Predicting Stock Market Index Trading Signals Using Neural Networks

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Abstract

This study forecasts trading signals of the Australian All Ordinary Index (AORD), one day ahead. These forecasts were based on the current day's relative return of the Close price of the US S&P 500 Index, the UK FTSE 100 Index, French CAC 40 Index and German DAX Index as well as the AORD. The forecasting techniques examined were feedforward and probabilistic neural networks. Performance of the networks was evaluated by using classification/misclassification rate and trading simulations. For both evaluation criteria, feedforward neural networks performed better. Trading simulations suggested that the predicted trading signals are useful for short term traders.

1. Introduction

A majority of previous studies have aimed at specially predicting the price levels of the stock market indices. However, some recent studies have suggested that trading strategies guided by forecasts on the direction of price change may be more effective and may lead to higher profits [1]. During the last few decades there has been growing interest in applications of artificial neural networks for predicting stock returns [2]. The most commonly used neural networks to predict the trading signals are the feedforward neural networks (FNN) and probabilistic neural network (PNN).

Many studies in this area have assessed the predictability of their methods but have inadequately considered model profitability. Predictability does not necessarily imply profitability. Profit depends not only on the accuracy of the forecasts but also on the trading strategy used and magnitude of the transaction costs [3]. Timely decisions must be made which result in buy signals when the market is low and sell signals when the market is high [4].

The results from trading are also useful in identifying better models when the predictive performances are not significantly different. There are four strategies used in literature: (i) buy stock index, or buy treasury bills, (ii) buy stock index, or short stock index, (iii) buy stock index, or stay out of the market, and (iv) select the best/worst performing stocks to form portfolios [2].

To compare the prediction performance of the backpropagation neural network with those of linear regression and random walk models, Qi and Maddala [3] used the proportion of times that the upward or downward movements of the excess stock returns of the S&P 500 index are correctly predicted. Their results showed that the predictability of neural networks outperform other two tools. However, linear regression forecasts outperformed those relating to the neural network by means of profitability. In their study based on the prediction of the KLCI index of the Kuala Lumpur Stock Exchange, Yao et al. compared the prediction performance of backpropagation neural networks with that of ARIMA models [5]. They evaluated the prediction performance by means of several measurements including percentage of directional correctness as well as a buy and sell trading strategy. In both cases neural networks performed better. Some other studies (such as [6] and [7]) focused on predicting the direction (up and down) of financial market indices showed that neural network is a better option to classify the future direction (trend) of the indices.

A study done by Kim and Chun [8] compared the prediction performance of an arrayed probabilistic neural network with that of recurrent neural network. This study suggested that former is better in all perspectives (classification rate and misclassification rate). They employed these techniques to predict the direction for the fractional change in Singapore stock price index. In their study, Chen et al. attempted to model and predict the direction of return of market index of the Taiwan Stock Exchange [9]. Directional forecast was done by PNNs and the performance of the PNN forecast was compared with that of the generalised methods of movements (GMM) with Kalman filter. Results showed that PNN forecasts outperform those from GMM. Moreover, the forecasts were applied to two trading strategies. Empirical results showed that the PNN-based investment strategies obtained higher returns. Leung *et al*. [10] evaluated the effectiveness of classification models for predicting the direction of stock market indices by means of number of correct forecast (hit rate) and rate of return obtained from index trading. They used the tools, PNN, linear discriminant analysis, logit and probit models to predict the direction (upward or downward trend) of monthly returns of the US S&P 500 Index, the UK FTSE 100 Index and Japanese Nikkei 225 Index. Results corresponding to the US S&P 500 Index and the UK FTSE 100 Index suggested that PNN is a better classification tool by means of the hit rate and the rate of return. However, the results obtained from the Japanese Nikkei 225 Index did not agree with this.

All the above studies based on various financial indices focus on classification of future values into two categories (up or down) which corresponding to the buy and sell signals. Also none of these studies compare the prediction performance of PNN with multilayer feedforward neural networks (FNN).

