Applying Self-Organizing Mapping Neural Network for Discovery Market Behavior of Equity Fund

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Abstract: - Maximizing the profit and minimizing the loss notwithstanding the trend of the market is always desirable in any investment strategy. The present research develops an investment strategy, which has been verified effective in the real world, by employing self-organizing map neural network for mutual funds tracking the trends of stock market indices according to macroeconomics indicators and weighted indices and rankings of mutual funds. Our experiment shows if utilizing strategy 3 according to our model during a period from January 2002 to December 2008 the total returns could be at 122 percents even though the weighted index fell 22 percents during the same period and averaged investment returns for random transaction strategies stand at minus 25 percents. As such, we conclude that our model does efficiently increase the investment return.

Key-Words: - Equity Fund, Neural Network, Self-Organizing Mapping, Investment Strategy

1 Introduction

Financial products are subject to rapid changes, and the development thereof has also come to flourish. Even so, it is very difficult for the general investing public to know everything about all kinds of derivatives. Of course, investors can choose to directly invest in the stock market, but doing so might only lead to substantial risk on the part of investors when the invested company is in deep financial trouble [1]. In the similar situations, small investors are more susceptible to risk or loss caused. Through investing mutual funds, the small investors may effectively reduce the overall associated risks considering the mutual fund bears the characteristics of pooling investment money together, sharing the risks associated with the investment, and enjoying the profit together [2]. As such, the present research chooses mutual funds as the investment objective.

Global financial tsunami led to recessions in many countries worldwide. In order to stimulate the capital market, Taiwan central bank lowered the deposit rates for many times, officially pushing the country to enter into an era of zero interest rate. Despite some people may simply put their money in the banks hoping to wither the storm, the inflation may cast the dark clouds over their deposits. Therefore, how people can earn the excess profit in the chaotic financial markets has become a hot topic. As a result, an effective model will be proposed in the present research to help invest in the financial market.

The traditional performance evaluation models, such as early Treynor indicator [3], the Sharpe indicator [4], and the Jensen indicator [5], are derived from the capital asset pricing model (CAPM). Though these models evaluate the relationship between risks and investment returns and serve as an important reference for the investors when it comes to mutual fund selections, they rarely provide any information regarding when to purchase or sell the mutual funds. From the perspective of the investors, how to timely respond to the turns of the markets always concerns them the most.

The macroeconomic indicators tend to represent the spatial and temporal context of the economy. There exists interdependence between the stock market and the macroeconomic indicators.

As the current computing devices possess large amount of computing power, how to fully utilize the computing resource becomes more and more critical. A self-organizing mapping (SOM) neural network [6], which mimics the human brain activities, could equip its output units with similar functions learned from inputs of the network. This characteristic is very suitable for research of behavior clustering in the context of different time and space between macroeconomics indicators and the mutual fund. Nobel Prize Laureate D. Kahneman proposed Prospect

Theory [7] successfully explaining that a certain degree of difference exists between real environment and efficiency market and proving regular behaviors of human beings are associated with irrationalities. Since then, relevant studies utilizing artificial intelligence (AI) to predict stock markets have been gaining their popularity [8][9][10]. Therefore, the present research utilizes the usage of SOM map neural network for appropriately grouping the mutual fund and the macroeconomics. Based on the results of the present research, another reference for investment decisions could be provided to help investors at the time of navigating the ever-changing market.

1.1 Research scope and limitation

Sample period and data source:

(1) Sample period: October 1998 to December 2008

(2) Sample data: Select 189 Taiwan-based mutual funds and 13 macroeconomics indicators from Taiwan futures data from Taiwan Futures Exchange while the Taiwan-based mutual fund is categorized by Dr. Lee and Dr. Chiu as the type “1” domestic stock-based mutual funds provided in Taiwan mutual fund evaluation website

(3) Data source: Taiwan Economic Journal (TEJ) and Taiwan Futures Exchange

Research Limitation:

(1) As there are a variety of mutual funds on the market and for the purpose of ranking the Taiwan weighted index (as a hypothetical mutual fund) relative to our mutual fund selections, only domestic stock-based mutual funds are selected

(2) When the selected domestic stock-based mutual funds were launched in a particular month, the mutual fund not launched then would not be ranked for that particular month

(3) To simplify our model, only purchasing transactional fee (1.5 percents) is taken into account in our simulated mutual fund transactions with no discount (such as 50-percent off in the transactional fee), other fees (such as procedural fee associated with “short-term” transaction), and 5-point deduction from transaction cost in a single simulated future transaction (buy and sell) [11]

(4) To further simplify our model, our simulated mutual fund transactions do not consider certain factors such as fluctuations in interest and commodity price.

2 Lecture Review

The present research combines the rank of mutual funds and macroeconomic indicators, employs a self-organizing map neural network for discovering market behavior in the mutual funds. This chapter is primarily devoted to introducing theories and concepts that could be found in the present research. Chapter 2.1 starts from researches according to conventional financial engineering while chapter 2.2 discusses the researches focusing on macroeconomics indicators. And chapter 2.3 discloses the researches related to self-organizing map neural networks.

