



Faculty of Economics and Business

Validation of Future Crude Palm Oil Futures (FCPO) Price Prediction

Yong Xhin Rong

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Validation of Future Crude Palm Oil Futures (FCPO) Price Prediction

Yong Xhin Rong

A thesis submitted

In fulfillment of the requirements for the degree of Master of Science

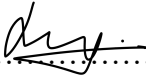
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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.


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Signature

Name: Yong Xhin Rong

Matric No.: 19020002

Faculty of Economics and Business

Universiti Malaysia Sarawak

Date: 26/9/2023

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ABSTRACT

The implementation of Artificial Intelligence (AI) towards the price prediction process is undoubtedly crucial as the importance of accurate price prediction has increased over the last few decades. The lack of accurate price prediction tools in the past has always been a challenge for investors to predict future prices. Thus, investors tend to use technical indicators to improve their trading strategy. However, with the large amount of different technical indicators in the market, it is tedious and time consuming to identify which technical indicators works the best for them. Crude palm oil plays an important role in the upbringing of Malaysia's economy. It is the largest Gross Domestic Product (GDP) contributor for the agricultural sector in Malaysia and is exported globally. It is important to predict the price of Crude Palm Oil Futures (FCPO) as it could allow us to hedge against any unforeseen risks and price changes. This study aims to predict FCPO price and optimize various technical indicators using AI. Thus, this study predicts the future price of FCPO using daily historical data such as the opening, high, low, and closing price of FCPO from year 2010 to year 2019 using the Extreme Learning Machine (ELM) model in the Matlab R2020a software. Besides that, various number of hidden neurons and activation function have been used to train and test the ELM model to identify which parameter works best with the technical indicators to provide the most accurate results. The main result shows that the radial basis function has the highest training and testing accuracy as compared to other functions such as the sigmoidal function, sine function and radial basis function when tested against different number of hidden neurons. As for the optimisation of technical indicators, the Williams Percent Range indicator has the highest prediction accuracy as compared to other technical indicators such as Relative Strength Index (RSI), Exponential Moving Average (EMA), Moving Average Convergence and Divergence (MACD) and Stochastic

Oscillator. The predictability of FCPO prices using ELM shows that it is possible to predict future prices and thus disputing the weak form of Efficient Market Hypothesis (EMH) that stated it is nearly impossible to predict prices based on historical data. This study could potentially contribute to businesses related to palm oil as business owners can predict future prices and hedge against any unforeseen risks. Not only that, investors and technical analyst can also contribute from this study by identifying technical indicator that has the highest prediction accuracy based on their trading strategy. The implementation of ELM towards the price prediction process can also guide policymakers to adjust their strategies and help them to obtain more agricultural related grants.

Keywords: Artificial Intelligence, ELM, FCPO, prediction, technical indicator.

Analisis Peramalan Harga Crude Palm Oil Futures (FCPO) dan Pengoptimuman Petunjuk Teknikal dengan Teknologi Kecerdasan Buatan

ABSTRAK

Pelaksanaan teknologi kecerdasan buatan terhadap peramalan harga semakin penting kerana peramalan harga yang tepat dapat membawa manfaat kepada semua pihak. Kekurangan modal peramalan harga yang tepat merupakan salah satu cabaran yang sering dihadapi oleh pelabur. Oleh itu, ramai pelabur menggunakan petunjuk-petunjuk teknikal untuk meningkatkan prestasi pelaburan. Namun begitu, kepelbagaian petunjuk teknikal sering menjadi beban untuk pelabur. Minyak sawit Malaysia dieksport ke seluruh dunia dan merupakan penyumbang utama kepada GDP Malaysia terutamanya dalam sektor pertanian. Tujuan kajian ini adalah untuk meramalkan harga Crude Palm Oil Futures (FCPO) dan mengoptimumkan beberapa petunjuk teknikal dengan menggunakan teknologi kecerdasan buatan. Dalam kajian tersebut, Extreme Learning Machine (ELM) dalam Perisian Matlab R2020a telah digunakan untuk memproses data harian FCPO seperti harga pembukaan, tinggi, rendah dan penutupan dari tahun 2010 sehingga tahun 2019. Selain itu, pelbagai fungsi telah digunakan untuk melatih dan menguji ELM tersebut untuk mengenal pasti fungsi yang paling sesuai dan tepat. Kajian ini mendapati bahawa fungsi radial basis dan petunjuk teknikal Williams Percent Range menunjukkan hasil ramalan yang paling tepat. Peramalan harga FCPO dengan menggunakan ELM menunjukkan bahawa peramalan harga boleh dicapai. Kejayaan dalam peramalan harga ini menyangkal kenyataan Efficient Market Hypothesis (EMH) yang mengatakan bahawa peramalan harga berdasarkan data bersejarah adalah agak mustahil. Selain itu, kajian ini boleh menyumbang kepada perniagaan yang berkaitan dengan kelapa sawit. Pemilik perniagaan dapat meramalkan harga kelapa sawit dan membuat keputusan untuk membeli sebelum harganya meningkat.

Di samping itu, pelabur juga boleh mendapat manfaat daripada hasil kajian ini menerusi pemilihan petunjuk teknikal yang sesuai dan efektif untuk peningkatan prestasi pelaburan.

Kata kunci: *Kecerdasan Buatan, ELM, FCPO, peramalan, petunjuk teknikal.*

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Crude Palm Oil Futures (FCPO) is a Ringgit Malaysia (RM) denominated futures contract traded on Bursa Malaysia Derivatives. In simpler terms, it is a contract that allows buyer or seller to buy and sell crude palm oil at a prearranged price at a specific time in the future. FCPO is standardised with 25 metric tons for a contract with a minimum price changeability of RM 1 per metric ton. FCPO are usually traded by two types of investors, the hedgers and speculators. For oil-related businessman, they would enter a FCPO contract to hedge themselves against unfavourable price increase in the future. As for speculators, they are traders who trade FCPO to obtain leverage and to earn through price movement and spread of crude palm oil.

Financial market or financial market movements and price prediction has always been a hot topic among researchers and investors. Price prediction or forecasting of market return is a tedious process and might cause the price generating process to deviate over time (Politis et al., 2002; Timmermann, 2008). Traditional stock price prediction usually revolves around using publicly available information or past trend and patterns, which is also known as fundamental and technical analysis. Obtaining high profit had always been a dream of all investors. In the financial market, there are many types of financial instruments that investors can choose to invest. A few examples of it are the trading of bonds, stocks, futures, foreign exchanges, commodities and many more.

Trading in futures is also becoming increasingly popular amongst traders because such instrument allows users to obtain rapid and high profit within a short period of time, unlike stocks and bonds which are usually invested longer. Investors can obtain profit by buying and selling futures at the right time. The main idea is to find the perfect entry and exit timing base on the investor's personal trading strategy, risk tolerance and knowledge of that instrument. Finding the right timing to enter and exit the financial market could be tough for many investors, especially for investors that just started trading.

Due to the importance of financial markets, trading decisions or investment strategy is usually aided by some form of prediction. The two main types of prediction method are through fundamental and technical analysis. The combination of fundamental and technical analysis is often used by investors when determining the timing of buying and selling. Technical indicators are based on past prices and historical data. According to Yan and Zheng (2017), fundamental analysis is the process of analysing the market's basic financial level. It mainly deals with the financial ratios of a business. The second method of stock or futures prediction is through technical analysis. Huang et al. (2012) stated that technical analysis deals with the historical price changes and chart patterns to assist investors in making decisions. In other words, technical indicator is a sequence of data points obtained from past price movement which comprises of the opening price, high, low, and closing price of the security. Some indicators may only require closing price or other singular information. Technical indicators offer a different perspective for investors. There are numerous simple technical indicators such as moving averages, volume, and so on. There are also harder to understand indicators such as Fibonacci level, Stochastic and so on. Regardless of the difficulties of technical indicators, it acts as one of the most important tips for investors when predicting price movement. Some commonly used technical indicators

include Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Exponential Moving Average (EMA), Williams Percent Range, Stochastic K and D.

Such massive amount of historical data could be a burden to investors and could also confuse investors. Therefore, data mining and AI have been frequently used to analyse such data and ease investors in predicting prices and investing. AI can be defined as the use of computer systems to perform tasks that could assist human in making certain decision. AI can range from speech recognition, facial recognition, translation, visual perception and many more. In simpler terms, AI is used to mimic the human brain and carry out tasks that are usually done by humans, therefore the possibility of AI is endless. In this study, AI will be used to optimize technical indicators related to Crude Palm Oil Futures (FCPO) and to aid investors in buying and selling futures. The primary objective of this study is to develop a novel decision support system using Extreme Learning Machine (ELM).