This study proposes a novel idea of classifying stock market trading signals into three classes. Its objective is to forecast the trading signals: 'Buy', 'Hold' and 'Sell', of the Australian All Ordinary Index (AORD) one day ahead. Such forecasts are useful to short term traders. It is worth holding shares if there is no significant rise or drop in the price index. Therefore, from the practical point of view, it is important to consider the 'hold' category.

Considering these three classes complicates the classification problem as these classes create imbalance in the data distribution. Usually the 'hold' class is dominating while other two classes are small. This study employs FNN and PNN to classify the next day's relative return of the AORD, thereby facilitating the comparison of the prediction performance of these two types of neural network.

The other importance of this study is the usage of the intermarket influences from the major global stock market indices to forecast the trading signals of the AORD. Recent studies have shown that the intermarket influences enhance the prediction accuracy [11, 12, 13]. Literature shows that the previous day's Close prices of the US S&P 500 Index (GSPC), the UK FTSE 100 Index (FTSE), French CAC 40 Index (FCHI), and German DAX Index (GDAXI) as well as the that of the AORD influence the current day's Close of the AORD [14, 15]. Therefore, this study also uses the current day's relative returns of the Close prices of the above markets to identify the next day's trading signals of the AORD.

The efficiency of the neural networks as a technique to predict the trading signals is studied by applying two different criteria. First, the problem of classifying trading signals as 'Buy', 'Hold', and 'Sell'. The classification results are measured by classification/misclassification rates. Second, a simple and very practical trading simulation to evaluate whether the traders can gain profits by using the predicted trading signals, is considered.

The outline of the paper is as follows: Section 2 discuses the methodology used in this study. It includes a description of classification techniques and the proposed trading simulations. Section 3 describes the data used for experiments. Section 4 presents the results relevant to prediction and trading simulations together with their interpretations. Finally Section 5 concludes the paper and proposes directions future research could take.

2. Methodology

This study classified the next day's relative return of the Close price of the AORD into three classes: (i) Buy, (ii) Hold and (iii) Sell, based on the current day's relative returns of the Close prices of the GSPC, FTSE, FCHI, GDAXI as well as that of the AORD (Section 1). Let $Y(t+1)$ be the predicted relative return of the next day's (t+1) Close price of the AORD. This study uses the following criterion to identify the trading signals which corresponding to the three classes:

$$\begin{aligned} &Buy \quad if \;\; Y(t+1) \geq 0.005 \\ &Hold \;\; if \;\; -0.005 < Y(t+1) < 0.005 \\ &Sell \quad if \;\; Y(t+1) \leq -0.005 \end{aligned} \tag{1}$$

The techniques used were FNN and PNN. These networks were trained with two sets of inputs: (1) current day's (day t) relative returns of the Close prices of the US and the three European markets as inputs (set 1); (2) current day's relative returns of the Close prices of the US and the three European markets together with that of AORD as inputs (set 2). Since the influential patterns vary with the time the analysis was performed for a number of moving windows [16].

2.1 Forecasting with FNN

Three-layered FNNs were trained 500 times using Levenberg-Marquardt algorithm. The above mentioned two sets of inputs were considered when training the networks. These networks output the next day's relative return of the AORD which was subsequently classified into the three classes of interest according to Equation (1). The average numbers of classifications/misclassifications into different classes were calculated. This procedure was repeated for six moving windows each of size three trading years.

Each window consists of 768 cases. The most recent 10% of data was used for testing. The next most recent 20% of data was used for validation while the remaining 70% was used for training. Each time the starting point was shifted by one year to get the starting point of the next window. Always, three neurons were used for the hidden layer while the learning rate and momentum were fixed at 0.003 and 0.01 respectively [16].

