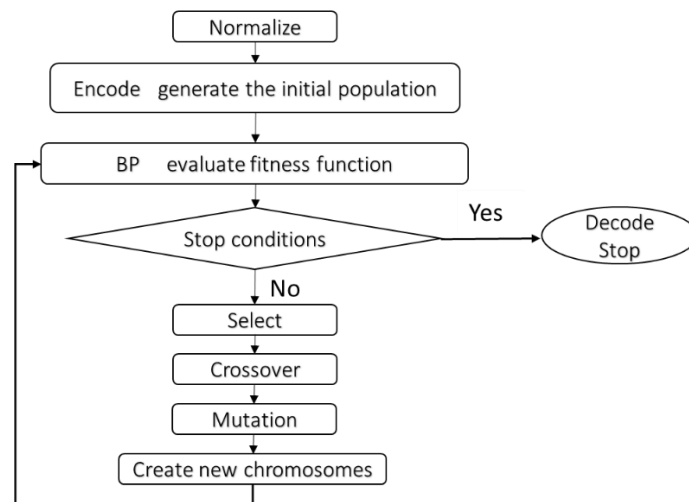


Fig. 5 Process of the hybrid GA and BP algorithm

Fig.5 shows the procedure of the hybrid GA and BP algorithm. The algorithm operated in this chapter consists of the following steps:

Step 1: Because of the wide range of the data, we normalized it to make sure that the value of all the variables scale down between zero to one. We normalized the

variables as follows:

$$RN = \frac{R - R_{min}}{R_{max} - R_{min}}, \quad (3.1)$$

where R is a sample variable. RN is the normalized value of R , R_{min} is the minimum value of R , R_{max} is the maximum value of R .

Step 2: 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 represent ANN with the certain set of wights and bias [37].

Step 3: Train 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.

Step 4: Rank all the individuals by the fitness proportion method, and then select the individuals with the higher fitness value to pass on to the next generation directly.

Step 5: Apply the genetic algorithms (e.g., crossover, mutation) to current population and then creat new chromosomes. Evaluate the fitness value of the new chromosomes, and insert the new chromosomes into the population to replace worse individuals of the current population. And then we get the new population.

Step 6: Repeat the Steps 3-5 until stopping conditions reach.

3.3 Improvement Using Simulated Annealing (SA)

SA, which is first presented by Kirkpatrick, Gelatt and Vecchi [33], is a famous optimization method that can be widely and successfully employed in solving global optimization problems in many research fields. The major advantage of SA is that it accepts both better and worse neighboring solutions that have a certain probability so as to jump out of a local optimum to search for the global optimum [55]. Many prior studies have successfully applied the SA algorithm to optimize the structure of an ANN model in various applications [1, 59, 66].

Yamazaki, De Souto and Ludermir [66] applied SA to the optimization of neural network weights and architectures. Their work showed that SA algorithm was able to produce networks with low complexity and better generalization performance than network trained with the BP algorithm for the odor classification task. Abbasi and Mahlooji [1] used ANN to estimate a response surface and applied SA to find the optimal or near optimal response. The results indicated that the proposed algorithm outperformed the classical method. Sudhakaran and Sivasakthivel [59] utilized a feed-forward BP network to predict the depth of penetration. Their work also proved the success of using SA in searching the optimum values of the process variables of penetration for stainless steel gas tungsten arc welded plates.

In this chapter, the SA technique is used to optimize the weights and bias of a BP-trained ANN model. The implementation of the SA algorithm is remarkably easier than the GA algorithm, and the process of hybrid SA and BP algorithm is shown in Fig.6.

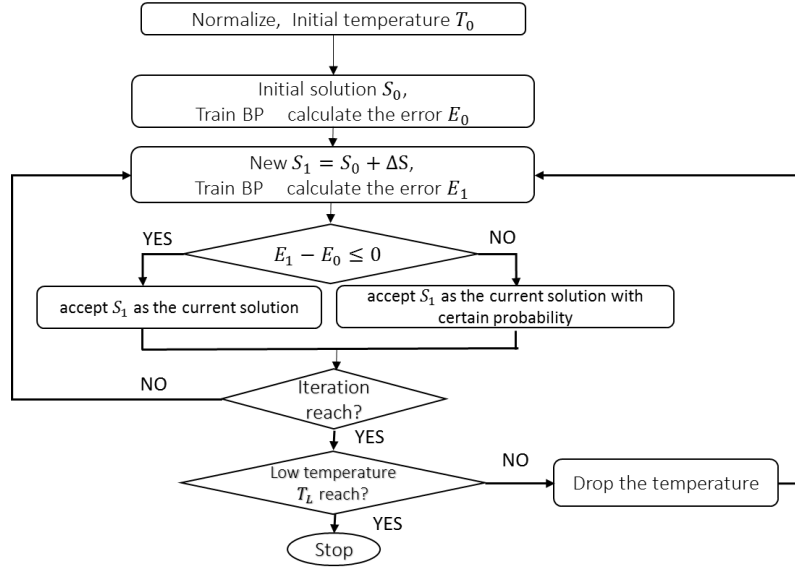


Fig. 6 Process of the hybrid SA and BP algorithm

The basic structure of SA algorithm is presented as follows:

Step 1: Normalize all the data to the range [0,1]. Initialize the SA control parameter T_0 and temperature reduction value.

Step 2: Set S_0 (the elements of S_0 are all the weights and biases of ANN model) as the initial solution. For all the training sample, we calculate the predicted output value of ANN which is trained with the BP algorithm. The sum of squared errors E_0 is calculated by the error between the predicted value and the real value.

Step 3: A new candidate solution S_1 is generated by means of small random perturbation ΔS of the current solution S_0 , $S_1 = S_0 + \Delta S$.

Step 4: Calculate the sum of squared errors E_1 based on the new candidate S_1 .

Step 5: If $E_1 < E_0$, we accept S_1 as the current solution.

else we accept S_1 as the current solution with the probability

$$P = \exp\left(\frac{-(E_1 - E_0)}{T_i}\right), \quad (3.2)$$

where T_i is the current temperature.

Step 6: Repeat Step 3 – Step 5 until the system reaches steady state or thermal equilibrium.

Step 7: Drop the temperature T according to the given temperature reduction strategy, and repeat Step 3 – Step 6 until $T=0$ or certain low temperature value T_L .

In SA, we started the algorithm with a relatively high value of T , to avoid being prematurely trapped in a local optimum. The most important feature of this algorithm is presented in Step 5, which is the possibility of accepting a worse solution, hence allowing it to prevent falling into a local optimum trap. There are two loops in the algorithm: in the outer loop the temperature is changed and the inner loop determines how many neighbourhood can be attempted at each temperature. The algorithm proceeds by attempting a certain number of neighbourhood moves at each temperature, while the temperature parameter is gradually dropped [12].

3.4 Numerical Results

Because of the superior in-sample performance did not always guarantee validity of forecasting accuracy, here the empirical evaluation of each model was based on the untouched out-of-sample data (January 2008 to July 2013; 67 months of observations).

The *MSE* and CPU time (for training and prediction) results of the performance evaluations for each algorithm are shown in Table 4. The models were tested by using the Windows 7 operating system. In addition, MathWorks MATLAB R2011a was employed in all experiments.

Table 4 Error analyses of different forecasting models

Models	BPNN	BPNN	GABPNN	GABPNN	SABPNN	SABPNN
	best	average	best	average	best	average
<i>MSE</i>	0.0044	0.1077	0.0043	0.0090	0.0725	0.0862
<i>CPU</i>	68		1080	1322	28	40
<i>Time</i> *						

* CPU Time for a 2.66 GHz Intel Core 2 Duo E6750

Nine hundred BP training experiments were executed, and we selected the best combination of parameters ($n = 10$, $ep = 3000$, $mc = 0.4$, $l = 0.1$) for the BPNN model as a baseline for comparison with the other models. The average performance of the BP algorithm is also shown in Table 4. Note that GABPNN denotes the hybrid GA and BP training algorithm used in the neural network. The cross probability and mutation probability values of the experiments were changed 81 times. This resulted in the best and average performances of the GABPNN model. SABPNN is a hybrid SA and BP training algorithm. The SABPNN experiments were performed 10 times, and the temperature of each experiment was 100. The best and average ability of the SABPNN to estimate stock returns are also shown in Table 4.

