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Modeling and simulation of the open-end equity mutual fund market in Taiwan by using self-organizing map

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ABSTRACT

This research applies artificial intelligence (AI) of unsupervised learning self-organizing map neural network (SOM-NN) to establish a model to select the superior funds. This research period is from year 2000 to 2010 and picks 100 domestic equity mutual funds as study object. This research used 30 days prior to the beginning of each month's prior 30 days, 60 days, 90 days on fund's net asset value and the Taiwan Weighted Stock Index (TAIEX) return as the fund's relative performance evaluation indicators classified by month. Finally, based on the superior rate or the average return rate, this research select the superior funds and simulate investment transactions according to this model.

The empirical results show that using the mutual fund's net asset value and the TAIEX's relative return as SOM-NN input variables not only finds out the superior fund but also has a good predictive ability. Applying this model to simulate investment transactions will be better than the random trading model and market. The experiments also found that the investment simulation of a three-month interval has the highest profitability. The model operation suggests that it is more suitable for short-term and medium-term investment. This research can assist investors in making the right investment decisions while facing rapid financial environment changes.

1. Introduction

1.1. Background and motivation

The mutual Fund is one of the most well-known financial investment products among public investors. The scale and diversity of funds and investor capital investment has shown explosive domestic market growth since the year 2000 [26,18]. More and more experts start to conduct research on the ranks of mutual fund performance, and the traditional performance evaluation models, early from the Treynor Index (1965), Sharpe Index (1966) and Jensen index (1968). Those are a clear performance evaluation index for investors to choose fund at that time. However, with regard to mutual fund performance [10], there is still no clear criteria for the recent development of a variety of fund performance evaluation rules. So how to properly measure the performance of mutual funds is the key factor for future successful investment [19].

The Taiwan government became active in capital markets to attract foreign investment [25]. Taiwan's oldest investment trust was founded in 1983 by the International Securities Investment Trust [1,10]. In the period from 1983 to 1986 the government opened three investment firms; Guanghua Investment Trust, the NITC and China Securities Investment Trust. The second wave of liberalization occurred in 1992, opening JF, Yuanta and CITIC 11 investment firms. The Taiwan Securities

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Investment Trust Company number increased to 15 levels, setting off a boom of investment in mutual funds [5,21,1]. The technology industry in Taiwan created an economic miracle and stock market rally [14]. Investors flocked to mutual funds. The number of investment firms and mutual fund total net assets increased after 1996. Ending in December 2010, according to the Securities Investment Trust & Consulting Association of ROC, the Taiwan Securities Investment Trust Company Number 38, issued a total of 555 mutual fund files, with the domestic equity fund numbering a total of 174 files and mutual funds scaling up to $18,958 billion.

Mutual funds can be pooled funds from individuals, corporations or social entities [12]. The experts responsible for the trades distribute the funds to dozens of stocks. Even though some stocks might fall, the loss can be recovered through the gains of other stocks in the same fund pool. This achieves risk diversification.

The equity fund is a stock investment target. The Fund's performance is a subject matter of great relevance [3]. A fund is able to effectively beat the market, but often investors are most concerned about the issue. For example, when the market began to collapse, the Fund was unable to rise, which can infer that there is a subtle dependency between the fund and stock markets. The Fund's operating performance, good or bad, is based on the Fund's net yearly return. The net value of the fund is in fact a transcript of the Fund's NAV Change rate for the stock index performance. This can help investors better understand the Fund. Properly measuring Fund performance is a key factor in determining the success or failure of an investment fund.

1.2. Problem definition

Investors attach great importance to the country's mutual funds. An increasing number of scholars are researching mutual fund performance. The majority of fund performance appraisal indices, the overall economic indicators are the main factors used to build statistical and non-statistical models (for example: neural networks).

The research on artificial intelligence (AI) in the financial sector has increased in recent years. Self-organizing unsupervised learning neural network mapping imitates the characteristics of human brain cells, "Like attracts like" [17]. When online learning is completed the output processing unit is close to those who would have similar functionality [8]. This feature is extremely suitable for the clustering phenomenon, used in stock funds [1]. This research uses mutual fund net and the Taiwan Weighted Stock Index, as evaluation indicators for the relative rate of return in mutual fund performance. The neural network clustering self-organizing map is used to identify equity fund advantages [20], and these Fund advantages are then used to invest in trading simulations.

This research provides a selective advantage to the Fund model and expects to achieve the following objectives:

1. Verify the relative rate of return of the mutual NAV and the Taiwan Weighted Stock Index for equity mutual fund performance assessment.
2. Uses open domestic stock mutual funds, neural network self-organizing map clustering to identify fund advantages.
3. Provide investment decision support tools for selecting mutual funds that perform better in practice.

2. Literature review

The relative rate of return for net mutual funds and the Taiwan Weighted Stock Index mutual fund performance are used as evaluation indicators. The neural network self-organizing map clustering is applied to domestic open-ended equity mutual funds to identify the fund advantages for investment transaction analog.

2.1. Traditional fund performance evaluation

Treynor [11] said that mutual funds are used to diversify investment risk characteristics, performance evaluation, and investment risk should be non-systemic risk exclusion. Only Funds that bear the systemic risk are considered so that the excess returns obtained can be used as a measure of mutual fund performance [1].