2.2 Forecasting with PNN

PNNs were also trained for the same six moving windows. For each window the most recent 10% of data was used for testing while the remaining 90% was used for training. Networks output the class ('Buy', 'Hold', or 'Sell') relevant to the next day's Close price of AORD.

Networks were trained with both sets of inputs. The joint distribution of the input variables was assumed to be Gaussian. The parameters of the distribution were estimated by using the training data. The average standard deviation of the individual input variables was considered as the standard deviation of the joint distribution. The cost of misclassification for each class was assumed to be equal.

2.3 Trading Strategies

This study assumes that at the beginning of each period, the trader has some amount of money as well as a number of shares. Furthermore, it is assumed that the value of money in hand and the value of shares in hand are equal. Each period consists of successive 76 trading days. Two types of trading strategies were used in this study: (1) response to the predicted trading signals which might be a 'Buy', 'Hold' or a 'Sell' signal (trading strategy 1); (2) do not participate in trading but hold the initial shares in hand and keep the money in hand until the end of the period (trading strategy 2). The second strategy was used as a benchmark.

2.3.1 First trading strategy

This study assumes index can be traded as a security in its own right. Let the value of the initial money in hand be M^0. The number of shares at the beginning of the period, $S^0 = M^0 / P_0$, where P_0 is the Close price of the AORD on the day before the starting day of the period.

Also let M_t, S_t, P_t, VS_t be the money in hand, number of shares, Close price of the AORD, value of shares holding on the day t (t=1, 2, …, T), respectively. This strategy assumes that always a fixed amount of money is used in trading regardless of the trading signal is 'Buy' or 'Sell'. Let this fixed amount be denoted as F^0 and be equal to M^0 / L, $L > 0$. In the calculations $L = 1, 2, \ldots, 10$ is considered. When $L = 1$, F^0 equals to M^0, when $L = 2$, F^0 equals to 50% of M^0 and so on. Let Δ_t^b and Δ_t^s be the number of shares buy and the number of shares sell at day t, respectively.

Suppose the trading signal at the beginning of the day t is a 'Buy' signal. Then the trader spends $F = \min\{F^0, M_{t-1}\}$ amount of money to buy a number of shares at a rate of the previous day's Close price.

$$M_t = M_{t-1} - F, \quad F = \min\{F^0, M_{t-1}\} \tag{2}$$

$$\Delta_t^b = \frac{F}{P_{t-1}} \tag{3}$$

$$S_t = S_{t-1} + \Delta_t^b \tag{4}$$

$$VS_t = S_t \times P_t \tag{5}$$

Suppose the trading signal is a 'Hold' signal, then;

$$M_t = M_{t-1} \tag{6}$$

$$S_t = S_{t-1} \tag{7}$$

$$VS_t = S_t \times P_t \tag{8}$$

Let the trading signal at the beginning of the day t is a 'Sell' signal. Then the trader sells $S' = \min\{(F^0 / P_{t-1}), S_{t-1}\}$ amount of shares.

$$\Delta_t^s = S', \quad S' = \min\{(F^0 / P_{t-1}), S_{t-1}\} \tag{9}$$

$$M_t = M_{t-1} + S' \times P_{t-1} \tag{10}$$

$$S_t = S_{t-1} - \Delta_t^s \tag{11}$$

$$VS_t = S_t \times P_t \tag{12}$$

It should be noted that a 'Buy' signal that immediately follows another 'Buy' signal will be treated as a 'Hold' signal. Also, if all shares have been sold, a 'Sell' signal is ignored.

2.3.2 Second Trading Strategy

In this case the trader does not participate. Therefore, M_t, $= M^0$ and $S_t = S^0$ for all t=1, 2, …, T. However, the value of the shares changes with the time and therefore, the value of shares at day t, $VS_t = S^0 \times P_t$.

