THAMMASAT REVIEW
PRINT ISSN: 0859-5747 ONLINE ISSN: 2630-0303

Volume 22 No 2 (July-December) 2019 [Page 150-167]

The Profitability of Moving Average Trading Strategies in the Thailand SET50 Index: Past and Future

Rujira Chaysiri *, Sucha Boontaricponpun, Piraya Sujjavanich and Kornchanok Ua-ampon

School of Management Technology, Sirindhorn International Institute of Technology, Thammasat University, Thailand

Received 1 May 2019; Received in revised form 1 September 2019
Accepted 19 September 2019; Available online 16 December 2019

Abstract

Technical analysis is one of the most popular methods that some investors believe can generate profit from stock markets. However, there is no consensus that technical analysis strategies can always make profits in different asset conditions. This study focuses on finding whether moving average trading strategies can outperform the buy and hold strategy in particular asset conditions. These asset conditions are constructed from the volatility and volume of a trading period of a stock in the Thailand SET50 index. In addition, this study forecasts the asset conditions of a stock for the next period by comparing the logistic regression and artificial neural network, to make the technical trading strategies useful in practice. The results show that the moving average trading strategies outperforms the buy and hold strategy in one asset condition. For forecasting the results of an asset condition, an artificial neural network has a higher accuracy rate than logistic regression for predicting asset conditions.

Keywords

Buy and hold strategy, Moving average, Logistic regression, Artificial neural network, Thailand SET 50 Index

*** Corresponding author:** rchaysiri@siit.tu.ac.th **DOI:** 10.14456/tureview.2019.17

Introduction

Many types of investments are available to investors, such as bonds, real estate, gold, currencies, and stocks. Stock investments are an attractive investment because they give a high return, but with high risk. Suciu (2013) as well as Elena-Dana and Ioana-Cristina (2013) said that there are two tools that help investors in making decisions about what stocks to buy and when to buy those stocks. Those tools are Fundamental Analysis, also known as Value Investing, and Technical Analysis. Fundamental Analysis is an analysis tool that uses financial records or the growth of a company to evaluate the value of the stock. This tool uses the buy and hold strategy in which investors buy stocks and hold them for a long period of time. These investors are not concerned about fluctuations in the market. Technical Analysis is another analysis tool that uses price trends and patterns to detect buy and sell signals. Technical analysis is normally used for short to medium term trades. There are many technical analysis trading rules, such as moving average, stochastic oscillator, relative strength index, Bollinger bands, and filter rules. In the Croatian stock market, both fundamental and technical analyses were evaluated. The results from Caljkusic (2011) confirm that both fundamental and technical analyses are able to identify buy and sell signals, which help investors in making decisions of when to buy or sell stocks. In addition, there is a study from Eiamkanitchat, Moontuy and Raminwong (2017) that tested both fundamental and technical analyses in the Thai stock market. The results from both studies show that both analyses can help to generate profit. The Chinese stock market was also examined by comparing both analyses, but the result from Moosa and Li (2011) shows that technical analysis is better than fundamental analysis. Petrusheva and Jordanosk (2016) concluded that although fundamental analysis and technical analysis are different strategies that give different results, they have their own advantages and disadvantages that can be adapted and applied together to give better results.

Many researchers have tried to find profitable technical trading rules in different stock markets such as the Sri Lankan Stock Market (Fernando, 2013) and other emerging markets (Heyman, Inghelbrecht & Pauwels, 2012). The results show that technical analysis is successful in defining the price movement, but it is not profitable when considering the transaction costs. However, the results from Metghachi, Yong, Garza-Gomez and Chen (2007), and Patari and Vilska (2014) show that technical trading rules without considering the transaction cost help in making profits. They can be used to design a strategy that can be more profitable than the buy and hold strategy.

Applying technical analysis without foreseeing future variables would offer no advantages in trading because we would be looking back only in hindsight. Therefore, no matter what variables are used when performing technical analysis, they need to be forecasted in real situations. Looking back in history, researchers have always been interested in using forecasting techniques, mostly to predict stock values or stock prices. For example, GARCH models were used for Zenith bank Plc in the Nigerian Stock Exchange to predict the stock price (Arowolo, 2013). GARCH-IV was used to predict the volatility on the German Stock Exchange (DAX) (Claessen & Mittnik, 2002). ARIMA was used to predict the stock price on stock data obtained from the New York Stock Exchange (NYSE) and the Nigerian Stock Exchange (NSE) (Adebiyi, Adewumi, & Ayo, 2014). Some papers have used many forecasting methods to compare performance (Barkoulas, Baum, & Travlos, 2000; Bhardwaj & Swanson, 2006; Bley & Olson, 2005). Atsalakis and Valavanis (2013) conducted a survey of 150 scientific articles using conventional models/techniques to forecast stock markets. They suggested that it is very difficult to state which method is the clear winner, but some models forecast better than others. Therefore, there is no clear consensus on which technique is the best. These models/techniques and examples of research include utilizing Autoregressive (AR), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA) and Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH).

