Technical Analysis Efficiency Enhancement in Moving Average Indicator Through Artificial Neural Network

Muhamad Sukor Jaafar, Ismail Ahmad, Zetty Zahureen Mohd Yusoff

Faculty Business and Management, Universiti Teknologi MARA, Shah Alam, Selangor.

***Abstract* — The technical approach to investment, essentially a reflection of an idea that prices move in trends which are determined by the changing attitudes of investors towards a variety of economy, monetary, political and psychological forces). The response of stock prices towards the changes in economic variables vary from one to another, hence, it makes trading decision to be very complex. Efficiency refers to the ability to produce an acceptable level of output using cost-minimizing input ratio. Thus, in technical analysis, efficiency refers to the ability of the indicators to indicate a good timing of entry and out of the market with profit. The levels of efficiencies are shown by actual output ratios versus expected output ratios. The higher the actual output ratios against the expected output ratios, the higher the efficiency level of the indicators. This research investigates several technical indicators and found none of the indicators reached the efficiency level. To improve the level, this study applies the Artificial Neural Network model that capable to learn the price and the moving average patterns and suggests a new pattern better than the previous, in term of efficiency level. This research found that the improvements are not just to the efficiency but also increase number of trading as per selected period hence, increase the changes of investor decisions to enter and to exit from the market with possibility of a better profit as compared to traditional technical analysis.**

Keywords: *MA, MACD, ROC, Stochastic, Technical analysis*

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I. Introduction

Technical analysis is a method of predicting the price movement of underlying assets. It is widely accepted by investors even though some may question the effectiveness of its tools. The development of technical analysis has grown rapidly since the end of last century when there are demands for better price prediction tool. This encourages more investors, professionals and researchers, especially from academic world, to study and develop tools that are much efficient and reliable in predicting price movement (Darie & Mircea, 2011, Smith, Wang, Wang & Zychowicz, 2016). Eventually, the prediction techniques can be done through the simulation of charts, price pattern, seasonality and computation rules. By using historical data, technical analysis attempts to find anomalies of stock price pre-reversal movement.
The technical approach to investment is essentially a reflection of the idea that prices move in trends which are determined by the changing attitudes of investors towards a variety of economy, monetary, political and psychological forces (Pring, 2001). These sets of data will allow the investors to select the best technical indicators and test them through the simulation for short term or long term periods and to combine them with other indicator(s) as a volume and money flow. However, the challenge comes as each stock moves differently. The response of stock prices towards the changes in economic variables vary from one to another, hence, it

make price prediction to be very complex (Darie et. al., 2011). This is where the enthusiasm of the researcher comes to beat the challenge of the difficulties with the introduction of much advanced model.

Currently, technical analysis software comes with a long list of indicators that helps investors to identify trend changes at an early stage and make best buying or selling decisions. Metastock software for instance, offers more than 150 different technical indicators including Moving Average (MA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Rate of Change (ROC) and Stochastic which employed by most of the technical analyst. Technical analysis software equips the investors with the ability to predict the next movement of the share prices. However, there is no guarantee that the investor can eliminate the risk of loss. In the case where the wrong signal has been given, or the investor wrongly interprets the signal, the risk might go higher. In fact, statistically significant loss appeared for the sell signal that may be attributed to the predictability involved in the volatility (Caginalp & Laurent, 1998). Meanwhile, one thing needs to be understood, none of the indicators will be accepted by experts if they cannot work efficiently.

Efficiency refers to the ability to produce an acceptable level of output using cost-minimizing input ratios (Farrel, 1957). Thus, in technical analysis, efficiency refers to the ability of the indicators to indicate a good timing of entry and out of the market with profit. The levels of efficiencies are shown by actual output ratios versus expected output ratios (Shao & Lin, 2001). The higher the actual output ratios against the expected output ratios, the higher the efficiency level of the indicators.