2.3.3 Rate of Return

At the end of the period (day T) the total value of money and shares in hand;

- for the first trading strategy,

$$TC = M_T + S_T \times P_T \tag{13}$$

- for the second trading strategy,

$$TC = M^0 + S^0 \times P_T \tag{14}$$

The rate of return ($R\%$) for each trading period is calculated as below;

$$R\% = \frac{TC - 2M_0}{2M_0} \times 100 \tag{15}$$

3. Data and Data Pre-processing

The data set consists of daily relative returns of the Close prices four influential stock markets and the AORD, from 2nd July 1997 to 30th December 2005. The selected influential markets are:

1. US S&P 500 Index (GSPC)
2. UK FTSE 100 Index (FTSE)
3. French CAC 40 Index (FCHI)
4. German DAX Index (GDAXI)

Since different stock markets are closed on different holidays, the regular time series data sets considered have missing values. If no trading took place on a particular day, the rate of change of price should be zero. Therefore, the missing values of the Close price were replaced by the corresponding Close price of the last trading day. Relative Returns, RR of the daily Close price of the stock market indices were used for the analysis.

$$RR(t) = \frac{P(t) - P(t-1)}{P(t-1)} \tag{16}$$

where RR(t) and P(t) are the relative return and the Close price of a selected index on day t, respectively. Returns are preferred to price, since returns for different stocks are comparable on equal basis.

The study period was divided into six moving windows, each of length three trading years (3×256 days). These six windows were considered for analysis. The most recent 10% of data (the last 76 trading days) in each window was accounted for out of sample predictions.

It is worth noting that the opening and closing times for many of the various markets do not coincide. For example, the Australian, French and German markets have all closed by the time the US markets open.

4. Results and Interpretations

4.1 Distribution of Classes in Test Samples

Firstly, the distribution of out of sample data among the three classes was investigated. Table 1 shows the distribution of the actual 'Buy', 'Hold' and 'Sell' signals within the test sample (the last 76 days) of each window.

Table 1: Distribution data belongs to test samples (percentages of data in each class are also shown in brackets)

Window Number	Class 1 (Buy)	Class 2 (Hold)	Class 3 (Sell)
1	20 (26.32%)	40 (52.63%)	16 (21.05%)
2	20 (26.32%)	44 (57.89%)	12 (15.79%)
3	23 (30.26%)	38 (50.00%)	15 (19.74%)
4	12 (15.79%)	56 (73.68%)	08 (10.53%)
5	11 (14.47%)	59 (77.63%)	06 (7.90%)
6	21 (27.63%)	40 (52.63%)	15 (19.74%)

The noticeable feature in the data distribution is that in each window, 50% or more signals are coming from the 'Hold' class (Table 1) with this signal accounting for over 70% in the 4th and the 5th windows.

4.2 Classification Results

Table 2 and Table 3 show the average rates of classification and misclassification (over six windows) relating to the results obtained from FNN and PNN respectively. These rates indicate the patterns of classification/misclassification of data belong to a class. Classification rate indicates the proportion of correctly classified signals to a particular class out of the total number of actual signals in that class whereas, misclassification rate indicates the proportion of incorrectly classified signals from a particular class to another class out of the total number of actual signals in the former class.

From a trader's point of view, the misclassification of a 'Hold' signal to 'Buy' class or 'Sell' class is a more serious mistake than misclassifying a 'Buy' signal or a 'Sell' signal as a 'Hold' signal. The reason is in the former case a trader will loses the money by taking part in an unwise investment while in the later case he/she only lose the opportunity of making a profit, but no monetary loss. The most serious mistakes are the misclassification of 'Buy' signal to 'Sell' signal and vice versa.

