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An Investment Decision Model of Fund of Funds Based on Technical Indicators and Variable Selection

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Mutual funds solve investor's lack of specialized investment knowledge and money management matters and how to choose suitable financial goods. With increases in mutual fund types, the fund of funds emerged to help investors select the most suitable mutual fund. Few scholars have examined relation between technical indicators and fund of fund's net asset value performance. This research used neural networks to help investors choose technical indicators, select the key index of the suitable fund of funds, to draft the investment strategy from technical indicator fast and effectively. A new fund of funds performance model was proposed and the assessment model was predicted through a partial neural network. The relationship among the performance of technical indicators, mutual fund and the net asset value for fund of funds, was examined to find some key indexes which influence the fund of funds net asset value, and its corresponding rule. The screening neural network matched the technical indicators, screened by the key parameters, to predict the fund of fund's performance. We compared with the back-propagation neural network, in order to verify the feasibility that the screening neural network applied to the fund of funds. The proposed neural network screening on the premise of maintaining and predicting the correct rate, effective screened parameters, and reduced network operation time, applied to the fund of funds performance forecast, gave satisfactory results.

JEL Codes: C81 and G15

1. Introduction

Taiwan's financial and investment environment is mature and stable. Accordingly, investment is gaining in popularity among its people. Investment risks exist no matter what financial investment tools one chooses, such as stocks, bonds, futures, options, and many other derivatives. If investors lack expertise in finance and investment, the complexity and difficulty of their investments tend to seem very high. Mutual funds provide a solution to the investor problem of lacking expertise and not knowing how to choose the right financial products. As the number and variety of mutual funds has grown, investors often are forced to rely on performance indicators for the underlying funds or assessing the fund managers' investment experience, history and background. This has given birth to fund of funds (FOF). A fund of funds is a portfolio of top performing or top quality funds selected from numerous mutual funds by fund managers for their investor clients. It can also be multiple portfolios based on risk return ratios, such as active growth, growth or balanced, etc., for investors to choose according to their risk preferences.

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The rest of the paper is organized as follows. Section 2 presents the artificial intelligence using in stock. Sections 3 and 4 provide a description of our model. I conclude the paper in Section 5.

2. Literature Review

Current research, both local and international, mostly focuses on either macroeconomic indicators or performance indicators for mutual funds (Ferreiraa et al. 2012, Indro et al. 1999; Klein and Rossin 1999; Chiang and Urban 1996). Most of these indicators are updated on a monthly basis and do not reflect daily fund performance in real time. Shu's (2002) findings reveal that those investing in large funds are mostly small investors. They tend to pursue past top performing funds, which they are inclined to sell in a short time as soon as they have profited from them. Monthly performance indicators are therefore not the right basis for assessing fund performance for investors whose fund operations strategy is short-term profit.

Artificial Intelligence (AI) has shown considerable advances in recent years and its applications range from engineering (Kalinli et al. 2011), to medicine (Arizmendi et al. 2012), Military (Rogers et al. 1995), meteorology (Perez and Reyes 2006, Luk et al. 2001) and business finance (Jasemi et al. 2011). Many decision-making problems that people encountered in the past can now be handed over to computers to resolve and obtain satisfactory results. AI's application to financial research has enjoyed reasonable success over the last few years (Jasemi et al. 2011, Baba and Kozaki 1992). In past studies, local and international alike, few scholars dwelled on the relationship between technical indicators for individual stocks and the net worth and performance of FOF. The main purpose of this study is, using neural network technology, to present a new model for assessing FOF performance and a selective neural network that boosts network efficiency. This network allows investment trust companies and investors to select the right key indicators for FOF from stock technical indicators in an effective and rapid manner, develop investment strategies, and use selected indicators as a basis for trading and a reference for selecting FOFs.

3. Methodology and Model

3.1 Research Data and Variables

This study used technical indicators as the input variables for the neural network. Subjects were the 680 listed stocks between January 2, 2001 and December 28, 2012 and served as the FOF investment targets after those lacking sufficient time data or missing information were removed.