Treynor index on behalf of the Fund to bear the excess return per unit of systematic risk, the greater its value, the better the fund performance. [26] said that the Treynor index ignores the non-systematic risk in the portfolio and advocates it should be based on the total risk-adjusted basis as the excess return. The Sharpe Index on behalf of the Fund bears the excess returns per unit of total risk, the greater its value, the better the fund performance. Jensen [13] said that capital markets do not fully disclose the rate of risk so fund managers have the advantages of information and so on, leaving the investment combination of expectations of remuneration does not fully equal to the capital asset pricing model (CAPM) the calculation of compensation, thus produces over-or underestimation bias. This is included in the intercept term in the Security Market Line (SML). Using the intercept to measure mutual fund abnormal return α is the Jensen Index value greater than zero; the mutual fund excess returns the fund manager has a good stock picking ability. If it is less than zero, indicating that the mutual fund excess returns, the fund manager does not have a good share selection capacity. It is equal to zero the fund can only provide the same reward as the expected as the capital asset pricing model return (CAPM).

The equity fund is a stock investment target. The Fund's performance is a subject matter of great relevance, whether the Fund can effectively beat the market, but often investors are most concerned about the performance issue [1]. This research uses mutual NAV and the relative rate of return of Taiwan's weighted Price Index for evaluating mutual fund performance.

2.2. Mutual funds

Mutual funds refer to the majority of investor money together managed by professional asset managers responsible for managing an asset management business, investment income and risk by the investors shared, very suitable as a small investment of financial instruments [3,5,21].

According to different criteria, to distinguish different types of funds, according to the release of transactions can be divided into two major categories – closed and open [1]. According to the investment area funds can be divided into a global type, area type and single-market funds [3]. According to the investment targets funds can be divided into stocks, bonds, money market and derivative financial commodity funds. In accordance with the investment objectives, funds can be divided into aggressive growth, growth, balanced and income funds [10]. In mutual funds in accordance with the distinction between investment targets, funds can be divided into stock funds, bond funds, money market funds, derivative financial commodity funds [27].

Carhart [16] from 1962 to 1993, equity funds for the research sample, and refer to the Fama and French [6] proposed the three-factor model, an additional kinetic energy factor, the four-factor model and to the mutual fund's excess return Sort by mutual funds to explore the persistence of mutual fund performance. The empirical results show that in mutual fund performance, even though last year's winners could become this year's losers, the performance of the winner or the winner, that is, mutual fund performance persistence.

Grinblatt and Titman [18] examined the fund performance persistence phenomenon and cash flow is expected fund returns. The empirical results show that mutual fund performance short-term (before and after three months) with persistence, but the performance of mutual funds long-term (before and after six months) non-persistent. Therefore, this research will depend on the performance of mutual funds for the future; select a mutual fund reference in order to obtain good remuneration.

2.3. Self-organizing map neural network

The self-organizing map (SOM) was proposed Kohonen scholars in 1980. It is a competitive type of artificial intelligence network structure [20]. The main principle is to mimic human brain cells with the characteristics of a flock of birds [17]. The human brain will be classified for outside input messages; the neural network self-organizing map uses the competitive learning rule and spatial mapping concepts. The sample space is the sample point of capture. The neural network self-organizing map utilized statistics from 1980 to 2000, producing a total of 4300 self-organized maps [24].

Deboeck [9] proposed a neural network self-organizing map applied in areas such as finance, economics and marketing [27]. The choice of mutual funds as a research subject was done by Deboeck first. He produced a Morningstar rating of 500 funds to identify the assessment for four-and five-star 50 files of global equity funds and then applied neural network self-organizing map clustering. The experimental results, through neural network will co-fund to be self-organizing map classification, and can provide fund investors in addition to fund ratings, and the other better fund investment decision index.

Chen and He [23] used the neural network self-organizing map with Windows Mobile to handle the Taiwan weighted index time series daily data. The trend graphic was divided into 36 groups using statistical analysis to identify the group buy signal and sell signal. The empirical results showed that using the trading strategies was significantly better than the buy and hold strategy.

The neural network self-organizing map used in Finance produced excellent clustering and predictive ability. Selecting the appropriate input variables, the self - organizing map can provide a good trading strategy, with better profitability than a random trading strategy. Therefore, this research expect to find the Fund advantages using self-organizing map input variables clustering, to produce better the relative rate of return on net mutual fund and the Taiwan Weighted Stock Index in a model investment transactions simulation.

3. Research design and methodology

This research began with a collection of experimental data to obtain the daily net open domestic equity mutual fund information and the Taiwan Weighted Stock Index daily closing price data from the Taiwan Economic Journal Database (TEJ) [2,4,7]. The mutual fund daily net weighted Stock Index daily closing price relative rate of return was calculated and used as the neural network self-organizing map input values [20].

The calculated data was divided into experimental and control groups.

The experimental group I was based on the winning rate for each fund group selected as the most advantageous in the first three fund groups for investment. Group II was based on the average rate of return for each group selected as the most advantageous from three groups of funds. Control group I consisted of randomly selected funds for a direct random trading strategy. The simulated trading strategies set the trading intervals to one month, three months and six months. The experimental group and control group results were analyzed for performance assessment. The experimental setup for this research is shown in Fig. 1.