II. Background of the study

Technical analysis is price forecasting tools using series of share prices which are then plotted in a graph. The price will then be calculated through several statistical models to create indicator lines. These lines help the investors to forecast the next movement of share price. The models were developed using the mixture of human, politic and economical events, hence the line created promise a good indication of demand and supply. According to Chan (2006), the underlying basis for technical analysis is that price not only reflects all the information about the asset, but also reflects the opinion of all market participants regarding that information (Chan, 2006). The information and market opinion reflected by the prices will result in recurring price patterns that provide clues to future price movement. Theoretically, technical analysis aims to predict the trend of stock prices using past data of price and volume, but how far the improvement of predictability made by technical indicators is still an open question (David & Robert, 1990). It is explained that technical analysis does not provide predictions of the future price, but it only predicts the sign of price changes whether the price is going to be uptrend or downtrend, yet it is sufficient to make net trading profits when the sign prediction is frequently correct.

Technical analysis greatly depends on strong empirical regularities (Liu & Lee, 1997). Empirical regularities do not always repeat in the same manner as the concept of *citeris paribus* is not applicable to the event which has a long list of influencing factors. The behaviours of stock prices vary from one security to another. The model may perfectly work on certain security but fail on the other security. . Hence, the inability of the previous models to integrate the linear and non-linear relationship haphazard the supremacy of technical analysis in the investment decision making.

Artificial Neural Network (ANN), on the other hand, is a collection of interconnected processing elements. The advantage of neural network lies on the ability to represent both linear and non-linear relationships and the ability to learn these relationships directly from the date being modelled. It is a nonparametric regression model with the capability to capture any phenomena, to any degree of accuracy (depending on the adequacy of the data and the power of predictor of technical analysis used) without prior knowledge of the phenomena. ANN is a powerful method for capturing complex phenomena, but their use requires a paradigm shift, from exploratory analysis of the data to exploratory analysis of the model (Kevin and Paul, 2007).

By following the traditional technical rules which have been proven effective over time, investor could perceive market buy and sell signals (Brock, Lakanshok & LeBaron, 1992). However, most chartists believed that the market is 10 percent logical and 90 percent psychological (Malkiel, 1999). Furthermore, models in technical analysis were developed through the observation of foreign data, the psychological thinking of investor in buying and selling stock particularly in developed market may differ from emerging market within Malaysia without exception. Therefore, there is the need to investigate and improve the efficiency of technical analysis in Malaysia market.

Previously, ANN has been used separately and serves as a second model in order to increase the predictive power. None of the researchers had combined both technical and ANN models and come up with a new hybrid model that increases the level of efficiency. Since volatility in technical analysis is random and non-linear, while ANN can process both linear and non-linear data, combination of both models could be run simultaneously. This posted a question whether a new technical-neural model would significantly increase the return efficiency of the traditional technical analysis in Malaysia market. It is expected that by merging both technical and ANN models, the level of efficiency and reliability will be upgraded. Ultimately, the knowledge in this approach will help technical analysts, fund managers as well as individual investors to construct a good timing of entry and out from the market with better return from their previous investments.

This research employed artificial neural network model to enhance the effectiveness of the technical analysis indicators in creating the stock market signal. The motivation behind this technique is its ability to identify changes in trends at an early stage, and to maintain an investment strategy until the weight of the evidence indicates that the trend has reversed, either at peak or at trough. This enables investors to set a good timing of buying and selling at technically much lower risk. Thus, the main objective of this study is to explore whether the technical indicators, using artificial neural network can increase the efficiency in giving the best return in each of the trading circle. The finding is expected to provide effective technical rules to analysts, fund managers as well as to individual investors in order to structure their technical indicators to the best economic signals.

Specifically, the objectives of this study are:

I. To develop a model combining both moving average indicator and artificial neural network.
II. To increase the level of return efficiency using the technical neural model.

III. The efficiency of technical indicators

The indicators are said to be efficient when the stock return is more than 90% of a maximum trough- peak buy and hold strategy (Bauer & Dahlquist, 1999). Any of the stocks having returned below 90% are material to this study since it would provide sufficient room for improvement which is also an important objective of this study.

The formula to calculate the efficiency return is as follow:

$$Efficiency = \frac{sellprice_t - buyprice_t}{highestpeak_T - lowesttrough_T} x\ 100 \qquad (1)$$

Where;
Sell price$_t$ = share prices of sell signals at *t* period
Buy price$_t$ = share prices of buy signals at *t* period
Highest peak$_T$ = highest peak at pre or post selling signal
Lowest trough$_T$ = lowest trough at pre or post buying signal

Significant differences of technical efficiency in moving average indicator was tested through independent sample t-test. This answered the research hypothesis as well as the first theorem that the current efficiency of the moving average indicator should less than 90% of a maximum trough-peak buy and hold strategy. Table 2 shows efficiencies level in six different sectors before ANN was employed. All sectors show that efficiency level of moving average indicator below 90%.