This study also calculated 26 technical indicators by referring to papers on technical analysis and indicators commonly used by market investors (Bessembinder and Chan 1995, Teixeira and Oliveira 2010, Atsalakis and Valavanis 2009, Lai and Lau 2006). Relevant variables are summarized in Table 1. The output variable for the neural network in this study was the NAV (Net Asset Value) of FOF.

3.2 Stock Fund Investment Strategy

This study developed an mutual funds investment strategy, simulated investment operations with equity mutual funds and calculated the daily net worth of these funds.

The net worth of a fund represented the net asset value per unit of a mutual fund, as shown in Eq. (1).

$$NAV=(Total\ assets - Intangible\ assets - Total\ liabilities) / Total\ outstanding\ shares \quad (1)$$

Table 1: Research Variables

Variable	Technical Indicators	Variable	Technical Indicators
X1	RSI(5)	X15	VD(9)
X2	MA(5)	X16	RSV(9)
X3	PSY(5)	X17	K%R(9)
X4	BIAS(5)	X18	+DM
X5	WMS%R(10)	X19	–DM
X6	MTM(10)	X20	TR
X7	OSC(10)	X21	+DI(14)
X8	K(9)	X22	–DI(14)
X9	D(9)	X23	DX
X10	DIF	X24	ADX(14)
X11	MACD(12)	X25	CMO(5)
X12	Max Price(9)	X26	Average CMO(5)
X13	Min Price(9)	Y	NAV of FOF
X14	VK(9)		

This study adopted technical analysis, well known to average investors, as the investment strategy for mutual funds. There are many technical analysis methods for determining future market trends. This study developed fund investment strategies using Granville's eight rules.

Granville's eight rules use the relationship between prices and their moving averages as a basis for buying and selling. According to the rules, price fluctuation has a certain rhythmic pattern. It is a trading signal when a price deviates from its moving average. When a security's short-term moving average breaks above its long-term moving average, it is called a "golden cross", a signal for a stock fund to enter a buy. When a security's short-term moving average breaks below its long-term moving average, it is called a "death cross", a signal for a stock fund to sell its held stocks. The profit to a stock fund was calculated based on general standard charges for small investors, i.e. a 0.1425% surcharge for both buying and selling stocks plus 0.3% securities transaction tax.

3.3 Investment Strategy of Fund of Funds

Similarly, investment strategies for FOF’s were developed using the Granville's eight technical analysis rules. As a result, the net transfer moving averages for stock funds were calculated in Eq. (2).

$$N\ days\ moving\ average\ of\ stock\ fund = Total\ NAV\ by\ N\ days\ of\ stock\ fund / N\ days \quad (2)$$

When the moving stock fund averages form a golden cross, FOF buys the stock. In contrast, FOF redeems a held stock fund when a death cross appears in its moving averages. FOF profits were calculated based on a general standard surcharge, i.e. 2% of investment principals. As for the surcharge for fund redemption, most existing funds do not charge such fees. This study also set manager and custodial fees for stock funds at common rates, i.e. 1.5% and 0.2% per year.

3.4 Topology of Partially Connected Neural Networks

This study presented a partially connected back-propagation neural network as the framework and used it to investigate the relationship between the one-day NAV of a FOF and technical indicators for stocks. The relationship among FOF, stock funds and stocks was initially examined, as shown in Figure 1. Figure 1 reveals that the FOF has three layers. Building a partially connected back-propagation neural network therefore requires four layers, i.e. 1 input layer, 2 hidden layers and 1 output layer, described in detail in Figure 2.

One input layer: This represented technical indicators for stocks. Since this study used 26 such indicators, it was assumed that the FOF invested in 5 stock funds of which each had 10 stocks according to diversification principle of. As a result, the input layer had 1,300 nodes.

Twohidden layers: The nodes in the first hidden layer represent the stocks held by stock funds while those in the second layer indicated the sub-funds invested by the FOF. Furthermore, both layers were not fully connected with the input layer.

One output layer: This layer had only one node, which represented the net worth of the FOF, and was fully connected with the second hidden layer.