1.2 Background of the Study

Department of Statistics Malaysia, DOSM (2020) states that the top five commodity exports of Malaysia are refined petroleum, palm oil, crude petroleum, aluminium, and coconut oil. Asian countries account for approximately 85% of global palm oil exports with Malaysia being in second place with 32.6% market share, just behind Indonesia who controls around 51.7% global export share. The agricultural sector has contributed 7.3% (RM 99.5 billion) to the national GDP in the year 2018. Oil palm was the main contributor at 37.9%, followed by agriculture, livestock, and other activities. With an experience in palm oil industry for 100 years, Malaysia has a comparative advantage over other countries in terms of productivity and research and development.

According to Norhidayu et al. (2017), the role of oil, especially crude palm oil becomes increasingly important as it contributes significantly to the economy of Malaysia. Nambiappan et al. (2018) stated that crude palm oil prices are affected by various factors such as supply and demand of other crop oils, climate patterns, import policies of importing countries, changes in taxation and regulations. The occurrence of such event could affect the crude palm oil price adversely, thus leading to strong fluctuations. An example of FCPO yearly price trend in Malaysia can be seen in Figure 1.1.



Figure 1.1: FCPO yearly price trend

Source: Fusion Media Limited (2020)

FCPO is a Ringgit Malaysia denominated futures contract traded on Bursa Malaysia. With an amazing track record of 30 years, FCPO derivatives in Malaysia acts as the reference point for market players in the oil palm business. Hedgers and speculators trade FCPO due to various advantages. Firstly, Bursa Malaysia (n.d.) states that FCPO is available globally as it is traded electronically on CME Globex, which is an international trading platform. Traders from all around the world could access to Bursa Malaysia Derivatives through the platform. Secondly, palm oil related businesses such as plantation businesses, millers, refineries, and exporters could use FCPO to hedge risks and manage uncertainties regarding

future price movement. Thirdly, speculators could also use FCPO to obtain leveraged exposure to CPO in the market. Besides that, managers, advisers and traders to get immediate exposure to an active commodity market.

FCPO price fluctuations in Malaysia depends on the supply and demand of it. There are various issues faced by the FCPO market such as the drop of demand for palm oil, economic growth, trade barriers, climate changes and many more. An example of issue faced by the FCPO market is the drop in demand for palm oil due to the COVID-19 pandemic, where many countries have implemented national lockdown, thus decreasing the consumption and usage of palm oil indirectly. The lack of new market catalyst could continue to diminish market sentiment, causing the price of CPO to dip further.

Financial market prediction has always been an important financial topic that has attracted the attention of researchers and analyst throughout the years. Kolarik and Rudorfer (1994) stated that prediction of the financial market often involves analysing past information and relate it to future price trend or pattern. An attempt to predict future prices is said to be opposing the Efficient Market Hypothesis (EMH). EMH stated that all publicly available information reflects the value of a particular financial instrument, therefore it is impossible to forecast future prices since the price already reflects all information.

Globalization and modernization of technologies has encouraged the emergence of Artificial Intelligence (AI) and allowing it to blend into individual's daily life. Besides that, the generation and accretion of financial data in this modern era allows engineers and programmers to maximize their potential. Financial data are complex and could be affected by economic factors, political factors, socioeconomic factors and many more. Ashour et al. (2018) have shown the effectiveness of artificial intelligence in solving financial data,

especially time series data. In their study, they manage to research the exchange rate fluctuation for the Egyptian financial market which was then under tremendous political pressure. In another socioeconomic study, Abdallah et al. (2020) found that implementation of artificial intelligence in solid waste management have shown positive results in tracking waste. Coccia (2020) on the other hand have found that the implementation of AI on cancer imaging have increase the effectiveness of better prognostication. As we know, the unceasing spike in such data creates problems that are complicated and might be tedious to be resolved by human beings. Jin et al. (2015) states that big data plays a significant role in our current era, and its application could be beneficial to our national development, industrial upgrades, and scientific researches, helping the society to better perceive the present and predict the future. This shows the importance of the need to solve such big data. Therefore, the need of developing automated systems that could solve such issues are highly recommended. As mention earlier, the emergence of AI has been a big step forward and could solve many complex issues. The use of AI has been incorporated into our daily life without us noticing through mediums such as smartphone applications, smart technologies, and wireless technologies and so on. Fintech which is the use of AI in the financial market has been one of the main priorities set by the government as economic wellness determines a country's performance.

According to various past studies, many forms of AI have been used to predict future prices and trends. Unlike traditional linear techniques, the adaptation of AI is said to be self-adaptive, non-linear and automated. Wang et al. (2019) have implemented machine learning in predicting price of air fare, whereas Rahim et al. (2018) and Aini et al. (2019) have used artificial intelligence methods such as fuzzy based rule and Artificial Neural Network (ANN)

in predicting future prices. These past studies have shown superiority over AI tools as compared to the traditional method.

Since the influential work of Fama, the role of technical indicators is still blurry, and the effect of such indicators are still debatable. Several prominent studies have shown that technical indicator does yield positive returns, while some concluded that technical analysis is not useful in predicting stock prices. Not only that, numerous studies have been carried out to determine the role of technical analysis on crude palm oil prices. M'ng et al. (2017a) has proposed an innovated technical analysis model using ANN to calculate the returns on crude palm oil futures. In another research conducted by M'ng et al (2016), neural network is used to enhance technical indicators to improve trading rule in Malaysia stock market. This studies shows that technical analysis could help to improve investor's decision-making process. According to Masry (2016), decision making is one of the most important factors during an investment process.

The study of technical indicators originated from a person named Charles Dow. Kirkpatrick II (2022) states that Dow started observing financial assets prices through charts and that Dow Theory have been introduced to the society in early 1900. Through his observation, he noticed that prices of the assets are reflected before information became publicly available. After years of studies, Dow concluded that prices move along a path which is predictable or recognizable. Such theory then evolved into Dow Theory. The emergence of computer then further enhances the role of technical indicators. In simpler terms, technical analysis could be defined as the prediction of future patterns through analysing graphs or charts. An example of technical analysis can be seen in Figure 1.2:



Figure 1.2: Technical Analysis on FCPO

Source: Fusion Media Limited (2020)

As shown in Figure 1.2, the red line indicates a downtrend whereas the green line indicates an uptrend. This trend could be recognized by identifying the general pattern of the price change. Study on technical analysis has been increasingly popular due to its simplicity and widespread of usage. Generally, technical analysis follows three rules which are the market includes all information, history will repeat itself and trends will remain the same until a reversal occurs. According to Hayes (2021), the market incorporates all information means that the prices of an asset is reflected through every information portrayed. The second rule which is history tend to repeat itself indicates that identical inducement from the past will encourage investors to respond similarly in the future. This shows that through the study of previous patterns and trend, it is possible for the particular trend to appear again in the future. The recurrence of such trend might not be totally identical as compared to the past, but it is sufficient for investors to identify the main crucial points. The third rule which is an existing trend remains until a certain reversal occurs means that a price movement is expected to move along its path if there is no reversal signal.

According to Wong et al. (2003a), technical analysis comprises detail scanning for recurring price patterns in stocks. This type of analysis is said to be created in the 16th century in Japan. Such analysis has evolved into Chartism in the 20th century. The change in technical analysis from the past to present is said to be due to globalization and the introduction of computer system and technology which makes complex mathematical nature of the technical indicators easier.

There are many different types of technical indicators catered to different situations. There are trend-based indicators such as Bollinger Bands, Exponential Moving Average (EMA) and many more. Oscillator indicators such as Relative Strength Index (RSI), Williams Percent Range, Stochastic Oscillators to indicate the overbuying or overselling of the security. There are also volume-based indicators such as the Chaikin oscillator, Volume and many more. With such a large number of technical indicators and data, it is difficult for traders to identify which is the most suitable indicator, and which indicator could predict future prices more accurately as compared to others. In order to master traditional technical analysis and to determine which indicator works better, it requires a lot of knowledge and time spent on analysing each and every indicator. The adoption of AI onto technical indicators may be able to reduce the burden on traders, thus allowing traders to identify the optimal technical indicator without much expertise.

Furthermore, the implication of technical analysis in trading has played a big part in investment decisions. Forecasting and predicting of prices have been studied by many researchers from various fields such as finance, engineering, computer science and others. Park and Irwin (2007a) stated that statistical models and AI such as Artificial Neural

Network (ANN) are often used to predict future prices. Due to the abundance of parameters for technical indicators, AI could also be used for the optimization of technical indicators.