Table 2: Average Classification/Misclassification ratio for two types of inputs for the results obtained by FNN

Actual Class	Average Classification/Misclassification Ratio for Input Set 1			Average Classification/Misclassification Ratio for Input Set 2		
	Predicted Class			Predicted Class		
	Buy	Hold	Sell	Buy	Hold	Sell
1	**0.223**	0.777	0.0	**0.231**	0.769	0.0
2	**0.042**	**0.896**	**0.062**	**0.037**	**0.901**	**0.062**
3	0.0	0.822	**0.178**	0.0	0.8444	**0.156**

As expected 'Hold' class shows higher classification rate irrespective of the input set (Table 2). When the FNNs were trained with the first input set (without AORD), on average, 22%, and 18% signals were correctly classified to 'Buy' and 'Sell' classes, respectively. On average, 78% of 'Buy' signals and 82% of 'Sell' signals were misclassified as 'Hold' signals. Although these figures are large, the consequence of such misclassification is not crucial. The percentage of signals misclassified from 'Hold' class to 'Buy' and 'Sell' classes were relatively small. Also there were no misclassifications into non-contiguous classes (that is no 'Buy' signals were misclassified as 'Sell' signals and vice versa). The FNNs trained with second set of inputs also gave similar results.

Table 3: Average Classification/Misclassification ratio for two types of inputs for the results obtained by PNN

Actual Class	Average Classification/Misclassification Ratio for Input Set 1			Average Classification/Misclassification Ratio for Input Set 2		
	Predicted Class			Predicted Class		
	Buy	Hold	Sell	Buy	Hold	Sell
1	**0.147**	0.853	0.0	**0.155**	0.845	0.0
2	**0.021**	**0.930**	**0.049**	**0.025**	**0.931**	**0.045**
3	0.0	0.841	**0.159**	0.0	0.841	**0.159**

The PNNs also show results similar to the FNNs (Table 2 and Table 3). The percentages of signals correctly classified to 'Hold' class were slightly higher than the case of the FNNs while those corresponding to 'Buy' class were slightly lower than in the case of the FNNs. However, as with the FNNs, the PNNs also do not show serious mistakes such as misclassification of 'Buy' signals to 'Sell' signals and vice versa (Table 3).

Having observed no serious misclassifications, both the FNNs and the PNNs give hope that traders can be benefited from the predictions obtained. As a result of lower classification rate corresponding to 'Buy' class, the PNNs may yield lower profits than the FNNs. However, trading simulations needed to be performed to clarify these matters.

4.3 Trading Simulations

Different trading simulations were performed on the prediction results obtained from the neural network is presented. Table 4 presents the total number of 'Buy' and 'Sell' signals predicted by the FNNs and the PNNs, trained with two input sets. The percentage of correctly predicted 'Buy' ('Sell') signals out of the total number of 'Buy' ('Sell') signals within each window are also shown within brackets.

For many cases, both types of networks predicted 'Buy' and 'Sell' signals correctly with an accuracy rate more than 50% (Table 4). However, the PNNs missed many trading signals and did not predict any signals in the last two windows. Both type of networks show better prediction performance when they were trained with the first set of inputs.

This study considered different proportions of money to respond to the trading signals. In other words, when calculating the rate of return, it was assumed the trader buy or sell shares that worth the full amount of money in hand at the beginning, half of this money, one third of this money and so on. Figures 1 and Figure 2 depict how the average rate of return (over 6 windows) changes with different proportions of money as well as the benchmark strategy. Figure 1 and Figure 2 are corresponding to the results obtained from the FNNs and the PNNs, respectively.

Table 4: Distribution of Buy and Sell signals relating to the results obtained from FNNs and PNNs (percentages of correct signals are shown in brackets)

Window Number	Input Set 1				Input Set 2			
	FNN		PNN		FNN		PNN	
	Buy Signals	Sell Signals	Buy Signals	Sell Signals	Buy Signals	Sell Signals	Buy Signals	Sell Signals
1	12 (67%)	12 (67%)	5 (80%)	12 (58%)	11 (64%)	14 (57%)	7 (71%)	12 (58%)
2	6 (67%)	6 (33%)	6 (83%)	8 (38%)	5 (80%)	5 (40%)	7 (71%)	7 (43%)
3	11 (64%)	10 (50%)	11 (73%)	6 (67%)	10 (60%)	7 (57%)	10 (80%)	6 (67%)
4	3 (100%)	0 (-)	1 (100%)	0 (-)	3 (100%)	0 (-)	1 (100%)	0 (-)
5	1 (100%)	0 (-)	0 (-)	0 (-)	1 (100%)	0 (-)	0 (-)	0 (-)
6	2 (100%)	1 (-)	0 (-)	0 (-)	2 (100%)	0 (-)	0 (-)	0 (-)