Nevertheless, besides utilizing numerical data such as stock prices directly by using the techniques above, some researchers would like to categorize data into binary values before a prediction. One of the forecasting techniques that can serve them is logistic regression. It has often been used in the stock market field. For example, the stock price trends were predicted for Shenzhen Development stock A (Gong & Sun, 2009), the KSA stock market price (Zaidi & Ofori-Abebrese, 2016), and the stock performance in the Pakistan Stock Exchange (PSX) (Ali & Mubeen, 2018). The advantage of logistic regression is that the variables may be either continuous, discrete, or any combination of both types. They do not necessarily need to have normal distributions (Lee, 2004).

Another method that is emerging and can also be used for non-binary or binary value prediction is the machine learning forecasting method. According to Henrique, Sobreiro and Kimura (2019), the most commonly used models for prediction involve support vector machines (SVMs) and neural networks. For example, Kim (2003) examined the potentiality of using SVMs in financial forecasting by comparing them with back-propagation neural networks (BPNNs) and case-based reasoning (CBR). The experimental results show that the SVM method was better than BPN and CBR. Kara et al. (2011) predicted the direction of movement in the daily Istanbul Stock Exchange (ISE) National 100 Index. Their result shows that an Artificial Neural Network (ANN) had slightly better performance than the SVM. Henrique, Sobreiro and Kimura (2019) concluded that this research area is still relevant, and the use of data from developing markets is a research opportunity. In addition, a machine learning technique was compared with the conventional technique. Wei (2018) compared the accuracy of logical regression, neural network, and SVM to predict whether a stock price rise rate or fall rate is greater than its industry average. The result from Wei (2018) demonstrates that the accuracy of logistic regression is lower than both neural network and SVM.

Our paper starts with evaluating some moving average trading strategies with various asset conditions. Then, we select an ANN as a forecasting technique to predict the asset conditions of 19 stocks in the Thai SET50 Index. The asset conditions are a binary (low or high) value of volatility and volume of trading periods. An ANN is able to capture the stock market nonlinear relationships by returning good forecasting results with no need for prior knowledge of input-data statistical distributions. In addition, this study compares the ANN with logistic regression, which is a basic model that is used to forecast a binary value. The study expects 1) to show which asset conditions generate more profits under the use of moving average trading strategies, as opposed to the buy and hold strategy, and 2) to accurately forecast the asset condition in the following period. This is to determine if moving average trading strategies work in this case.

Materials and Methods

Since there is no consensus on timing or that a moving average trading strategy will generate profits, our study performs the full steps of trading. These steps include the trading simulation and asset conditions for forecasting, so that our model can work effectively in practice. Therefore, our study would like to test the two hypotheses below:

Hypothesis 1: In some specific asset conditions, a moving average trading strategy can outperform the buy and hold strategy.

Hypothesis 2: The asset condition prediction rate of the artificial neural network is more accurate than logistic regression.

Our methodology is separated into four parts, which are data preparation, asset conditions, trading simulation, and forecasting asset conditions.

Data Preparation

The daily closing price and trade volume of 19 stocks from 2007 to 2018 are used for experiments together with moving average trading strategies. These 19 stocks are not only well-known companies in Thailand but were also continuously listed on the Thailand SET50 index from 2007 to 2018. Thus, these stocks are likely to be traded by investors. These 19 stocks are the following:

1. ADVANC	8. DELTA	14. PTT
2. AOT	9. GLOW	15. SCB
3. BANPU	10. IRPC	16. SCC
4. BBL	11. KBANK	17. TCAP
5. BDMS	12. LH	18. TMB
6. BH	13. MINT	19. TOP
7. CPF		

We obtained raw data that consisted of the date, closing price, and volume of the 19 stocks from finance.yahoo.com. We deleted some data from particular dates that were holidays and the volumes were zero. In addition, we needed to eliminate some data from other dates where the volume was zero but those dates were not holidays. Particular companies decided not to sell their stock on those dates. Those particular stocks and dates are the following.

- TMB on November 11, 2007

- TCAP on March 29, 2007

- MINT on January 22, 2009

- PTT on December 12, 2007

and December 17, 2007

- CPF on November 25, 2011

Asset Conditions

Although forecasting the index values or stock prices allows investors to be able to make trading decisions based on the predicted value, we are inspired to perform technical trading strategies by Hayes et al (2016). We categorize stock data into a binary value of low or high for volatility and volume in the trading period (month). Grouping data in terms of the asset conditions makes it simple to observe the performance of technical trading strategies. This classification could help to distinguish which asset conditions are appropriate for a particular technical trading strategy to generate profit.

