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Using Neural Networks to Enhance Technical Trading Rule Returns: A Case with KLCI

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In this paper, we test the profitability of technical trading rules which are enhanced by the use of neural networks on the Kuala Lumpur Composite Index (KLCI), a proxy of the Malaysian stock market traded in Bursa Malaysia. The profitable returns on KLCI from 2/1/2008 to 31/12/2014 offer a piece of evidence on the ability of technical trading rules using neural networks to outperform the buy-and-hold threshold benchmark. The test results here suggest that it is worthwhile to investigate, design and develop more robust machine learning algorithms, like neural networks enhanced technical indicators that enhance portfolio returns. The conclusion that can be drawn from this research work is that neural network may be used as tools in technical analysis for future price prediction. The findings from this work will interest all market participants, research analysis and fund managers who want to enhance their portfolio returns globally.

Introduction

Technical analysts test historical data to establish specific rules for buying and selling securities with the objective of maximizing the profit at the minimal risk (Gencay and Stengos 1998). More than 60% of commodity trading advisors and 40% of foreign exchange currency traders use technical analysis in making investment decisions at trading firms and investment banks (Allen and Taylor 1990, Fernandez-Perez et al. 2012). Within the area of algorithmic trading, the interest in high frequency trading and online trading algorithm has grown remarkably over recent years (Neely et al. 2009, Masteika and Rutkauskas 2012). Accompanying this interest is the number of studies about technical trading rules (Lukac et al. 1988, Brock et al. 1992, Park and Irwin 2009) and recently, computational trading algorithms that users find useful for timing investment decisions (Gencay 1998, Gencay and Stengos 1998, Fernandez-Rodriquez et al. 2000). The works of Gencay (1998), Gencay and Stengos (1998) and Fernandez-Rodriquez et al. (2000) are amongst the seminal works evaluating the predictability power of technical trading rules using neural networks while successive contributions involving more advanced

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techniques include those of Gehrig and Menkhoff (2006) and Fernandez-Perez et al. (2012).

In the works of Brock et al. (1992), the most popular moving average rule is the 1-200 rule, of which the short period is one day and the long period is 200 days. Other common standards include the 1-50, 1-150, 5-200, and 2-200 rules. Gencay (1998) uses a 1-200 moving average and a 1-200 moving average with volume. The evidence produced by these studies shows that technical trading rules can produce abnormal profits (Lukac et al. 1988, Brock et al. 1992, Park and Irwin 2009). Nevertheless, many have also indicated a slow-moving downtrend for this kind of profitability over the recent decades (Olson 2004, Neely et al. 2009). To outperform the stock markets, increasingly complicated trading rules are needed (Lee and Mathur 1996, Olson 2004). Recently, artificial neural networks (ANNs) have been extensively used in time series forecasting (Zhang 2003).

The aim of this paper is to demonstrate that profitable returns for KLCI above the passive threshold buy-and-hold can be earned by the use of artificial neural networks to enhance the ability of technical analysis indicators. To achieve this aim, three trading strategies involving ANNs predicted values for the next period, are tested against the passive benchmark buy-and-hold strategy. The ANNs inputs are the closing prices and the technical analysis indicators used by Yao et al. (1999) like moving averages (MA), Resistance Strength Index (RSI) and Stochastics D% and K%. Extending the research of Yao et al. (1999) on KLCI, this study investigates the viability of the ANNs method. Different from the one of Yao et al. (1999), this study uses a base method which compares the predicted output with the current close. The profitable results of these trading strategies are in accordance with recent findings that statistical learning methods have produced better out-of-sample results (Andrada-Felix and Fernandez-Rodriquez 2008).

This paper evaluates the efficacy of three trading strategies. First it compares the predicted output with the current close, then, the current predicted output with its preceding predicted output, and finally the predicted output with the previous close. The passive buy-and-hold strategy serves as the control.

The rest of the paper is organized as follows. The next section presents a brief description of the data. Subsequently, estimation techniques are described and empirical results are discussed. Last, we present the conclusions.

Data Description

The data series include daily data of the Kuala Lumpur Composite Index (KLCI), collected from January 2nd 2008 to December 31st 2014, a total of 1,725 observations from Bloomberg. The training period is determined as about 70% of these observations, from January 2nd 2008 to December 31st 2012; the validation period is about 15% from January 2nd 2013 to December 31st 2013 and the out-of-sample period is about 15% from January 2nd 2014 to

December 31st 2014. The daily closes of the KLCI are transformed into daily returns as follows:

$$R_i = ln\left(\frac{C_t}{C_{t-1}}\right) \qquad [1]$$

where R_t is the daily return of the closes of the KLCI while C_t and C_{t-1} are the closes at day t and t-1 respectively. The summary of the statistics of the returns are shown in Table 1.

Table 1. *Summary Statistics of Daily Returns of KLCI*

Mean	Min	Max	Std. Dev.	Variance	Kurtosis	Skewness
0.0001	-0.0998	0.0406	0.0077	0.0001	18.9303	-1.4093

Source: Authors' estimations.