2.1 Conventional Financial Engineering

Treynor [12] adopted security market line (SML) according to CAPM to obtain β coefficient for market risk. A larger coefficient corresponds to a larger fluctuation associated with an investment portfolio, which in turn corresponds to a larger investment risk. A larger Treynor indicator corresponds to a larger excessive income per system risk, which indicates that investment performance of the mutual fund is better. Sharpe [13] suggested when evaluating the investment performance taking into account a risk and an income is necessary. As such, Sharpe treated a standard deviation associated with a percentage of the investment portfolio as another risk factor that is capable of impacting on the income of the investment portfolio when evaluating the investment portfolio.

Accordingly, Sharpe derived a Sharpe indicator representative of a larger return ratio that comes from a higher inherent risk and concluded that a mutual fund is better when the return is larger after the consideration of risk factors. Jensen [14] utilized an absolute performance indicator for evaluating whether the performance of the mutual fund investment portfolio is better than other investment portfolios of the same risk level. A positive Jensen indicator suggests the performance of the mutual fund investment portfolio is better than that of the market investment portfolio.

Wermers [15] selected U.S. mutual funds from Jan. 1975 to Dec. 1994 as research sample only to find that mutual funds of higher turn-over rates outperform Standard Poor (S&P) 500 index. Such conclusion suggests that the managers of the mutual funds of higher turn-over rates are capable of picking better stocks. Goetzmann and Ibbotson [16], on the other hand, selected 728 mutual funds from 1976 to 1988 and compiled monthly data of these mutual funds to verify whether the performance continuity of the mutual funds actually exists. Goetzmann and Ibbotson further utilized Jensen indicator and return ratio in terms of S&P 500 index as market return ratio for leading and trailing test on basis of a fixed period of time. Jensen indicator in any period that leads a median is defined as a “winner” while a label of “loser” indicates Jensen indicator trails the median. Experiment shows that whether Jensen indicator or return ratio indicator is used performances of mutual fund and growth fund continue to exist.

2.2 Macroeconomic indicators

Lin [17] employed neural network and multi-degree regression using 33 macroeconomic indicators with 62 corporations’ samples for predicting the return ratio of stock investment. Lin concluded that:

(1) prediction error associated with return ratio of the investment portfolio could be reduced when the number of the investment portfolios increases; many factors may impact on individual stocks and risks could be offset through the investment portfolio; and

(2) neural network outperforms multi-degree regression model in predicting the performance of the sampled stocks; as to stocks not included in the samples multi-degree regression model outperforms the neural network; with the increase of the investment portfolios the neural network gradually outperforms the multi-degree regression model, indicative of the neutral network is better than the multi-degree regression model when it comes to predicting the return ratio of the investment portfolio

Chen [18] adopted the multi-degree regression model in showing a relationship between changes in each macroeconomic factors and changes in stock index and whether foreign investment, when allowed to invest in domestic stock market, has any impact on such relationship. Lin found out:

(1) money supply monthly variation rate is positively correlated to stock index monthly variation rate before or after the foreign investment is allowed to invest in the domestic stock market;

(2) interest monthly variation rate seems having nothing to do with stock index monthly variation rate before allowance of foreign investment in domestic stock market but becomes negatively correlated to stock index monthly variation rate after the allowance;

(3) exchange rate monthly variation rate is negatively correlated to stock index monthly variation rate before the foreign investment is allowed to invest in domestic stock market but becomes insignificant to the stock index monthly variation rate after the foreign investment is allowed to invest in the domestic stock market;

(4) wholesale price index monthly variation rate is positively correlated to stock index monthly variation rate before the foreign investment is allowed to invest in the domestic stock market but becomes insignificant to stock market monthly variation rate after the allowance; and

(5) leading indicator composite index monthly variation rate is positively correlated to stock index monthly variation rate before or after the foreign investment is allowed to invest in the domestic stock market Chen [19] chose 16 Taiwan macroeconomic indicators and 10 U.S. macroeconomic indicators to further filter out recombination variables through factor analysis or other systematic approaches for establishing a verification assumption and an experiment model via time sequence analysis. The experiment shows:

(1) past Taiwan stock index return ratio may predict future stock index return ratio; and

(2) Taiwan macroeconomic indicators predicts future Taiwan stock index return ratio while U.S. macroeconomic indicators do not; and

(3) Taiwan macroeconomic variable model and past Taiwan stock index return ratio model outperform the stock index though Taiwan macroeconomic variable model is superior to past Taiwan stock index return ratio model in this regard.