Here, we exclude computing time and give a simple comparison of the error indicator values. Note that smaller criterion values indicate better prediction effects. Compared to the BPNN average, GABPNN and SABPNN overcome the local minimum weakness and greatly improve prediction accuracy. SABPNN models with lower *MSE* values are superior to the average level of the BPNN experiments, especially for the hybrid GA and BP approach. Note that the *MSE* value of the best model is

0.0043. Compared to the BPNN average, the average *MSE* of the GABPNN model is also effective, demonstrating a value of 0.0090. The best BPNN model also demonstrate effective performance with an *MSE* value of 0.0044.

In terms of running time for the three models, the BPNN models may demonstrate the shortest time because they easily fall into the local minimum with bad performance. If not, the time requires to reach convergence is very long; i.e., approximately one hour for each parameter combination with a large number of hidden neurons. There is no sense to provide the average CPU time for the BPNN. Computing time is 68 seconds when the best BPNN model is not caught in the local minimum. Although the running time of the best BPNN is short, excessive time is required to search for the most appropriate parameter combination for the BPNN models. The SABPNN requires only 28 seconds, which helps the BP algorithm jump out of the local search. The average time for the SABPNN is less than the other models. The GABPNN requires longer time than the SABPNN; 18 minutes of run time is required, but it reduces the *MSE* value significantly.

The run time of the SABPNN is faster than any other models, and the prediction accuracy is higher than the normal BP model levels. By synthesizing the performances of the accuracy of prediction and the running time of the experiments, we consider that GABPNN demonstrates better market return prediction performance and higher accuracy than the other models.

Chen et al. [8] applied BP neural networks and Support Vector Machines (SVM) to construct the prediction models for forecasting the six major Asian stock market indices. They followed the previous research and determined the five input variables that were transformed from the daily closing price. They applied the ANN model with BP

algorithm to the six Asian markets and the value of *MSE* for Nikkei 225 index was 0.048. Dai et al. [10] proposed a time series prediction model (NLICA-BPN model) by combining nonlinear independent component analysis and neural network to forecast Asian stock markets. Their experimental results showed that the forecasting model could produce lower prediction error and improve the prediction accuracy of the neural network approach with the value of *RMSE* for Nikkei 225 was 50.44. Lu [28] applied an integrated independent component analysis based denoising scheme with neural network in stock price prediction. Four forecasting variables were used for predicting the Nikkei 225 index, including the previous day's cash market closing index and three Nikkei 225 index futures. The empirical results showed that the proposed ICA-BPN method performed well in forecasting the Nikkei 225 index and the value of *RMSE* was 43.54.

Compared with the prior research and according to the experimental results, we find that even though most of the proposed 18 input variables have not been used in previous studies, their effect on prediction is remarkable. Thus, these input variables are considered a good choice for prediction of stock market returns. The optimization afforded by the GA or SA has demonstrated strong potential for obtaining globally optimal solutions. The GA can quickly achieve the best prediction accuracy for the ANN model while the BP algorithm requires to test a large number of parameter combinations.

3.5 Conclusion

In this chapter, we applied GA and SA for improving the accuracy of ANN model with BP algorithm. In the light of significant drawbacks of BP algorithm, we proposed to use global search techniques, such as GA and SA, to optimize the weights and bias of the ANN. The experimental results showed that hybrid approach of SA and BP overcame the weakness of local minima and greatly improved prediction accuracy. We synthesized the performance of the prediction accuracy and running time, and considered that the hybrid GA and BP approach provided higher accurate forecasting of future values than other prediction models. In addition, the effect on prediction of the combined 18 input variables was effective and can therefore be a good alternative for predicting stock market returns.

Chapter 4 Predicting the Direction of Stock Price Index Movement

4.1 Introduction

In this chapter, we predict the direction of the daily Nikkei 225 index by using ANN with genetic algorithm (GA).

It is a difficult task to predict the exact value of a stock market index, hence there are many researches that are concerned with the prediction of the direction of stock price index movement. The direction of the stock market index is the sign of price index or the trend of the stock market index in the future. Mark and Leung [38] hold the view that trading could be profitable by an accurate prediction of the direction of movement. Their work suggested that financial forecasters and traders should be focus on accurately predicting the direction of movement so as to minimize the estimates' deviations from the actual observed values. Mostafa [44] also believed that accurate predictions of the direction of stock price indices were very important for investors.

Previous studies have applied various models in forecasting the direction of the stock market index movement. Huang et al. [25] forecasted stock market movement by support vector machine (SVM), and concluded that the model was good at predicting the direction. Kara et al. [29] applied artificial neural networks (ANN) and SVM in predicting 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. In addition, scholars predict the movement of the stock market indices of various countries. Leung et al. [38] forecasted the direction of the return for

three globally traded broad market indices, S&P for the US, FTSE 100 for the UK and Nikkei 225 for Japan by various models. Their research shows that the classification models perform better than the level estimation counterparts in terms of the number of times the predicted direction is correct. Senol and Ozturan [54] applied seven different prediction system models for predicting the direction of the stock market index in Turkey, and concluded that ANN could be useful in forecasting. The main contribution of this chapter is that we predict the direction of the next day's price of the Nikkei 225 index by using the GA-ANN hybrid model.

The forecasting of financial index is characterized by data intensity, noise, non-stationary, unstructured nature, high degree of uncertainty, and hidden relationships [21, 30, 60]. Many factors, such as political events, general economic conditions, and traders' expectations, may have influence on the price of stock market. Many researches use similar indicators to forecast the stock market index. The core objective of this chapter is to compare two basic types of input variables to predict the direction of the daily Nikkei 225 index by using ANN model with GA algorithm. In this chapter, we demonstrate and verify the predictability of stock price direction by using ANN with GA, and then compare the performance with prior studies. Empirical results shows that input variables Type 2 can generate higher forecast accuracy.

The remainder of this chapter is organized as follows. Section 4.2 describes the data, and input variables that are used in the ANN model. Then, we show the procedure of predicting the stock market direction in Section 4.3. Section 4.4 provides the experimental results of two types of indicators, and compares the results with similar studies. Finally, Section 4.5 contains the discussion and conclusion. Formulas and the summary statistics for each feature of input variables are given in

Section 4.6.

4.2 Research Data

4.2.1 Data

The research data used in this chapter are technical and fundamental indicators which are calculated by the daily price of the Nikkei 225 index. The total number of samples is 1707 trading days, from January 2007 to December 2013. The total 1707 data points of the daily Nikkei 225 closing cash prices in the data set are shown in Fig. 7. We divide the entire data into two parts, 78.6% of the data is used for in-sample training and 21.4% for out-of-sample data. The in-sample data is used to determine the specifications of the model and parameters while the out-of-sample data is reserved for the evaluation of model. The financial data used in this chapter is obtained from the Yahoo Finance.

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 [51]. Tables 5 and 7 give selected features and their formulas, and we select technical indicators as feature subsets by the review of prior researches [2, 24, 54].

The original data are standardized before being applied to the ANN experiments. We normalize the data as follows,

$$XN = \frac{X - X_{min}}{X_{max} - X_{min}}, \quad (4.1)$$

where 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 [31].



Fig. 7 The daily Nikkei 225 closing prices from January 23, 2007 to December 30, 2013

4.2.2 Input Variables

In this chapter, we want to compare the performances of two sets of input variables. From the prior studies we notice that, most of scholars want to choose the input variables as shown in Table 5, meanwhile others want to use the variables in Table 6. In this chapter, we conduct the experiments by using ANN model with the two types of input variables, and then compare the performance of these two experiments with prior studies.

4.2.2.1 Input Variables Type 1

We set 13 technical indicators as Type 1 feature subset by the prior researches [29, 32]. Table 5 shows these indicators, their formulas and the summary statistics for each feature of Type 1 are presented in the appendix.

Table 5 Selected technical indicators and their formulas (Type 1)

Name of feature	Formulas
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 5 days	$C_t / MA_5 \times 100,$
Disparity 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)	$100 - 100 / (1 + \frac{\sum_{i=0}^{n-1} Up_{t-i}}{n} / \frac{\sum_{i=0}^{n-1} DW_{t-i}}{n}),$

where C_t is the closing price of the Nikkei 225 index at time t ,

L_t is the low 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 high 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 price in the last n days,

$$MA_n = (\sum_{i=1}^n C_{t-i+1})/n, \quad (4.2)$$

$$M_t = \frac{H_t + L_t + C_t}{3}, \quad (4.3)$$

$$SM_t = (\sum_{i=1}^n M_{t-i+1})/n, \quad (4.4)$$

$$D_t = (\sum_{i=1}^n |M_{t-i+1} - SM_t|)/n, \quad (4.5)$$

Up_t is the upward price change of the Nikkei 225 index at time t ,

Dw_t is the downward price change of the Nikkei 225 index at time t .