Similar to Yao et al. (1999), the simple 5-days moving average (MA$_5$), 10-days moving average (MA$_{10}$), 50-days moving average (MA$_{50}$), Resistance Strength Index (RSI), Momentum (M), and Stochastic %K and %D are extracted from Bloomberg.

Estimation Techniques

The analysis ascertains if one or more of the technical trading rules are superior to the passive buy-and-hold strategy which is commonly used as a benchmark (Fama 1965). Through a combination of technical indicators as inputs for a layered neural network, the two trading strategies using predicted values (Yao et al. 1999) and a base trading strategy are employed to find abnormal returns as a part of market anomalies. The technical indicators are selected as inputs to the neural network to discover the implicit relationship between the technical indicators and future predicted output. The technical indicators used as inputs, besides the actual close (C_t) and previous close (C_{t-1}), are a simple 5-days moving average (MA$_5$), 10-days moving average (MA$_{10}$), 50-days moving average (MA$_{50}$), the Resistance Strength Index (RSI), Momentum (M), and Stochastic %K and %D. The output is the next predicted close $\hat{C}_{t+1}$. The moving average of x-days is the x-days average of the most recent closes. The formula for RSI, M, %K and %D are given as follows:

$$RSI = 100 - \frac{100}{1 + RS} \qquad [2]$$

where, RS = Average Gain/Average Loss,
Average Gain = Sum of Gains over the past 14 periods/14,
Average Loss = Sum of Losses over the past 14 periods/14,

$$M = CCP - OCP \qquad [3]$$

where,   CCP = Current closing price,
                OCP = Old closing price for a predetermined period (5 days),

$$\%K = \frac{(CCP - L9)}{(H9 - L9)} \times 100 \qquad\qquad [4]$$

where,   L9 = The lowest low of the past 9 days,
                H9 = The highest high of the past 9 days,

$$\%D = \frac{H3}{L3} \times 100 \qquad\qquad [5]$$

where,   H3 = The three day sum of (CCP − L9),
                L3 = The three day sum of (H9 − L9).

A trading model is considered ideal if it meets the following criteria: i) it should not produce huge losses or exhibit any net large losses in any of the years; ii) the model should work well both in testing stage and in practice, and that it should adjust automatically to shifts in parameters; and iii) it must produce abnormal returns even after accounting for transaction and slippage costs.

Hence, this study adopts a similar testing approach based on the technical trading rules specified by Yao et al. (1999). The estimation is made using the Artificial Neural Networks (ANNs) model.

Inspired by biological systems, Artificial Neural Networks consist of a collection of highly interconnected processing units called neurons or nodes. These neurons are organized in layers, specifically in an input layer, one or more hidden layers and an output layer. Each neuron is associated with a weight that represents the strength of a connection between two neurons in the network. The weight values are determined by an iterative flow of learning processes. Backpropagation is one of the commonly used training procedures that fall in a class of feedforward networks, where the information is passed from the input layer towards the output layer through the hidden layer(s). The advantages of ANNs include its robustness, its ability to approximate non-linear functions and the fact that it is less sensitive and has greater fault tolerance. Thus, ANNs are powerful supervised learning algorithms which have been widely applied in various fields such as in pattern recognition (Gencay 1998), data and image classification (Ganesan et al. 2010) as well as in other financial applications.

In this paper, a multilayer feedforward neural network is employed and implemented using Matlab. Such a model is applied because through a learning process that seeks to minimize the Normalized Mean Square Errors (NMSE) trading model, the ANNs predicted output is quite close to the actual close and thus the implemented trading strategies do not produce excessive losses not only in testing and validation periods, but also in an out-of-sample period.

We follow Yao et al. (1999) and consider nine inputs (C_t, C_{t-1}, MA_5, MA_{10}, MA_{50}, RSI, M, %K and %D). The final output is an estimated value of $\hat{C}_{t+1}$. The three trading strategies are:

Strategy 1: if $\hat{C}_{t+1} > \hat{C}_t$, then buy else sell [7].

Strategy 2: if $\hat{C}_{t+1} > C_t$, then buy else sell [8].

Base Strategy: if $\hat{C}_t > C_t$ then buy else sell [9].

Here, C_t is the actual close at time *t* and $\hat{C}_t$ is the prediction output obtained from the neural networks estimation process.

Empirical Findings

In this section, performances of the trading models, including the base strategy, are evaluated against that of the passive buy-and-hold strategy (Tables 2, 3, 4 & 5).

Table 2. *Trading Strategies Results on KLCI Returns from 2/1/2008 to 31/12/2012*

Training Period: 2nd January 2008 to 31st December 2012				
Year	**Buy-and-hold**	**Strategy 1**	**Strategy 2**	**Base Strategy**
2008	-39%	-1%	37%	2%
2009	38%	6%	54%	13%
2010	18%	-1%	6%	26%
2011	0%	6%	28%	7%
2012	12%	10%	19%	-1%

Source: Authors' estimations.