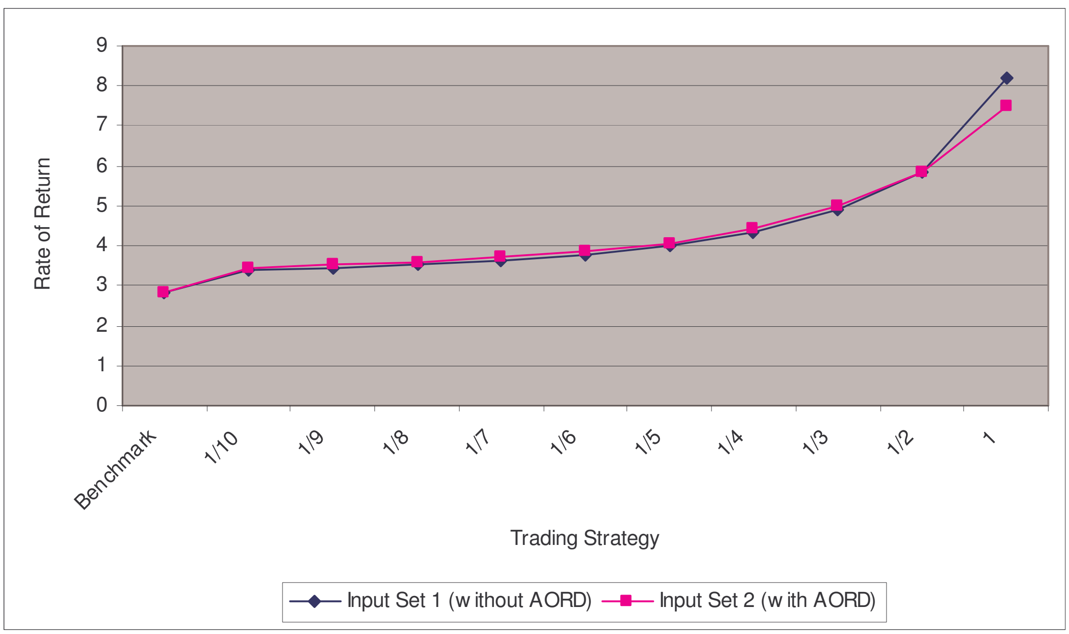

Figure 1: Average rate of return versus trading strategy for the results obtained from FNNs

Figure 1 indicates that when more money involves in trading the profit gain increases. When the money involves in trading is 50% or less, the profits generated is the same for the FNNs trained with the first input set and the FNNs trained with the second input set. However, the trading which involves the full amount of money initially in the hand, gives substantially higher profits in the case of the first input set (without AORD).