4.2.2.2 Input Variables Type 2

We set 9 technical indicators as Type 2 feature subset from the prior researches [54, 60]. Table 6 shows these indicators, the definitions and the summary statistics for each feature of Type 2 are presented in the appendix.

Table 6 Selected technical indicators' formulas (Type 2)

Name of indicator	Formulas
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	$ASY_1 = SY_{t-1},$

where V_t is the volume of trade of the Nikkei 225 index at time t ,

$$\Theta = \begin{cases} +1, & C_t \geq C_{t-1} \\ -1, & C_t < C_{t-1} \end{cases}, \quad (4.6)$$

Θ is positive when the closing price is above the prior closing price, and Θ is negative when the closing price is below the prior close.

4.3 Prediction Process

As we have mentioned the algorithms of BP, GA and SA in the last two chapters, empirical results show that the GA-ANN hybrid model has the most effective predictive ability. In this chapter, we propose to apply the GA algorithm to optimize the weights and bias of ANN model, and then predict the direction of daily closing price movement

of Nikkei 225 index.

The architecture of our experimental process is shown in Fig. 8. First we calculate all the data of two types of input variables. Then we standardize the data to reduce the experiments' errors. We apply two types of indicators for predicting the direction of next day's movement by the GA-ANN hybrid model respectively. After we finish all the experiments, we compare the performance among the two types of input variable set and prior studies.

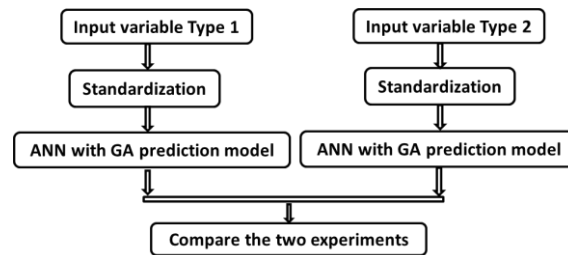


Fig. 8 Architecture of the experimental process for comparing two types of input variables

4.4 Experimental Results

4.4.1 Comparison of the Performances between the Two Types of Input Variables

In the period of training the GA-ANN hybrid model, we use the in-sample data. Then we test the performance of the two sets input variables by applying out-of-sample data which includes 300 data points. Table 7 shows the performances of the two types of input variables. Hit ratio denotes the ratio when the predicted direction is correct. The hit ratio for forecasting the direction of next day's price correctly by applying input variables Type 1 is 60.87%, and 81.27% by input variables Type 2. We can conclude

that input variable Type 2 is more effective in predicting the direction of daily closing price of Nikkei 225 index than input variable Type 1.

Table 7 The comparison between two types of input variables

	Type 1	Type 2
<i>Hit ratio (%)</i>	60.87	81.27

According to Fig. 9, we can find that the good performance obtained by input variable Type 2, and the direction of real value line is as similar as the predicted one. The probability of the prediction for the direction of the next day's closing price is 81.27%. We infer that the accurate prediction performance of the ANN model by using input variables Type 2 is useful for investors and can become a good candidate for predicting the direction of next day's closing price.

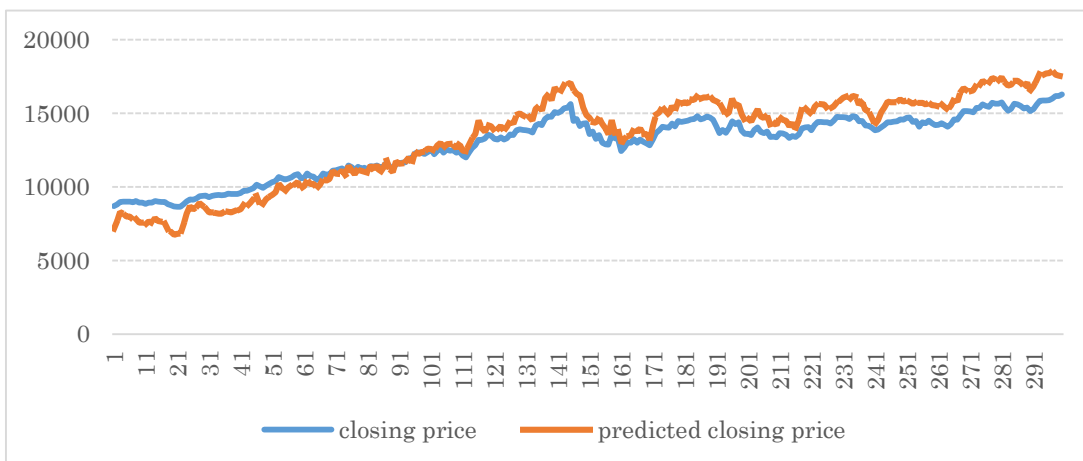


Fig. 9 Performance of the predicted closing price by applying input variables Type 2

4.4.2 Comparison of Results with Similar Studies

Predicting the direction of the stock market index is an important topic for the investors. Accurate prediction of stock prices movement may generate attractive benefits for investors. There are many studies that are focus on the prediction of movements. Table 8 shows the prior studies that are aim to predict the direction of stock market indices by various methods. The result of this chapter is also compared with these researches in Table 8.

Table 8 Comparison of our study with prior papers

Studies	Methods	Stock market	Hit ratio (%)
Kim and Han [32]	GA feature discretization	Korea	61.70
Leung et al. [38]	Classification model	US, UK, Japan	68 (Nikkei 225)
Huang et al. [25]	SVM	Japan	75
Kara et al. [29]	BPNN	Istanbul	75.74
Our study	GA-ANN hybrid model	Japan	81.27

According to the table, we find that the performances are significantly different in various stock markets, and our model is superior to other models. Thus, we consider that the set of input indicators and GA algorithm adopted in this chapter can be considered as more appropriate for prediction.

4.5 Conclusion

In this chapter, we tried to apply two types of technical indicators to predict the direction of next day's Nikkei 225 index movement. We adjusted the weights and bias of ANN model by GA algorithm, then we tested the performance of the GA-ANN hybrid model by applying two types of input variables. The experiments implied that input variables Type 2 can generate higher performance, and the probability for predicting the direction was 81.27%. We also compared the performance of the GA-ANN hybrid model with similar studies, the results showed that our method was more effective and can generate higher prediction accuracy.

However, the prediction performance of this chapter can be improved by two ways. The first way is to combine the two types of input indicators, or test some subset of these variables. In addition, we can add some other macroeconomic variables such as variables showed in Chapter 2. Second, not only GA algorithm, other optimal methods can be used to adjust the parameters of ANN model. We can even use other models, such as probabilistic neural network for predicting the movement of Nikkei 225 index. These two improvements can be a future work for our study.

4.6 Appendix: Description of the Input Variables

In this appendix, we describe two types of input variables which are applied to forecast the direction of Nikkei 225 index.

The descriptive statistics for Type 1 input variable is shown in Table 9. Stochastic Oscillator is an indicator that is used for predicting price turning points by comparing

the closing price of a security with its price range. It includes *K* line and *D* line.

Table 9 The summary of statistics (Type 1)

Name of feature	Max	Min	Average	Standard deviation
Stochastic %K	100.000	0.000	53.302	33.525
Stochastic %D	98.731	1.450	53.287	27.594
Stochastic slow %D	98.229	2.121	53.269	25.485
Momentum	1492.680	-2196.660	-2.319	366.566
ROC	119.742	76.969	100.041	3.281
LW%R	100.000	0.000	46.698	33.525
A/O Oscillator	4.483	-2.919	0.577	0.936
Disparity 5 days	113.795	86.815	99.999	1.819
Disparity 10 days	113.316	79.788	99.998	2.690
OSCP	0.067	-0.097	0.000	0.015
CCI	166.667	-166.667	5.408	93.381
RSI	99.875	0.000	51.831	18.234

The descriptive statistics for Type 2 input variable is summarized in Table 10. On Balance Volume (OBV) measures buying and selling pressure as a cumulative indicator that adds volume on up days and subtracts volume on down days. It is also an indicators for measuring positive and negative volume flow. A rising OBV reflects positive volume pressure that can lead to higher prices. Conversely, falling OBV means that negative volume pressure can foreshadow lower prices [19].

$BIAS_n$ measures the divergence of current stock price from an n day simple moving average of the stock prices. Normally scholars and investors choose n to be 6 days. The value of $BIAS_n$ may be above or below the moving average when the closing price is far away from the average level.