The data for this research was 100 open domestic equity mutual fund files from the TEJ daily net data and the Taiwan Weighted Stock Index (TAIEX) daily closing price data. The data collection period from January 4, 2000 to 2010 December

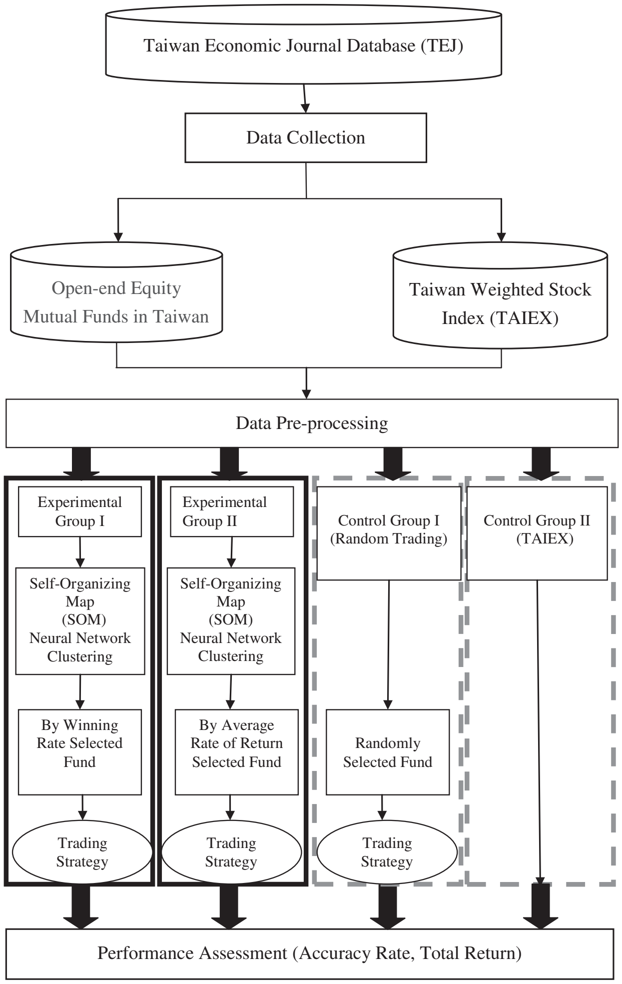

Fig. 1. Experimental architecture in this research.

31, 2010, a total of 2755 pen daily trading data. The experimental data was split and the training information and optimum ratio test was 8:2. In this research, prepared since January 4, 2000–2008 December 31, 2010, a total of 2253 pen daily trading data for the training of information. Test period data from January 5, 2009 to December 31, 2010, a total of 502 pen daily trading data for the test period data.

3.1. Data pre-processing

The mutual fund past performance was referenced for mutual fund selection. The equity mutual fund is a stock used as the main investment target. The Fund performance, good or bad, is fully rendered in NAV.

Therefore, this research assessed the relative rate of return for net mutual funds and the Taiwan Weighted Stock Index Mutual Fund Performance Indicators before the beginning of each month, a day before the 30 day, 60 day and 90 day periods and the TAIEX of relative return on R30, R60 and R90 as the SOM input-variables, for a total of 90 input values. The formula is as follows:

$$R_n = \ln\left(\frac{P'_n}{P'_1}\right) - \ln\left(\frac{P_n}{P_1}\right); \quad n = 30, 60, 90 \tag{3.1}$$

P'_n, monthly beginning of NAV; P'_1, monthly beginning of the first n trading days of NAV; P_n, monthly beginning of the TAIEX closing price; P_1, monthly beginning of the first n trading days of the TAIEX closing price.

Data were taken from the TEJ direct access data, not the model input data format. The raw data were preprocessed to generate the input data format needed by the research model. The model input data for the first 30 days of the beginning of each month, 60 days and 90 days of net mutual fund. The TAIEX closing price relative rate of return on R30, R60, and

R90 were used as the SOM input-variables. Table 3-1 shows the original data format of file 100 equity mutual funds. The data is from January 4, 2000 to December 31, 2010.

This research used the Mutual fund daily net and the TAIEX daily closing price of the daily data refers to the opening of the trading day, rather than calendar days. January 2, 2002 is the date of the input variables and clustering. Over the past 30 days used the November 20, 2001 to December 31, 2001, the daily opening transaction.

The raw data format conversion of the mutual funds for the input format of the SOM. The input variables were D1-R30, D1-R60, D1-R90, D30-R30, D30-R60, and D30-R90 total of 90. D1-R30 is the beginning of each month of the previous trading day 30 days before the net mutual fund, and the TAIEX relative rate of return. D1-R60 is the beginning of each month of the previous trading day 60 days before the net mutual fund, and the TAIEX relative rate of return. D1-R90 is the beginning of each month of the previous trading day 90 days before the net mutual fund, and the TAIEX relative rate of return.

3.2. Self-organizing map neural network model parameter settings

1. *Network input layer*: 30 days before the beginning of each month daily the first 30 days, 60 days, 90 days in mutual funds, and the TAIEX relative rate of return R30 R60, and R90. The total of 90 input variables. Input unit for data pre-processing, and then input to the network to conduct learning.
2. *Network output layer*: in this study, decided that the network output matrix for 6×6 grid topology. The total of 36 output units.
3. *Neighboring function*: function close to a Gaussian function for learning.
4. The initial learning rate value was set to a neighborhood distance of 5. The stop condition was divided into learning the number of times stop to stop with the learning error. The default learning more than 10,000 or output neural stop learning by the average error is lower than 0.0000001.

3.3. Experimental design

Fig. 2 for the experimental group's operational processes are described below:

1. The mutual fund net of the monthly first trading day and TAIEX closing price input to this model.
2. The fund selection model is based on the winning rate or average rate of return on fund selection advantage.
3. First determine whether the Fund has three groups that fall into the advantage.
4. If it falls into the advantage of the first three groups, followed to determine the number of funds within the group is greater than 10. If not, holds the current cash investment funds.
5. If the number of funds within the group is greater than the 10, 10 funds are to be elected using the distance advantages of the group distance from small to large. If the number of funds within the group is less than 10 select 10 files that fall into three fund advantage groups.
6. Trading strategy will invest in the simulation interval set respectively for one month, three months and six months. Windows Mobile to simulate investment.