IV. Feed-forward Neural Network (FNN)

FNN has been widely used in financial forecasting due to its ability to correctly classify and predict the dependent variable (Vellido, Lisboa & Vaughan, 1999). To run FNN, MATLAB R2010b software with Neural Network Toolbox was used. The process was divided into three different stages namely, training, validating and testing. The training data were collected from six different index sectors in Bursa Malaysia. About 70% of the data was used for training while 30% was for validating the target output. Each index was simulated separately. Fig. 1 illustrates the process.

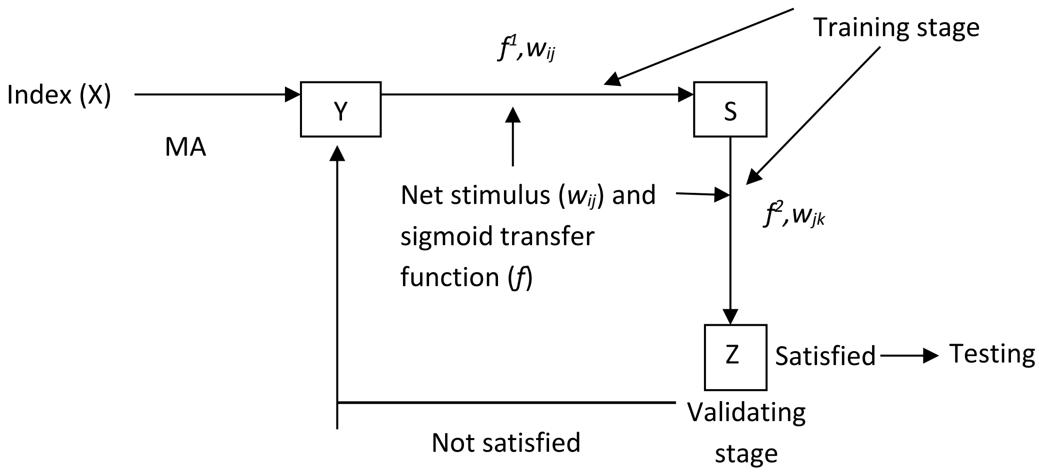

Figure 1: Supervised training Feed-forward Neural Network process using back propagation

The input data, *X* which is sector index is fed simultaneously into a layer of neuron units and the data are converted into moving average. Each of the indices is individually tested and at this point, the process did not involve any training activity. The output of this process is a 20-day and 50-day smoothed volatility data of moving average, *Y*. Next, the output *Y* was trained in sigmoid function, *f*, controlled [+1-1] vector value, *w*, represent the upward and downward directions. The control value [+1-1] is assigned manually in neural network and this process is called supervised training method. The training of *Y* neurons produced an output *S* and the process was repeated with the same or different vector value to produce a final output *Z*.

The goal of back propagation is to allow the adjustment of weight in the network to produce the desired output by minimizing the output error. It works with a training set of input *X*, going into a teaching and learning process to generate a desired output *Z*, and compared with the target variable (*T*). The peak and the trough were used in setting of the target output using a pattern image.

As mentioned earlier, one of the objectives of this study is to enhance the capability of technical indicator particularly in this case, the Moving Average Indicator. Discussion on (1) is crucial to understand the significant of the result. Pre ANN efficiency testing has been done to prove that Moving Average Indicator does not performed to the efficiency level as defined by Bauer & Dahlquist (1999). To run the whole analysis, this study had divided the testing data as in table 1.

Table 1: Data testing procedure

Structure 1 Ratio 70:15:15		Structure 2 Ratio 60:20:20	
Number of hidden layers	Number of training	Number of hidden layers	Number of training
5	5	5	5
10	5	10	5
15	5	15	5
20	5	20	5

V. The robustness

One of the most important things in this research is to prove that the robustness of the technical analysis really works when of ANN is applied to MA. It means that to prove the efficiency of moving average increases significantly as compared to previous procedure without using ANN. Table 2 displays that the efficiency in returns were increased throughout the whole data irrespective of any industry the data was used. Even though the mean returns do not reach the 90 percent efficiency level, but the robustness of all efficiency returns is significant enough to offer a good return to the investor. Apart from an improvement of MA efficiency return, the result also indicates significant increase in number of trading. The trading circles or roundtrips have tremendously increased through the length of study. Some experience an increase of more than 600 percent which is a success to this study.