PSY_n is the Psychological line, which is a sentiment indicator, and it is made to look behind the obvious mood of the market and to detect undertones for a trend change. PSY_n is the ratio of the number of rising periods over the n days period. A is number of the rising days in the last n days.

SY_t is 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.

Table 10 The summary of statistics (Type 2)

Name of feature	Max	Min	Average	Standard deviation
OBV	1769930.000	-1188269.000	255381.867	340334.874
MA_5	18209.158	7177.696	11507.384	2947.335
$BIAS_6$	18199.282	7211.380	11504.454	2944.715
PSY_{12}	0.126	-0.147	0.000	0.020
ASY_5	0.917	0.000	0.514	0.132
ASY_4	0.048	-0.056	0.000	0.007
ASY_3	0.045	-0.065	0.000	0.008
ASY_2	0.077	-0.068	0.000	0.010
ASY_1	0.085	-0.088	0.000	0.012

Chapter 5 Dogs of the Dow Investment Strategy

5.1 Introduction

In the stock market, one of the aims of investors is to “beat the market,” i.e., to outperform benchmarks such as the Dow Jones Industrial Average or Nikkei Average. This aim, however, is not easily achieved even by professional fund managers. For example, a study on the American funds reported that 75% of them underperformed benchmarks [13], and the situation for the Japanese fund managers is even worse. As for individual investors, most of them lack advanced professional skills or do not have enough time to study the stock market. As a consequence, most of them are losers in the market. Therefore, effective investment strategies, which should be simple and easy-to-practice, are necessary for both professional and individual investors.

Investments in stock market have always been built around some kind of investment philosophy or strategy, some naïve, others more complex. While some investment strategies have paid off, others have not proved as effective [52]. Nevertheless, considerable research continues to be made in searching of effective strategies, scholars and investors continue to yearn for new strategies to beat the market and achieve abnormal returns out of investments made in the stock market. Among many effective strategies which have been tested in recent years, one strategy which has gained great popularity in the investment community and has been studied extensively by academia. The strategy was first proposed by analyst John Slatter, and the article was published in a Wall Street Journal. This strategy involves investing equal amounts in the 10 highest-yielding stocks of the Dow Jones Industrial Average (DIJA) index at

the end of the year, and then holding these high-yielding stocks for 1 year [11]. According to the effective performance of these highest-yielding stocks, which was proved by investors, these stocks tend to be called “Dog” stocks. Therefore, Slatter’s investment strategy is commonly referred to as the “Dogs of the Dow” strategy. This strategy, also known as the Dow 10 strategy, is a very popular and successful investment strategy in the United States. Slatter examined the performance of the Dogs of the Dow strategy for the years 1973 through 1988, and found that the 10 highest-dividend-yielding stocks of DJIA outperformed DJIA.

Since then, many papers have been written on the American stock market. O’Higgins and Downes [47] and Knowles and Petty [34] published books examining the performance of the Dogs of the Dow strategy over longer time horizons. These studies show the effectiveness of this strategy from 1973 to 1991. While these books increased the popularity of the strategy, they also raised new concerns. Nonetheless, they attracted more investors and scholars to apply the strategy. The first academic study on the Dogs of the Dow strategy was performed by McQueen et al. [42]. They used statistical methods to examine the performance of the portfolio over 50 years (1946–1995), and concluded that this strategy’s superiority is statistically significant.

Encouraged by its success in the United States, scholars in many countries have examined the strategy [9, 18]. Visscher and Filbeck [63] showed that the Dogs of the Dow strategy performed well against the Toronto 35 and TSE 300 indices in the Canadian stock market. The strategy was also widely examined in Latin American and Polish stock markets. Furthermore, Eemeli and Sami [50] concluded that the Dogs of the Dow strategy can be successfully applied to the Finnish stock market. In Japan, Song and Hagio [57] proposed the application of this strategy to the Tokyo Stock

Exchange, and concluded that it performed well when it was applied in NIKKEI 225 for the 2002–2006 data.

Our purpose is to analyze the performance of the Dogs of the Dow strategy in the Japanese stock market for a longer term and the Hong Kong stock market in order to examine its validity.

For the Japanese stock market, first we conduct a simulation using the 1981–2010 data and compare the performance of the Dogs of the Dow strategy with that of NIKKEI 225 index. The results show that the strategy outperforms the index remarkably. This provides empirical evidence for the effective application of the strategy in the Japanese market. Second, because of the higher standard deviation of the Dogs of the Dow strategy, we make risk adjustments by using the Sharpe Ratio, drawing the comparison one more time. The results after adjusting for risk and transaction costs make the strategy more convincing and rigorous. Third, this study explores various versions of the Dogs of the Dow strategy, which provide more implications for investors of the Japanese stock market.

For Hong Kong stock market, we conduct a simulation for the 2001–2011 data and compare the performance of Dogs of the Dow strategy with that of the market index. Further, in addition to the most popular version of the Dogs of the Dow strategy, which uses the 10 highest-dividend-yielding stocks, we also test less well-known version of the strategy which involves fewer Dogs.

This chapter is organized as follows: in Section 5.2, we show the simulation results of Dogs of the Dow strategy in Japanese stock market. In the Section 5.3, we apply Dogs of the Dow strategy to the Hong Kong stock market. Then we make a summary in Section 5.4.

5.2 The Application for the Japanese Stock Market

5.2.1 The Simulation

NIKKEI 225 (also known as NIKKEI average or the NIKKEI) is the most widely used market index for the Tokyo Stock Exchange. It includes 225 stocks, which are weighted equally, and has been calculated daily since 1950.

We implemented the simulation of the Dogs of the Dow investment strategy in three steps. In step 1, we collected data for all 225 companies of NIKKEI 225 on March 31, and then selected the 10 highest-dividend-yielding stocks. On April 1, we invested in the 10 stocks with equal weighting. In step 2, we held these stocks for one year and then sold them at the end of March of the following year. After updating the list of NIKKEI 225, we invested in the new top-10 stocks with equal weighting on April 1. In step 3, we repeated the process for each year.

We searched for the stock prices on the internet and in newspapers and obtained the expected dividend price data of 225 companies of NIKKEI 225 from [61]. April 1 was chosen as the investing date because it is the beginning of the fiscal year for most Japanese companies.

In this section, we implemented the simulation for the 1981–2010 data.

5.2.2 Comparison of Dogs of the Dow Strategy and NIKKEI 225

Table 11 presents the average returns and standard deviations of the Dogs of the Dow strategy and NIKKEI 225. The Dogs of the Dow strategy had an average return of 13.61% and a standard deviation of 32.27%. The NIKKEI 225 portfolio had a

lower mean return and deviation at 3.97% and 24.17%, respectively. The table also provides data on the difference between the two strategies. The Dogs of the Dow strategy had a 9.64 percentage points higher return on average and the difference of the standard deviation was 8.10 points. The data show that in the last 30 years, the Dogs of the Dow strategy outperformed NIKKEI 225 on average, although the former had a higher risk.

Table11 The annual return summary of statistics for the Japanese stock market
(1981-2010)

<i>Portfolio</i>	<i>Average annual return</i>	<i>Standard deviation</i>
<i>Dogs of the Dow</i>	<i>13.61%</i>	<i>32.27%</i>
<i>NIKKEI 225</i>	<i>3.97%</i>	<i>24.17%</i>
<i>difference</i>	<i>9.64%</i>	<i>8.10%</i>

To check the statistical significance of the result, we conducted a T-test at a 5% significant level. In the test, $p = 0.022705 < 0.05$, and thus the higher performance is statistically significant at a 95% confidence level.

Fig. 10 plots the differences between the Dogs of the Dow strategy and NIKKEI 225 annual portfolio returns for each year. Here, a positive difference indicates that the Dogs of the Dow strategy outperformed the NIKKEI 225 portfolio.