Finally, according to the simulation result of the investment, respectively, the total rate of return and the accuracy of performance assessment.

3.3.1. Control group I (random trading)

Traditional financial engineering scholars generally agree that the stock market is not predictable, the share price trend of the random walk hypothesis. Market stock prices will reflect all the possible information in the market, because the information on the occurrence of random changes in the prices will be random.

Fama [6] proposed the random walk theory to deduce the market efficiency hypothesis. The hypotheses assumed that a stock's past price movements predict its' future price movements. Therefore, the random trading strategy refers to every time shares are bought or sold in the market are randomly generated. This strategy has no expected stock prices. In this study, random trading simulation stock mutual funds, random fixed the beginning of each month selected 10 funds to invest. Finally, calculate the accuracy rate and total return for one month, three months and six months, and evaluate the stock group performance.

3.3.2. Control group II (TAIEX)

Control group II is the Taiwan Weighted Stock Index (TAIEX). Calculation during the same period of TAIEX in the one month, three months and six months, the total return and the accuracy rate (rise rate), performance evaluation and experimental group.

3.4. Trading strategy

In order to compare the selection accuracy rate and total return of the Advantage Fund model in different trading strategies, this study implemented six simulated trading strategies. Each simulation strategy is described below:

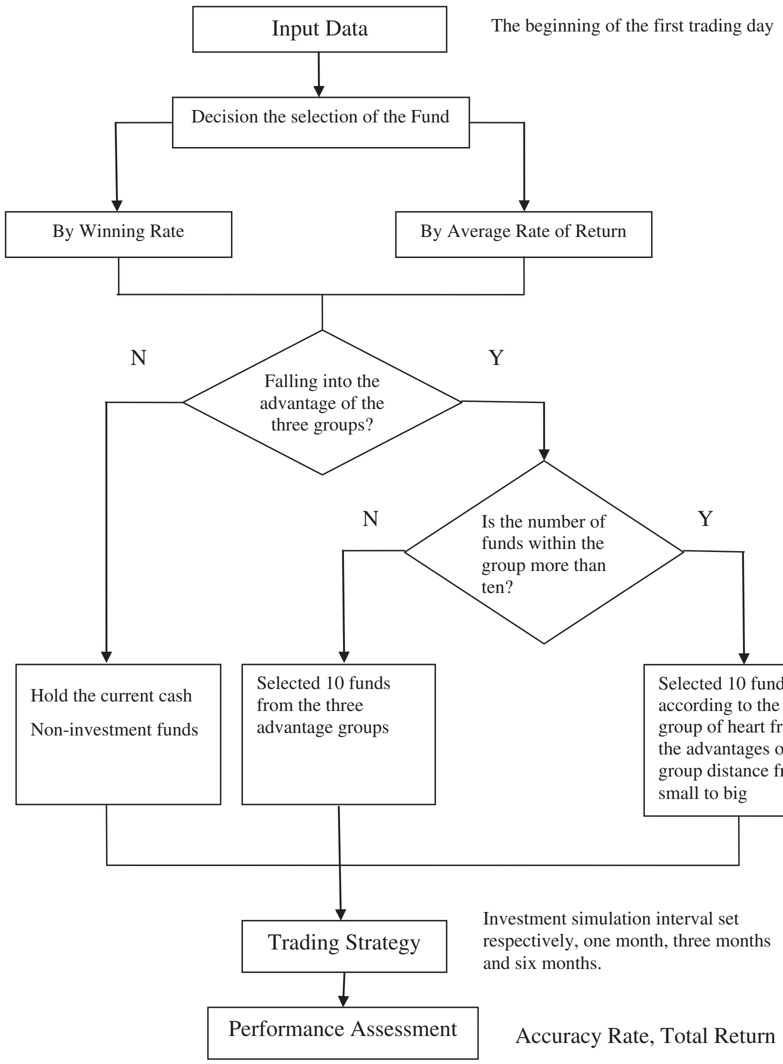

Fig. 2. The operation flow chart for the experimental group.

1. *Simulated trading strategy I*: selected according to the winning rate of fall into three groups Advantage Fund, you can choose up to 10 files simulation interval had once traded for each month.
2. *Simulated trading strategy II*: selected according to the winning rate of fall into three groups Advantage Fund, you can choose up to 10 files, analog range trading once every three months.
3. *Simulated trading strategy III*: selected according to the winning rate of fall into three groups Advantage Fund, you can choose up to 10 files, simulation interval once every six months trading.
4. *Simulated trading strategy IV*: selected according to the average rate of return fall into three groups Advantage Fund, you can choose up to 10 files, simulation interval had once traded for each month.
5. *Simulated trading strategy V*: selected according to the average rate of return fall into three groups Advantage Fund, you can choose up to 10 files, analog range trading once every three months.
6. *Simulated trading strategy IV*: selected according to the average rate of return fall into three groups Advantage Fund, you can choose up to 10 files, simulation interval once every six months trading.

3.5. Performance evaluation methods

The performance evaluation method is divided into two accuracy assessment methods and profitability assessment methods. In accordance with the assessment criteria, the performance compensation rate less 1.5% handling fee.

3.5.1. Accuracy rate

Upon completion of the classification of self-organizing map neural network, the predictions arising from the fund rate of return in the reality in order to calculate the accuracy of the forecast period. Accuracy rate of forecast period rate of return is greater than zero of the items divided by the total number of transactions is calculated as follows.

$$\text{Accuracy rate} = \frac{\sum_{i=1}^{n} \text{Correct}_i}{N} \tag{3.2}$$

Correct_i, the i pen return is greater than zero information; N, total number of transaction document.