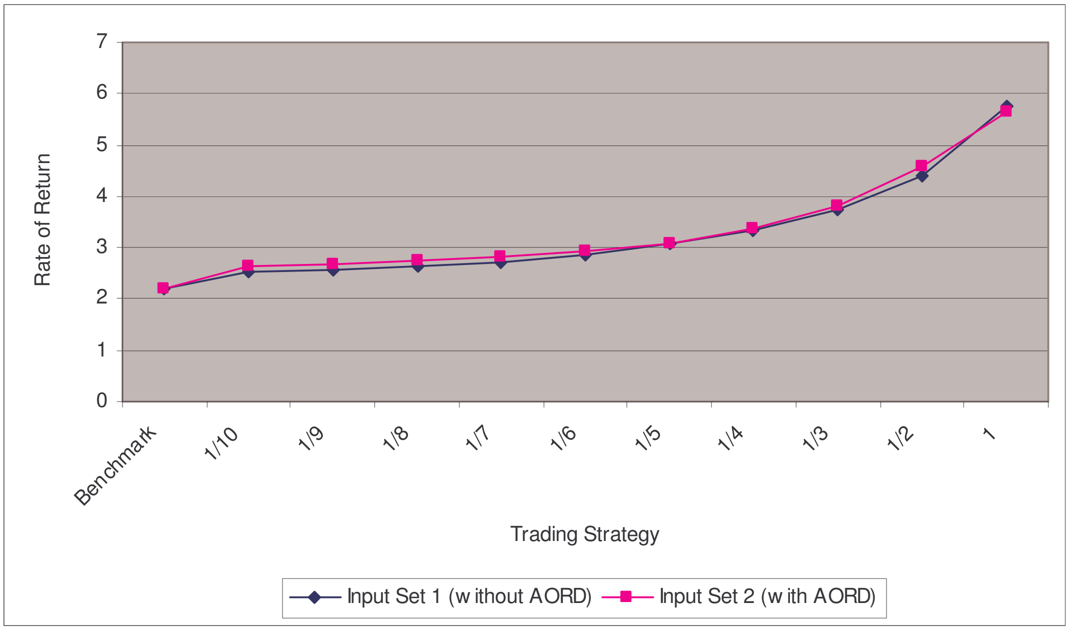

Figure 2: Average rate of return versus trading strategy for the results obtained from PNNs

Figure 2 also implies that the profit gain increases when more money involves in trading. Irrespective of the proportion of money used in trading, the profit gain relating to the PNNs trained with the second input set almost the same as those relating to the PNNs trained with the first input set.

Both Figure 1 and Figure 2 suggest that the highest profit can be gained when the full amount of money initially in hand involves in trading. For the corresponding proportion of money involved in trading, the signals predicted by the FNNs always gave higher profits than those predicted by the PNNs. The highest profit was obtained when the FNNs were trained with the second input set which includes the previous day's (day *t*) relative return of the AORD. However, further analysis needs to be carried out to decide whether adding the previous day's relative return of AORD helps improve prediction accuracy.

Irrespective of the network type and the input set, the maximum rate of return of each window was obtained when the full amount of money involved in trading. Table 5 shows the maximum rate of return obtained for each window.

Window number	Maximum rate of return for the second trading strategy (Benchmark)	Maximum rate of return for the first trading strategy			
		FNN		PNN	
		Input set 1	Input set 2	Input set 1	Input set 2
1	1.0048%	9.4509%	8.5757%	3.4064%	2.2819%
2	4.4693%	8.7695%	7.1632%	7.7815%	8.6736%
3	1.3297%	7.2124%	7.5140%	8.2424%	8.2424%
4	1.9952%	4.2450%	4.2450%	3.5767%	3.5767%
5	5.6149%	10.8493%	10.8493%	-	-
6	2.6287%	8.5929%	6.7227%	-	-

For both sets of inputs, the highest the lowest maximum rates of return corresponding to the FNNs are 10.8493% and 4.2450%, respectively. The highest and the lowest maximum rates of return obtained by the PNNs trained with the first input set are 8.2424% and 3.4064%, respectively. The corresponding values related to the PNNs trained with the second input sets are 8.6736% and 2.2819%, respectively.

By considering the results obtained from the proposed trading strategies, it can be suggested that a trader can make substantial profits (within about three and half months) by responding to the trading signals predicted by this study. Furthermore, the prediction performance of the FNNs seems to be better than that of PNNs.

5. Conclusions and Further Studies

According to the results obtained from the trading simulations, the predicted trading signals are useful to the short term traders. FNN performed better than PNN by means of prediction evaluation with classification/misclassification rate as well as trading simulations.