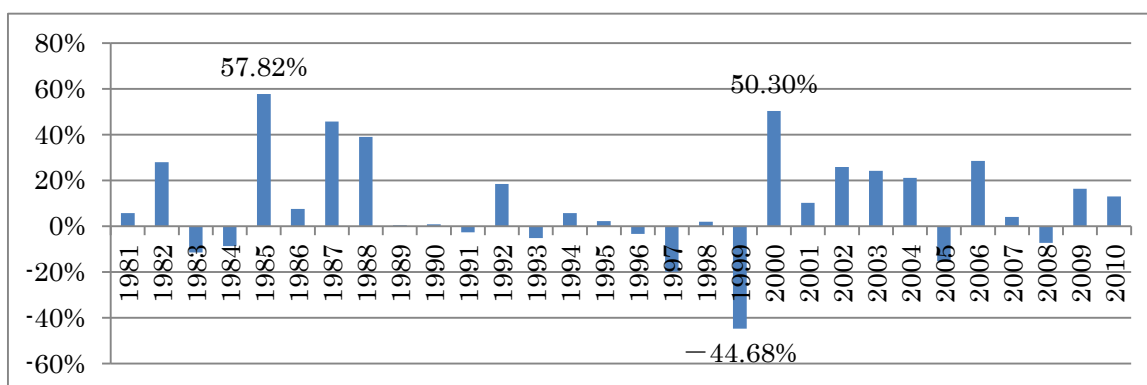


Fig. 10 Annual difference in returns between the Dogs of the Dow strategy and NIKKEI

225

Fig. 10 indicates that the Dogs of the Dow strategy outperformed NIKKEI 225 on 21 occasions. Especially in 1985, the Dogs of the Dow strategy was 57.82 percentage points greater than NIKKEI 225. In 2000, the Dogs of the Dow strategy was 50.30 percentage points more than NIKKEI 225. Since 2000, the Dogs of the Dow strategy has outperformed NIKKEI 225 nine times in 11 years. On the other hand, the worst performance of the Dogs of the Dow strategy was in the year 1999, when the difference between the two strategies was -44.68 percentage points. Therefore, the Dogs of the Dow strategy may occasionally perform quite miserably in the short term. In order to make the most out of this strategy, we suggest implementing it for a long period.

Next, we compared the accumulated performances of the Dogs of the Dow strategy and NIKKEI 225. Fig. 11 shows the results. Supposing that the asset value of both portfolios was 100 in 1981, at the end of the 2010 fiscal year, the Dogs of the Dow strategy had an accumulated value of 1,372, which is approximately 14 times the value in 1981. The accumulated performance was especially notable in 2006, when the Dogs of the Dow strategy had the highest accumulated value at 2,059. Moreover, from 1981 to 2010, the Dogs of the Dow strategy always had a higher accumulated

performance than that of NIKKEI 225. By contrast, the NIKKEI 225 line in the lower part of the graph shows a steady trend. The accumulated performance of NIKKEI 225 for 2010 was only 139, which implies that the asset value of the portfolio increased merely 39% in the 30 years.

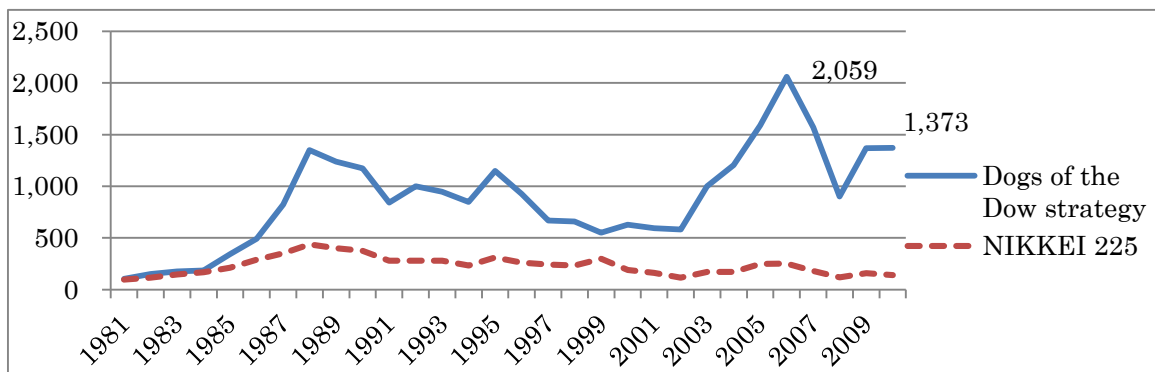


Fig. 11 Accumulated performance of the Dogs of the Dow strategy and NIKKEI 225

In this section, we provide a 10-year subperiod analysis of the Dogs of the Dow strategy. In the first subperiod, Japan experienced the so-called “bubble economy” and NIKKEI 225 reached a historical 38,916 points at the end of 1989. The last decade of the 20th century, the second subperiod, is named “the lost decade” of the Japanese economy because of the long-lasting recession. Then, in the first decade of the new century, which is the third subperiod, the Japanese economy recovered from the recession, but seriously suffered again because of the Lehman crisis.

Table 12 reports the mean return and nominal difference between the Dogs of the Dow strategy and NIKKEI 225. We can see that the Dogs of the Dow strategy outperformed NIKKEI 225 in all the three 10-year subperiods. In the 1981–1990 period, the difference between the Dogs of the Dow strategy and NIKKEI 225 was very large, at 16.53 percentage points. In the second subperiod, although the difference was

very small (0.32 percentage points), the Dogs of the Dow strategy performed better than NIKKEI 225. In the 2001–2010 period, the Dogs of the Dow strategy showed a good result, with a difference of 12.08 points.

Table 12 Subperiod analysis for the Japanese stock market

<i>Subperiod</i>	<i>Mean return</i>		<i>Standard deviation</i>		<i>Nominal difference</i>
	<i>Dogs of the Dow</i>	<i>NIKKEI225</i>	<i>Dogs of the Dow</i>	<i>NIKKEI225</i>	
<i>1981–1990</i>	<i>31.69%</i>	<i>15.17%</i>	<i>31.51%</i>	<i>14.87%</i>	<i>16.53%</i>
<i>1991–2000</i>	<i>–4.09%</i>	<i>–4.41%</i>	<i>19.98%</i>	<i>20.62%</i>	<i>0.32%</i>
<i>2001–2010</i>	<i>13.24%</i>	<i>1.16%</i>	<i>33.03%</i>	<i>30.05%</i>	<i>12.08%</i>
<i>1981–2010</i>	<i>13.61%</i>	<i>3.97%</i>	<i>32.27%</i>	<i>24.17%</i>	<i>9.64%</i>

The results imply that the Dogs of the Dow strategy was successful in all economic environments. In particular, it was quite robust even during the recession and performed very well in the period of boom.

5.2.3 Risk Adjustment

While Table 11 shows that the Dogs of the Dow strategy has a mean return higher than that of NIKKEI 225, it also shows that in most periods, the Dogs of the Dow strategy has standard deviations higher than those of NIKKEI 225. With only 10 stocks in the portfolio, there are some unsystematic risks that led to the higher standard deviations. Therefore, we need to adjust the risk of the Dogs of the Dow strategy to

more precisely judge the performances of different strategies.

The Sharpe Ratio is the most popular and powerful technique for comparing the returns of two portfolios with different risks [12]. By assuming that the investor allocates a part of his portfolio to some risk-free assets, the Sharpe Ratio eliminates the risk premium from the portfolio, thereby enabling the comparison of portfolios with different degrees of risk.

Here, we use Japanese government bonds as the risk-free asset. In this scenario, the adjustment for the entire 30-year period is the same to invest some 75 percent ($24.17\% / 32.27\% = 74.90\%$) of the wealth in the Dogs of the Dow strategy and the remaining 25 percent ($1 - 75\%$) in government bonds. With this 25% investment in the national debt, we can adjust the higher risk of the Dogs of the Dow strategy to have nearly the same standard deviation as that of NIKKEI 225. Then, by using the government bonds mean annual return of 2.68%, the return of the Dogs of the Dow strategy can be transformed to 10.87% (i.e., $(13.61\% - 2.68\%) (24.17\% / 32.27\%) - 2.68\%$). The Dogs of the Dow strategy clearly outperformed NIKKEI 225 even after the adjustment, although the difference of average return now shrinks to 6.90 percentage points (Table 13).

Table 13 The difference between the risk-adjusted Dogs of the Dow and NIKKEI 225

<i>Subperiod</i>	<i>return of risk-adjusted Dogs of the Dow</i>	<i>return of NIKKEI 225</i>	<i>Risk-adjusted difference</i>
<i>1981–1990</i>	<i>16.37%</i>	<i>15.17%</i>	<i>1.20%</i>
<i>1991–2000</i>	<i>−3.88%</i>	<i>−4.41%</i>	<i>0.53%</i>
<i>2001–2010</i>	<i>12.29%</i>	<i>1.16%</i>	<i>11.13%</i>
<i>1981–2010</i>	<i>10.87%</i>	<i>3.97%</i>	<i>6.90%</i>

The second column in Table 13 is the risk-adjusted average return of the Dogs of the Dow strategy, and the fourth column is the difference between the return of the risk-adjusted Dogs of the Dow strategy and that of NIKKEI 225. Before the adjustment, the Dogs of the Dow strategy performed better than NIKKEI 225 for all three 10-year subperiods, and this remained true even after the adjustment. Note that for the 1991–2000 subperiod, the difference was greater because NIKKEI 225 had higher risk before the adjustment. Consequently, the Dogs of the Dow strategy is superior to NIKKEI 225 even after eliminating the risk factors.