3.5.2. Total return

Upon completion of the classification of self-organizing map neural network, the predictions arising from the fund rate of return in the reality in order to calculate the total return of the forecast period. The total remuneration rate plus the average rate of return of the fund each month, calculated as follows.

$$\text{Total return} = \sum_{j=1}^{m} \left(\sum_{i=1}^{nj} R_i / N_j \right) \tag{3.3}$$

R_i, the total return of month i; N, the number of investment fund files; m, the number of investment; n, the month selected by the fund.

4. Experimental results

4.1. The experimental results of the experimental group

Experimental group I the operation process is described as follows:

Step 1: closing price in early the first day of trading of mutual funds net and TAIEX input to the model.
Step 2: advantage to pick funds based on each group winning rate model.
Step 3: judgment the Fund whether there fall into the advantage of the first three groups.
Step 4: if you fall into the advantages of the first three groups, then determine the number of funds within the group is greater than 10. If you do not fall into the advantage in the first three groups, investment funds currently cash no longer held.
Step 5: if the number of funds in the group is greater than 10, in accordance with the group from the advantages of group heart distance, steeled selected 10 fund. If the number of the group within the Fund is less than 10, in order to elect the first three groups of 10 mutual funds fall into advantage.
Step 6: trading strategy investment simulation interval setting of one month, three months and six months respectively, and to take the way of the moving window to simulate investment.
Step 7: finally, in accordance with the investment simulation results, respectively, to a total rate of return on the accuracy of performance assessment.

Table 1 of the experimental group I, the experimental results can be found, 58.05% of the total remuneration rate for one month (simulated trading strategy I) raised to 70.23% of the months (simulated trading strategy II), then dropped to 39.35% of six months (simulated trading strategy III). Therefore, Advantage Fund is selected based on the winning rate of each group with the highest total return for the three months set in the simulation interval. The accuracy rate from 65.08% in a month (simulated trading strategy I) raised to three months (simulated trading strategy II) 75.02%. Although a higher accuracy rate of 76.39% on six months (simulated trading strategy III), but total return only had 39.35%. The six-month total return was lower than that for three months, inferring the domestic open-ended equity mutual fund does not have long-term performance persistence. Therefore, this research simulated investment better profitability in the short and medium term. The experimental group I, the total rate of return changes can be clearly seen that the total rate of return in three months reached

Table 1
The experimental results for the experimental group I.

Simulation interval performance assessment	One month (simulated trading strategy I) (%)	Three months (simulated trading strategy II) (%)	Six months (simulated trading strategy III) (%)
Total return	58.05	70.23	39.35
Accuracy rate	65.08	75.02	76.39

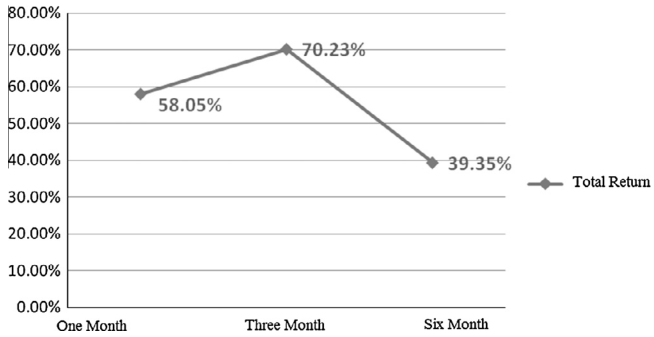

Fig. 3. The total return changes for the experimental group I.

a peak, followed by a gradual downward trend. The total return of the experimental group I change finishing shown in Fig. 3. Fig. 3 presents the total return in three months, reached a peak, followed by a gradual downward trend.

Experimental group II the operation process is described as follows:

Step 1: early April the first trading day of the NAV and the closing price of the TAIEX input to the model.
Step 2: advantage of the model based on the average rate of return for each group to pick funds.
Step 3: judgment the Fund whether there fall into the advantage of the first three groups.
Step 4: if you fall into the advantages of the first three groups, then determine the number of funds within the group is greater than 10. If you do not fall into the advantage in the first three groups, investment funds currently cash no longer held.
Step 5: if the number of funds in the group is greater than 10, in accordance with the group from the advantages of group heart distance, steeled selected 10 fund. If the number of the group within the Fund is less than 10, in order to elect the first three groups of 10 mutual funds fall into advantage.
Step 6: trading strategy investment simulation interval setting of one month, three months and six months respectively, and to take the way of the moving window to simulate investment.
Step 7: finally, in accordance with the results of the sale and purchase transactions, respectively, to a total rate of return on the accuracy of performance assessment.

Table 2 of the experimental group II, the experimental results can be found, the total compensation rate to 61.99% in a month's (simulated trading strategy IV) Increased to 68.64% in three months (simulated trading strategy V), then dropped to 40.36% in six months (simulated trading strategy VI). Therefore, the advantages of fund selection based on each group's

Table 2
The experimental results for the experimental group II.

Simulation interval performance assessment	One month (simulated trading strategy IV) (%)	Three months (simulated trading strategy V) (%)	Six months (simulated trading strategy VI) (%)
Total return	61.99	68.64	40.36
Accuracy rate	62.83	76.17	78.83

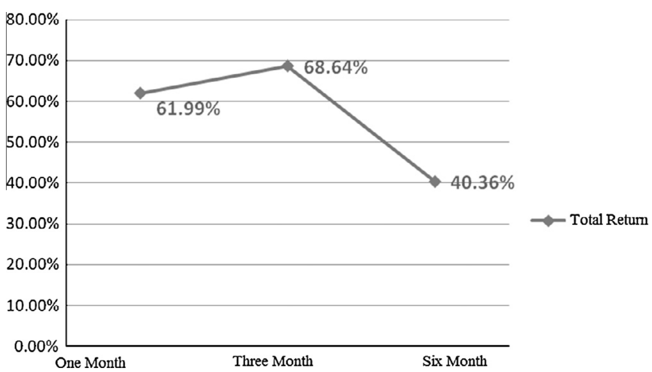

Fig. 4. The total return changes for the experimental group II.