Thus, we define four asset conditions which consist of high or low "volatility of a trading period" and high or low "volume of a trading period" as shown in Table 1.

Table 1 Four asset conditions

Volatility of a trading period	**Volume of a trading period**	
	High	**Low**
High	HH	HL
Low	LH	LL

For volatility, we classify volatility in each month, whether it is high or low, by comparing the volatility over 132 periods (132 months). Since we assume that there are no prevailing trends over an 11-year period, volatility is used to compare stocks across 11 years by using the median. We classify them by using these formulas (Equation 2.1 - 2.2).

$$x = \frac{(P_t - P_{t-1})}{P_{t-1}} \times 100 \tag{2.1}$$

$$\text{Volatility}= \sqrt{\frac{\sum(x-\bar{x})^2}{(n-1)}} \tag{2.2}$$

where x = daily % change, P_t = closing price at a particular period t, and n = number of days in one month. Volatility of a trading period is high when it is greater than the median, otherwise, it is classified as low volatility.

For volume, Figure 1 shows that the volume trend increases continuously. We assume that the volume changes linearly during a year. Therefore, it must be de-trended yearly before we can make a comparison. We assigned a yearly trend line to each stock. Then, we subtract the daily volume from the trend line estimation. This adjusted volume was then summed monthly. If the summation is above zero, it is considered to be high volume. Otherwise, it is classified as low volume.

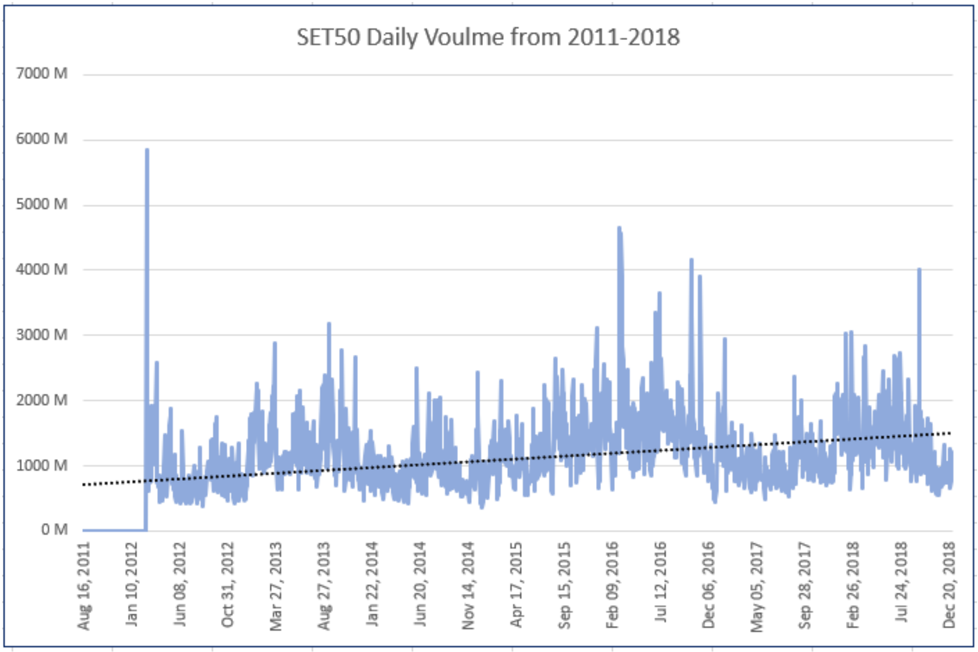

Figure 1 SET50 daily volume from 2011-2018

Trading Simulation

Four moving average trading strategies are applied to the price data of 19 stocks from 2007 to 2017. In our experiment, we allow short selling because short selling is not prohibited in the Stock Exchange of Thailand (SET). The basic structure of the four moving average trading strategies is defined in this section.

Trading Rules:

1. Sell (buy) when the short period (1 day) moving average crosses the long period (50 days/ 100 days/ 150 days/ 200 days) moving average from above (below) by more than 1 %.

2. Close any open positions if the short period (1 day) moving average crosses the long period (50 days/100 days/150 days/200 days) moving average.

We also use the buy and hold strategy to benchmark the moving average strategies. The buy and hold strategy buys at the beginning of the month and sells at the end of the month.

After applying the trading rules, we calculate the profit or loss according to the four asset conditions and benchmark this with the buy and hold strategy.