5.2.4 The Performance for Other Numbers of Dogs

We also tested other portfolios with fewer Dogs, and compared the performance of each portfolio using the Dogs of the Dow strategy and NIKKEI 225 between 1981 and 2010. We named the portfolio with the top N stocks as Dow N strategy. The simulation of this strategy was conducted in a manner similar to that of the Dogs of the Dow strategy but by using the top N stocks instead of the top-10 stocks.

Fig. 12 exhibits the average annual returns of the portfolios. We can see that all portfolios of the Dogs of the Dow investment strategy outperform NIKKEI 225 during the 1981–2010 period. After the risk adjustment, the Dow 6 portfolio has the highest average annual return. The Dow 10 strategy, which is the original Dogs of the Dow strategy, has the fifth-highest return, with a value of 10.87%. The return of NIKKEI 225, however, is as low as 3.97%. Hence we conclude that portfolios with fewer Dogs are also effective in the Japanese stock market.

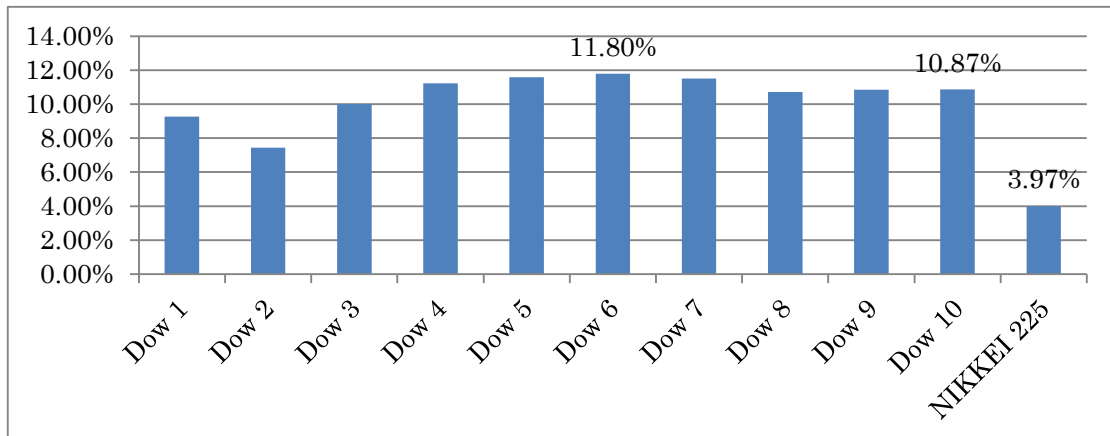


Fig. 12 Average annual returns of the risk-adjusted Dow N strategies and NIKKEI 225

5.2.5 Advantages of the Strategy

The results in previous sections have shown the superior performance of the Dogs of the Dow strategy. In the long term, it outperformed the benchmark before and after risk adjustment. As stated in the Section 5.1, three quarters of the professional funds underperformed benchmarks. Hence, the performance of this strategy can beat most professional fund managers.

Hereafter, we discuss the advantages of the strategy from a practical viewpoint, especially for individual investors.

Most individual investors lack the advance skills of professionals. Hence, simple investment strategies are preferable. As described above, the Dogs of the Dow strategy is very simple. With elementary arithmetic, each investor can understand the method without any difficulty.

Usually individual investors do not have enough time to study the market. Hence, an easy-to-implement strategy is an advantage for them. Each year, investors need to

perform only two operations: selling 10 old stocks at the end of the fiscal year and buying 10 new stocks at the beginning of the fiscal year. It only takes a few hours for the investor to select the 10 stocks.

Transaction cost is a factor that needs to be further investigated. In Japan, to invest in a fund, the average purchase commission is approximately 1%. In addition, investors need to pay a trust fee each year, which varies from 2% to 10%. However, the average commission of purchasing or selling stocks is approximately 1% for non-internet trading, and 0.1% for internet trading. Therefore, the transaction cost for maintaining a Dogs of the Dow portfolio is same or less than purchasing a fund in the 1981–2000 period, and much less than purchasing a fund after 2001.

For simplicity, we assume that the transaction costs for the Dogs of the Dow portfolio and NIKKEI 225 portfolio are the same, and conduct simulation again for 1981–2010 data. As indicated by Table 14, the accumulated performance of the Dogs of the Dow strategy was 1015.39%, whereas that of NIKKEI 225 was 103.28%, with 1% transaction costs. When the transaction costs increased, the return of the two portfolios fell sharply. However, even after calculating for the highest transaction cost, the Dogs of the Dow strategy still had a high value of 550.47%. For all transaction cost rates, the performance of the Dogs of the Dow strategy was remarkably higher than the returns of NIKKEI 225.

In fact, after calculating the turnover of the 10 companies of the Dogs of the Dow strategy, we found that the annual rate of the turnover was 5.4, which means that there were approximately 5.4 companies changed in the 10 stocks for ever year. Hence, in actual practice, the transaction costs of the Dogs of the Dow strategy must be remarkably lower than the simulation in Table 14, which states the returns after

adjusting the transaction costs for all 10 stocks.

Consequently, even assuming that the transaction costs are same for both portfolios, the Dogs of the Dow strategy outperforms the bench mark. Moreover, because most individual investors have been trading stocks via the Internet since the end of the last century, the maintenance cost of the Dogs of the Dow portfolio is much less than buying a fund. The superiority of the Dogs of the Dow strategy is therefore even more evident.

Table 14 Comparison of accumulated performance after adjusting transaction costs

<i>Portfolio</i>	<i>Transaction costs</i>			
	<i>0%</i>	<i>1%</i>	<i>2%</i>	<i>3%</i>
<i>Dogs of the Dow</i>	<i>1372.71%</i>	<i>1015.39%</i>	<i>748.79%</i>	<i>550.47%</i>
<i>NIKKEI 225</i>	<i>139.62%</i>	<i>103.28%</i>	<i>76.16%</i>	<i>55.99%</i>

5.2.6 Conclusions of the Application for the Japanese Stock Market

In this section, we applied the Dogs of the Dow strategy to the Japanese stock market and compare the performance of the strategy with NIKKEI 225 on the basis of the results of a simulation. We found that the Dogs of the Dow strategy outperformed NIKKEI 225 in Japanese stock market during the 1981–2010 period. The results were statistically significant. Even after adjusting for risk by using the Sharpe Ratio, the Dogs of the Dow strategy outperformed NIKKEI 225. Moreover, we observed that even portfolios with fewer than 10 Dogs outperformed NIKKEI 225. Moreover, in practice, the Dogs of the Dow strategy was simple to understand, easy to operate, and

had lesser transaction cost than investing in a fund. Therefore, we concluded that the Dogs of the Dow strategy was powerful and practical in the Japanese market.

The results presented in this section show that the Dogs of the Dow strategy performs better in long-term investment rather than short-term investment. Hence, it is recommended that investors view the Dogs of the Dow strategy as a long-term investment strategy.

For further exploration of this topic, we plan to extend the simulation to 50 years and analyze more detailed information on the Dogs of the Dow strategy. We also intend to investigate whether the Dogs of the Dow strategy is effective even after adjusting for tax.

5.3 The Application for the Hong Kong Stock Market

5.3.1 The Simulation

In this section, we propose applying the Dogs of the Dow strategy to the Hong Kong stock market. For the market, the Hang Seng Index (HSI), which has been calculated since 1969, is the main indicator of the market performance in Hong Kong. At the end of year 2011, 48 stocks are capitalization-weighted to calculate the index and they represent about 60% of capitalization of the Hong Kong Stock Exchange.

We implemented the simulation of the Dogs of the Dow investment strategy in three steps: In step 1, we collected data for all the companies of HSI on December 31 (or the last trading day of the year), and then selected the 10 highest-dividend-yielding stocks. On the first trading day of the new year, we invested in the 10 stocks with equal

weighting. In step 2, we held these stocks for one year and then sold them at December 31 of the year. After updating the list of HSI, we invested in the new top-10 stocks with equal weighting on the first trading day of the next year. In step 3, we repeated the process for each year.