Statistically, results in Table 2 have proven that ANN is able to increase the return efficiencies of all indices. To support the findings in table 2.0, this study has run two different Wilcoxon Rank Test, one for test of robustness of pre versus post ANN and the second test is the pro ANN test against the 90 percent efficiency level as tested in table 2.0 for pre ANN. Table 3.0 shows a Wilcoxon Rank test for pre ANN against the post ANN efficiency level. Negative ranks explain number of trading where the return efficiency in pre ANN below than return efficiency in post ANN. Positive ranks explain otherwise. Both Tables 3 and 4 are referred to.

Table 2: Pre and Post ANN results of MA index return

PRE ANN

No.	*Index*	*N*	*Min%(n)*	*Max%(n)*	*Mean%*
1.	*MA Construction*	11	16(1)	66(1)	41
2.	*MA Consumer*	7	13(1)	50(1)	28
3.	*MA Finance*	13	11(1)	64(1)	38
4.	*MA Industrial*	12	5(1)	72(1)	32
5.	*MA Plantation*	11	19(1)	84(1)	45
6.	*MA Property*	6	20(1)	60(1)	35

POST ANN

No.	*Index*	*N*	*Min%(n)*	*Max%(n)*	*Mean%*
1.	*MA Construction*	57	8(1)	100(3)	67
2.	*MA Consumer*	32	21(1)	100(3)	76
3.	*MA Finance*	72	16(1)	100(3)	71
4.	*MA Industrial*	60	12(1)	100(3)	67
5.	*MA Plantation*	56	-3.5(1)	100(4)	69
6.	*MA Property*	38	0.5(1)	100(4)	66

The pre and post ANN on the construction index, there are eleven trading in pre ANN and 57 trading in post ANN. Two trading in pre ANN record a better return compared to post ANN while one trading record in ties, which means the returns are the same. Post ANN is excelled by 54 trading and this result proves the robustness of using ANN to the technical analysis. At 0.00 significant level, this study rejects the null hypothesis for construction and conclude that ANN is able to increase the efficiency of MA.

Testing on consumer indices, the pre ANN recorded seven trading and post ANN recorded 32 trading. Comparing the first 7th trading efficiency from both pre and post ANN, none of the return from pre ANN managed to outperform the post ANN. It means that post ANN significantly outperform the whole pre ANN trading efficiencies. At 0.00 significant level, this study rejects the null hypothesis and conclude that ANN is able to increase the efficiency of MA.

For finance indices, the pre ANN witnessed 13 trading while post ANN holds 72 trading. Comparing the first 13threturns of pre and post ANN, the pre ANN managed to outperform the post ANN by four trading while the rest (68 trading) accomplished by post ANN. At 0.00 significant level, this study rejects the null hypothesis.
Industrial indices, the pre ANN recorded 12 trading with 3 of it exceed the return efficiencies of post ANN that hold 60 trading all together. Once more, the post ANN outnumbers the efficiency by 57 trading. At 0.00 significant level, this study rejects the null hypothesis and conclude that ANN is able to increase the efficiency of MA. In plantation, there are 11 trading recorded in pre ANN and 56 trading recorded in post ANN. Two out of eleven trading in pre ANN beat post ANN while 54 remaining proved that post ANN is much better in efficiency. At 0.00 significant level, this study rejects the null hypothesis and conclude that ANN is able to increase the efficiency of MA. In property indices, the pre ANN have six trading while post ANN have 38 trading. In the first six returns recorded by both pre and post ANN, one return from pre ANN managed to outperform the post ANN. The 37 trading favour to post ANN. At 0.00 significant level, this study rejects the null hypothesis and conclude that ANN is able to increase the efficiency of MA.

Lastly, the Wilcoxon Rank Test on post ANN is against the 90 percent efficiency level (Table 4). The results revealed that none of all the 60 trading in pre ANN are able to reach or outperform the 90 percent level as suggested in this research. Table 4 compares the post ANN efficiencies against the 90 percent level on each index.