As technology keeps improving, analysts have begun to combine economic data with new technology to produce better returns. Recently, AI technologies such as fuzzy logic, artificial neural network (ANN), genetic algorithms (GA) and many more have been implemented onto the financial market to ease trading process and to generate higher returns. Artificial Neural Network (ANN) is a quantitative model that mimics the brain of a human being. Such model uses a computational brain connectivity approach to receive external signals through internal nodes and subsequently processes it and transfers such signals to the output node. Many people have the misconception that ANN is programmed to execute a certain task. But in reality, it is not programmed but trained to execute a certain task. An example of the structure of ANN can be seen in Figure 1.3:

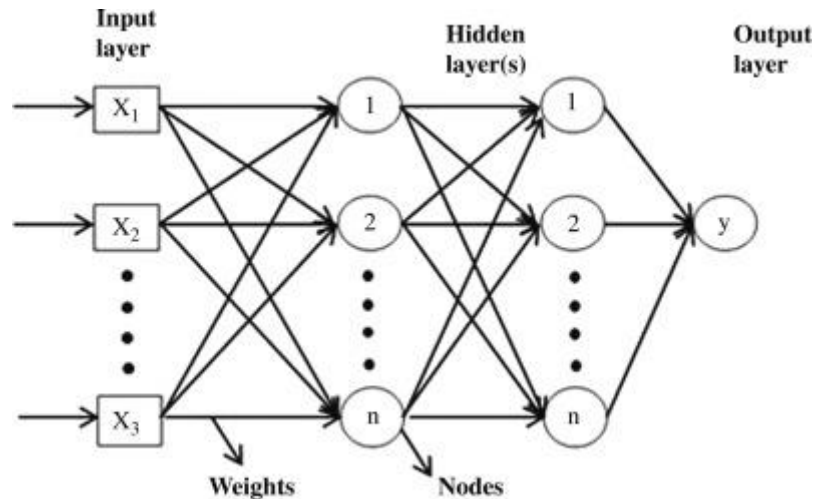


Figure 1.3: Basic structure of ANN

Source: Sairamya et al. (2019)

As shown in Figure 1.3, the input is multiplied by a certain weightage (strength of the signals) and the neural network sums the weighted signals. If the sum of the weighed inputs exceeds the threshold set, the activation function will then produce an output. In this study, we focus on using ANN trained by Extreme Learning Machine (ELM) to predict FCPO price and to optimize technical indicators. According to Frances-Villora et al. (2018), Wang et al. (2018) fast computational speed and high generalization performance of ELM is recommended to predict future prices.

1.3 Problem Statement

Dow Theory have stated that market price reflects all available information for any financial instrument. However, Efficient Market Hypothesis (EMH) have stated that price of a certain instrument is reflected all publicly available information, thus being impossible to predict future prices. The weak form of EMH assumes that current prices have already reflected available security information. In short, this form of EMH stated that past prices and volume have no effect on the future direction of the security price, thus extra profit could not be generated through the use of technical analysis. Salami et al. (2018) have found that the use of price of Malaysia's Crude Palm Oil as the reference price is stable and sustainable as it supports the weak form of efficiency. This indicates that any changes in price in the short run might not lead to arbitrage profit as the cost of transaction is not covered.

Besides that, Li and Bastos (2020) have also stated that a large number of technical analysis claims that reoccurring patterns may be identified through historical data, which constitute to lower risk and higher profit generation trades. All of this study is in line with the Dow Theory, which acts as the foundation of technical analysis. This theory implies that

the market moves in trend and it could be used by investors to understand and identify such trend.

According to Chisambara (2019), traditional price prediction is often carried out by human judgment. When humans are face with intricate interactions, they perform worse than machines. This is because human error and biases often affects their judgment and prediction. Besides that, Nguyen (2018) have conducted an experiment to compare traditional human prediction and machine prediction on important words in a document and have found that the automated approach performs better than the traditional approach. In the study, it was found that human prediction could not overcome the biasness of data. Furthermore, Patalay and MadhusudhanRao (2019) stated that human prediction relies heavily on previous experience, knowledge, and instinct. Such feelings affect the prediction process and may produce negative result. Güth and Kliemt (2004) also stated that the bounded rationality of human could cause cognitive biases and mistakes during prediction. Goldstein and Gigerenzer (2009) also maintained that the prediction and decision-making ability of human are subjected to cognitive biases, thus affecting the accuracy of prediction. Additionally, Gigerenzer and Selten (2002) also state that human tend to make predictions and decisions under limited knowledge, time, and experience, thus decreasing the prediction accuracy. DeMatthews et al. (2015) outlined that deficits in human's ability to extrapolate and interpret past evidences weaken the accuracy of their prediction. Moreover, human tend to ignore information so that they could make faster predictions. Hu et al. (2018) also found that the human could not maximize their cognitive potential and is poor in predicting complex data. According to Beaton (2017), human predictions are less accurate due to their emotional aspects. Human tend to make predictions that would be beneficial to them.

Next, it is important to have accurate prediction on commodity prices as it is significant to policymakers, investors, and researchers. Karia et al. (2012a) maintained that an accurate prediction of commodities, especially FCPO is important due to the unforeseen risks associated with it. Furthermore, Khalid et al. (2018a) stated that the accurate prediction of FCPO price is important as it ensures stable future price and enhances trading decision. Kim and Kim (2019) have also mentioned that it is important to forecast price as it helps trader in setting up trading strategy and to determine the buying and selling point in the future. In a recent study, Sedighi et al. (2019) have maintained that accurate price prediction maximizes the profit of investors greatly. Rahim et al. (2018) stated that accurate prediction of FCPO price is important in order to uphold the production of palm oil in Malaysia.

Malaysia's palm oil industry has contributed greatly towards the local economy and plays a significant part in the ASEAN economy. It is important to forecast FCPO prices accurately as it will benefit the local industry, thus improving our country's performance. In this study, the prediction of FCPO price is carried out by using AI hoping to predict future price with higher prediction accuracy. Besides that, the role of technical indicator in predicting FCPO price is also heavily debated. Initially, traders started off using the naked trading strategy during trading. Naked trading usually requires high level of knowledge and experience in order to execute trades solely based on price chart. According to Boulton and Braga-Alves (2012), naked trading is deemed as abusive and unscrupulous and could negatively affect the profit of the trade. Butler (2012) maintained that naked trading exposes risks to traders. Such risk could potentially decrease the profit of trades. Devos et al. (2014) also maintained that naked trading could adversely affect the trading performance.

According to Petrusheva and Jordanoski (2016), the importance of technical analysis in trading have increased over time. M'ng et al. (2017b) have found that the return of FCPO when using technical analysis is greater than the traditional buy and hold strategy. This result is consistent with studies conducted by Andrada-Félix and Fernández-Rodríguez (2000a). Mandelbrot and Hudson (2004) also claim that price changes are not random and could be predicted through the use of technical indicators. Masry (2017a) have found that technical analysis could reveal the possibility of abnormal return and is more effective in predicting stock price in the Egyptian market. The increasingly importance of technical analysis in predicting prices were also supported (Xavier et al., 2010; Assaleh et al., 2011; Wafi et al., 2015). Besides that, Chong and Ng (2008a) have also found that technical indicators such as MACD and RSI have increased the return on trades as compared to trading without indicators. Masry (2017b) have also conducted the effect of technical analysis on the Jordan stock market and have found that the returns are higher as compared to traditional trading. In another study, Rapach and Zhou (2013) have found that technical analysis has improve the trading return significantly.

Furthermore, EMH argues about the random walk which stated that past movement or trends have no effect on the future price movement of the security. In this study, AI is incorporated into the prediction process to identify which technical indicator could predict FCPO prices most accurately. AI could potentially capture the random walk and identify the optimal technical indicators used to predict FCPO price. With tons of different technical indicators in the market, which technical indicators provides better prediction accuracy as compared to others is the issue that is focused in this study. With the usage of AI, the prediction accuracy of various technical indicators could potentially be obtained and compared to identify which technical indicator performs better.

According to Khalid et al. (2018b), crude palm oil prices are affected by determinants such as total demand of palm oil, stock of palm oil, exchange rates, and price of other similar replaceable oil. The relationship between FCPO price prediction and technical optimization is continued to be study heavily amidst all the puzzling and contradicting empirical evidences and theoretical disagreement documented in the extent of empirical finance and information technology related literature. Many of such literatures are based on the traditional human approach, and very little is known about how AI could affect prediction of price especially in the futures market. In other words, AI might play a different role in predicting prices and optimizing technical indicators on futures as compared to traditional human prediction.

1.4 General Objective of the Study

This main objective of this study is to validate FCPO prices and optimize various technical indicators through the implementation of AI. ELM which is a form of single layer neural network will be used to predict the price of FCPO. Training data will then be fed into the model to obtain the output. The output will then be compared and validated against a set of testing data, which is the actual price of the FCPO. Detailed steps in price prediction can be seen in chapter three.

Based on the research objective, various research questions such as:

RQ1: What type of technical analysis are widely used to predict FCPO prices?

RQ 2: What are the common methods/model to predict FCPO prices?

RQ 3: How do we test the accuracy of predicted output?

1.4.1 Specific Objectives

- To validate FCPO prices from historical data through the usage of ELM.
- To determine the optimal parameters for technical indicators price prediction on FCPO using ELM.
- To identify the optimal technical indicator on price of FCPO using ELM.

1.5 Significance of the Study

The objective of this study is to predict and validate FCPO price and to optimize technical indicators of FCPO using AI, specifically ELM. This study is significant to traders whom are looking to reduce the risk in trading as it allows them to predict future prices and to hedge themselves against any unforeseen price fluctuations. Not only that, this study also allows traders to maximize their profit by predicting future price and to enter and exit the market at a suitable time.