2.3 SOM

From 1980, when SOM neural network was firstly introduced, to 2000, around 4300 corresponding researches have been published. Kohonen indicated that conventional grouping methods may only obtain results of the grouping without any information regarding the structure of the grouping. Compared with the conventional multi-variable analysis, SOM neural network is not only better in generating the grouping results but also capable of displaying high-dimension data in terms of low-dimension relationship. Deboeck [20] proposed application of SOM neural network to finance, economics, and marketing areas with mutual fund selection as primary focus of research. Deboeck identified 50 global stock-based mutual funds from Morningstar-graded 500 mutual funds, and applied SOM neural network for grouping these selected mutual funds. Deboeck concluded SOM neural network may provide investors with another superior mutual fund investment decision indicator in addition to mutual fund evaluations.

3 Research model development

The present research is conducted accounting to the flow chart shown in Fig. 1.

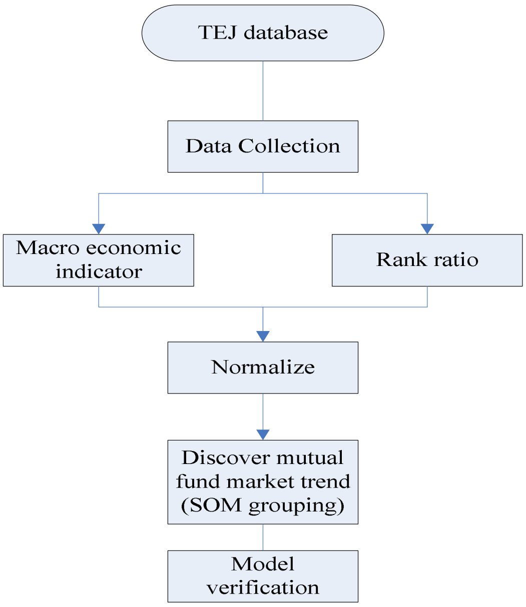


Fig. 1 Research flow chart

3.1 Data collection

(1) Taiwan weighted index data, mutual fund information, and macroeconomics indicators (13 in total) from TEJ
(2) Taiwan futures index data from Taiwan Futures Exchange
(3) Sample period: October 1998 to December 2008
Sample data: 189 Taiwan-based mutual funds from Taiwan mutual fund evaluation website and categorized by Dr. Lee and Dr. Chiu as the type "1" domestic stock-based mutual funds

3.2 Macro economic indicator and Rank ratio

3.2.1 Macro economic indicator

Macroeconomics indicators may possess certain capability in predicting trend of finance market behaviors. Based on past researches, the present research uses 13 macroeconomics indicators, which are listed in table 1, as one set of inputs to the presently proposed research model.

Table 1 Macroeconomics indicators as inputted variables

	Lin 2005 [13]	Chen 2005 [14]	Chen 2002 [15]	Hsu 2004 [16]	Lee 2008 [7]	Selected
Money supply (M1b) annual increase rate		V	V	V	V	V
Taiwan wholesale price index	V	V	V	V	V	V
business cycle signal score	V		V	V	V	V
Taiwan coincident indicator composite index	V				V	V
Taiwan leading indicator composite index	V	V			V	V
export	V			V	V	V
import	V			V	V	V
Taiwan rediscount rate	V		V		V	V
Dow Jones Industrial index					V	V
NTD v. USD		V			V	V
one-month fixed term interest rate					V	V
one- year fixed term interest rate		V			V	V
money supply amount-M2 annual increase rate			V		V	V

3.2.2 Rank ratio between weighted index and mutual fund

To prepare a monthly rank ratio between weighted index and mutual funds, following steps are taken:
(1) Consider weighted index as a hypothetical mutual fund, and add it to our selected 189 stock-based domestic mutual funds to form a group of 190 mutual funds,
(2) Rank the weighted index relative to our selected mutual funds by computing net value variation percentages for the weighted index and selected mutual funds,
(3) Divide the rank of the weighted index and the number of the mutual funds in a particular month to come up with a percentage for the weighted index. For example, if the rank for the weighted index in October 2008 is 152 and the number of all mutual funds stands at 190 the percentage for the weighted index in that particular month is 80 percents, and
(4) The percentage obtained from step (3) is rank ratio between the weighted index and mutual fund.

3.3

3.3 Normalization

Consider macroeconomics indicators and ranking ratio between weighted index and mutual funds may be different in value range definition, and the input could be so concentrated or widespread that the grouping is affected, before any data is inputted into SOM neural network, min-max normalization is employed to normalize values between 0 and 1. The normalization is performed according to an equation as follows:

$$X_i = \frac{X_i - \min_i}{\max_i - \min_i}$$

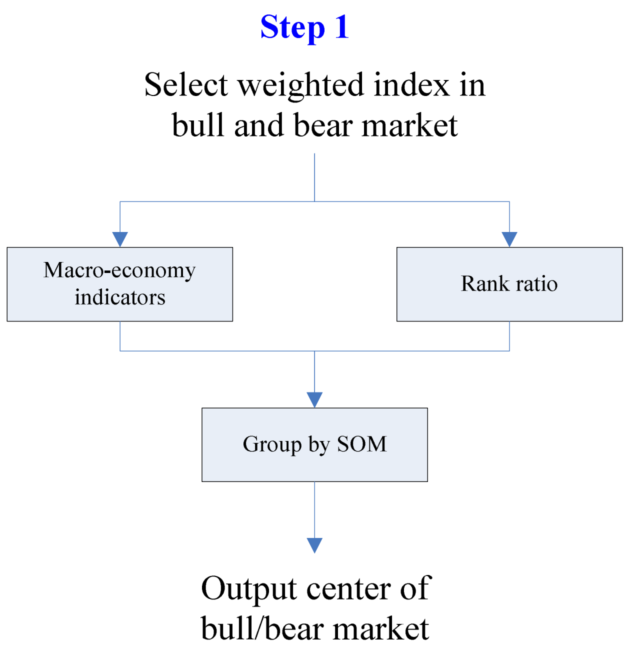
wherein Xi is the original value of ith indicator, mini is the smallest original value for ith indicator and maxi is the biggest original value of ith indicator.

3.4 Discover mutual fund market trend

Network algorithm and parameter configuration are as follows:
Network initial weight
To render each location in a coordinate plane to represent the same, instead of selecting a random value the present research configures the initial weight according to "Same weight increment method" proposed by Dr. Huang with same increment on basis of coordinate location from output module. Such method is described in the below:

$$W_{ijmn} = \frac{m+n}{M \times N}$$

Wijmn: weight of ith element of character vector corresponding to jth output unit on a two-dimension plane as (m, n)
M: length of network output matrix X
N: length of network output matrix Y
m: length of output unit matrix X
n: length of output unit matrix Y
Network input layer: 13 macroeconomics indicators and one rank ratio between weighted index and mutual fund.
Network output layer: 10 by 10 network topology matrix (100 output units)
Neighbor function: Gaussian function
Neighbor diameter: 2
Learning rate: 0.2
Learning times over 10,000 or averaged errors associated with output neural unit less than 0.0000001
Step 1: Mutual fund trend discovery model selects macroeconomics indicators and rank ratios between weighted index and mutual funds when the weighted index is in bull market and bear market, respectively and inputs them to SOM neural network to be grouped by learning. Thereafter, our approach obtains centers of the distribution of the data in terms of the 2-dimention plane.



Step 2: Select macroeconomics indicators and rank ratios between the weighted index and mutual fund for our selected months respectively and input them into SOM neural network to be grouped by learning. Each result of the group by learning is represented in terms of a location in the 2-dimension plane. Compute distance between the results and the centers in the bull and bear markets obtained in Step 1. When the result is closer to the center of the bull market, a "bull market" signal is generated. While the result is closer to the center of the bear market, a "bear market" signal is generated. Fig.2, as a flow chart showing a discovery of a mutual fund, provides the details of Step 1 and Step 2.

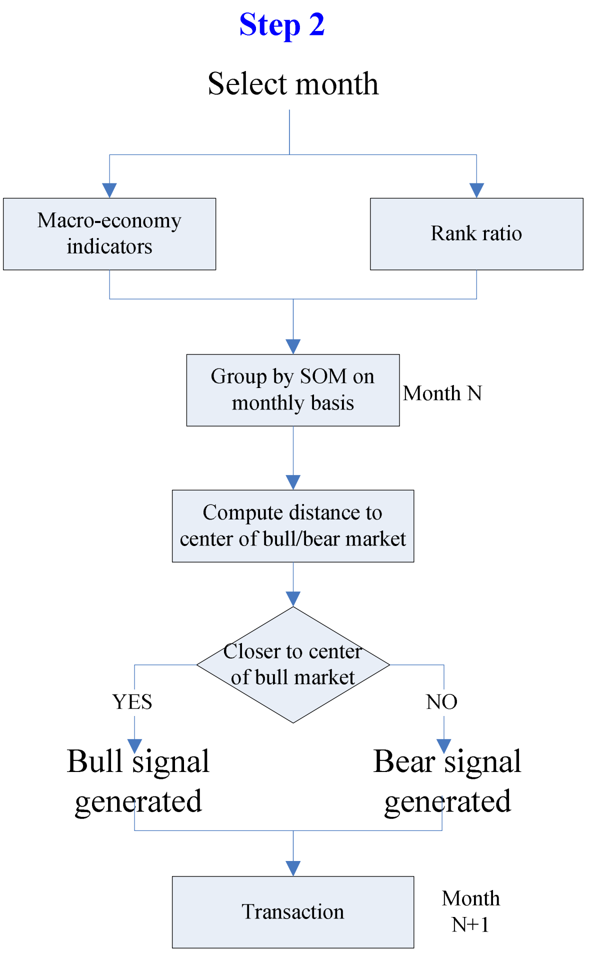


Fig. 2 Mutual Fund Market Discovery Flow Chart

3.5 Random walk model

Traditional finance engineering generally admits the unpredictability of stock market and thus the trend of the market is consistent with Random Walk theory. As such, the stock price generally reflects all possible information in the market. Since the occurrence of the information is random, the change in stock price is random as well. Fama [21] proposed efficiency market theory based on an assumption that price moving trend in the past has nothing to do with that in the future. Therefore, a random trading strategy for each "buy" and "sell" of stock in the market should be randomly generated without any prediction on the trend of price moving.