Figure 1: Framework of FOF

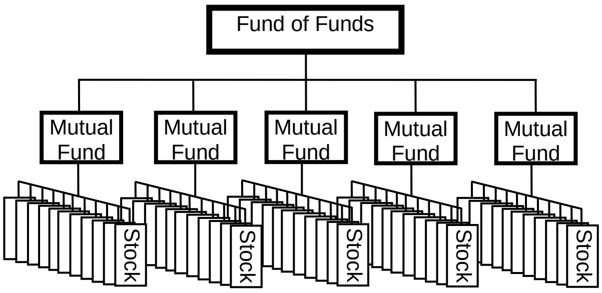
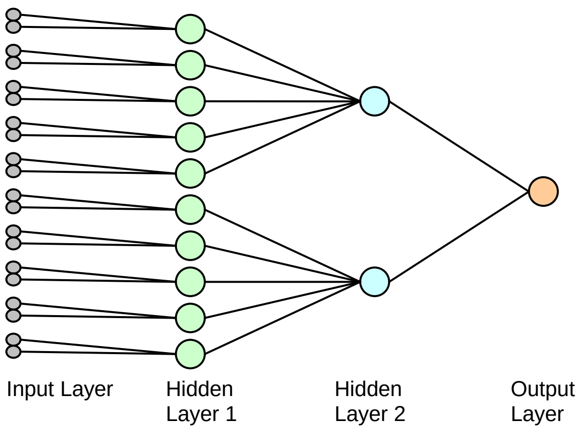


Figure 2: Topology of Neural Network by FOF



To verify whether the partially connected back-propagation neural network was applicable to the performance forecast of the FOF, this study compared training results between this network and network models of two different network topologies.

Model 1: Presented a fully connected neural network that shares the same number of hidden layers and nodes as a partially connected back-propagation model for the purposes of comparison. The network structure is shown in Figure 3.

Model 2: According to Beale (1990), one hidden layer is sufficient to reflect the interaction between input and output variables. This accounts for the one hidden layer used in this model. Since there were no fixed rules for determining the number of nodes in one hidden layer, the rule suggested by this study was used for determining the number of nodes in this model. The network structure is shown in Figure 4.

Figure 3: Topology of Model 1

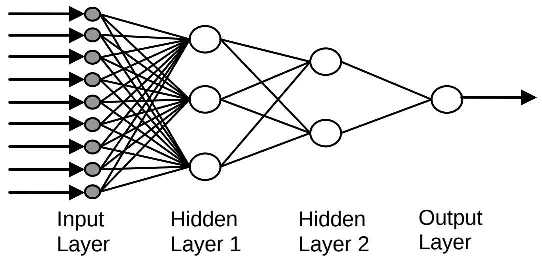
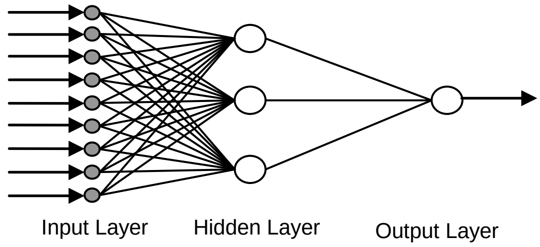


Figure 4: Topology of Model 2



3.5 Topology of the Selective Neural Network

The selective neural network (SNN) presented in this study utilized a back-propagation network. It selected variables and entered the selected technical indicators into the back-propagation network for training, thereby reducing network operation times. The operational process was divided into two stages, as shown in Figure 5. In the first stage, the response variable Y, i.e. the net worth of the FOF, was set as the input layer and the number of nodes in the hidden layer, set as Eq. (3), while having taken into account the efficiency of variable selection.