According to Gan and Li (2014), Malaysia is the second larger palm oil exporter and this industry acts as one of the main contributors towards the local economy. Thus, it is important for businesses that are related to palm oil to predict future FCPO prices. This study is significant to palm oil related businesses and industry players as it allows them to foresee future business trends. Ahmad (2010) stated that prices of FCPO are high volatile and could be difficult to predict in the long run without the assistance of automated systems. This study aims to develop an automated price prediction system that could allow businesses to identify main drivers of FCPO price, changes in price and to make plans accordingly.

In short, the contributions and implications of this study are primarily used for traders and industry players to recognize the importance of accurate FCPO price prediction and

technical indicator optimization on maximizing trading performance. Besides that, this study is carried out hoping that traders and palm oil related businesses could fully utilise the information provided to make rational trading decisions and to increase profit in trading.

1.6 Scope of the Study

There are many methods to predict FCPO prices and to optimize technical indicators. In this study, we focus on using Extreme Learning Machine (ELM) to predict future prices of FCPO and to optimize prominent technical indicators such as MACD, EMA, RSI, Stochastic and Williams Percent Range. The period of the data is set starting from year 2010 to 2019. The daily opening, high, low and closing price of FCPO throughout our sample period is downloaded from Bursa Station.

Furthermore, this study does not consider external factors and only focuses on internal factors such as the historical prices of FCPO. External factors that could affect the price of FCPO includes unfavourable weather conditions, diseases, political agenda and many more. The inclusion of external factors are not taken into consideration because this study uses ELM that only requires past historical prices to run, such data is also chosen because it could not be altered in any way. Besides that, this study also incorporates information from different fields such as finance, engineering, and information technology. The use of AI on futures optimization and price prediction is considerably new as past studies focuses mainly on traditional approach and stock price prediction only. Raw data related to futures will be inputted into the AI system to generate results that could improve the quality of trades.

1.7 Organization of the Study

This study consists of five different chapters. Chapter one includes the introduction and background of the study. This is very important as it provides readers a good first impression towards the whole study. Besides that, this chapter also includes the problem statement, objectives of the study, significance of the study, scope of the study, organization of the study and also the summary of this chapter.

As for chapter two, it will be literature reviews that are related to AI, technical indicators and futures. This chapter starts with an introduction and is followed by the review of certain theories that helpful for the study. Theories used are the Dow Theory and the Efficient Market Hypothesis Theory. Not only that, hypothesis development will also be included in this chapter.

As for chapter three, it focuses mainly on the research methodology used in this study. Methodology is one important aspect in a research as it allows readers to know how the data is generated and formulated. It also allows readers to evaluate the reliability and feasibility of the study. This chapter will start with an introduction, followed by research design and methodology that will be used to optimize technical indicators. Chapter four will be about the results and findings of this study, whereas chapter five is about conclusion and discussion of findings.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter focuses on explaining previous studies that have been done by scholars which are related to this study. Literature review is important as it tells us the difference between the findings of previous studies from different journals and the possible drawbacks of that study. This study is conducted to examine the relationship between futures contract, particularly the Future Crude Palm Oil (FCPO) contract and the role of AI in optimizing the selection of such contracts. Therefore, the journals with topics related to our study is reviewed and explained. Not only that, theories used by previous researchers will also be discussed in this chapter.

This chapter consists of four parts which are the explanation of past studies, hypothesis development, research framework and summary.

2.2 Dow Theory

According to Kilgore (2018), Dow Theory or Dow Jones Theory was initially based on the assumption made by Dow Jones using the Dow Jones Industrial Average (DJIA) and the Dow Jones Transportation Average (DJTA). The Dow Theory is closely related to the modern technical analysis because investors have to watch closely for numbers and patterns on the stock chart. Furthermore, Dow Theory also acts as the fundamental of technical analysis. The basic concept of Dow Theory is that the market price of a certain stock reflects all available information. Not only that, Dow Theory also consists of 6 main tenets.

The first tenet of this theory is that the market moves based on three main trends. Such trend includes the primary trend, the intermediate trend, and the minor trend. This trend indicates the duration of a certain price pattern. The primary trend can be years, the intermediate trend can last weeks to months, whereas the minor trend lasts only a few days or hours. The second tenet of Dow Theory is the market trends have three stages. During uptrend, stages such as the accumulation, public participation and excess phase will occur. As for downtrend period, the distribution, public participation, and panic phase will occur. An example of such changes in phase can be seen in Figure 2.1:

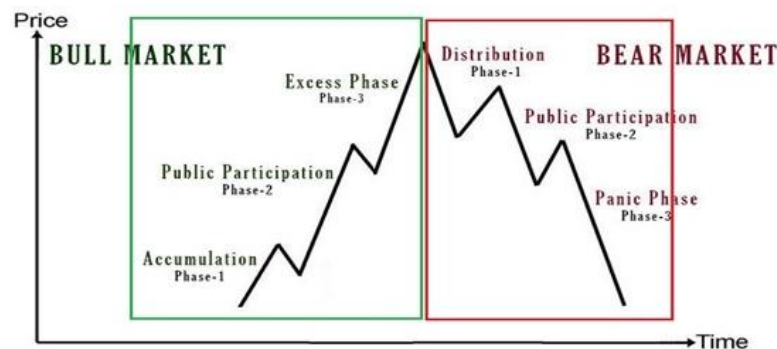


Figure 2.1: Second Tenet of Dow Theory

Source: Kayyumi (2018)

The third tenet of Dow Theory is that all news is discounted in the market. This means that the market price of a stock will be reflected by all possible information and expectation. As for the fourth tenet, it is averages or indices of the stock must confirm. Dow insists that for a trend to appear, the market averages, in this case the DJIA and DJTA must confirm each other. Next, the fifth tenet of Dow Theory suggest that the volume must confirm the trend. This means that the volume should shadow the price change. If the volume increases, the price of the certain stock should also increase, vice versa.

The sixth and last tenet of Dow Theory is that the price trend shall continue if there are no reversal patterns. According to this principle, Dow maintained that the price movement of a stock should be continuous until a certain force is acted upon it, causing the price trend to reverse.

According to Cervelló-Royo (2018), technical analysis has a certain extend of predictive power for return. In their study, they have tested certain technical rules using the Dow Jones Industrial Average and have rejected the hypothesis stating that technical indicator has no predictive power towards future return. This finding is important because other researchers such as Selvin et al. (2017) have adopted a similar approach to in their study and have obtained a similar result.

Besides that, Brown et al. (2002) have found that investors whom are following the Dow Theory have earned 90% profit, while bearing 30% risk exposure. In their study, neural networks were used to analyse chart patterns. If the prediction of FCPO prices with the addition of technical indicators are accurate with low error, the technical indicator is said to be effective, thus agreeing with Dow Theory, which stated that technical analysis could benefit traders in making trading decision and obtain higher profit.

Heo and Yang (2016a) states that many technical indicators have been developed using the Dow Theory or Dow Jones Industrial Average (DJIA) as the basis. Thus by incorporating various technical indicators in this study, this study aligns with the Dow Theory. Besides that, the collection of the historical daily opening, high, low and closing price of FCPO was identified through historical candlesticks. According to Uyar et al. (2020), Dow Theory states that historical price might repeat itself in the future, which makes

prices predictable. This study intends to predict FCPO price and validate it against the actual price.

2.3 Efficient Market Hypothesis (EMH)

Lo (2004) defines the Efficient Market Hypothesis as the market price of a stock contains and reflects all the information of the stock. In this case, neither fundamental analysis nor technical analysis could provide investors with excess return as stocks always trade at their fair prices.

However, many researchers have critiqued such hypothesis and have conducted research to show that fundamental and technical analysis does allow investors to buy undervalue stocks or buy stocks at the optimal timing. Mirzaee Ghazani and Jafari (2021) study states that a market could not be perfectly efficient or else there would be no motivation or incentive for financial analysts to uncover the information of stocks or futures. Delcey (2019a) stated that the main problem of EMH is that such theory assumes all market participants or traders have a homogenous thinking regarding the stock or futures market. He argued that if all the market participants have the same idea and expectations, there would be no point in trading. He also maintained that markets consist of different type of traders with different mindset, thus creating heterogeneous expectations. Such difference in expectations will cause the stock or futures market to fluctuate and generates bullish and bearish trends. In this case, the efficient market hypothesis is irrelevant and full of flaws.