3.6 Model verification

To compare investment returns of different strategies from models proposed by the present research, explanations for those strategies for transaction simulations are as follows:

(1)Simulated transaction strategy 1: sample data includes information of stock-based domestic mutual funds at the beginning and end of months from January 2002 to December 2008. Buy if any "bull" signal was generated in the preceding month or sell if any "bear" signal was generated in the preceding month. Buy and sell for every three month during the above-mentioned period.

(2) Simulated strategy 2: sample data includes information of stock-based domestic mutual funds at the beginning and end of months from January 2002 to December 2008. Buy if any "bull" signal was indicated in the preceding month or wait if any "bear" signal was generated in the preceding month. When compared with strategy 1, no mandatory "buy/sell" limitation (i.e., transact every three months) is set. Any buy and sell in the current month is dependent on buy and sell signals in the previous month.

(3) Simulated strategy 3: sampled data includes information of stock-based domestic mutual funds at the beginning and end of months from January 2002 to December 2008, and Taiwan futures index data at the beginning and end of the months during the same period. Buy if any "bull" signal was indicated in the preceding month or short futures if any "bear" signal was generated in the preceding month, no mandatory "buy/sell" period (e.g., every three month) is set in this strategy. Any buy and sell in the current month is dependent on buy and sell signals in the previous month.

4 The experiment and result

The goal of the experiment of the present research is to establish a stock-based mutual fund transaction system according to SOM neural network with inputs from rank ratios between the weighted index and mutual funds and macroeconomics indicators. In doing so, the trend of Taiwan weighted index could be predicted in a more accurate manner. The model invests the capital according to the generated "bull" or "bear" signal. The experiment flow shown in Fig. 3 includes data collection, data processing, and model verification.

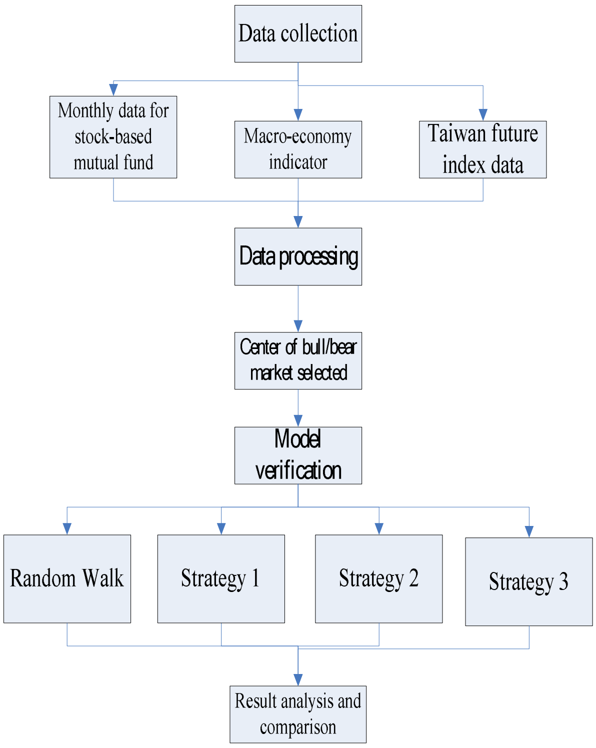


Fig. 3 Experiment flow chart

4.1 Research objective and period

Sample data for the present experiment includes Taiwan weighted index (TAIEX) of Taiwan Security Exchange, stock-based domestic mutual funds, and Taiwan index futures of Taiwan Futures Exchange from October 1st 1998 to December 31st 2008 (without considering October 1st 2001 to December 31st 2001). The detail is shown in Fig. 4.

The data includes a group of 120 end-of-month Taiwan weighted indices, 120 start-of-month and end-of-month data for the selected mutual funds, and 120 start-of-month and end-of-month Taiwan index futures data. In Fig. 4, the period from Oct. 1st 1998 to Sep. 30th is a training period while the period from Jan. 1st 2002 to Dec. 31st, 2008 is a simulation period. More specifically, the present research utilizes data from October 1st 1998 to March 31st 2000 as training data for "center of bull market" while using the data from April 1st 2000 to September 30 2001 as training data for "center of bear market."

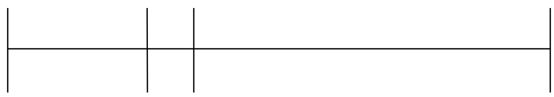


Fig. 4 Sampling period for present research

4.2 Training result for center of "Bull Market" and center of "Bear Market"

The training data during October 1998 to March 2000 indicates that the center of "bull market" is (3.06, 2.67), and the center of the bear market is (7.83, 5.67) in terms of a 2-dimension plane.