Figure 5: Topology of SNN

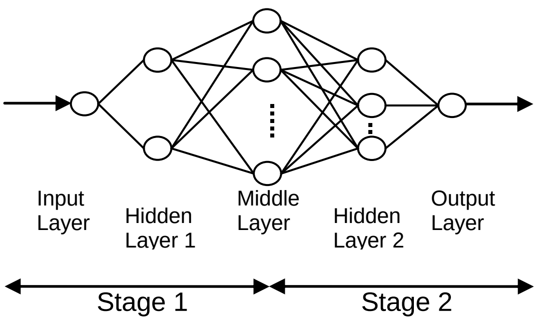
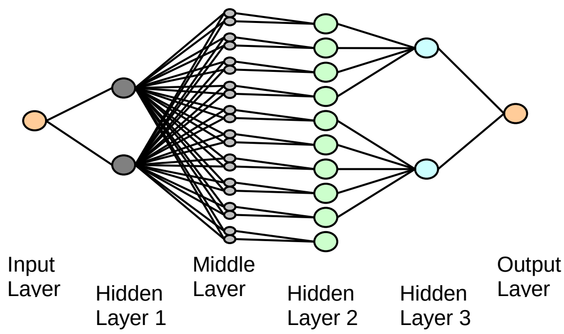


Figure 6: Topology of FOF by SNN



$$\textit{Number of Hidden Node} = \textit{Number of Input Node} * 2 \qquad (3)$$

The middle layer of the selective network was dedicated to explaining Variable X, i.e. the technical indicators for individual stocks held in stock funds in this study. At this stage, the back-propagation network was used for stage one training. After the training, the selective network selected key independent variables and set the weights of non-key independent variables for the second stage as 0, which meant excluding these variables from stage two network training. After stage one training, the selective network calculated the actual and predicted values of each node using Eq. (4) and the MSE value of each node represented the contributions of each variable. This study assumed that the smaller the MSE value, the greater the correlation between its independent variable X and the response variable Y in the first section.

$$MSE = \frac{\sum_{i=1}^{n} \left(T_i - Y_i\right)^2}{n} \tag{4}$$

n: Number of Sample

The second stage was the partially back-propagated neural network, which had two hidden layers. The number of nodes in these layers determined stock funds and the number of stocks they held. The output layer was the response variable Y.

The main advantage of the selective network was that the network itself could conduct variable selection while maintaining its predictive performance. The time required for the entire process from indicator selection to the completion of prediction was significantly less than that required for entering all the variables into the network for training without selection.

With the knowledge of the structure of the FOF's back-propagation neural network, it was possible to construct a predictive model using the selective neural network. The prediction model hence had 6 layers, including 1 input layer, 3 hidden layers, 1 middle layer, and 1 output layer, as in Figure 6 and described as:

One input layer:	This layer had only one node, which represented the FOF's net worth.
Two hidden layers:	The first hidden layer served to facilitate the selection of variables in the middle layer and had only two nodes. The nodes in the second hidden layer represented the stocks held by stock funds. The third hidden layer showed the sub-funds invested by the FOF. The second hidden layer was not fully connected with both the middle and the third hidden layers.
One middle layer:	Representing the technical indicators for stocks.
One output layer:	This layer had only one node, which represented the FOF's net worth.

To verify the predictive performance of the key independent variables selected by the selective neural network and the network's effectiveness, this study compared it with the model that produced better training results from the partially connected back-propagation neural network and Models 1 and 2.

In this study, the selective and partially connected neural networks both used the sigmoid function as the conversion function. Since the value of the function gradually approached 0 and 1, this caused the 0, 1 and nearby differentials to be close to 0 and the resultant error signals to be too small, thereby delaying the network learning process. To prevent this problem, this study used the maximum and minimum mapping approach for linear mapping and limited the range of the values between 0.15 and 0.85.

While learning at a fixed rate, the back-propagation neural network often encountered a delay and a skip, which means that the error function either did not reached or skipped the minimum weight and could be avoided by varying the learning rate. To prevent such delays and skips during experiments, this study employed the EDBD (Extended-Delta-Bar-Delta) algorithm developed by Minia et al. (1990) as Eq. (5) to (8), which adds one inertial term into the weight adjustment equation. By controlling the proportion of the inertial term through inertia, it was possible to reduce oscillations during convergence and accelerate such convergences.

$$\Delta W_{ij}^{n}(k) = -\eta \frac{\partial E}{\partial W_{ij}^{n}} + \alpha_{ij}(k)\cdot \Delta W_{ij}^{n}(k-1) \tag{5}$$