The results of this study may be further improved by adding two extra classes which denotes the strong buy and strong sell signals. An example for identification criterion of training signals could be as follows;

$$\begin{array}{lll} \textit{Strong Buy} & \textit{if} & Y(t+1) \geq 0.007 \\ \textit{Buy} & \textit{if} & 0.005 \leq Y(t+1) < 0.007 \\ \textit{Hold} & \textit{if} & -0.005 < Y(t+1) < 0.005 \\ \textit{Sell} & \textit{if} & -0.005 \geq Y(t+1) > -0.007 \\ \textit{Strong Sell} & \textit{if} & Y(t+1) \leq -0.007. \end{array} \tag{17}$$

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6. References

1. Y. Wu and H. Zhang. Forward premiums as unbiased predictors of future currency depreciation: A non-parametric analysis. *Journal of International Money and Finance*, 16:609–623, 1997.
2. S. Thawornwong and D. Enke. Forecasting stock returns with artificial neural networks. In G. P. Zhang, editor, *Neural Networks in Business Forecasting*, chapter 3, pages 47–79. Idea Group Publishing, 2004.
3. M. Qi and G. S. Maddala. Economic factors and the stock market: A new perspective. *Journal of Forecasting*, 18:151-166, 1999.
4. A. J. Chapman. Stock market trading systems through neural networks: developing a model. *International Journal of Applied Expert Systems*, 2:88-100, 1994.
5. J. Yao, C. H. Tan, and H. L. Poh. Neural networks for technical analysis: A study on KLCI. *International Journal of Theoretical and Applied Finance*, 2:221-241, 1999.
6. D. Wood and B. Dasgupta. Classifying trend movements in the MSCI U.S.A. capital market index – A comparison of regression ARIMA and neural network methods. *Computers and Operations Research*, 23:611-622, 1996.
7. S. Zemke. Nonlinear index prediction. *Physica A*, 269:177-183, 1998.
8. S. H. Kim and S. H. Chun. Graded forecasting using an array of bipolar predictions: Application of probabilistic neural networks to a stock market index. *International Journal of Forecasting*, 14:323-337, 1998.
9. A. S. Chen, M. K. Leung, and H. Daouk. Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index. *Computers and Operations Research*, 30:901-923, 2003.
10. M. T. Leung, H. Daouk, and A. S. Chen. Forecasting stock indices: a comparison of classification and level estimation models. *International Journal of Forecasting*, 16:173-190, 2000.
11. D. Olson and C. Mossaman. Cross-correlation and predictability of stock returns. *Journal of Forecasting*, 20:145–160, 2001.
12. H. Pan, C. Tilakaratne, and J. Yearwood. Predicting the Australian stock market index using neural networks exploiting dynamical swings and intermarket influences. *Journal of Research and Practice in Information Technology*, 37(1):43–55, 2005.

13. C. D. Tilakaratne. A neural network approach for predicting the direction of the australian stock market index. Master's thesis, School of Information Technology and Mathematical Sciences, University of Ballarat, Australia, 2004.
14. C. D. Tilakaratne, M. A. Mammadov, C. P. Hurst. Quantification of intermarket influence based on the global optimization and its application for stock market prediction. *International Workshop on Integrating AI and Data Mining* (*AIDM' 06*), *aidm*, 42-49, 2006.
15. C. D. Tilakaratne, S. A. Morris, M. A. Mammadov, and C. P. Hurst. Quantification of intermarket influence on the Australian all ordinary index based on optimization techniques. *Proceedings of the 13th Biennial Computational Techniques and Applications Conference*, *ANZIAM Journal*, 48, C104-C118, 2007.
16. C. D. Tilakaratne. A study of intermarket influence on the australian all ordinary index at different time periods. In *Proceedings of the 2nd Australian Business and Behavioural Seiences Association (ABBSA) International Conference*, Adeliade, Australia, 2006.