With the location of the center of the "bull market" and the center of "bear market" in place, the flow of the present research computes the distance to the two centers indicated above. According to the result of the distance computation, when the location closer to center of "bull market" a "bull" signal is prepared; otherwise, a "bear" signal is generated.

Fig. 5 shows a 2-dimension plane coordinates during bull markets and bear markets between Oct. 1998 to Sep. 2001 indicating centers of the bull and bear markets. The bull market coordinates are generally at the left bottom corner while the bear market coordinates are at the right top corner.

Trade simulation shown in chapter 4 is processed according to distance of the coordinates of the centers of the bull markets and the bear markets. As such, the selection of the centers of the bull markets and the bear markets plays a critical role in determining whether the model is accurate.

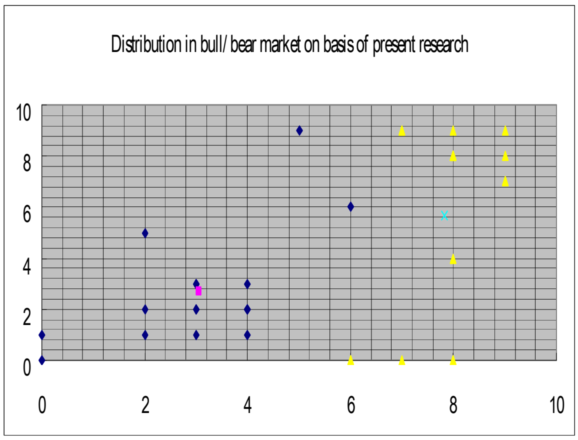


Fig. 5 Distribution in bull/ bear market on basis of present research

4.3 Illustration of Trade Strategy

4.3.1 Random Walk
The present research utilizes information at beginning and end of months between Jan. 2002 to Dec. 2008 for domestic stock-based mutual funds. The simulation invests 10 millions in 10 randomly selected mutual funds and transacts the mutual funds every three month with transaction fees of mutual fund purchase standing at 1.5 percents. The simulation further calculates the amount of the benefit/loss and the return ratio at the end of the years.

4.3.2 Strategy 1
Fig. 6 illustrates a flow chart for Strategy 1 according to the present research. The simulation for Strategy 1 utilized the same information of the stock-based mutual funds from Jan. 2002 to Dec. 2008. The simulation is conducted with following principles: (1) when the end of the preceding month indicates a bull market the investment portfolio makes purchase, otherwise the portfolio stays pat; (2) the purchase is made for top 10 mutual funds in the preceding month with the transaction fee standing at 1.5 percents; and (3) the simulation calculates the benefit/loss and the return ratio for comparison with other investment strategies.

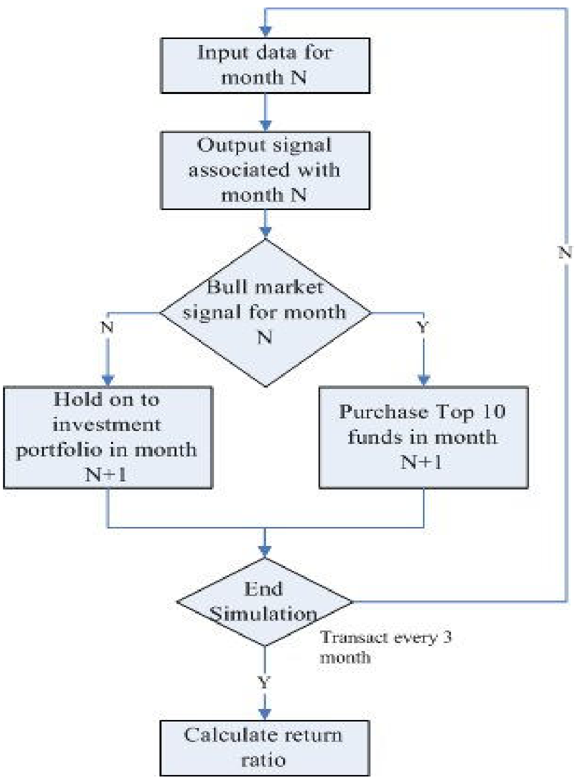


Fig. 6 Flow chart for implementation of Strategy 1

The flow for Strategy 1 includes: input the data of month N into the model established by the present research for generation of signal of bull market or bear market, when the signal of bull market is generated purchase top 10 mutual funds in month N or otherwise hold on to the current investment portfolio, transact every three months to determine whether to terminate simulated transaction, and, calculate benefit/loss associated with transaction performed according to the generated signal.

4.3.3 Strategy 2
Strategy 2 is substantially similar to Strategy 1 except for no mandatory limitation on when to transact is imposed. In other words, the transactions according to Strategy 2 could take place in any month pursuant to the bull market signal or the bear market signal generated in the preceding month. Fig. 7 shows a flow for implementation of Strategy 2.

