Forecasting stock market with neural networks

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Abstract

Prediction of stock market returns is an important issue in finance. The aim of this paper is to investigate the profitability of using artificial neural networks (ANNs). In this study, the ANNs predictions are transformed into a simple trading strategy, whose profitability is evaluated against a simple buy-hold strategy. We adopt the neural network approach to analyze the Taiwan Weighted Index and the S&P 500 in the States. Consequently, we find that the trading rule based on ANNs generates higher returns than the buy-hold strategy.

Keywords: neural networks; investment strategy

1. Introduction

Taiwan's financial market has become increasingly active in recent years. With the prevalence of wealth management concepts, people turn to invest in diversified financial instruments rather than merely placing their money in a bank account. In the financial market, numerous investment products are offered for selection. Investment in stock markets, however, remains to be the preferred option for most people. To achieve the desired return in a dramatically changing stock market, however, investors need to precisely grasp the market movements. Scholars and public investors, therefore, share a common interest in identifying the method to "accurately forecast stock markets trends".

Stable and high profit through successful investment is no doubt an important goal for all investors. Apart from stock markets, investors may also access financial instruments in the bond and bills market. These markets provides not only fund-raising channels for enterprises, but also additional investment choices for the general public on top of term deposits. The bond and bills market are both very large in terms of the whole transaction volume, which could be many times the size in the stock market. The main products in these two markets, however, demand either a larger investment amount or other thresholds for investment. They are, as a result, less accessible to individuals for direct investment. Most of individual investors therefore choose to invest in Securities Investment Trust Enterprise (SITE) Funds to access to these financial products. The stock market, on the other hand, allows high flexibility in investment amount as well as trading in odd-lot units. Investors are given the liberty to buy or purchase stocks at anytime depending on their fund availability.

Stock prices are influenced by numerous factors including human issues, political reasons, economic situation, competition or other incidents. Different approaches, such as fundamental analysis, technical analysis or psychological research, etc., are adopted to study the stock market movements. The purpose is to find out some rules in stock price fluctuation by analyzing trading behaviors. Through the analytical process, people can often identify good reference material to support their investment decision-making. The stock market, however, is facing dramatic changes, as well as rapid information exchange all the time. Investors are, therefore, strongly aspiring toward an effective instrument to optimize their investment return in this highly unpredictable market. Whilst most investors spend great efforts in technical analysis to support their decision-making in the stock market because of its practicality and reference ability, the diversity and inconsistency of technical indices sometime cause hesitation in the decision making process and, consequently, the missing of best timing.

With the development of electronic technologies, the calculating and data processing abilities of computers have been significantly improved now. When integrated with artificial intelligence, computers can provide solutions to complicated problems that involve huge volumes of information. Neural networks, as a type of artificial intelligence, are featured by their good error tolerance and, consequently, their capability for accurate prediction of performance in spite of the irrelevant information. So far, neural networks have been sufficiently developed to provide non-linear forecasting models. They are also capable of continuous learning through the new information received. Once the network operations have converged to a certain extent, the system will memorize the new knowledge obtained and arrive at a stable status. When specific information is input into the stabilized network, therefore, it will generate forecasts on the corresponding results in future. Neural networks have been extensively utilized for different purposes, including construction inspection, character recognition, speech recognition, image processing, construction of expert systems and analysis for the decision-making process, etc. Comprehensively used in the prediction and analysis of stock markets, futures and bond evaluation process in the financial market, it has proven to be a reliable instrument with good error tolerance, capable of handling large and complicated information and achieving satisfactory forecasting results.

Stock price forecasting models based on neural network not only saves the time of small investors for decision-making, but also helps them to reduce investment risk and loss caused by market fluctuation. The objective of this research, therefore, is to provide an inexpensive and efficient way for the users to identify their investment targets. Small investors are, in general, individual investors from the general public who need to ensure their investment return from the stock market. In this research, we adopt the neural network approach to analyze the Taiwan Weighted Index and the S&P 500 in the States. Through historical data input, we try to train the system and construct a best model for trade decision-making, so as to help the investors to grasp the trend of the General Index for their investment decisions. The research results will provide a good reference indicator for public investors, thereby increase the profitability and reduce risks.