Forecasting an Asset Condition

Although we know the successful trading strategies from the trading simulation, in real life, we never know the asset conditions for the next trading period. Therefore, this part covers the forecasting of asset conditions for successful trading strategies. An asset condition consists of two variables which are the volume of a trading period (high or low) and the volatility of a trading period (high or low). Therefore, we forecast the volatility and volume separately. These two variables are binary data since they have only two values, which are high or low. According to the nature of our data, we decided to predict the asset conditions with logistic regression and an artificial neural network, to compare the forecasting accuracy.

Logistic regression

Logistic regression is used when the dependent variable is binary. It is used to describe the data by explaining the relationship between one dependent variable with one or more independent variables. Dutta, Bandopadhyay and Sengupta (2012) used Logistic regression to classify companies into “good” or “poor” categories, based on financial ratios in the Indian market. Their results showed that logistic regression can perform with around 75% accuracy.

In this paper, we separated data into a training set and a testing set. The training set consists of data from 2007 to 2017, and the testing set consists of data from 2018. Then, data is predicted using logistic regression by using the sigmoid function (Eq. 2.3).

$$y = \frac{1}{(1+e)^{-((coefficient \times X)+intercept}} \tag{2.3}$$

Where y = 0 (low), 1 (high), and X = volatility of a trading period, volume of a trading period.

Artificial Neural Network

Artificial neural networks are a popular research field, especially in the stock market. They are used with a variety of indexes and measurements in various markets. For instance, neural networks were used to forecast the monthly futures trading volume for the Winnipeg Commodity Exchange (WCE) (Kaastra & Boyd, 1995). Song, Zhou and Han (2018) surveyed and compared the predictive power of five neural network models, namely, back propagation (BP) neural network, radial basis function (RBF) neural network, general regression neural network (GRNN), support vector machine regression (SVMR), and least squares support vector machine regression (LS-SVMR).

Moreover, other researchers compared the predictive ability of an ANN with conventional prediction methods such as multiple regression (Kimoto & Asakawa, 1990), ARIMA (Adebiyi, Adewumi & Ayo, 2014), and GARCH (Kim & Enke, 2016). The results of previous studies mostly show that an ANN has more prediction accuracy than those conventional methods. Nevertheless, Laily, Warsito and Maruddani (2018) compared the stock closing-price forecasting performance between the ARCH/ GARCH model and the ERNN model, based on the MSE value. In their study, the best model was GARCH (1, 1) which has the smallest MSE value. Therefore, we would like to compare the predictive ability of an ANN with a conventional technique, logistic regression.

We used Rapid Miner 5.0 to perform an ANN on our data set. The data from 2007 to 2017 are the training set, and the data from 2018 are the testing set (same as in the logistic regression experiment). For the structure of the network, we used the trial-and-error method to find the best structure for this kind of problem by trying from 1 node and 1 layer to 10 nodes and 10 layers. After trying every node and layer, we found that from 3 layers to 10 layers gave low accuracy of results. Therefore, we tried only from 1 node 1 layer until 10 nodes 2 layers. Then, we used the best structure to predict trading period volume and volatility. We predicted whether they were high or low and compared them with the results from the logistic regression experiment.

Results and Discussion

Moving Average

Table 2 Tukey's test grouping

Asset Condition	**Strategies**				
	B&H	MA50	MA100	MA150	MA200
HH	1	1	1	1	1
HL	2	1	1	1	1
LH	1	1	1	1	1
LL	1	1	1	1	1

We compared the moving average of 50, 100, 150, and 200 days with the buy and hold strategy by using the Tukey's test. The result shows that the moving average trading strategies make significantly higher profits than the buy and hold strategy for the HL asset condition. For the HH, LH, and LL asset conditions, the buy and hold strategy is not statistically different from the moving average trading strategies. Thus, investors can use moving average trading strategies to generate higher profit than the buy and hold strategy for the HL asset condition. While in other asset conditions, investors can use either moving average trading strategies or the buy and hold strategy.

Logistic Regression

For volatility, year ahead (Figure 2), we forecast the volatility of a trading period one year ahead. The percentage of accuracy starts around 49-50% at the cutoff of [0, 0.61]. After that, the percentage is around 51% from a cutoff of 0.62 to 1, except for the cutoffs of 0.63, 0.64, and 0.65 that give the highest percentage at 52.19%.