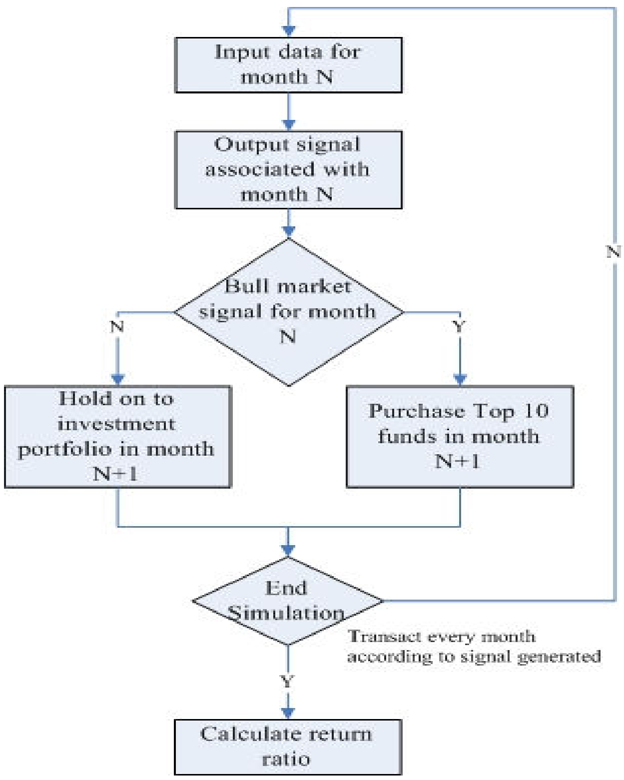


Fig. 7 Flow chart for implementation of Strategy 2

The flow for the implementation of Strategy 2 includes: input the data of month N into the model established according to the present research for generation of signal of bull market or bear market, in event of bull market signal for month N in month N+1 purchase top 10 mutual funds in the preceding month (month N) while holding on to the portfolio when the bear market signal is generated, and in any given month purchase or sell the mutual funds according to the signal generated in the preceding month.

4.3.4 Strategy 3

Compared with Strategy 1 and Strategy 2, Strategy 3 proposed by the present research further utilizes information at beginning and end of months for Taiwan stock index-basis futures during the period from Jan. 2002 to Dec. 2008. Strategy 3 is implemented by making the purchase for top 10 mutual funds in the preceding month when the signal associated with the preceding month is a bull market signal, and by selling the mutual funds and shorting the futures when the signal associated with the preceding month is a bear market signal. The extent of shorting the futures depends on the amount of cash in the portfolio when such emptying is to be performed. And both purchasing and shorting require 5-point transaction fee. Same as Strategy 2, Strategy 3 has no limitation on when such transaction could be implemented.

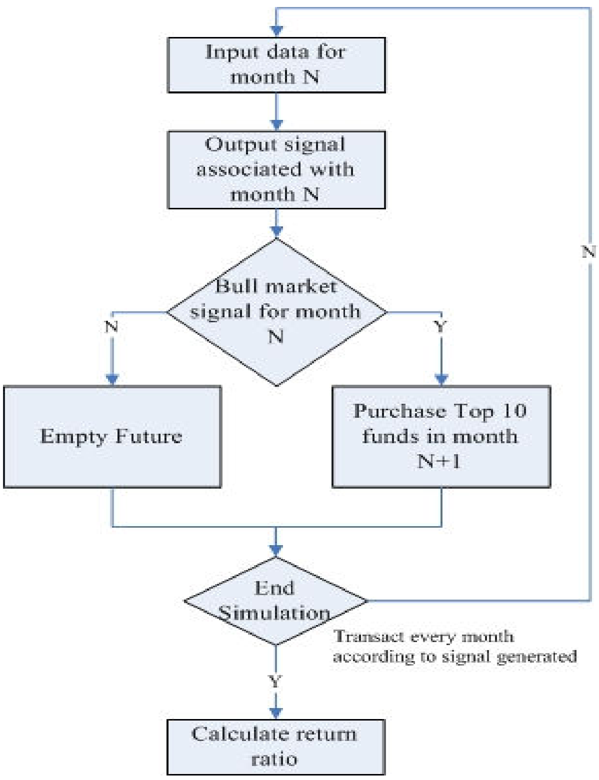


Fig. 8 Flow chart for implementation of Strategy 3

Fig. 8 illustrates the implementation of Strategy 3. Strategy 3 includes: input the data of month N into the model established by the present research for generation of bull market or bear market signal, and when bull market signal is generated for month N in month N+1 the investment portfolio purchase top 10 mutual funds in month N while emptying the futures in the same month (month N+1) when bear market signal for month N is generated. Table 2 in the below summarizes each of investment strategies previously discussed.