According to Hodnett and Hsieh (2012), the market efficiency hypothesis consists of three forms. Such forms include strong form, semi-strong form and weak form. Strong form in the EMH shows that prices of a current financial asset reflects fully on all information, which includes private and public information. It also says that outperforming the market is

nearly impossible as all readily available information are already reflected on the price. As for the semi-strong stage, it shows that prices fully reflect any publicly available information and prospects in the future. This propose that prices regulate themselves almost instantly to new readily available public information. Furthermore, the weak form of EMH is the smallest part of the three forms. This form indicates that past information and patterns such as prices, trends, returns and other statistics could not be used to forecast future prices. The weak form of EMH basically renounces technical analysis. The three forms of EMH can be seen in Figure 2.2:

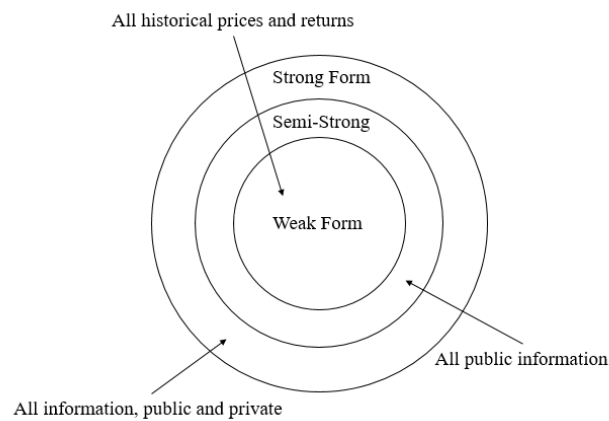


Figure 2.2: Three Forms of EMH

Source: Lin (2016)

The weak form of EMH stated that in an efficient market, historical prices could not be used to predict future price and that excessive profit could not be generated because the security's price have already reflected all available information. In this study, the historical prices such as the daily opening, low, high, and closing price of FCPO is used to predict its future price. AI will be introduced into the prediction process to obtain the minimum error and to test whether it is possible to predict future prices with high accuracy solely based on historical prices.

Furthermore, Delcey (2019b) also maintained that the EMH structure implies that the buy and hold strategy is the same as any other strategy such as fundamental and technical analysis because the market prices of stocks and futures always reflect the intrinsic value of the financial asset. If a neural network could outperform the market or predict the price trend, the validity of EMH is questionable. In their study, the application of neural network onto financial system have found that neural network predicts the market movement accurately 92% of the time, whereas linear regression could only predict with an accuracy of 60%. In another study, Shastri et al. (2019) also predicted future stock price with an accuracy of greater than 90% using neural network.

This study aims to predict and validate FCPO prices which is against the weak form of EMH, which states that historical prices could not be used to predict future prices. If the prediction of FCPO prices are similar against the actual output, which is the testing data, this study then refutes the EMH theory. Furthermore, this study relies solely on the daily historical price of FCPO as the sample data to predict future price.

2.4 Empirical Review on Technical Analysis

According to Wong et al. (2003b), technical analysis is the process of finding and identifying past price patterns and trends and predicting it in the future. Several studies have questioned the usefulness and effectiveness of such analysis and recommended the buy and hold strategy when buying stocks or commodities for a better return. Shah and Shah (2020) stated that if cost of transaction were taken into consideration, traders might even incur losses when using technical analysis in picking certain financial assets. Prices of stocks or futures tends to reflect according to information obtained from experience and history in an efficient market. Such history and trends allow investors to use technical analysis to pick stocks and

futures. Several widely used technical analysis such as Moving Average (MA), Relative Strength Index (RSI) were used in the study conducted by Wong et al. (2003c). A simple illustration of technical analysis chart of FCPO can be seen in Figure 2.3:

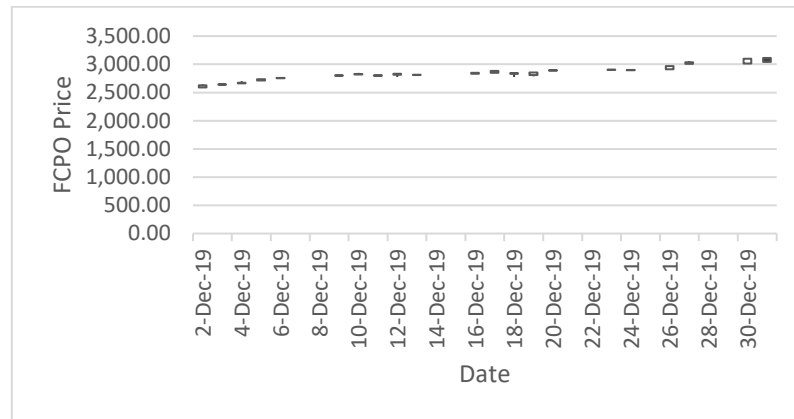


Figure 2.3: Candlestick Chart for FCPO

Source: Fusion Media Limited (2020)

The role of technical analysis in predicting prices and trends have been studied heavily in the past, both in academic and professional institutions. Gehrig and Menkhoff (2006) stated that although the heavy usage of technical analysis in investing, there are still numerous studies that go against it. This could be due to the initial assumptions made by Fama which insist that the prices of any financial securities are align with the efficient market hypothesis, which stated that the prices fully reflect all available information.

According to Park and Irwin (2007b), there are positive evidence of technical indicators affecting the profitability of traders in the modern era. For their study, Park and colleague included a total of 137 samples which includes securities from the stock market, foreign exchange and futures market. The study was further divided into two parts which are the early study (1960-1987) part and the modern part (1988-2004). Based on their findings, the profitability of technical analysis trading shows a higher proportion in the modern era,

whereas the usefulness of technical trading can be neglected in the earlier part. Furthermore, Fernandez-Rodriguez et al. (2000b) have incorporated technical trading and ANN to test the profitability of the Madrid Stock Market and have noticed that the technical trading technique generates higher return in a bearish or stable market. Metghalchi et al. (2012) have also maintained that the predictions by technical analysis trading are greater in small and medium sized markets. Heyman et al. (2011) also stated that the predictive power of technical analysis is greater in emerging markets, which is suitable in the FCPO market.

Besides that, there are also studies which remains in a neutral position. Todea et al. (2009) stated that the achievement of technical analysis could not be generalized and is temporary, which goes along with the Adaptive Market Hypothesis. This hypothesis links the EMH and behavioural finance closely together as it proposes that humans are blinded by self-interest and tend to make mistakes, and to learn from it afterwards. Khuntia and Pattanayak (2018) also maintained that any kind of strategy, in this case the technical analysis might or might not perform well in certain market conditions. Taylor (2014) have also supported the statement by stating that the success of technical analysis trading depends on market condition primarily liquidity and macroeconomic factors.

Many other researchers have also emphasized the importance of technical analysis in investment and have found out that market professionals tend to include technical analysis when making a buy or sell decision. Not only that, there is also alteration from fundamental analysis to technical in the 1980s. The main principle of technical analysis is to follow the price trend. Whenever a pattern or trend occurs, be it started by market or fundamental factors, technical indicators tend to signal a certain uptrend or downtrend pattern for traders to follow. Besides that, Barla et al. (2021) states that prediction made by technical indicators

are said to be self-fulfilling, this is because despite the random price movement of the financial asset, technical indicators will still reinforce the original trend. Investors that are irrational when trading using technical analysis have affected the volatility of the stock market in the US and might have caused the October 1987 stock market crash.

According to Oyemade et al. (2020), two of the easiest technical trading rules are trading at the support and resistance level. Moving average rule can be used as a buy or sell signal when a long period average and a short period average converges. In short, traders are encouraged to buy the stock when the short moving average rises above the long moving average, vice versa. When such phenomenon occurs, the stock price trend is said to be bullish. Another type of technical analysis that are often used by traders is the trading range break out (TRB). A buy signal is generated when the stock pierces through the resistance level. The resistance level is also known as the local maximum where past prices linger below this level. This happens mainly due to psychological factor of traders. Oppositely, as the price drops below the support level, it shows a sell signal. In simpler terms, technical analysts recommend traders to buy when the price penetrates the previous peak (resistance) and sell when the price drops below the previous low (support).