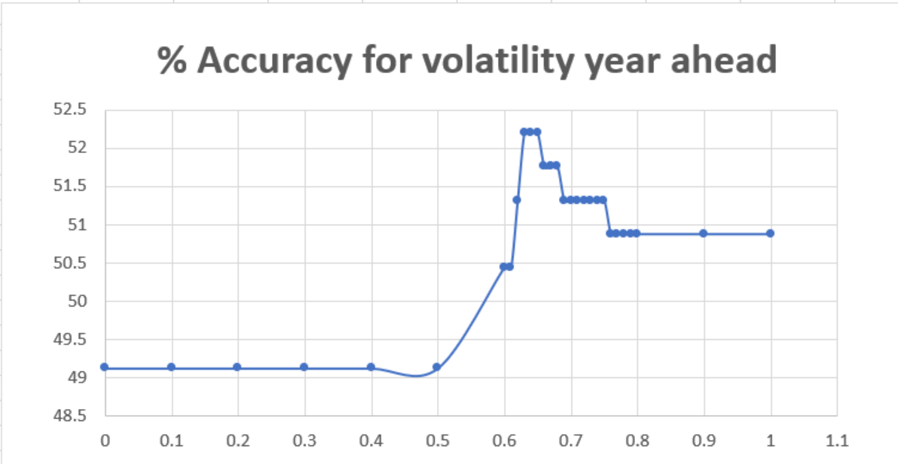

Figure 2 Percentage of accuracy for volatility, year ahead.

For volatility, month ahead (Figure 3), we forecast the volatility of a trading period one month ahead. The percentage of accuracy starts around 49% at the cutoff of [0, 0.5]. For a cutoff from 0.51 to 1, the percentage is above 50%, and the cutoff of 0.62 gives the highest accuracy at 55.7%. The procedure is similar for forecasting the volume of a trading period.

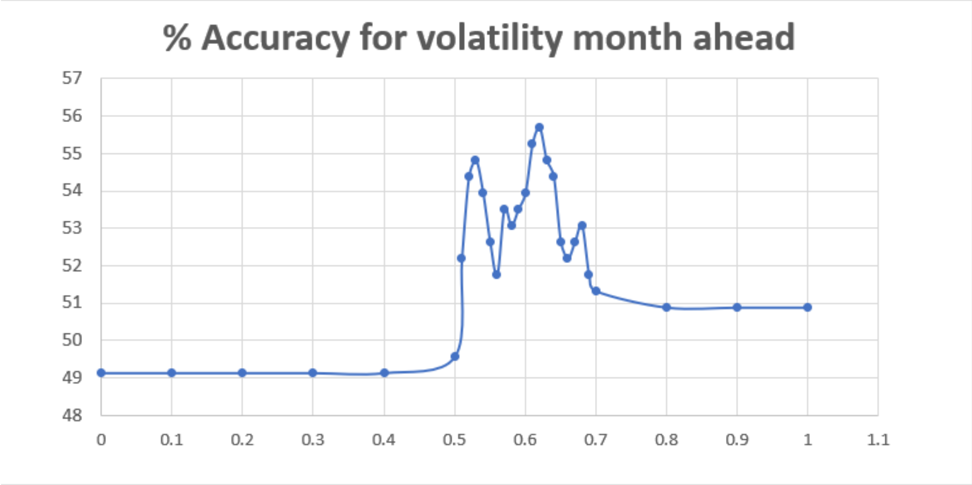

Figure 3 Percentage of accuracy for volatility, month ahead.

For volume, year ahead (Figure 4), the percentage of accuracy starts around 47-49% at the cutoff of [0, 0.7]. After that, the percentage is 50.88% when the cutoff is [0.8, 0.82] and is the highest at 51.32% when the cutoffs are 0.83, 0.84, 0.85 and 0.86. The percentage declines to 50.88% again when the cutoff is [0.87, 1]

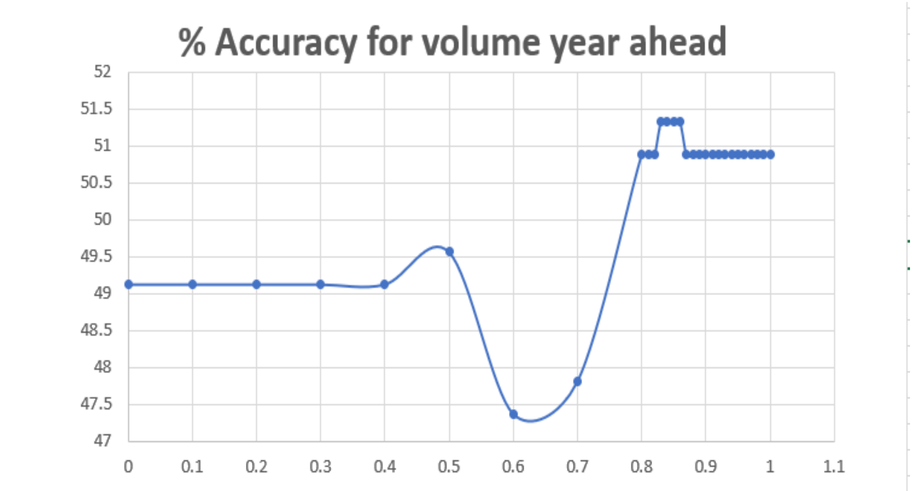

Figure 4 Percentage of accuracy for volume, year ahead.