The paper is organized as follows. The Related Works is discussed in Section 2.Section 3 presents the model used to generate predictions. The empirical results are shown in Section 4. Finally, Section 5 provides some concluding remarks.

2. Related Works

When reviewing various documents studying the actual stock price movement or predicting its future trends, we found that most of these researches are based on fundamental, technical or information analysis. Diversified approaches have been adopted in selecting the variables for the research, no matter in terms of fundamental or technical analysis. Many scholars, also, have conducted empirical research on the correlation between trade volume and stock prices. In this section, therefore, we shall focus on documents relating to the application of a neural network on stock price forecasting.

2.1. The Neural Network

Artificial intelligence has long been utilized by domestic and foreign scholars in financial research, aiming to achieve a reliable decision-making process through scientific approaches. A neural network is a data processing system that simulates the behaviors of biological neural network. With the capability of high-speed calculation, memory, learning and error tolerance, the computer system is a good solution for complicated classification or prediction (Yen, 1999).In fact, the initial design and basic structure of a neural network are both similar to the structure of a neuron in Neurobiology. In general, the function of neurons in the neural network is quite similar to real neurons, i.e., the system enables the assignment of different weights to the input value, based on their importance. The weighted value are then summed up and converted through a transfer function incorporated in the neuron, thereby arriving at an output value. The mechanism is as follows:

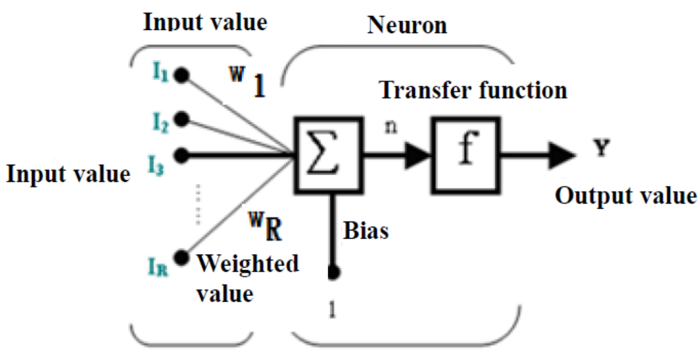

Fig. 1: A Processing Unit of the Neural Network

$$Y = f(\sum_{1}^{R} I_R w_R + B) = f(n) \tag{1}$$

In equation (1), R stands for the number of input variables for the neuron, and $I_1, I_2, I_{3,\ldots\ldots} I_R$ each represent an input variable. $w_1, w_2, w_{3,\ldots\ldots} w_R$ are the respective weights of each input variable. B stands for the bias of the neuron. f(n) is the transfer function for the neuron and n is the summation function.

2.2. Related Researches in Taiwan and Other Countries

Neural networks have been extensively applied to the calculation and prediction of stock prices in recent years. Tsai et al. (1999), for example, tried to predict the best timing for investment by integrating various technical indices and constructing a stock forecasting model based on neural networks. The result was that, through the cross utilization of neural network and stop-loss strategies, one can effectively forecast the best timing for stock purchase and achieve better returns from the in vestment. Ma (2003) also applied the fuzzy neural network technology in his simulated investment in Taiwan's stock market. In his empirical study, he used the general technical indices of Taiwan's General Index as input variables. He then compared the results with the actual results of using merely the 12-day moving average. The discovery was that, by adopting the fuzzy neural network approach, one can avoid the misleading effect of cheat lines, which are more likely to happen when merely using the moving average approach. The investment return, also, is significantly better than the return achieved through the buy-hold strategy or the traditional moving average strategy. Lee (2003), in her efforts to predict the overnight closing indices of Taiwan Stock Index Futures and identify the most suitable forecasting model, also applied the neural network and the statistical approach of regression analysis, using the daily information of Taiwan Weighted Index from 21 December 2000 to 18 December 2002 as samples. Wu (2004) adopted the Back Propagation Neural network (BPN) for his stock price research, based on the transaction volume, trade price and the technical indices of the General Index. The result shows that the investment return received by applying the crossed MACD (Moving Average Convergence and Divergence) is better than the return of merely using individual technical indices.