Table 3
Comparison of the two experimental results for experimental group I and experimental group II.

Experimental group	I	II	I	II	I	II
Simulation interval (simulated trading strategy)	One month (simulated trading strategy I) (%)	One month (simulated trading strategy IV) (%)	Three months (simulated trading strategy II) (%)	Three months (simulated trading strategy V) (%)	Six months (simulated trading strategy III) (%)	Six months (simulated trading strategy VI) (%)
Total return	58.05	61.99	70.23	68.64	39.35	40.36
Accuracy rate	65.08	62.83	75.02	76.17	76.39	78.83

average return in the simulation interval to set the highest total rate of return for three months. The accuracy rate from 62.83% in a month's (simulated trading strategy IV) increased to 76.17% in three months (simulated trading strategy V). The six months had a higher accuracy rate of 78.83% (simulated trading strategy VI), but the total return was only 40.36%. Experimental group II was selected based on the average rate of return funds, the experimental group I fund selected was based on the winning rate. Investment between the simulations results are similar, little difference. Similarly, it is the experimental group B, the total rate of return change is clear that the total rate of return in three months reached a peak after a gradual downward trend. The total return of the experimental group II change finishing shown in Fig. 4. Fig. 4 presents the total return in three months, reached a peak, followed by a gradual downward trend.

The following focuses on experimental group I and experimental group II. Two experimental results were compared with the experimental results summarized in Table 3.

Table 3 shows the results for experimental groups I and II experimental. The results for experimental group II show that both the total rate of return and accuracy are similar to the experimental group I results. The total returns forecast for the

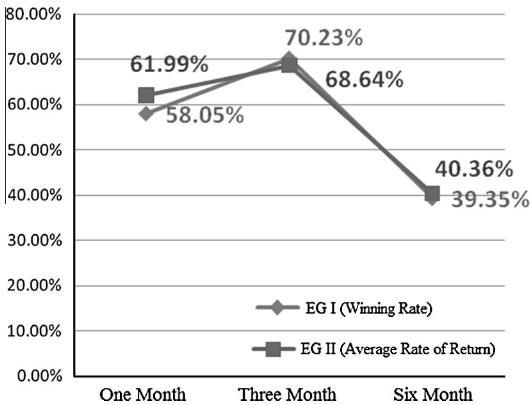

Fig. 5. Comparison of the total return for experimental group I and experimental group.

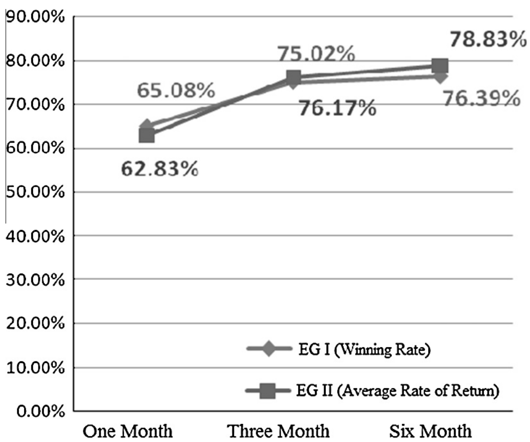

Fig. 6. Comparison of the accuracy rate for experimental group I and experimental group II.

experimental group II (simulated trading strategy V) three month total return rate was 68.64%, while that for experimental group I was 70.23% total (simulated trading strategy II). In group II the one month (simulated trading strategy IV) total return was 61.99% while the six months (simulated trading strategy VI) total return was 40.36%. This was more than the group I one month (simulated trading strategy I) rate of total return 58.05% and six months (simulated trading strategy III) total return of 39.35%. The forecast accuracy for experimental groups I and II were more than 75% accuracy in the three months set in the simulation interval. That shows SOM has good learning results. Experimental group I showed a higher total return of 70.23% for the three months (simulated trading strategy II). Fig. 5 shows the total return for experimental groups I and II experimental. Fig. 6 shows the results for experimental groups I and II experimental. The experimental accuracy for groups I and II shows that were both exhibited a gradual upward trend.

4.2. The experimental results for the control group

4.2.1. Control group i (random trading)

Experimental trading patterns for the random trading model involved buying 10 funds randomly at a fee of 1.5% with the simulation interval is set to one, three and six months. The total return and accuracy performance were evaluated using this as a basis of comparison for the experimental results. The random trading model experimental results are summarized in Table 4.

The experimental results can be found in Table 4 of the control group I (randomized trading). The highest total return was 30.32% for the three months set in the simulation interval. The accuracy rate of 48.31% and accuracy of the random trading model in the test period ranged from 45% to 53%. The total return through the random trading model changes show that the random simulated trading model set for three months with a total return of 30.32%. In Fig. 7, this was higher than the one month total return of 19.55% and the six months total return rate of 9.28%.

4.2.2. Control group II (TAIEX)

This research used the information during the period January 2009 to December 2010 TAIEX closing price. The simulation interval is one month, three months and six months. The total rate of return and accuracy (up ratio) performance evaluation, used this as a basis for comparing experimental results. The Taiwan Weighted Stock Index return rising ratio was used as the accuracy measure. Table 5 shows the same during the TAIEX experimental results. Fig. 8 shows the total return changes for control group II.