For volume, month ahead (Figure 5), the percentage of accuracy starts around 49-60% at a cutoff of [0, 0.6]. The percentage is greater than 61% when the cutoff is [0.1, 0.71], and the highest accuracy is 65.79% when the cutoff is at 0.64. For cutoffs of 0.72 and higher, the percentage of accuracy is no more than 61%.

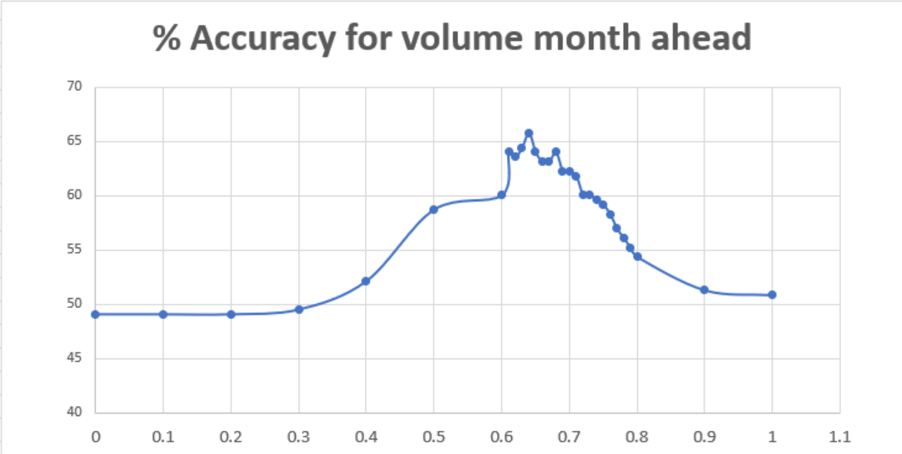

Figure 5 Percentage of accuracy for volume, month ahead.

Artificial Neural Network

We conducted a trial and error experiment to find the number of layers and number of nodes that can apply to every stock and give the highest percentage of accuracy for forecasting the volume and volatility of a trading period. The results show that 1 layer with 4 nodes, 1 layer with 5 nodes, 1 layer with 9 nodes, 2 layers with 2 nodes and 2 layers with 7 nodes give the highest percentage of accuracy at 97.37%, followed by a range from 95% to 96% of accuracy for forecasting the volatility of a trading period, as shown in Figure 6. For the volume of a trading period (Figure 7), the results show that 1 layer with 3 nodes, 1 layer with 7 nodes, and 2 layers with 5 nodes give the highest percentage of accuracy at 99.56%, followed by a range from 97% to 99.12% of accuracy. If we compare the results from logistic regression with the ANN, we can conclude that the forecasting accuracy of both the volatility and the volume of a trading period is greater when applying the ANN than when applying logistic regression.

(See Table A and B in the Appendix for more detail).

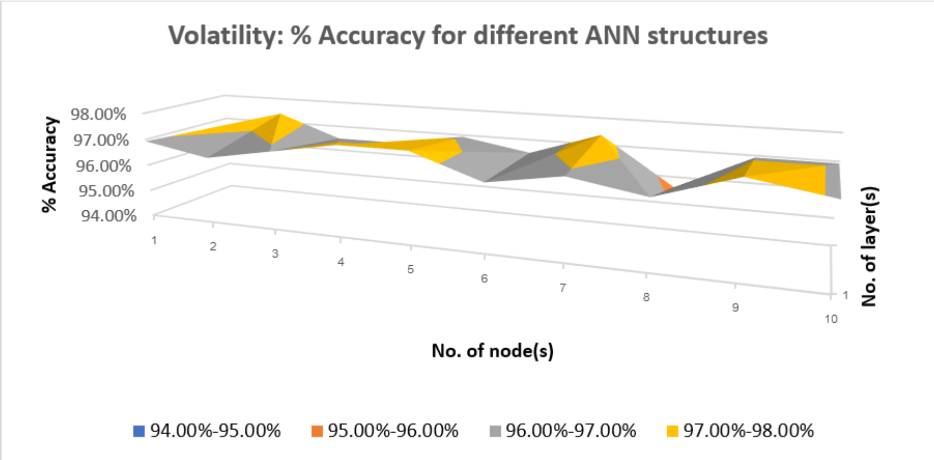

Figure 6 Percentage of accuracy for different ANN Structures for the volatility of a trading period.