Through the neural network, Kimoto et al. (1990) also constructed their forecasting model based on the Nikki Stock Price Index. The model turned out to be effective in predicting the Japanese stock price, and contributed to an excessive investment return. Fernando et al. (2000) used the BPN to construct his forecasting model for Madrid Stock Exchange General Indices. The result of his empirical study also showed that the model is an effective forecasting model for the Madrid Stock Exchange General Indices and helped to achieve better investment return. Antonio et al. (1996), in their research, used the 240-day trade information of the Santiago Stock Exchange as samples and the indices and transaction volume of the preceding 10 days as the input data, trying to predict the overnight closing indices of the San Diego Stock Exchange through the neural network approach. The result showed that, through the neural network approach, he achieved an accuracy rate of 63.3% in predicting directions in the rising range of the stock market; and a 74.7% accuracy rate in the falling range.

3. Research Methods

When conducting the research, we first collected the relevant general indices and computed the return rate for the preceding nine days. The information was normalized and used to construct a forecasting model through the neural network. The neural network, after having gone through a training process, was evaluated. We then selected a model with the better investment return to compare with the investment return derived from the buy-hold strategy.

3.1. Data Source

The data collected for the research covers the basic information for Taiwan Weighted Index during the period of 1 January 1970 to 31 December 2005, and the S&P 500 in the United States during the period of 1 January 1970 to 31 December 2005. The information included the opening/closing price and day low/day high obtained from the InforWinner Plus Database System and the Hong Kong Yahoo Website.

3.2. Investment Strategies

In this research, we evaluated the performance of different investment strategies, which are outlined as follows:

(1). Buy-Hold Strategy

For the purchase price, we adopted the closing index of the first trading date of the year when the investment period begins. In accordance with the different holding period defined, we used the full amount of assets to purchase securities and held them until the end of the investment period.

(2). Full Trading Strategy

To execute a full trading strategy, we performed a full conversion of the total asset value between risk assets and non-risk assets when the trading signal appeared.

3.3. Neural Network Model

In this research, we adopted a back-propagation network model for the neural network. A brief introduction of the network structure, including the input layer, output layer and hidden layer, is provided below.

(1). Input Layer

The input data used for the neural network of this research was the investment return for the preceding nine days ($R_{t-1}R_{t-2}....R_{t-9}$) (Fernando et al., 2000). The calculation formula is as follows:

$$R_t = \frac{P_t}{P_{t-1}} \tag{2}$$

Where **R_t** = The investment return on Day t.

As different ranges of value are involved, we need to avoid the situation that the significance of variables with a smaller range is obscured by those with a larger range in the neuron. Under the circumstances, variables with a larger range of value will dominate the network learning and adversely impact the neural network training results. To avoid this undesirable situation, we need to normalize the range of value of the variables. This will improve the efficiency of the neural network training. The approach is to execute a "preprocessing" prior to the network input process to ensure that the value will always fall within the specified range of 0-1 (Yen, 1999). All data has to be normalized first before being used. The formula for normalization is as follows:

$$\mathbf{y} = \frac{(\mathbf{x} - \mathbf{x}\min)}{(\mathbf{x}\max - \mathbf{x}\min)} \tag{3}$$

Where **x** stands for the raw data before normalization; **xmin** stands for the minimum value of raw data prior to normalization and **xmax** stands for the maximum value of raw data prior to normalization.