$\alpha_{ij}(k)\cdot \Delta W_{ij}^{n}(k-1)$ ：Momentum term

$\alpha_{ij}(k)$ ：Momentum coefficient， $0 \le \alpha_{ij}^{n}(k) \le 1$

$$\eta_{ij}(k+1) = Min[\eta_{\max}, \eta_{ij}(k) + \Delta\eta_{ij}(k)] \tag{6}$$

$\eta_{\max}$ ：The upper limit of the learning rate

$$\alpha_{ij}(k+1) = Min[\alpha_{\max}, \alpha_{ij}(k) + \Delta\alpha_{ij}(k)] \tag{7}$$

$\alpha_{\max}$ ：The upper limit of the momentum coefficient

$$\Delta\eta_{ij}(k) = \begin{cases} \kappa_l \exp\left(-\gamma_l \left|\bar{\delta}(k)\right|\right) & if\ \bar{\delta}(k+1)\cdot \delta_{ij}(k) > 0 \\ -\phi_l \eta_{ij}(k) & if\ \bar{\delta}(k+1)\cdot \delta_{ij}(k) < 0 \\ 0 & otherwise \end{cases} \tag{8}$$

To compare the network performance of the two models presented in this study, i.e. the selective and partially connected back-propagation neural networks, all the relevant network parameters had the same settings. The number of learning cycles was set at 10,000, the inertial term was set at 0.9 given the absence of a standard setting, and the range of the learning rate was between 0.001 and 0.3. Moreover, neural networks often encounter the problem of local minima during operations. For this reason, this study repeated each experiment 30 times to obtain the best network performance as experimental results and reduce the effect of local minima on the research.

3.6 Design of Experiments

To fully investigate the relationship between technical indicators for stocks and FOF, the stock selection strategies of stock funds were divided into five experiments that examined the relationship between different strategies and the FOF's net worth. In the experiments, eight to twelve stocks were randomly selected as investment targets for each stock fund using different strategies. Since the FOF in this study invested in only five stock funds, each experiment had a maximum of sixty stocks and a minimum of forty stocks. The five experiments pertaining to stock selection strategies are described as follows:

Experiment 1: Subjects were mainly MSCI TAIEX constituents. After the exclusion of those lacking sufficient time data or missing other information, 47 stocks in total served as the investment targets.

Experiment 2: Average earnings per share more than 0.8 served as the investment target.

Experiment 3: Average rate of return more than 0.02 served as the investment target.

Experiment 4: Average market value more than NT$10 billion served as the investment target.

Experiment 5: Average trading volume more than 4 million shares served as the investment target.

4. The Findings

4.1 Results of FOF Investment Strategy

In each of the five experiments, eight to twelve stocks were randomly selected as the investment targets of the FOF using different selection strategies. The selection results are described as follows: In Experiment 1, 54 stocks in total were selected; in Experiment 2, 50 stocks in total were selected; in Experiment 3, 52 stocks in total were selected; in Experiment 4, 51 stocks in total were selected; in Experiment 5, 50 stocks in total were selected.

The FOF in this study used an investment strategy based on a two-stage technical analysis to reduce risks and greatly increase return on investment (ROI). To verify the effectiveness of this strategy, this study compared the trading results of the five FOF with TAIEX rates of return (ROR). Eq. (9) shows how the FOF ROR was calculated.