2.4.1 Relative Strength Index (RSI)

RSI is a momentum gauge that calculates the magnitude of recent market price changes to appraise overbought and oversold situation. In conventional interpretation of RSI, an RSI reading of less than 30 indicates that the financial asset is oversold and undervalued, whereas an RSI value above 70 indicates that the security is overbought and overvalued. The price will retrace slightly after surpassing these values. An example of the RSI indicator on the price of FCPO can be seen in Figure 2.4:

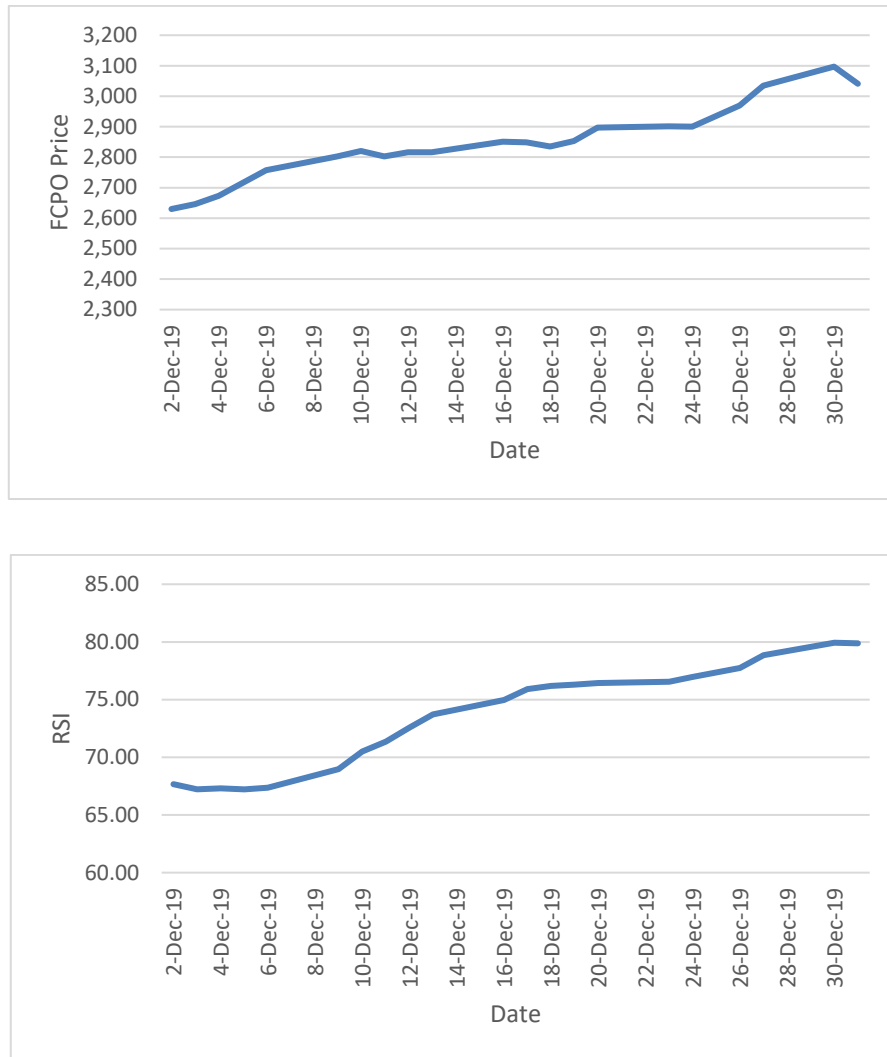


Figure 2.4: RSI of FCPO Malaysia

Source: Fusion Media Limited (2020)

According to Taran-Morosan (2011), RSI is one of the most popularly used technical analysis indicator. Rodríguez-González et al. (2011) maintained that RSI have been used worldwide and is one of the most prominent technical analysis indexes, it is also used to aid trader in generating higher profit trades. According to Sundlöf and Krantz (2016), RSI and MACD are both suitable to be optimized as one represents an oscillator whereas the other represents a trend follower. Gumparthi (2017) also stated that RSI is popular and is strong in predicting the trend of price movement. Halilbegovic et al. (2018) also maintained that

RSI is one of the five most popular oscillator indicators among traders and is useful in predicting returns, even inexperienced investors tend to use RSI because it is easier to understand. Chong and Ng (2008b) also found that RSI and MACD rules could generate excess returns in the context of London Stock Exchange. In another study conducted by them, Chong et al. (2014a) have tested the two indicators on five other OCED countries and have found that RSI and MACD could generate significant abnormal returns. Cohen and Cabiri (2015) have also found that RSI could outperform DJIA and FTSE 100 and achieve excess return as compared to the buy and hold strategy.

Abbey and Doukas (2012) have stated that RSI could have a negative impact on performance. In their study, RSI and various other technical indicators is seen to be detrimental to performance, especially when trading currencies. In their study, they managed to regress R^2 from the technical currency model and have found that technical indicator such as RSI, MACD, MA, BB have negative impacts towards currency exchange performance. Investors whom used such widely-known indicators have lower performance compared to their peers who did not rely on the same strategy.

Sezer et al. (2017a) maintained that RSI compares losses and gains over a specific period, which is usually 14 days or 14 weeks. The formula of RSI consists of 2 steps as shown in Equation 2.1 and Equation 2.2:

$$RSI = 100 - \frac{100}{(1 + RS)} \quad \text{Equation 2.1}$$

$$RS = \frac{\text{Average Gain over } n \text{ period}}{\text{Average Loss over } n \text{ period}} \quad \text{Equation 2.2}$$

2.4.2 Exponential Moving Average (EMA)

Nakano et al. (2017) stated that Exponential Moving Average is a well-known indicator and is suitable in observing the price trend (Huang et al., 2008; Patel et al., 2015). In an earlier study, Harrou and Nounou (2014) stated that EMA is included in the early work of econometrics as it is easy to be plotted, interpreted and its control limits are easily obtainable. Džikevičius and Šaranda (2010) also stated that moving average is one of the most frequently used technical indicator when trading. In their study, they compared EMA against SMA and have found that EMA has a lower bias level and the forecast is more accurate, thus showing the effectiveness of EMA in predicting price. Boobalan (2014) also supports the usage of EMA as one of the most useful indicators and could aid traders in making better trading decisions. Kim et al. (2010) have also found that EMA provides high accuracy in forecasting.

However, Heng and Niblock (2014) have found that EMA could not achieve abnormal returns as compared to the buy and hold strategy in the Southeast Asia stock index. McMillan et al. (2000) also stated that EMA provide marginal superiority which means that it is not efficient when it comes to return.

An example of EMA technical indicator on the price of FCPO can be seen in Figure 2.5:

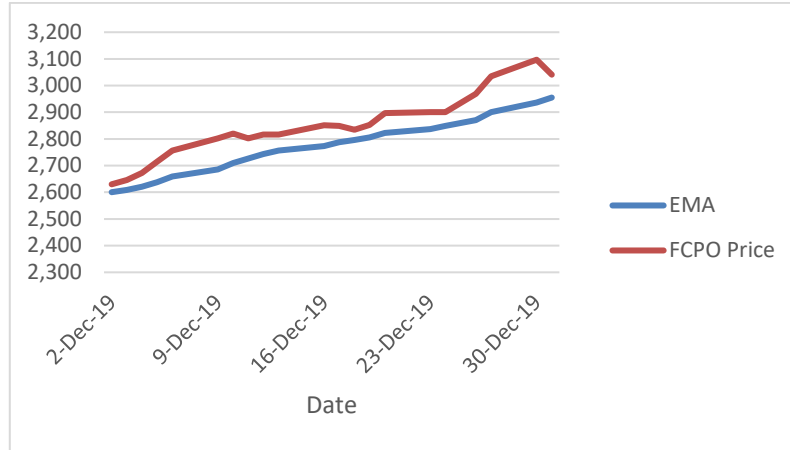


Figure 2.5: EMA of FCPO Malaysia

Source: Fusion Media Limited (2020)

EMA can be presented in two ways. The first way is the percent based EMA which indicates a percentage and is single parameter. The second way is the period based EMA, where the parameter consists of a certain duration. The formula of EMA can be seen in Equation 2.3:

$$\text{EMA} = ((\text{Current closing price} - \text{previous EMA}) \times \text{EMA multiplier}) + \text{previous EMA} \quad \text{Equation 2.3}$$

2.4.3 Moving Average Convergence and Divergence (MACD)

MACD is informative and could produce higher profit as compared to the buy and hold strategy. Chong et al. (2014b) have also found that MACD can generate excess returns in the case of trading in London Stock Exchange. In another study, Vezeris and Schinas (2018) have compared three automated trading system and have found that the MACD system generates the most profit as compared to the PIVOT and SMA systems. Chong et al.

(2008) have also found that MACD have performed well in stock markets of Germany and Hong Kong.

However, Hejase et al. (2017) have tested the effect of MACD on the Lebanese stock market and have found that MACD has no significant relationship with profitability. Subramanian and Balakrishnan (2014) have also found that MACD reported negative returns although the overall performance was satisfactory. Braga et al. (2015) also stated that MACD performs weaker as compared to the buy and hold strategy.