(2). Output Layer

To determine the timing for trade, we adopted the FK indicator for decision making (Zhang, 1993). The range of value for FK indicators is from 0 to 1. When the stock price is rising, the value of FK indicator will move toward 0; and it will move toward the opposite direction to 1 when the price is falling. Through the FK indicator, investors will be able to grasp the position and trend of the General Index. In other words, the value of FK indicator predicts the corresponding level of the current stock index at a specific time point in future. Investors, therefore, can set up a threshold value to determine the timing for trade. A buy-trade can be executed when the value of FK indicator falls below a specific threshold; and a sale-trade can be considered when the value has exceeded the established threshold. In this research, we have established the buy and sell thresholds at 0.2 and 0.8 respectively. In other words, the system will output a "buy" signal (value = 1) when the value of FK indicator is below 0.2; and the "sell" signal (value = -1) when the value of FK indicator is higher than 0.8. In other situations, the system will output a "hold" (value = 0) signal.

Table 1: Output Variables

Output Variables	Significance
1	Buy
0	Hold
-1	Sell

The FK indicator is modified from the K indicator. The formula is as follows:

$$FK_N^{J,K} = \frac{C_N - MIN_{i=N-J}^{N+K}(L_i)}{MAX_{i=N-J}^{N+K}(H_i) - MIN_{i=N-J}^{N+K}(L_i)} \tag{4}$$

Where $FK_N^{J,K}$ means the FK value on the N_{th} trading day. The reference trading period for this

FK value shall be from the J_{th} day prior to the N_{th} trading day till the K_{th} day after to the N_{th} trading day. C_N means the closing index on the N_{th} trading day; L_i means the day low on the i_{th} trading day; H_i means the day high on the i_{th} trading day; $MAX_{i=N-J}^{N+K}(H_i)$ stands for the maximum value of the day high's during the period from the $N\text{-}J_{th}$ trading day to the $N\text{+}K_{th}$ trading day and $MIN_{i=N-J}^{N+K}(L_i)$ stands for the minimum value of the day low's during the period from the $N\text{-}J_{th}$ trading day to the $N\text{+}K_{th}$ trading day.

(3). Hidden Layer

The hidden layer shows the cross-influence among neurons. There is no standard way to determine the most adequate number of neurons to be processed, apart from trial and error. A neural network may contain more than one hidden layers, or no hidden layer at all. When adopting the BPN to solve problems, the non-hidden-layer approach should be adopted first for analysis. If, however, the predicting ability by using the non-hidden layer approach turns out to be better than that by using the hidden-layer approach, it is then not necessary to use the BPN, because the results of using a non-hidden layer BPN would be similar to the results of using linear regression analysis (Li, 2003).

We recommend that using one or two hidden layers would lead to the best converging effect. Based on the experience gained in the research process, one hidden layer would be sufficient in normal situation (Li, 2003). The converging speed would be slowed down with the increase in the number of neurons processed by the hidden layer, but the error value would be minimized at the same time. On the other hand, if the number of neurons processed is too small, it would be insufficient to build up a non-linear relationship between the input and output variables to solve the problem; in the meantime lead to a larger error value. When the number of neurons processed has exceeded a specific level, it is likely that the network would be over-trained. Freisleben (1992) held the view that the most suitable number of neurons can be achieved by multiplying the number of input variables (n) by K, then minus 1.

$$\text{Number of Neurons Processed in a Hidden Layer}=(k*n)-1 \tag{5}$$

Refenes et al. (1994) believed that, considering the convergence and generalization, a neural network structure of "3-32-16-1" would be relatively stable. Currently, there are two frequently used methods for this purpose. The first method is to take the square root of the value achieved by "multiplying the number of input by the number of output"; and, for the second hidden-layer, take the logarithm value (ln) of the "number of neurons processed in the upper hidden layer". The next method is to take the arithmetic average of the "number of input variables and the number of output variables".

$$\text{Number of Neurons for the First Hidden-Layer}=\sqrt{\text{input}*\text{output}} \tag{6}$$

$$\text{Number of Neurons for the Second Hidden Layer}=\ln(\text{Number of Neurons for the First Hidden Layer}) \tag{7}$$

$$\text{Number of Neurons for the Hidden Layer}=\frac{\text{input}+\text{output}}{2} \tag{8}$$

There is no precise theory or formula to determine the most suitable number of neurons for each hidden layer in the network. It is normally determined through the trial and error method.