$$R_t = (P_t - P_{t-1}) / P_{t-1} \tag{9}$$

P_t: *NAV in Period t*

Figure 7: NAV in the Experiments

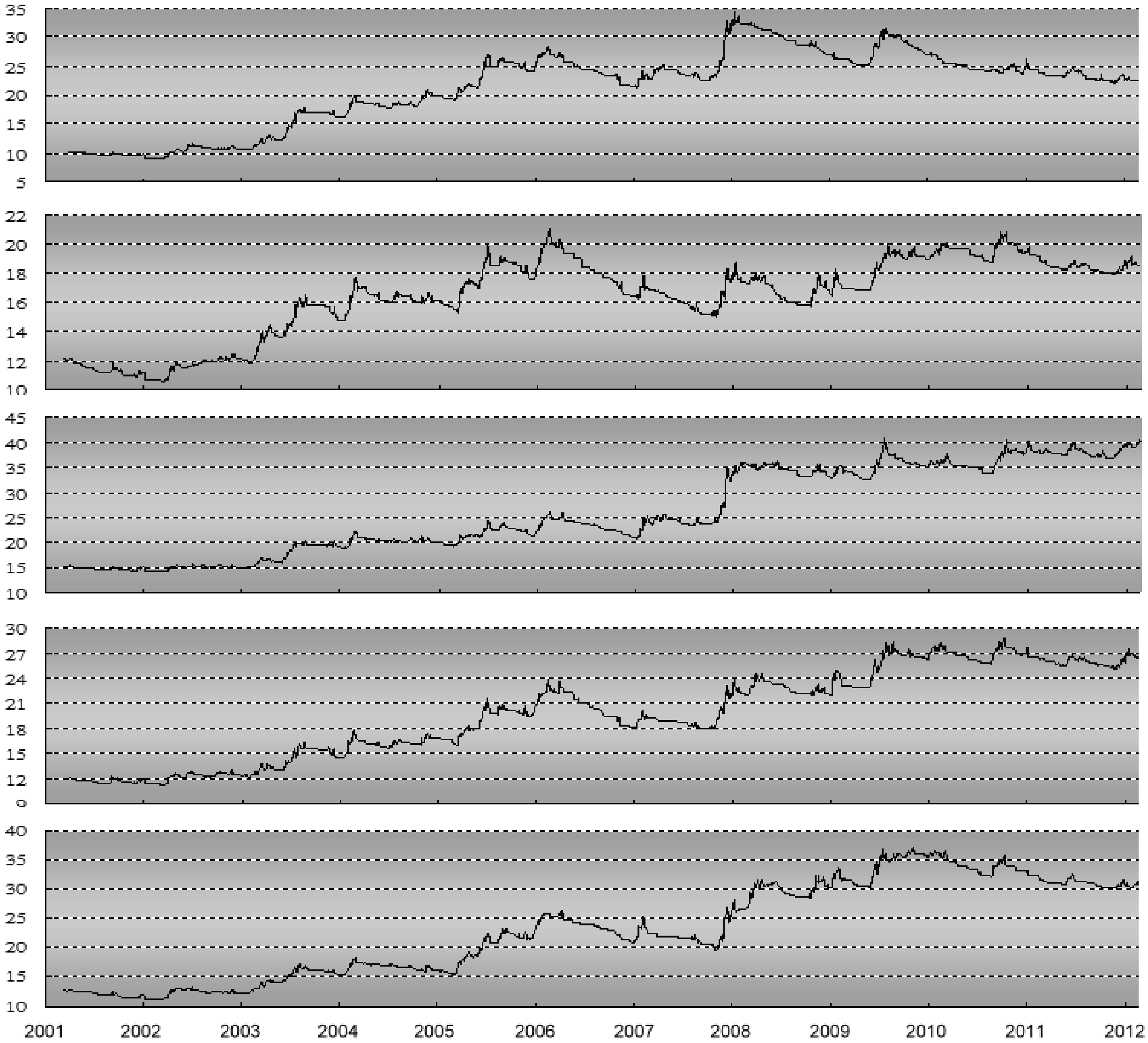


Table 2: Experimental Results

Exp	Model	Training			Testing			Total Connect	Training Time
		RMSE	Correlation Coefficient	Accuracy Rate	RMSE	Correlation Coefficient	Accuracy Rate		
1	Proposed Model	0.007835	0.999100	92.3	0.009676	0.998654	85.8	1409	03:30:25
	Model 1	0.184595	0.000000	1.5	0.187712	0.005783	2.4	70569	10:42:37
	Model 2	0.508262	0.043345	0.0	0.523353	-0.027234	0.0	48708	07:20:51
2	Proposed Model	0.010536	0.998352	99.8	0.013517	0.997209	98.3	1328	02:47:31
	Model 1	0.182262	-0.082624	18.1	0.187299	0.000000	17.0	62676	09:19:50
	Model 2	0.563633	0.114611	0.0	0.561920	0.080321	0.0	44625	07:01:28
3	Proposed Model	0.007634	0.999412	91.3	0.009706	0.999111	85.2	1274	02:41:58
	Model 1	0.223154	-0.003247	1.7	0.227550	0.000000	1.2	57674	08:44:47
	Model 2	0.503331	-0.061298	0.0	0.500713	0.000000	0.0	41582	06:47:45
4	Proposed Model	0.008465	0.999195	96.8	0.010073	0.998852	95.2	1436	03:31:42
	Model 1	0.209521	0.215481	5.4	0.217553	0.000935	5.4	73304	11:13:24
	Model 2	0.564187	0.000000	0.0	0.574317	0.000000	0.0	51023	07:33:16
5	Proposed Model	0.009066	0.999107	87.1	0.010774	0.998752	80.2	1355	02:50:12
	Model 1	0.214874	0.000000	4.2	0.213653	0.003387	4.8	65255	10:35:21
	Model 2	0.505234	-0.358849	0.0	0.495432	0.000000	0.0	46836	07:11:40

During the experiment, the rate of return for the FOF in Experiment 1 was 124.5%, Experiment 2 saw 51.9%, Experiment 3 was 162.9%, Experiment 4 had 121.7%, and Experiment 5 was 143.6%. Figure 7 shows the NAV trend in the five experiments. To verify the effectiveness of a two-stage technical analysis as the investment strategy for the FOF, this study used the golden and death crosses in Granville's eight rules as a basis for TAIEX trading and compared the TAIEX with the FOF. Experimental results revealed that the TAIEX ROR from stimulated trading was about 58.3%. The average FOF ROR in the five experiments was 120.9%, far higher than the 2.3% TAIEX ROR through long-term holding and the 58.3% TAIEX ROR from technical analysis. It follows that two-stage technical analysis is an effective investment strategy of FOF.