Table 2 Summary of investment strategies

Strategy	Description
Random Walk	Randomly purchase 10 mutual funds, transact every three months, and average 30 simulated transactions
Weighted Stock Index Return Ratio	5872.14 (Jan. 2002) and 4591.22 (Dec. 2008)
Strategy 1	According to signal generated, purchase top 10 mutual funds when bull market signal is generated, and transact every three months
Strategy 2	According to signal generated, purchase top 10 mutual funds when bull market signal is generated while staying put when bear market signal is generated (no transaction timing restriction imposed)
Strategy 3	According to signal generated, purchase top 10 mutual funds when bull market signal is generated while emptying futures when bear market signal is generated (no transaction timing restriction imposed)

4.4 Experiment result analysis and comparison

Invest hypothetical 10 millions according to three strategies developed by the present research and Random Walk strategy, the end-of-year investment return is shown in Table 3 and Table 4.

Table 3 End of Year Investment Return

Year	Rnd. Walk	Strategy 1	Strategy 2	Strategy 3
2002	7,507,130	7,984,410	8,916,745	9,611,353
2003	11,341,446	11,409,613	11,137,585	10,468,139
2004	9,034,728	10,687,036	10,754,867	11,629,824
2005	12,923,707	12,278,177	15,011,452	16,136,171
2006	11,098,198	11,537,225	10,580,551	9,358,935
2007	10,393,863	9,821,865	11,790,144	11,112,584
2008	5,198,642	8,625,725	9,542,658	13,852,124

Table 4 Investment Return Ratio

Year	Rnd. Walk (%)	Strategy 1 (%)	Strategy 2 (%)	Strategy 3 (%)
2002	-24.92	-20.16	-10.83	-3.88
2003	13.41	14.09	11.37	4.68
2004	-9.65	6.87	7.54	16.29
2005	29.23	22.78	50.11	61.36
2006	10.98	15.37	5.80	-6.41
2007	3.93	-1.78	17.90	11.12
2008	-48.01	-13.74	-4.57	38.52
Max*	29.23	22.78	50.11	61.36
Min*	-48.01	-20.15	-10.83	-3.88
Sum*	-25.02	23.44	77.34	121.69

Max: maximum annual averaged investment return
Min: minimum annual averaged investment return
Sum: Accumulative investment return from 2002 to 2008

From our experiment, Strategy 3 outperforms Strategy 2, Strategy 1, and Random Walk in terms of annual investment return during 2002 to 2008. Further, Strategies 1, 2, and 3 defeat the weighted index and Random Walk strategy. Result of experiment is summarized in Table 5.

Table 5 Simulated Transaction Comparison

Description	Rtn %
Weighted Index: Investment return on basis of 5872.14 in 2002/01 and 4591.22 in 2008/12	-21.8
Random Walk: Randomly purchase 10 mutual funds, buy/sell every three months, average 30 simulated transactions	-25.0
Strategy 1: Purchase top 10 mutual funds, buy when “bull,” wait when “bear,” and “buy/sell every three months	23.4
Strategy 2: Purchase top 10 mutual funds, buy when “bull,” wait when “bear” without any mandatory buy/sell period	77.3
Strategy 3: Purchase top 10 mutual funds, short futures, buy when “bull,” short futures when “bear” without any mandatory “buy/sell” period	121.7

5 Conclusion

Many factors, whether they are man-made or not, may affect the stock markets and the mutual fund markets. Many scholars ever considered the markets were not predictable. Though investors tend to maximize the benefits while minimizing the losses as much as possible, they might not have transparent guidelines in hand. By purchasing the mutual funds of best performances in the bull market, and by selling the mutual funds or even emptying the futures to get extra benefits in the bear market apparently are viable options for the investors [22] [23]. But when to implement the purchasing or selling/emptying creates a challenge to the investors. The current research selects 189 stock-based mutual funds and a variety of macroeconomics indicators as inputs to SOM neural network. The present research also proposes an approach of determining the trend of the market so as to develop an investment model accordingly. While investing on basis of the proposed model, the investment return is far greater than Random Walk strategy and outperforms weighted index.

According to our experiment, the present model is:

(1) With superior market trend discovery capability,

(2) A superior decision-making aiding tool helping the investor in analyzing potential market trends in the future, and

(3) With higher investment return than that from fixed term interest return or adoption of Random Walk transaction strategy.

Though our model outperforms the weighted index and Random Walk trading strategy, it does not predict the future trend in price moving with 100 percents of accuracy. Therefore, the accuracy rate and investment return of the current model could be further improved in the future researches. Couple of potential improvements could be:

(1) Selection of centers of “bull” and “bear” markets could be through artificial intelligence and adjusted dynamically at different points of time to render our model to be more accurate,

(2) Assignment of different weights to the data according to the dates associated with the data to render our model to be more in line with what actually takes place,

(3) Many researches [24][25][26][27], such as growing ring SOM, supervised SOM, hybrid SOM-FBPN, SOM of SOMs, have been proposed to improve efficacy of SOM. Subsequent researches could focus on whether different SOMs may enhance accuracy and return ratio.

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