Table 4
Experimental results for the control group I (random trading).

Simulation interval	One month (%)	Three months (%)	Six months (%)
Total return	19.55	30.32	9.28
Accuracy rate	45.13	48.31	52.45

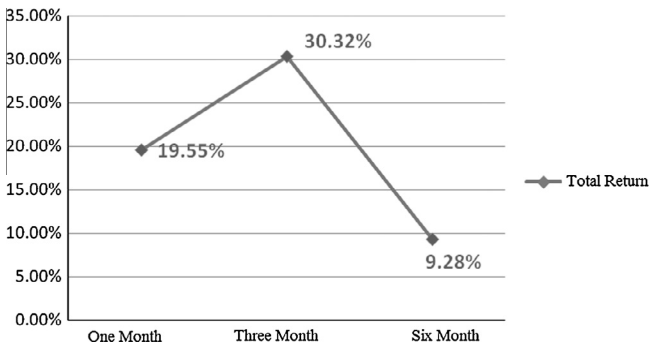

Fig. 7. Control group I (random trading) changes in the total return.

Table 5
Experimental results for control group II (TAIEX).

Simulation interval	One month (%)	Three months (%)	Six months (%)
Total return	48.91	62.12	44.74
Accuracy rate	56.52	70	87.5

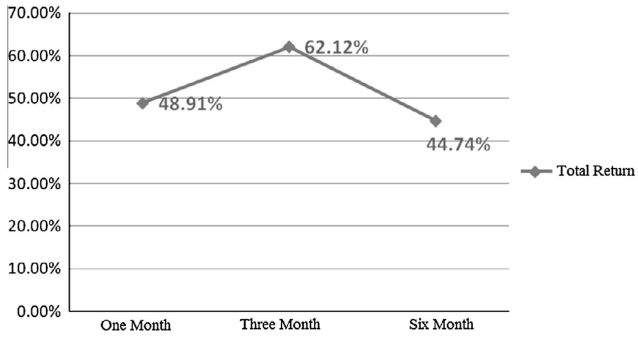

Fig. 8. Control group II (TAIEX) changes in the total return.

Table 5 of the control group II (TAIEX) of the experimental results can be found in the TAIEX in the simulation interval was set to three months. The highest total return was 62.12%. The accuracy rate (up ratio) was 70%. The three-month total return was 62.12%, which was higher than the one-month total return of 48.91% and a six-month total return of 44.74%.

4.3. Comparison of performance evaluation

Following the experimental group's self-organizing map neural network model, experimental results, the random trading model experimental results, the control group I and control group II during the same period of the TAIEX experimental results a comprehensive comparison.

Table 6 shows the experimental results with the simulation interval set to one month. Experimental group II (based on the average rate of return on the selection of fund) had the best total rate of return at 61.99%, followed by experimental group A (selected according to the winning rate Fund) with a total return of 58.05%. Control group II (TAIEX) showed a total rate of return of 48.91%. The worst total return was control group I (randomized trading) at 19.55%. When the simulation interval was set to one month trading was significantly better than random transactions and beat the market.

Experimental group I (based on the winning rate) showed the best the total return rate of 70.23% at three months simulation interval, followed by experimental group II (based on the average rate of return on the selection of funds) with a total return of 68.64%. Control group II (TAIEX) showed a total rate of return of 62.12%. The worst total compensation rate was 30.32% by control group I (randomized trading). Similarly, when the simulation interval was set for three months the transactions were significantly better than random transactions and beat the market.

With the simulation interval set to six months the best total return was 44.74% by control group II (TAIEX), followed by experimental group I (based on the average rate of return on the selection of funds) with a total return of 40.36% (selected based on the winning rate of the Fund). The total return was 39.35% by experimental group II. The worst total return was 9.28% by control group I (randomized trading). Fig. 9 shows the total return for the experimental groups and control groups.

When the simulation interval was set for one month and three months the total rate of return was better than random trading and beat the market. However, the six month simulation interval experimental results for groups I and II were slightly worse than the market but better than random trading. This simulated investment model representing short and medium term investment (one month and three months), does not apply to long-term investment (six months). The results for one month, three months and six months were better than random transactions. The SOM clustering application provides a comparative investment advantage, making the proposed investment model relatively good.

The experimental group I (selected in accordance with the winning rate of the Fund) achieved the highest total return of 70.23% when the simulation interval was set for three months (simulated trading strategy II).

Table 7 shows the experimental results when the simulation interval was set to one month in the experimental group I (based on the winning rate). The accuracy rate was 65.08% (which was best), followed by experimental group II (based on the average rate of return on the selection of funds) with an accuracy rate of 62.83%. With a control group II (TAIEX) accuracy rate of 56.52%, the worst result was the control group I (randomized trading) with an accuracy rate of 45.13%. When the simulation interval was set for one month this model achieved better results than random trading and beat the market.

Table 6
Total returns for the experimental group and control group.

Performance assessment	Total return		
Simulation interval	One month (%)	Three months (%)	Six months (%)
Experimental group I (winning rate)	58.05	70.23	39.35
Experimental group II (average rate of return)	61.99	68.64	40.36
Control group I (random trading)	19.55	30.32	9.28
Control group II (TAIEX)	48.91	62.12	44.74

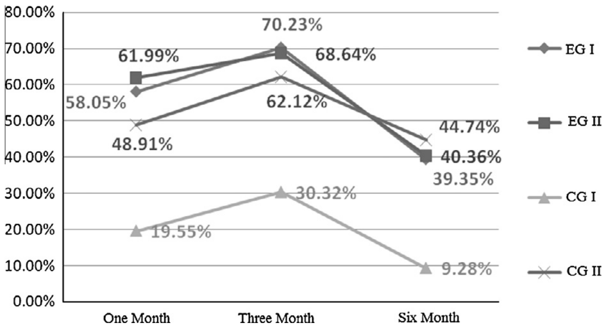

Fig. 9. Comparison of the total return for experimental groups and control groups.