The TAIEX ROR through the strategy of long-term holding during the experiments was about 2.3% and the highest ROR reached as high as 59%, on February 19, 2000. This alone was not able to prove the effectiveness of the two-stage technical analysis investment strategy, simply comparing FOR ROR with TAIEX ROR achieved through the strategy of long-term holding. This study therefore further used the golden and death crosses in Granville's eight rules as a basis for TAIEX trading. Through technical analysis, the ROR achieved by simulating Taiwan’s index trading was about 58.3%.

Two-stage technical analysis as a trading strategy achieved a significantly higher FOF ROI compared with the strategy of long-term TAIEX holding. Furthermore, four of the experiments yielded ROI figures almost twice those from the TAIEX technical analysis strategy, except in Experiment 2 where the difference was only 6.4%. It follows that two-stage technical is an effective investment strategy for FOF trading and will yield higher ROI values compared with the strategies of long-term holding and technical analysis for the TAIEX.

4.2 Results of Partially Connected Neural Network

To fully investigate the relationship between technical indicators for stocks and FOFs, the FOF stock selection strategies was divided into five experiments, in which calculations were made using a non-fully connected back-propagation neural network. Experimental results are shown in Table 2 and described as follows:

In the five experiments, the partially connected network yielded better results for model training and testing in terms of RMSE, correlation coefficient and accuracy compared with the other two models. The RMSE was less than 0.001, with a correlation coefficient greater than 0.99 in all the experiments, indicating a positive correlation, and accuracy of more than 80%. Moreover, the required network operation time was merely 3 hours since the partially connected network had less links compared to the other models.

The network operation time was reduced by having the selective neural network first select variables and the selected technical indicators entered into the other neural network for training. The selection and calculation results from the first and second stages are shown in Table 3.