Table 3: Wilcoxon Rank Test – Pre ANN against Post ANN

		N	*Mean Rank*	*F-value*	*Sig.*
PRECONSTRUCTION - POSTCONSTRUCTION	Negative Ranks	54	29.42	-6.448	0.00
	Positive Ranks	2	3.75		
	Ties	1			
	Total	57			
PRECONSUMER – POSTCONSUMER	Negative Ranks	32	16.50	-4.937	0.00
	Positive Ranks	0	.00		
	Ties	0			
	Total	32			
PREFINANCE – POSTFINANCE	Negative Ranks	68	38.12	-7.172	0.00
	Positive Ranks	4	9.00		
	Ties	0			
	Total	72			
PREINDUSTIAL – POSTINDUSTRIAL	Negative Ranks	57	31.86	-6.633	0.00
	Positive Ranks	3	4.67		
	Ties	0			
	Total	60			
PREPLANTATION – POSTPLANTATION	Negative Ranks	54	28.50	-6.045	0.00
	Positive Ranks	2	28.50		
	Ties	0			
	Total	56			
PREPROPERTY – POSTPROPERTY	Negative Ranks	37	20.00	-5.359	0.00

Table 4: Wilcoxon Rank Test – Post ANN against 90 percent efficiency level

		N	*Mean Rank*	*F-value*	*Sig.*
90% benchmark - POSTCONSTRUCTION	Negative Ranks	9	10.33	-5.752	0.00
	Positive Ranks	47	31.98		
	Ties	1			
	Total	57			
90% benchmark – POSTCONSUMER	Negative Ranks	8	10.00	-3.441	0.00
	Positive Ranks	24	18.67		
	Ties	0			
	Total	32			
90% benchmark – POSTFINANCE	Negative Ranks	17	17.18	-5.735	0.00
	Positive Ranks	55	42.47		
	Ties	0			
	Total	72			
90% benchmark – POSTINDUSTRIAL	Negative Ranks	9	11.67	-5.964	0.00
	Positive Ranks	51	33.82		
	Ties	0			
	Total	60			
90% benchmark – POSPLANTATION	Negative Ranks	15	19.40	-4.136	0.00
	Positive Ranks	41	31.83		
	Ties	0			
	Total	56			
90% benchmark – POSTPROPERTY	Negative Ranks	6	6.67	-4.797	0.00
	Positive Ranks	32	21.91		
	Ties	0			
	Total	38			

Overall, the results are very significant and able to explain the robustness of efficiency on post ANN. In construction indices, the result shows nine negative ranks, 47 positive ranks and one ties. This explains that out of 57 trading in post ANN, nine trading have succeeded to beat the 90 percent efficiency level while one traded at par. In consumer index, the results show eight trading in negative ranks, 24 trading positive ranks and no ties, which explains that out of 32 trading in post ANN, eight trading beat the 90 percent level. In finance indices, 17 from 72 trading in post ANN surpassed the 90 percent level. This result is remarkable as it represents almost 25 percent chances of high return.

Testing in industrial indices, nine trading from the total of 60 outperformed the 90 percent level, proven the continuity of the successful ANN. In plantation indices, 15 of 56 trading recorded the returns efficiency beyond the 90 percent level. This is about 27 percent of the total trading. Lastly, post ANN record six out of 38 trading beat the 90 percent level and put the ANN as a reliable technique to enhance the return efficiency in MA.

VI. Conclusion

This study is conducted with the intention to achieve certain goal. The mainstream of this research is on the efficiency of MA. The study believed that the technical indicators are not reaching the best efficiency level, hence, research should be conducted in order to improve the efficiency level. There are hundreds of technical indicators but among all, there are few that remain common to the technical analysts. These are moving average indicator, moving average convergence divergence indicator, rate of change indicator and relative strength index indicator. The main purpose of this study is to analyse the indicator efficiency level, to develop a robustness model and to increase the level of efficiency of MA.

After the completion of 240 simulations, the results show a significant increment in two aspects; the number of trading and the efficiency level. As to the efficiency level, the result indicates that average return of all indices increases significantly, therefore it provides the investor much better return on their investment. This result answers the second objective of the study that is to create an artificial neural model that helps to increase the efficiency level and the result also supports the second theorem.

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