When designing the number of neurons for each hidden layer for testing, we used formula (6) to arrive at the value “3” for the first layer; and formula (8) to arrive at the value “5”. We also referred to the structure of the neural network model recommended by Fernando et al. (2000) for our test. The transfer function used for the output layer was the hyperbolic tangent function. As for the transfer function used for the hidden layer, it was found after some testing that the best effect can be achieved by using Sigmoid Function as the transfer function. The decision is that we will use the Hyperbolic Tangent Function and Sigmoid Function as the transfer functions for the neural network. Through different experiemental set-up in the hidden layer number, number of neurons and transfer function, we endeavor to construct a model suitable for solving complicated problems. Table 2 shows the structure of the neural network used for the experiment:

(1). Sigmoid Function: The output value is between 0 and 1.

$$f(n) = \frac{1}{1 + \exp^{-n}} \tag{9}$$

(2). Hyperbolic Tangent Function: Symmetrical with respect of the origin, with an output value of between -1 and 1.

$$f(n) = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}} \tag{10}$$

Table 2: The Neural Network Structure for the Experiment

Network Structure
9-3-1
9-4-1*
9-5-1

* The network structure was extracted from reference document.

3.4. Measurement of Investment Performance

For this research, we adopted an investment strategy of a single buy-and-sell trading signal. In other words, after the show-up of the first “buy” signal, any other “buy” signals prompted before the show-up of the “sell” signal will not be executed. Similarly, after the show-up of the first “sell” signal, any other “sell” signal appeared before the show-up of the “buy” signal will not be executed, either.

(1). Formula for calculating the investment return:

$$\text{Return} = \frac{\text{Selling Price - Handling Fee for Sale - Capital Gains Tax}}{\text{Price and Handling Fee for Purchase}} \tag{11}$$

(2). Formula for calculating the investment return against the “Buy-hold” Strategy:

$$\text{Return} = \frac{\text{Selling Price at the Last Day of the Research Period - Handling Fee for Sale - Capital Gains Tax}}{\text{Purchasing Price at the First Day of the Research Period + Handling Fee for Purchase}} \tag{12}$$

(3). Formula for calculating the annualized return:

$$\sqrt[n]{\prod_{k=1}^{n} R_k} - 1 \qquad (13)$$

Where n = period of holding; R_k = Return on Investment.

(4). Research Hypotheses

In this research, we applied the neural network in the prediction of the Taiwan Weighted Index and the S&P 500 in the States. The following hypotheses are followed throughout the research process:

(a). When the trading signal showed up, always use the “closing price” of the day as the price at the trading time.

(b). If the same trading signal shows up after the transaction has been executed, no action should be taken before a different trading signal shows up.

(c). The rate of handling fee for each purchase or sale shall be 0.1425%.

(d). A capital gains tax of 0.3% shall be charged for each sale of stocks.

(e). If there are any untraded stocks at the end of the research period, execute the trade by using the latest closing price available during the research period.

(f). Potential dividends or bonus gained through long-term holding are ignored in this research.

(g). All investment performances applied in the research represent performances in the past. They are not necessarily indicative of the future performance.

4. Empirical Results

For this research, we used the General Index for the period of 1 January 1970 to 31 December 2005 (36 years) as the target of our test, and compared the information with the results of buy-hold. Apart from the buy-hold strategy, we also used other neural network models to compare the investment returns. The examples used for training purpose include the data during the periods of bullish (1986.10.01- 1987.10.01), bearish (1989.10.01- 1990.10.01) and stable (2005.01.01-2005.12.31) markets of Taiwan General Index, as well as the data during the periods of bullish (1982.07.01- 1983.07.01), bearish (1974.01.01 - 1974.12.31) and stable (1971.01.01 - 1971.12.31) markets of the S&P 500 in the States.