Table 7
Accuracy rate for the experimental group and control group.

Performance assessment	Accuracy rate		
Simulation interval	One month (%)	Three months (%)	Six months (%)
Experimental group I (Winning rate)	65.08	75.02	76.39
Experimental group II (Average rate of return)	62.83	76.17	78.83
Control group I (random trading)	45.13	48.31	52.45
Control group II (TAIEX)	56.52	70	87.5

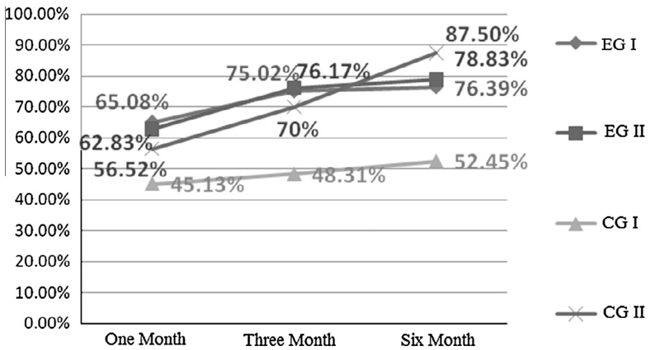

Fig. 10. Comparison of the accuracy rate for experimental groups and control groups.

Experimental group II (to select funds based on the average rate of return) achieved an accuracy rate of 76.17% for the best with the simulation interval set at three months, followed by experimental group I (selected according to the winning rate of the Fund) with an accuracy rate of 75.02%. Control group II (TAIEX) achieved an accuracy rate of 70%. The worst result was the control group I (random transaction) with an accuracy rate of 48.31%. Similarly, when the simulation interval was set for three months the simulated trading model achieved better results than random trading and beat the market.

When the simulation interval was set to six months control group II (TAIEX) achieved an accuracy rate of 87.5%, followed by experimental group II (based on the average rate of return on the selection of the Fund) with an accuracy rate of 78.83%. Experimental group I (selected according to the winning rate funds) achieved an accuracy rate of 76.39%, lower than the accuracy of experimental group II and control group II. Control group I (randomized trading) achieved the worst accuracy rate of 52.45%. Fig. 10 shows the accuracy rate for the experimental groups and control groups.

One and three month simulation intervals produced better accuracy than random trading and beat the market. However, when the simulation interval was set for six months the experimental results for experimental groups I and II lost to the market. The accuracy rate of change trend gradually increased to the accuracy of the experimental and control groups and consistent broader market trend.

The above experimental results show that after SOM learning in the investment simulation interval setting for one month and three months the performance was better than random trading and beat the market. SOM model for the experimental group performed better, both in terms of total returns and accuracy.

The prediction accuracy of experimental group I with experimental group II through SOM learning, at one and three months was better than random transactions and beat the market. When the simulation interval was set to six months the prediction accuracy was relatively high but failed to go beyond the market. Based on the above observation and analysis, the six-month simulation had high accuracy, but lost profitability to the broader market.

In total returns the best performance was three months. In accuracy the best performance was six months. Under the premise of better than random trading and beating the market, mutual fund net and TAIEX the relative rate of return on fund performance evaluation indicators achieved the best performance when the simulation interval was set to three months.

Experimental groups and control group I (randomized trading) comparison found that using SOM in the artificial intelligence field for the classification of mutual funds is effective. The total rate of return and accuracy were superior to the results of general fund investors randomly selecting stocks for investment. The artificial intelligence methodology used to help investors get higher returns was successful.

5. Conclusion

This research used AI's SOM-NN clustering of domestic open-end equity funds from which to construct the model of selective advantage fund. On the Figs. 9 and 10 shown that the empirical results found using the model to do the investment transactions, one to three month period higher investment profitability was achieved. The accuracy rate and profitability are significantly better than random trading model and beat the market.

Therefore, the proposed model Advantage Fund to invest in trading simulation, and summarize the following conclusions based on the experimental results:

(1) The mutual fund net TAIEX relative rate of return was used as the SOM input variables with good predictive ability and is therefore suitable as mutual fund performance evaluation indicators.
(2) The prediction accuracy rate and profitability in the simulation interval set for one and three months were significantly better than the random trading model and beat the market. The SOM application was proven to produce effective clustering.
(3) Higher investment profitability was achieved when the simulation interval was set at one and three months. Three months produced the best profitability results. By inference, the model is more suitable for application to short and medium term investment.
(4) The profitability of the random trading model control group produced worse predictive accuracy than the SOM application. The experimental results show that investors who do not use artificial intelligence methodologies to complement their investment decisions expose themselves to considerable risk and loss.

The AI's SOM-NN clustering constructs a selective advantage to the fund model for open domestic stock funds. This model makes accurate and profitable investment transactions that are significantly better than the random trading model and beat the market.

5.1. Future research proposals

Processes and research experiments conducted by the foregoing chapters can be found through this study uses SOM-NN clustering of equity funds, advantage fund can be found. In order to make this study experimental processes and model more perfect, the following recommendations for further extended in the future research direction of improvement recommendations.

(1) In this study, the month as a clustering of units. The further studies can be used every day as a clustering of units.
(2) In this study, open-ended equity mutual funds for the study. Recommended follow-up studies can be based on different fund types.

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