According to Hayes (2019), MACD is a momentum indicator that compares two moving averages of a particular security price. This indicator is useful in showing the trend of a stock price. The traditional formula of MACD can be seen in Equation 2.4:

$$MACD = (12Days EMA - 26Days EMA) \quad \text{Equation 2.4}$$

2.4.4 Williams Percent Range

Sezer et al. (2017b) stated that Williams Percent Range is a momentum-based indicator that is almost similar with RSI but focusing more on short term trades. This technical indicator fluctuates between 0 to -100. It is also used to indicate whether a security is overbought or oversold. The security is overbought when the Williams Percent Range reading reaches 0 to -20 and it is considered oversold if the reading reaches -80 to -100. The equation of Williams Percent Range indicator can be seen in Equation 2.5 and the example of Williams Percent Range indicator on FCPO can be seen in Figure 2.6:

$$\%R = \frac{(Highest\ High - Current\ Close)}{Highest\ High - Lowest\ Low} \times -100\% \quad \text{Equation 2.5}$$

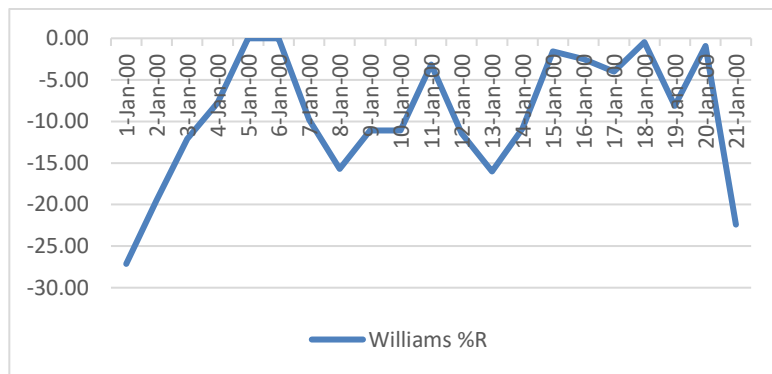


Figure 2.6: Williams Percent Range on FCPO Malaysia

Source: Fusion Media Limited (2020)

2.4.5 Stochastic Oscillator

According to Hwa (2007), Stochastic is a powerful technical indicator that could analyse the momentum of the market. It is used to identify bullish and bearish divergences. Dourra and Siy (2002) stated that Stochastic Oscillator provides insight on the stock's last closing price against its recent trading range, and it is one of the most recognised momentum technical indicator. Loh (2007) have also maintained that Stochastic is used to improve forecast accuracy. Ni et al. (2015) have found that Stochastic could improve the stock performance in the Chinese stock market. Jawade et al. (2015) have also found that Stochastic Oscillator is useful in predicting trend reversals. Ijegwa et al. (2014) have also tested four technical indicators which includes the Stochastic Oscillator against the Nigerian Stock Exchange and have found that Stochastic has a positive impact on the performance. Ghobadi (2014) also stated that Stochastic could produce positive returns when used in trading.

Oppositely, Coe and Laoethakul (2010) stated that the Stochastic Oscillator could not outperform the market and could not outperform the buy and hold strategy.

According to Dash and Dash (2016), Stochastic Oscillator allows traders to measure the velocity of a certain price movement. Stochastic K or K% is used to measure the relative position of present closing price in a particular time range, whereas Stochastic D or D% stipulates the 3-day MA of K%. The equations of K% and D% can be seen in Equation 2.6 and Equation 2.7:

$$K\% = \frac{CP - L(t)}{H(t) - L(t)} \times 100 \quad \text{Equation 2.6}$$

$$D\% = \frac{(K\%(i-2) + K\%(i-1) + K\%(i))}{3} \quad \text{Equation 2.7}$$

Where:

CP = Closing price

L(t) = Lowest price of last t days

H(t) = Highest price of last t days

An example of the Stochastic Oscillator on FCPO price can be seen in Figure 2.7:

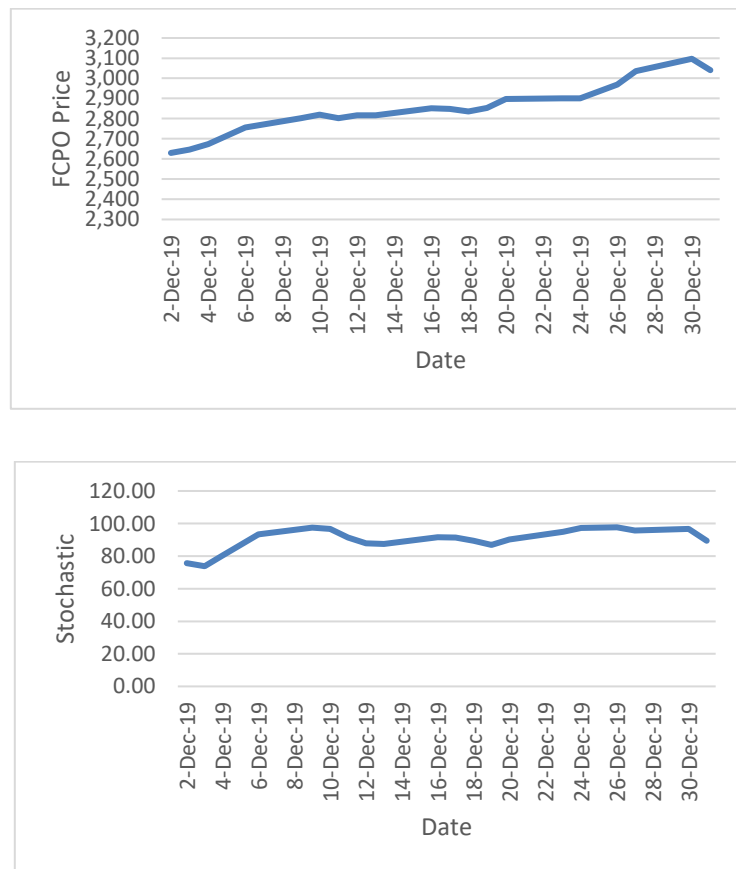


Figure 2.7: Stochastic Oscillator on FCPO

Source: Fusion Media Limited (2020)

2.5 Empirical Review on Price Prediction using AI

Recently, the financial market has started to shift from the traditional platform to a highly automated platform incorporating new concepts such as neural networks, support vector machine, genetic algorithms, fuzzy logic and many more. In many studies, the efficiency and effectiveness of AI on the yield of financial market have proven to be quite high. The commonly adopted models are Artificial Neural Network (Di Persio & Honchar, 2016), genetic algorithm (Chung & Shin, 2018a), Support Vector Machine (SVM) (Nti et al., 2020) or a mixture of two or more concepts (Lahmiri, 2020; Sharma et al., 2021).

Rather et al. (2015) forecasted stock returns by using a hybrid AI model which is a combination of the rule-based system technique and the recurrent neural networks technique. However, the technique used in their study differs from other studies. In the study, the rule-based system is assisting the neural network by providing it with training examples which would feed them with tons of historical data. Not only that, reasoning neural networks (RN) is used instead of Back Propagation networks as it has a smaller number of nodes and have a much faster learning speed. Empirical results show that the hybrid AI model performed better than the conventional buy and hold strategy carried out by traders.

Besides that, Singh and Khushi (2021a) stated that artificial network does improve the accuracy and credibility in the picking of stocks and futures. Artificial Neural Network (ANN) was introduced by these researchers in their study by setting up a system that specially recognizes patterns and algorithms. The conventional and traditional method of solving complex problems often involves the use of an expert system. But in their study, expert system is deemed inappropriate due to the high cost of programming and maintenance. The

main reason in choosing ANN as the main approach in the study is because such method learns by observing past data and experience and there is no need for the researcher to interview the experts personally. Not only that, the parallel nature of ANN allows problem solving even if certain neurons do not function properly, which means that stable configuration patterns will still be generated and form even if the neural network is being fed by inaccurate or fuzzy information. Tahar et al. (2017) uses the Boltzmann Machine (BM) to adjust the stated of neurons during the learning stage and the computing stage. The BM appears to be successful in the picking of stocks and futures as they show great precision when picking stocks. However, superior decisions and precision could be further improved if the number of learning cases increases.

Gorgulho et al. (2009) stated that the use of AI especially Genetic Algorithms (GA) is significant in optimizing technical indicators when trading. In this study, their study adopts a strategy where AI could aid the researcher in finding overvalued stocks. Wagman (2003) has conducted a similar study whereby the use of a simple Genetic Programming (GP) to optimize a technical indicator, which is the Moving Average (MA). The approach used by Wagman was firstly to generate a random population and tries to converge the population by using an evaluation function that would consider the weight of each assets against the degree of satisfaction of the MA. Besides that, Yan et al. (2008) have conducted a similar study by using genetic programming to find the ideal model to classify stocks within the stock market. The higher performing stocks adopt long positions whereas the underperforming stocks adopts a short position. Their study focuses on the fundamental analysis of the stocks. The main drawbacks of this study are the difficulty in obtaining such financial data and the credibility of such data due to the company's self-interest.

Devadoss and Ligori (2013) stated that Artificial Neural Network (ANN) is suitable in predicting the price movement of stocks or any similar financial assets. According to them, the ANN have the potential to discover nonlinear relationship between the input data set without prior knowledge and experience against the output. Artificial Neural Network is defined as a data processing system which consists of many artificial neurons which mimics the cerebral cortex of the brain. Various researchers such as Moghaddam et al. (2016), Gupta and Nigam (2020), Soon et al. (2018) have conducted a similar study to investigate the relationship between ANN and stock prediction and have found that AI significantly enhances the process of stock prediction. Based on such past study, ANN is shown to improve the results significantly as compared to linear and logical regression models.