Table 3 shows a comparison of investment return between the full trading strategy under the neural network and the buy-hold strategy, using the Taiwan General Index as the testing target. The result shows that the annualized return from the full trading strategy is significantly higher than that of the buy-hold strategy. The annualized return received by adopting a neural network of 9-3-1 structure is 17.79%, which is obviously higher than the annualized return of 14.63% obtained from the 9-4-1 neural network recommended by Fernando et al. (2000). The annualized return from the 9-5-1 neural network, through not higher than the above two, is still significantly higher than the annualized return from the buy-hold strategy.

Table 3: Overall Performance Comparison between the Buy-hold Strategy and the Full trading Strategy (Based on Taiwan Weighted Index)

Network Structure	Annualized Return from the Full trading Strategy		Annualized Return from the Buy-hold Strategy
9-3-1	17.79%		11.98%
9-4-1	14.63%		
9-5-1	13.61%		

Individual investors account for nearly 80% of the investor population in Taiwan's stock market. This, plus the unique political and economic environment of Taiwan, has resulted in the "Shallow-Plate Market" characteristic of the local stock market over a long period, and dramatic fluctuations are frequently seen in the market. For example, the latest and largest stock market rise, on a yearly basis, occurred during the period of October 1986 and October 1987, marking a rising range of 400% and ranked the second in the world, only next to Philippines. The latest and most significant drop in the market occurred during the period of October 1989 and October 1990. The range of price falling was then 74.9%, being the first in the world. These facts evidence the high volatility of Taiwan's stock market. The neural network recommended in this research, under the circumstances, has proved to be sufficiently effective in its forecasting ability in a highly volatile market. Apart from effectively detecting the trading signals, the neural network also generates a return that is significantly higher than the buy-hold strategy. The performance from the buy-hold strategy would be heavily impacted by the poor performance of the General Index. While this may not necessarily cause losses, the return would be barely satisfactory when compared with the return from the full trading strategy under the neural network forecasting model.

Table 4 shows a comparison of investment return between the full trading strategy under the neural network and the buy-hold strategy, using the S&P 500, USA as the testing target. The result also shows that the annualized return from the full trading strategy is significantly higher than that of the buy-hold strategy. The annualized return received by adopting a neural network of 9-3-1 structure is 10.214%, which is obviously higher than the annualized return of 8.325% obtained from the 9-4-1 structure recommended by Fernando et al. (2000). The annualized return from the 9-5-1 neural network, though not higher than the one specified in this research, is still significantly higher than the annualized return from the buy-hold strategy.

Table 4: Overall Performance Comparison between the Buy-hold Strategy and the Full trading Strategy (Based on S&P 500)

Network Structure	Annualized Return from the Full trading Strategy		Annualized Return from the Buy-hold Strategy
9-3-1	10.214%		7.46%
9-4-1	8.325%		
9-5-1	8.61%		

During the research period for predicting the USA S&P 500 indices, the index for the "purchase" trade for the buy-hold strategy is 93, the closing index for 2 January 1970; and the index for the "sell" trade is 1248.29, the closing index for 30 December 2005. The annualized investment return is 7.46%. The annualized return rates from the full trading strategy under the neural network proposed in the research are higher than the return from the buy-hold strategy. The results proved that the neural network, when integrated with the full trading strategy, is able to effectively detect the trading signals and improve the investment return, which is relatively better than the return from the buy-hold strategy.