Table 3. *Trading Strategies Results on KLCI Returns from 2/1/2013 to 31/12/2013*

Validation Period: 2nd January 2013 to 31st December 2013				
Year	**Buy-and-hold**	**Strategy 1**	**Strategy 2**	**Base Strategy**
2013	11%	1%	1%	21%

Source: Authors' estimations.

Table 4. *Trading Strategies Results on KLCI Returns from 2/1/2014 to 31/12/2014*

| Out-of-Sample Period: 2nd January 2014 to 31st December 2014				
Year	**Buy-and-hold**	**Strategy 1**	**Strategy 2**	**Base Strategy**
2014	-6%	0%	9%	6%

Source: Authors' estimations.

Table 5. *Trading Strategies Results on KLCI Returns from 2/1/2008 to 31/12/2014*

Entire Test Period: 2nd January 2008 to 31st December 2014				
	Buy-and-hold	**Strategy 1**	**Strategy 2**	**Base Strategy**
2008 - 2014	34%	21%	154%	74%

Source: Authors' estimations.

The graph of KLCI and the predicted values for the out-of-sample period are illustrated in Figure 1.

Figure 1. *Prediction Values of KLCI Daily Stock Price Index for Out-of-Sample Period (02/01/2014 to 31/12/2014)*
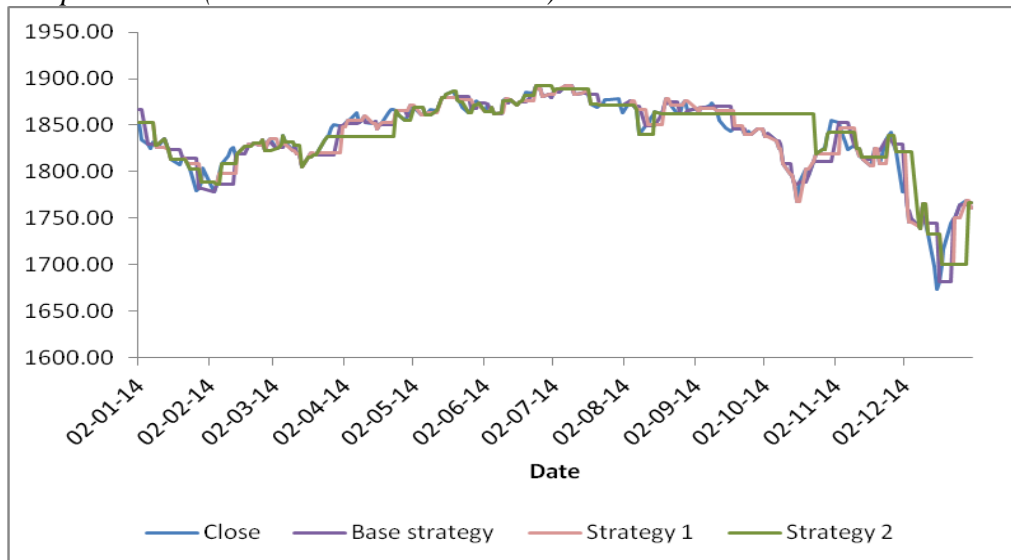
Source: Authors' estimations.

In summary, the results show that two out of the three trading rules using ANNs have performed better than the passive buy-and-hold strategy (BH) over the entire period of seven years with Strategy 2 performing the best with a return of 154%, while Base Strategy gives a return of 74%. Strategy 1 gives a lower return (21%) than the buy-and-hold strategy of 34%.

Conclusions

Using KLCI for the period from 2008 to 2012 as a training period, 2013 for the validation period and 2014 as the out-of-sample period, this study assesses the efficacy of the nine technical trading indicators namely C_t, C_{t-1}, MA_5, MA_{10}, MA_{50}, RSI, M, %K and %D.

Period	Buy-and-hold	Strategy 1	Strategy 2	Base Strategy
Training	29%	20%	144%	47%
Validation	11%	1%	1%	21%
Out-of- Sample	-6%	0%	9%	6%
Total	34%	21%	154%	74%
Annual Mean Return	4.86%	3%	22%	10.57%

Strategy 2 and the Base Strategy outperform the passive buy-and-hold strategy with annual mean returns of 22% and 10.57% respectively, compared with the annual mean return of 4.86% if the investor had bought and held.

By and large, the results show that two out of three trading models are able to outperform the passive buy-and-hold strategy. Strategy 2 is by far the most robust. This is consistent with the studies conducted by Lukac et al. (1988), Brock et al. (1992) and Andrada-Felix et al. (2008) that the machine learning technical indicator strategies perform better than the simple buy-and-hold.

To conclude, overall, this paper demonstrates the efficacy of neural network enhanced technical indicators using KLCI, with Strategy 2 and the Base Strategy showing abnormal returns above the benchmark buy-and-hold. The study is limited to one market, a relatively short period of time and fixed technical indicators. Thus, it is worthwhile further exploring ANNs enhanced technical indicators for other stock and foreign exchange markets in future research. Against this backdrop, for researchers and academics, neural network enhanced technical indicators, as demonstrated in this piece of research, point to a new direction for science and the future of machine learning on time series.

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