We searched for the stock prices and the real dividend data (2001-2003) on the Internet and in newspapers and obtained the expected dividend data (2004-2011) of all the companies of HSI from the China Company Handbook (TC Financial Research, 2003-2010). In this section, we implemented the simulation for the 2001–2011 data.

5.3.2 Comparison of Dogs of the Dow Strategy and Hang Seng Index

Table 15 presents the average returns and deviations of the Dogs of the Dow strategy and HSI. The Dogs of the Dow strategy had an average return of 11.14% and a standard deviation of 27.21%. HSI had a lower mean return, with the value of 5.55%. The standard deviation of HSI was higher than the Dogs of the Dow strategy, the value was 24.17%. Therefore, not only the return of the Dogs of the Dow strategy was higher than HSI, the risk of the Dogs of the Dow strategy was also lower than HSI. The table also provides data on the difference between the two portfolios. The Dogs of the Dow strategy had a 5.59 percent points higher return on average and the difference of the standard deviation was –1.66 percent points. The simulation result shows that the Dogs of the Dow strategy outperforms HSI from 2001 through 2011.

Table 15 The annual return summary of statistics for the Hong Kong stock market
(2001- 2011)

<i>Portfolio</i>	<i>Average annual return</i>	<i>Standard deviation</i>
<i>The Dogs of the Dow</i>	<i>11.14%</i>	<i>27.21%</i>
<i>HSI</i>	<i>5.55%</i>	<i>28.87%</i>
<i>difference</i>	<i>5.59%</i>	<i>-1.66%</i>

To check the statistical significance of the result, we conducted a T-test at a 5% significant level. In the test, $p=0.15842 > 0.05$, and thus the higher performance is not statistically significant.

Next, we compared the accumulated return of the Dogs of the Dow strategy and HSI. Fig. 13 shows the results. The upper line stands for the accumulated performance of the Dogs of the Dow investment strategy. And the lower line expresses the accumulated performance of HSI. Supposing that the asset value of both portfolios was 100 in 2000, at the end of fiscal year 2011, the Dogs of the Dow strategy has an accumulated value of 253.34. Especially in 2010, the Dogs of the Dow strategy has the highest accumulated value at 325.64, which is about 3 times the value in 2000. We can also observe that from 2000 through 2011, the Dogs of the Dow strategy always has a higher accumulated performance than that of HSI. By contrast, HSI line in the lower part of the graph shows relatively worse trend. The accumulated performance of HSI for 2011 is only 122.12, which implies that the asset value of the portfolio increased merely 22.12% in the 11 years.

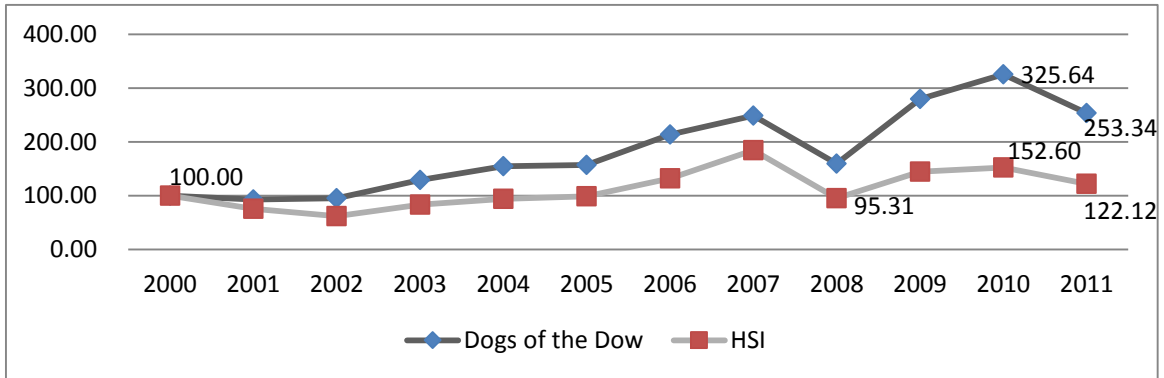


Fig. 13 Accumulated performance of the Dogs of the Dow strategy and HSI

Fig. 14 plots the difference between the Dogs of the Dow strategy and HSI annual portfolio returns for each of the 11 years. Here, a positive difference indicates that the Dogs of the Dow strategy outperforms HSI. From Fig. 14, we can observe that the Dogs of the Dow strategy outperforms HSI at 8 occasions from 2001 through 2011. Especially in 2002 and 2009, the Dogs of the Dow strategy was 20.21 percentage points and 19.77 percentage points greater than HSI, respectively. On the other hand, the worst performance of the Dogs of the Dow strategy was in 2006, when the difference between the two strategies was -21.17 points.

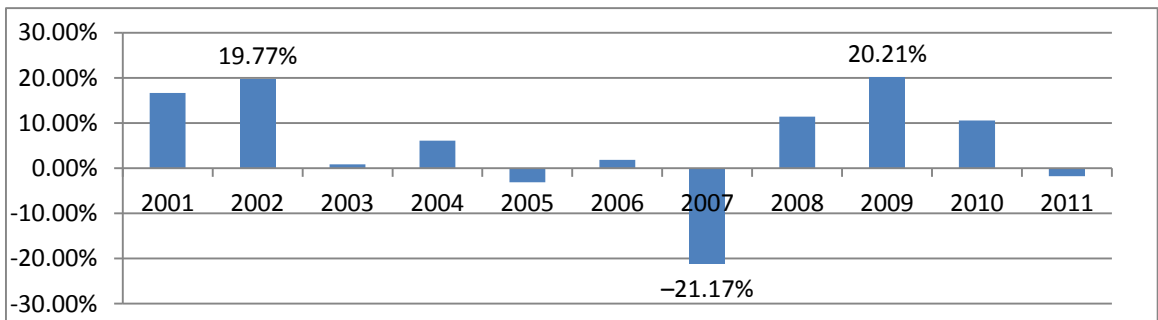


Fig. 14 Annual difference in returns between the Dogs of the Dow strategy and HSI

In this section, we also provide a 5-year subperiod analysis of the Dogs of the

Dow strategy. Table 16 reports the mean return and nominal difference between the Dogs of the Dow strategy and HSI. The data show that the Dogs of the Dow strategy outperforms HSI in all the 5-year subperiod. In 2001-2005, the difference between the Dogs of the Dow strategy and HSI is very large, at 8.06 percentage points. At the same time, the standard deviation of the Dogs of the Dow strategy is lower than that of HSI. Hence in 2001-2005, the Dogs of the Dow strategy has quite higher return and lower risk. In 2006–2010, the return of the difference between the two strategies is 4.58 percentage points, and the standard deviation of the Dogs of the Dow strategy is lower than that of HSI.

Table 16 Subperiod analysis for the Hong Kong stock market

<i>Subperiod</i>	<i>Mean return</i>		<i>The standard deviations</i>		<i>Nominal difference</i>
	<i>Dogs of the Dow</i>	<i>HSI</i>	<i>Dogs of the Dow</i>	<i>HSI</i>	
<i>2001-2005</i>	<i>9.80%</i>	<i>1.74%</i>	<i>14.84%</i>	<i>20.83%</i>	<i>8.06%</i>
<i>2006-2010</i>	<i>19.32%</i>	<i>14.74%</i>	<i>33.25%</i>	<i>34.01%</i>	<i>4.58%</i>
<i>2001-2011</i>	<i>11.14%</i>	<i>5.55%</i>	<i>27.21%</i>	<i>28.87%</i>	<i>5.59%</i>

5.3.3 The Performance for Other Numbers of Dogs

Here, we tested other portfolios with fewer Dogs, and compared the performance of each portfolio using the Dogs of the Dow investment strategy and HSI between 2001 and 2011. We named the portfolio with the top N stocks as Dow N strategy. The simulations of these strategies were conducted in a manner similar to that of the Dogs of

the Dow strategy but by using the top N stocks instead of the top-10 stocks.

From Fig. 15, we can conclude that all the portfolios of Dogs of the Dow investment strategy outperform HSI during the 2001–2011 period. The Dow 1 portfolio has the highest average annual return, but it also has the highest standard deviation of 35.56%. The Dow 10 strategy, which is the original Dogs of the Dow strategy, has the fifth-highest return, with a value of 11.14%. The return of HSI, however, is as low as 5.55%.