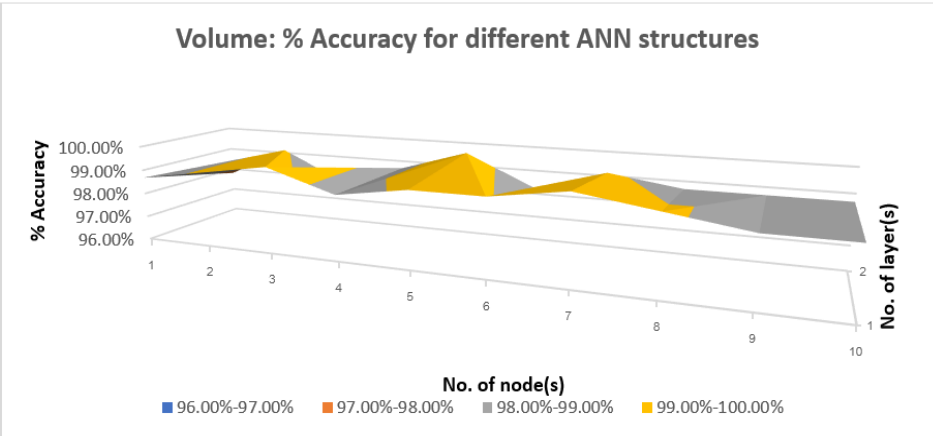

Figure 7 Percentage of accuracy for different ANN Structures for the volume of a trading period.

Conclusion

In this paper, we compare the performance of different moving average trading strategies (50, 100, 150, and 200 days) with the buy and hold strategy to detect which trading strategies can be utilized in particular asset conditions. We conclude that using MAs is better than using the buy and hold strategy in one of the four asset conditions, and it is not statistically significant in three out of the four asset conditions. This means that investors should use MAs rather than the buy and hold strategy for the HL asset condition. Thus, Hypothesis 1 is accepted. However, we only apply moving-average trading strategies in our study without including other advanced trading strategies, such as Bollinger Bands (BBs) and the Commodity Channel Index (CCI). BBs and CCI were found to be the most robust strategies as they beat the buy and hold strategy according to Hayes et al. (2016) for some asset conditions. We also compare the prediction performance of logistic regression and an artificial neural network. This confirms Hypothesis 2 since the result shows that an ANN clearly outperforms logistic regression with more than 97% accuracy for the volatility of a trading period and more than 99% accuracy for the volume of a trading period. Future research might apply other technical indicators, such as BBs and CCI, and thus different strategies in different asset conditions. This is to better match a particular technical indicator with its proper asset condition.

References

Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). *Stock price prediction using the ARIMA model.* Paper presented at UKSim-AMSS 16th International Conference on Computer Modelling and Simulation. doi:10.1109/UKSim.2014.67

Ali, S. S., Mubeen, M., Lal, I., & Hussain, A. (2018). Prediction of stock performance by using logistic regression model: Evidence from Pakistan stock exchange (PSX). *Asian Journal of Empirical Research, 8*(7), 247-258.

Arowolo, W. B. (2013). Predicting stock prices returns using GARCH model. *The International Journal of Engineering and Science (IJES)*, *2*(5), 32-37.

Atsalakis, G. S., & Valavanis, K. P. (2013). Surveying stock market forecasting techniques - part I: Conventional methods. In C. Zopounidis (Ed.), *Computation Optimization in Economics and Finance Research Compendium* (pp. 49-104). Hauppauge, NY: Nova Science Publishers.

Barkoulas, J. T., Baum C. F., & Travlos, N. (2000). Long memory in the Greek stock market. *Applied Financial Economics, 10*(2), 177-184.

Bhardwaj, G., & Swanson, N. R. (2006). An empirical investigation of the usefulness of ARFIMA models for predicting macroeconomic and financial time series. *Journal of Econometrics, 131*(1-2), 539-578.

Bley, J., & Olson, D. O. (2005). An analysis of relative return behavior: REITs vs. stocks. *Academy of Accounting and Financial Studies Journal, 9*(2), 71–88.

Caljkusic, V. (2011). Fundamental and technical analysis on Croatian stock market. *Croatian Operational Research Review*, *2*(1), 71-80.

Claessen, H., & Mittnik, S. (2002). Forecasting stock market volatility and the informational efficiency of the DAX-index options market. *The European Journal of Finance, 8*(3), 302-321.

Dutta, A., Bandopadhyay, G., & Sengupta, S. (2012). Prediction of stock performance in the Indian stock market using logistic regression. *International Journal of Business and Information*, *7*(1), 105-136.

Eiamkanitchat, N., Moontuy, T., & Ramingwong, S. (2017). Fundamental analysis and technical analysis integrated system for stock filtration. *Cluster Computing*, *20*(1), 883-894.

Elena-Dana, B., & Ioana-Cristina, S. (2013). Technical and fundamental anomalies, Paradoxes of modern stock exchange markets. *Annals of the University of Oradea, Economics science series*, *22*(1), 37-43.

Fernando, P. (2013). Profitability of technical trading strategies in emerging Sri Lanka stock market. *Kelaniya journal of management*, *2*(2), 32-50.