In this research, we also tried to determine the predicting ability of the neural network model by consolidating the trading information in the period of 1995 to 1997, based on the Taiwan Weighted Index. The results were compared with the performance of neural network model proposed by Tsai et al. (1999). The empirical test results are shown on Table 5:

Table 5: Overall Performance Comparison by Full trading Strategy - between the Results of this Research and that of Tsai et al. (1999)
(Based on Taiwan Weighted Index)

Network Structure & Investment Strategy	1995 Annualized Return	1996 Annualized Return	1997 Annualized Return	Averaged Annualized Return for 3 years
9-3-1	-12.79%	18.75%	24.4%	8.8112%
9-4-1	-30%	43.4%	12%	3.98%
9-5-1	-26.31%	39.4%	10.89%	4.437%
28-15-3*	-12.81%*	9.34%*	30.06%*	7.43%
Buy-hold Strategy	-27.05%	33.95%	19.34%	5.25%

* The data was extracted from reference document (Tsai et al., 1999).

In Table 5, we provided a summary on the annual performance of 1995, 1996 and 1997 against the respective investment strategies. As a whole, Taiwan had a bearish stock market in 1995, with a sharp fall in the general weighted index to nearly 2000, a drop of 27%. With the passing of the sluggish year, 1996 showed a dramatic rise in the general weighted index of more than 2000 points, marking a growth of 34%. Continuing the bullish market of 1996, there was an increase of more than 1300 points, or 19%, in year 1997. These figures evidenced the drastic fluctuation of the General Index during the period. Impacted by various unfavorable events, the General Index of Taiwan suffered a significant fall of 27.05% in year 1995. The return against buy-hold strategies, which was heavily influenced by the poor performance of the General Index, was consequently the worst of all. The return against the full trading strategy proposed by Tsai et al. (1999), fully relying on the neural network forecasting model, also reported a loss of 12.81% during the period. The results of this research, based on a neural network model proposed by the researcher, also showed a 12.79% loss. The performance of the neural network, however, is relatively superior to the results against the buy-hold strategy.

With the fading away of the depressing market conditions in 1995, in 1996 we had a 33% soar in the general weighted index. With the favorable turn of the General Index, the return against the buy-hold strategy also climbed up dramatically to 33.95%. The results against the full trading strategy proposed by Tsai et al. (1999), however, was merely 9.34% during the period, which was not satisfactory. For the year, the performance against the full trading strategy lagged far behind the results against the buy-hold strategy. The excessive return received by the full trading strategy during the previously year, therefore, has been entirely offset this year. The return from the full trading strategy adopted in this research was 18.75% for the year, which was obviously better than the results achieved by Tsai et al. (1999). In 1997, the stock market remains bullish and the General Index has once broken 10,000 points. In spite of the pullback at the year's end, there was still an approximate 19% increase in General Index for year 1997. Restricted by the investment nature, the buy-hold strategy did not lead to the expected profit under the high index of 10,000.The full trading strategy in this research, nevertheless, has created an investment return of 24.4% for the period. Also, the return from the strategies proposed by Tsai et al. (1999), for the same period also reached 30.06%. In other words, the full trading strategy enabled full grasp of the business opportunities arising from the booming market, and resulted in outstanding investment performance for the year. Finally, the neural network model proposed in the research has created an averaged annual return of 8.8112%, which is significantly higher than the return resulted from the buy-hold strategies under the neural network proposed by Tsai et al. (1999).

To train the neural network system, we used the data during the periods of bullish (1986.10.01- 1987.10.01), bearish (1989.10.01- 1990.10.01) and stable (2005.01.01- 2005.12.31) markets of Taiwan General Index. The results of this study are compared with the costs of buy-hold strategy, as well as the performance against the fuzzy neural network system proposed by Ma (2003) and the results of adopting the traditional 12-day moving average, on a consolidated basis. The period covered was from 13 December 1999 to 30 December 2000.

Table 6: Performance Comparison between the Investment Strategies Used in this Research and the One Proposed by Ma (2003) (Based on the Taiwan General Index)

Trade Period	Results against Traditional 12-day Moving Average	Results against the fuzzy neural network	Results against the Buy-hold Strategy	Results against the Neural Network Proposed in this Research (Network Structure: 9-3-1).
1999-12-13~ 2000-12-30	3787.09*	4796.51*	-3154.2563	5467.38

* The data are extracted from reference document (Ma, 2003).