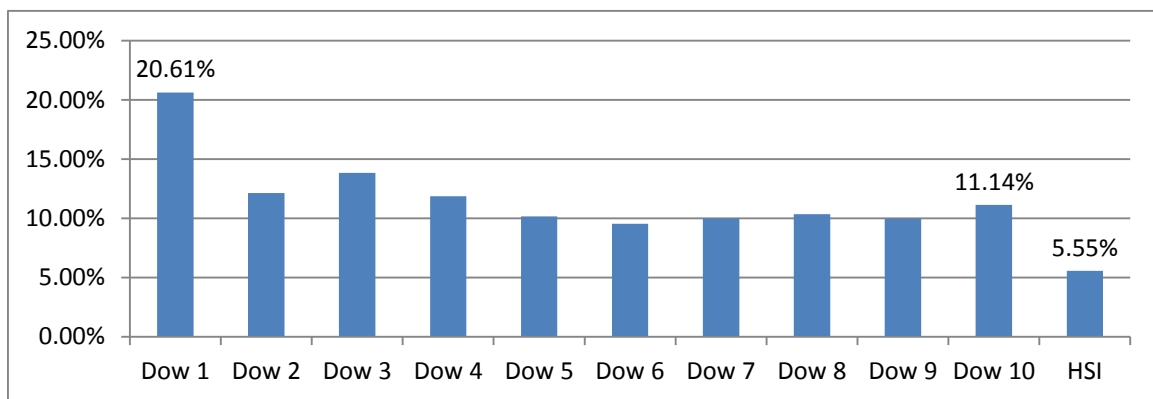


Fig. 15 The average annual return of all the portfolios of the Dogs of the Dow strategy and HSI

5.3.4 Conclusion of the Application for the Hong Kong Stock Market

In this section, we proposed to apply the Dogs of the Dow strategy to the Hong Kong stock market and compared the performance of the Dogs of the Dow strategy and HSI on the basis of the results of a simulation. We found that the Dogs of the Dow strategy outperformed HSI in the Hong Kong stock market during the 2001–2011 period. However, the result was not statistically significant. We also found that the portfolios

with fewer than ten Dogs outperformed HSI. Thus we can conclude that the Dogs of the Dow strategy is effective in the Hong Kong stock market.

Our future work is to extend the simulation for a longer period and analyze more detailed information of the Dogs of the Dow strategy. We also intend to investigate whether the Dogs of the Dow strategy is effective even after adjusting for the tax and transaction costs.

5.4 Conclusion

In this chapter we introduced the Dogs of the Dow strategy and applied it to the Japanese and Hong Kong stock markets. According to the simulation of different numbers of the Dogs of the Dow strategy, we found the favorite portfolio for each stock market.

After applying the Dogs of the Dow strategy to Japanese stock market, we can conclude that the Dogs of the Dow strategy is an effective strategy and has a good performance in the period from 1981 through 2010. Even after adjusting the risk of the Dogs of the Dow strategy by Sharpe Ratio, the performance of the strategy still outperforms NIKKEI 225. We also try other numbers of the Dogs of the Dow strategy to Japanese stock market, and we find that Dow N portfolios also outperform NIKKEI 225. Here Dow 6 portfolio has the highest return after risk adjustment. We also calculate that after adjusting for the risk and the transaction cost, the strategy also outperforms NIKKEI 225.

For Hong Kong stock market, the performance of the Dogs of the Dow strategy is also effective. Data show that the portfolio also has a good performance in Hong Kong stock market from 2000 through 2010. Not only the return of the Dogs of the

Dow strategy is higher than HSI, the risk of the Dogs of the Dow strategy is also lower than HSI. Furthermore, other numbers of the strategy all outperform HSI from 2000 through 2010.

We can conclude that the Dogs of the Dow strategy is effective in both Japanese and Hong Kong stock markets. For the future work, we want to check whether the Dogs of the Dow strategy is consistent with the market overreaction hypothesis.

Chapter 6 Conclusion and Discussions

In this study, we have examined methods to predict the return of Nikkei 225 index using an ANN. To search for new and effective input variables for an ANN, we collect 71 variables with respect to different aspects of the Japanese stock market. We select new combinations of input variables of 18 explanatory variables by fuzzy surfaces and utilize the combination to predict market returns. We employ monthly data obtained using the 18 variables to predict the return of the Nikkei 225 index, and then compare the prediction performance of the different models. The empirical results show that the proposed 18 input variables can successfully predict the stock market returns.

For the classic BP training algorithm, we conduct an experiment of 900 parameter combinations. Afterwards, we select the best model and the average level of the parameter setting experiments to compare with the conventional linear regression model. We find that the forecasting accuracy of ANN based on BP algorithm is much more effective than the conventional linear regression.

We apply GA and SA for improving the basic learning algorithm of the ANN model. We compare the performance of improved models with the BP-ANN hybrid model. The best model of the 900 parameter combinations of ANN, based on BP algorithm, has an effective performance. Compared to the average level, hybrid SA and BP approach overcomes the weakness of local minimum, and greatly improves the accuracy of prediction. We find that the forecasting accuracy of the neural network with weights and biases estimated by hybrid global search algorithms outperform the one that is trained by the BP algorithm. In addition, we synthesize the performance of the accuracy of prediction and the running time, and suggest that the GA-ANN hybrid model provides a more effective forecast of future values than other prediction models

because the prediction accuracy is much higher.

When the data is huge and complex, we consider that it is better to use the nonlinear models rather than the linear function for the weak ability of capturing nonlinear relationships among large number of variables. It is apparent from this research that a global search technique, such as the GA or SA, may be more suitable for solving nonlinear problem. However, when you have the high request on the precision of the prediction, we suggest to conduct numerical parameter setting experiments of BP algorithm which is the most popular method for training the ANN model.

For future research, we want to use a combination of the 18 good explanatory variables to forecast the returns of the other stock markets. Furthermore, we want to predict the direction of the stock market index movement by using ANN with other algorithms.

After we confirm the successful performance of the ANN model with GA algorithm in forecasting the return of Nikkei 225 index, we suppose to apply the hybrid model in forecasting the direction of the next day's price of the Nikkei 225 index. We try to apply two types of technical indicators to predict the direction. First we train the two types of data by ANN model which is adjusted the weights and bias by GA algorithm. Then we test the performance of ANN model with GA algorithm by applying each type of input variables. The experiments imply that input variables Type 2 can generate higher performance, and the probability for predicting the direction is 81.27%. We also compare the performance of our study with similar studies, the results show that our method is more effective and can generate higher prediction accuracy.

In this study, we also try to apply the Dogs of the Dow strategy to the Japanese and

Hong Kong stock markets, and then compare the performance of the strategy with bench market index on the basis of the results of a simulation. We observe that the Dogs of the Dow strategy outperforms NIKKEI 225 in Japanese stock market during the 1981–2010 period. The results are statistically significant. Even after adjusting for risk by using the Sharpe Ratio, the Dogs of the Dow strategy outperforms NIKKEI 225. Moreover, we find that even portfolios with fewer than 10 Dogs outperform NIKKEI 225.

In addition, we find that the Dogs of the Dow strategy outperforms HSI in the Hong Kong stock market during the 2001–2011 period. However, the result is not statistically significant. We mention that the portfolios with fewer than ten Dogs outperform HSI. Therefore, we can conclude that the Dogs of the Dow strategy is effective in the Hong Kong stock market.

Furthermore, in practice, the Dogs of the Dow strategy is simple to understand, easy to operate, and has lesser transaction cost than investing in a fund. Therefore, we conclude that the Dogs of the Dow strategy is powerful and practical in the Japanese and Hong Kong stock markets. In addition, the results presented in this study show that the Dogs of the Dow strategy performs better in long-term investment rather than short-term investment. Hence, it is recommended that investors view the Dogs of the Dow strategy as a long-term investment strategy.

For further exploration of this topic, we plan to extend length of the data and analyze more detailed information on the Dogs of the Dow strategy. We also intend to investigate whether the Dogs of the Dow strategy is effective even after adjusting for tax.

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Journal papers:

- 1 Yan H., Song Y., Qiu M. and Akagi F., An Empirical Analysis of the Dogs of the Dow Strategy for the Taiwan Stock Market, *Journal of Economics, Business and Management*. Vol. 3, No. 4, pp.435-439 (2014)
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- 1 Song Y., Qiu M. and Akagi F., Application of Artificial Neural Network in Predicting Stock Market Returns, *Proceedings of the 2014 FIT-NUST Joint Seminar for Double Degree Students*, Nanjing, China. (2014-11) (印刷中)
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