Gong, J., & Sun, S. (2009). *A new approach of stock price trend prediction based on logistic regression Model.* Paper presented at International Conference on New Trends in Information and Service Science. doi:10.1109/NISS.2009.267

Hayes, R. L., Wu, J., Chaysiri, R., Bae, J., Beling, P. A., & Scherer, W. T. (2016). Effects of time horizon and asset condition on the profitability of technical trading rules. *Journal of Economics and Finance*, *40*(1), 41-59.

Henrique, B. M., Sobreiro, V. A., & Kimura, H. (2019). Literature review: Machine learning techniques applied to financial market prediction. *Expert Systems with Applications, 124*, 226–251.

Heyman, D. Inghelbrecht, K., & Pauwels, S. (2012). Technical trading rules in emerging stock markets. *World academy of science, engineer and technology*, *59*, 2241-2264.

Kaastra, I., & Boyd, M. S. (1995). Forecasting futures trading volume using neural networks. *The Journal of Futures Markets*, *15*(8), 953-970.

Kara, Y., Boyacioglu, M. A., & Baykan, Ö. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. *Expert systems with Applications*, *38*(5), 5311-5319.

Kim, Y., & Enke, D. (2016). Using neural networks to forecast volatility for an asset allocation strategy based on the target volatility. *Procedia Computer Science*, *95*, 281-286.

Kimoto, T., & Asakawa, K. (1990). *Stock market prediction system with modular neural network.* Paper presented at IJCNN International Joint Conference on Neural Networks, San Diego, CA. doi:10.1109/IJCNN.1990.137535.

Laily, V. O. N., Warsito, B., & Maruddani, D. A. I. (2018). *Comparison of ARCH / GARCH model and Elman recurrent neural network on data return of closing price stock.* Paper presented at Journal of Physics: Conference Series 2018. doi:10.1088/1742-6596/1025/1/012103

Lee, S. (2004). Application of likelihood ratio and logistic regression models to landslide susceptibility mapping using GIS. *Environmental Management, 34*(2), 223-232.

Metghalchi, M., Glasure, Y., Garza-Gomez, X., & Chen, C. (2007). Profitable technical trading rules for the Austrian. *International business& economics research journal stock market*, *6*(9), 49-58.

Moosa, I., & Li, L. (2011). Technical and fundamental trading in the Chinese stock market: Evidence based on time-series and panel data. *Emerging markets finance & trade*, *47*(1), 23-31.

Patari, E., & Vilska, M. (2014). Performance of moving average trading strategies over varying stock market conditions: The Finnish evidence. *Applied economics*, *46*(24), 2851-2872.

Petrussheva, N., & Jordanoski, I. (2016). Comparative analysis between the fundamental and technical analysis of stocks. *Journal of process management*, *4*(2), 26-31.

Song, Y. G., Zhou, Y. L., & Han, R. J. (2018). Neural networks for stock price prediction. *arXiv preprint arXiv:1805.11317*.

Suciu, T. (2013). Elements of stock market analysis. *Bulletin of the Transilvania University of Brasov*, *6*(2), 153-160.

Wei, Y. (2017). The application of machine learning in stock market (Master's thesis, University of Southern Callifornia). Retrieved from https://search.proquest.com/docview/2114972156?pq-origsite=gscholar

Zaidi, M., & Ofori-Abebrese, A. A. G. (2016). Forecasting stock market trends by logistic regression and neural networks: Evidence from KSA stock market. *Euro-Asian Journal of Economics and Finance, 4*(2), 50-58.

Appendix

Table A The percentage of accuracy for each structure of layers and nodes. The structures that provide highest accuracy for volatility per month are highlighted.

No. of layer(s)	No. of node(s)	% Accuracy
1	1	96.93
1	2	96.49
1	3	96.93
1	4	97.37
1	5	97.37
1	6	96.49
1	7	96.93
1	8	96.49
1	9	97.37
1	10	96.93
2	1	96.49
2	2	97.37
2	3	96.49
2	4	96.49
2	5	96.93
2	6	96.49
2	7	97.37
2	8	95.61
2	9	96.93
2	10	96.93

Table B The percentage of accuracy for each structure of layers and nodes. The structures that provide highest accuracy for volume per month are highlighted.

No. of layer(s)	No. of node(s)	% Accuracy
1	1	98.68
1	2	99.12
1	3	99.56
1	4	98.68
1	5	99.12
1	6	99.12
1	7	99.56
1	8	99.12
1	9	98.68
1	10	98.68
2	1	97.81
2	2	99.12
2	3	97.81
2	4	98.68
2	5	99.56
2	6	98.25
2	7	99.12
2	8	98.68
2	9	98.68
2	10	98.68