Table 6 shows that, during the empirical testing period of one year or so, the performance against the traditional 12-day moving average is 3787.09 points; the performance against the fuzzy neural network is 4,796.51 points; and the one against the buy-hold strategy, -3154.2563 points. Apparently, the performance against the neural network model proposed in this research is better than the fuzzy neural network proposed by Ma (2003) and the traditional 12-day moving average, which is, in turn, superior to the buy-hold strategy. The findings support the fact that the traditional 12-day moving average is a practical approach. It also proves that the neural network model proposed in this research can successfully remove the problem with the traditional 12-day moving average, i.e., the misleading cheat line, and achieve an improved performance.

Under the buy-hold strategy, only a single trade will be conducted at the early stage of the simulation period. It can therefore properly reflect the movement of the General Index. The moving average strategy, on the other hand, does not guarantee good performance all the time. It is doubtless, however, that the moving average strategy sometimes generates misleading signals. For example, in a number of cases the moving average system triggered a “buy” signal whilst the market turned to be going downwards. This caused loss to the investors. The incorrect signals are normally referred to as “Cheat lines”. What would be the probability, then, of being misled by a “Cheat Line”? This is a quite interesting question, as the probability would stand for the potential risk behind the moving average strategy. On the other hand, it also implies that there is still room for improvement for the moving average, more or less.

When adopting the full trading strategy, the investor will completely rely on the neural network and follow the system recommendations in their investment decision-making. When we compare the profitability between the buy-hold strategy and the full trading strategy, we may arrive at the conclusion that the neural network model is more effective if the comparison results show a higher performance from the full trading strategy. This will also prove that the neural network model has a better forecasting ability. It can accurately predict the timing for buy and sale, thereby creating a better investment performance against the full trading strategy. The conclusion is that, by incorporating the full trading strategy with the neural network proposed in this research, one can receive the best investment return.

5. Conclusion

For investors, wealth management is becoming increasingly important nowadays. Professional investment managers, as well as individual investors, all long for efficient and effective instruments to grasp the stock market trend, minimize investment risk and improve their return. Some people hold the view that it is very difficult to predict stock prices. In the real business world, however, top traders around the world successfully complete thousands of transactions every year. It is hardly convincing to say that investment in the stock market is purely speculative. The story of Warren Buffett, a master of investment, has always been the mostly-talked-about issue by investors, and an unexplainable mystery for economists. Based on the neural network, the stock market forecasting model proposed in this research will not only reduce investment risk, but also helps small investors to protect their investment returns against market volatility. Through the research, we wish to provide an efficient and inexpensive method to investors to ensure a good investment return. From our comparisons on investment returns, we confirmed that the neural network model had created good profitability both in the Taiwan Weighted Index and in S&P 500, USA. It also showed a better profitability when compared with those proposed by Tsai et al. (1999) and Ma (2003). The neural network model proposed in this research is equipped with good forecasting ability.

Whilst we have achieved good research result by adopting the stock indices of Taiwan and USA as our basis, we appreciate that there are always diversified solutions for predicting stock price. Each method has its advantages and disadvantages. Our recommendation, therefore, is that further in-depth study should be made in future, taking into account the following factors:

(1). Considering the different nature of each sector and individual stock, we may focus our future study on a specific sector or individual stock and develop a suitable system to support the trade decision-making.

(2). The market structure varies from country to country. In future, we may also conduct empirical researches on the stock markets of countries at different stages of economic development, so as to find out whether the theories developed in this research may apply to different markets; and to probe the adequacy of the ”Efficient Market Hypothesis” in different markets.

(3). With respect to the neural network, we adopted the BPN model in this research. There are many other types of neural networks, including the Radial Basis Function Network (RBFN) and Self-Organizing Map (SOM), etc. We may consider providing more network options to the users, so that they can compare the respective results for reference.

(4). We may develop different investment strategies and identify the best solutions to support the investment decision-making by incorporating these strategies.

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