Table 3: Experimental Results of SNN

Exp	Total Variable	Training RMSE	Training Correlation Coefficient	Training Accuracy Rate	Testing RMSE	Testing Correlation Coefficient	Testing Accuracy Rate	Training Time
1	612	0.021614	0.993175	50.1	0.021673	0.993131	51.6	01:13:04
2	584	0.016852	0.995651	95.3	0.018022	0.995631	94.8	01:00:07
3	579	0.017488	0.996947	57.2	0.018570	0.996540	54.0	00:57:49
4	635	0.016633	0.996855	77.4	0.018765	0.996204	72.0	01:22:41
5	588	0.014796	0.997612	64.3	0.016777	0.997026	61.8	00:59:09

In the five experiments, the number of selected variables represented one half of the original variables and the results of training and testing manifested in RMSE at about 0.015, with a correlation coefficient of more than 0.99 in all the experiments, indicating a positive correlation. Since the number of variables were reduced to half, the network operation time was also lessened to about 1 hour 20 minutes on average.

This section summarizes and discusses the above mentioned experimental results to further understand the results from the partially connected and selective neural networks and compare their respective performance and required times.

4.3 Network Operation Time

When excessive input variables or too much training data is entered into neural networks, it inevitably requires prolonged network training to obtain training results. The selective neural network not only can select key variables, but can also lessen network operation times while maintaining prediction accuracy, thereby reducing time costs. Operation times required for the two networks are summarized in Table 4.

The partially connected and selective neural networks required an average 3 hours 4 minutes and 22 seconds and 1 hour 21 minutes and 7 seconds of network training time respectively, which significantly reduced the total operation time.

4.4 Analysis of Network Performance

The purpose of this study is to select key technical indicators from those for the numerous stocks held by a FOF using the selective neural network. Then, apply the selected key technical indicators to the stage two training of the selective neural network in the hope that the post-selection training results maintain a certain degree of predictive accuracy and reduce network operation times in order to reduce time costs.

Table 4: Network Operation Time

Network Model	Exp	Operation Time
Partially Connected Neural Network	1	03:30:25
	2	02:47:31
	3	02:41:58
	4	03:31:42
	5	02:50:12
Selective Neural Network	1	01:13:04
	2	01:00:07
	3	00:57:49
	4	01:22:41
	5	00:59:09

Training accuracy was higher than 91% in four of the five experiments using the partially connected neural network and over 87% in the remaining experiments. The testing accuracy remained higher than 95% in two of the five experiments and over 80% in the other two. After the selective neural network had selected variables using the two selection models, this study also compared the training results from this network and the partially connected one. In Experiment 2, 54.16% of the original variables were selected using the selective neural network. The decline rates in network training and testing accuracy were as high as 4.51% and 3.56%.

The research summary shows that the numbers of selected variables using the two selection models were about 50% of the original variables in the five experiments. Furthermore, Experiment 2 yielded higher degrees of accuracy in training and testing compared with the other experiments whether using the partially connected network or the selective one. Further examination of the issue reveals that Experiment 2 yielded merely 51.9% ROR, significantly lower than the other experiment’s ROR. Experiment 2 had a mere 10.5 amplitude, which was considerably lower than the amplitudes in the other experiments and resulted in the highest degrees of accuracy in training and testing among all the experiments.

5. Summary and Conclusions

The application of technical analysis to investment has become natural. Nevertheless, the versatility of Taiwan's investment environment means that it is not easy for average investors to analyze and select key technical indicators that may affect the FOF they have invested in a timely manner. This study used the selective neural network to help investors solve this problem in an effective and rapid manner and make investment analysis processes simpler and faster.

This study proposed the application of two-stage technical analysis as the investment strategy for FOFs. Research results show that FOF performance was much better than TAIEX ROR through long-term holding in the five experiments, and FOF ROR was twice higher than TAIEX ROR through technical analysis in four of the five experiments except in Experiment 2 where the difference between the two was merely 6.4%. It follows that two-stage technical analysis is an effective investment strategy for FOF trading and will yield a higher ROI compared with the strategies of long-term holding and technical analysis for TAIEX.

Research findings also reveal that the selective neural network could select variables effectively and reduce network operation times significantly while maintaining accuracy in prediction. The numbers of selected variables were 50% of the original variables using the two selection models and the network operation times were lessened to 50% of the time required for the partially connected neural network in the five experiments. The two have a positive correlation.

The limitations for this research are: data was collected from the Taiwan stock market only and this study assumed that all of the transactions were completed.

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