Besides that, Yildiz and Yezegel (2010a) stated that fundamental analysis with the assistance of AI could significantly increases the efficiency in stock picking. AI includes ANN which simulates a human brain which sums up all input and comes up with an output. A simple sample of artificial neuron can be seen in Figure 2.8:

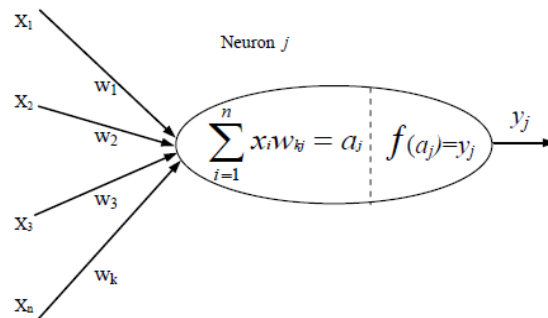


Figure 2.8: Sample of Artificial Neuron

Source: Yildiz and Yezegel (2010a)

According to Yildiz and Yezegel (2010b), the major compartments of a neural network are the neurons, weightage or connections and the learning algorithm. Neural

network consists of neurons which collect inputs (X_i) and generate an output (Y_i). An artificial neural network is connected by a large network of neurons. ANN consists of multiple layers which include the input, hidden and output layer. The basic structure of ANN can be seen in Figure 2.9:

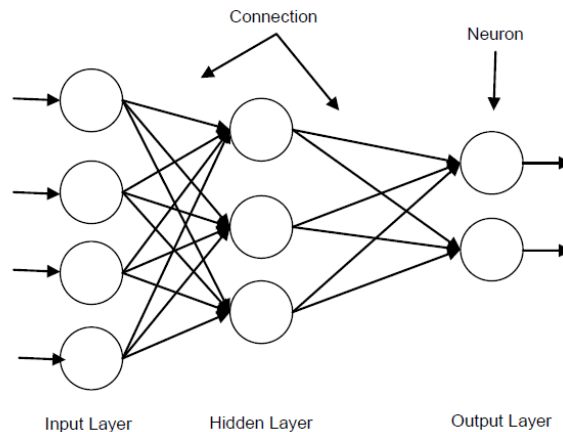


Figure 2.9: Basic structure of ANN

Source: Yildiz and Yezegel (2010b)

According to Adebiyi et al. (2014), ANN model is more suitable in predicting prices as compared to the Autoregressive Integrated Moving Average (ARIMA) model. In their study, both of the models were used to predict stock price. The empirical results obtained shows that both model have good generalization performance but ANN demonstrated superior performance over ARIMA. Another similar study conducted by Ma (2020) also shows that the performance of ANN is more superior compared to the ARIMA model. In another study, Sen and Chaudhuri (2018) have compared various models such as ANN, Long and Short Term (LSTM) memory network and have found that ANN produces results with highest accuracy when predicting two stocks listed in National Stock Exchange (NSE). In a recent study, Shankar et al. (2022) found that ANN has a lower Mean Absolute Percentage

Error (MSE) as compared to ARIMA and LSTM regression models when predicting stock prices listed in India's stock exchange.

In this study, ELM was chosen as the predictive model as it is simple to understand and the parameters does not need fine tuning. According to Wang et al. (2021), ELM is a single layer feed forward neural network that performs much faster than traditional methods, and produces accurate results. Kukreja et al. (2016) states that neural networks is an imitation of the human's brain, which is capable to learn new things, identify trends and patterns, adapt to ever-changing circumstances. Huang et al. (2006) have proposed the ELM model, which is specifically to train single layer hidden feed forward neural networks. In their study, it was found that ELM was different from traditional gradient based models. This model allocates random values to the weightage between the input layer and the hidden layer. This randomness of the model allows it to converge faster than traditional algorithms as it learns without iteration.

2.6 Empirical Review on Technical Indicator Optimization

There are various studies linking the computer and engineering field with AI, especially Genetic Algorithms. However, the scarcity of studies linking GA and finance acts as a major concern as Fintech has been a growing interest of many industries. According to Chung and Shin (2018b), GA is a suitable approach in discovering and optimizing technical analysis. Besides that, Sin and Wang (2017) also developed a new GA based system and applied it towards predicting bitcoin prices. Similar approach has also been conducted by Deng et al. (2015) on foreign exchanges.

Fernández-Blanco et al. (2008) stated that technical indicator could offer a different perspective to investors. In their study, Evolutionary Algorithm (EA) is used to optimize

technical indicators such as RSI, EMA, MACD and Weighted Moving Average (WMA). EA allows researchers to set up parameters for the technical indicator. For example, MACD has 3 parameters whereas EMA has 2 and RSI has 1. With such parameters, an additional gene named N is included to signify the time window. All these parameters are then implemented into MATLAB with tight linkage EA. Selection, crossover and mutation operators are used. EA is chosen in the study due to its flexibility, where it modifies itself while maintaining a fixed window length. Not only that, EA also allows the algorithm to continue processing although the underlying fitness keep changing.

Sahin and Ozbayoglu (2014) have also used a similar approach in their study. In their study, Genetic Algorithm (GA) is used to optimize technical indicator such as RSI and Trend-Normalized RSI (TNRSI). GA consists of a population of chromosomes which consists many genes. Each chromosome is said to be a candidate solution whereas each gene are the parameters of the solution. The chromosome is then evaluated with a fitness function. The algorithm then creates generations that could evolve itself into another generation. The evolution methods used in their study are selection, crossover and mutation. After the selection of parents are conducted, a crossover occurs to produce child chromosomes. The mutation operator is then introduced to change selected genes in the chromosome. The quality of selection process used in their study is 0.1 elitism rate. The crossover is set at 0.7 whereas the mutation rate is set as 0.02. The profit from the parameters are set as the fitness function. The results obtained are compared against the traditional Buy and Hold strategy (B&H).

Fayek et al. (2013) have also conducted a similar study by conducting a multi-objective optimization on technical indicators using GA. In their study, technical indicators

such as Double Exponential Moving Average Crossovers (DEMAC), MACD and Moving Average Relative Strength Index (MARSI) is used. GA is used to optimize the parameters of these technical indicators. The GA parameters has a population size of 1000, number of generations of 1000, rank based selection process, crossover probability of 0.8 and a mutation probability of 0.05. The Vector Evaluated Genetic Algorithm (VEGA) is adopted as the multi objective optimization technique.

Besides that, Širůček and Šíma (2016) have conducted a study to optimize technical analysis on the New York Stock Exchange (NYSE). In their study, the time period chosen for the optimization of technical indicators are from November 2013 to October 2014. As for the back testing of technical indicators, the time period elected was from November 2014 to October 2015. The selected instrument is the Cyclical Index of S&P 500. According to them, optimization of technical indicators is carried out to aid investors in their investing strategies and to maximize profit. The selected indicators in the study are SMA, MACD, RSI and Bollinger Bands (BB). As for the evaluation of performance, the net profit, total number of trades, average profit and loss, and number of profitable trades are used.

2.7 Chapter Summary

In this chapter, Efficient Market Hypothesis (EMH) or random walk theory and Dow Theory have been applied to provide a better understanding of technical analysis in predicting FCPO movement. EMH stated that it is nearly impossible to predict future price movement as all information are already reflected in the price. However, this study aims to oppose the theory. Next, Dow Theory acts as the base of technical analysis as it stated that the price movement of any financial instrument have certain pattern and trend. Besides that,

various technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic are optimized to predict the price movement of FCPO.

CHAPTER 3

METHODOLOGY

3.1 Introduction

The purpose of conducting this study is to predict the FCPO price in Malaysia and to optimize various technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator. Extreme Learning Machine (ELM) is used to predict future prices and optimize the technical indicators. MATLAB R2019a is used to process the training and testing data.

3.2 Research Design

According to Bloomfield and Fisher (2019), quantitative research focuses on obtaining mathematical or statistical data and results through mediums such as questionnaires, surveys or altering existing data to fit into the current research. Furthermore, secondary data is used in conducting this study. Koedel and Dietrich (2020) maintained that the reliability of the source is important in dealing with secondary data. When using secondary data, the data should be derived from various reliable sources. Researchers must also make sure that the data obtained are relevant and matches the subject matter or research objectives.

The examined data consists of daily prices of Malaysia's FCPO listed on Bursa Malaysia. For this study, the opening, high, low and closing price of FCPO is recorded daily to ensure we have enough data samples to avoid unnecessary skewness of result. A variety of technical indicators have also been chosen to identify how different technical indicators

could affect the prediction and validation of prices. Using the historical price of FCPO and value of technical indicators, the stimulation and modelling is done using ELM. The research has used quantitative approach for the prediction and validation of FCPO price. Besides that, this research has an exploratory or predictive design.

3.3 Extreme Learning Machine (ELM)

ELM is a single-hidden layer feed forward neural network (SLFN) which chooses the hidden nodes randomly and assigns random weightage to the outputs. Zhu et al. (2005) stated that ELM requires a higher number of hidden neurons due to the random assignment of input weightage and hidden biases. The main advantage of using ELM is that the hidden layer of the algorithm still works without much tuning as it has a number of activation functions such as sigmoidal function, sine function, hard limit function, triangular basis function and radial basis function. An example of the basic structure of ELM can be seen in Figure 3.1.

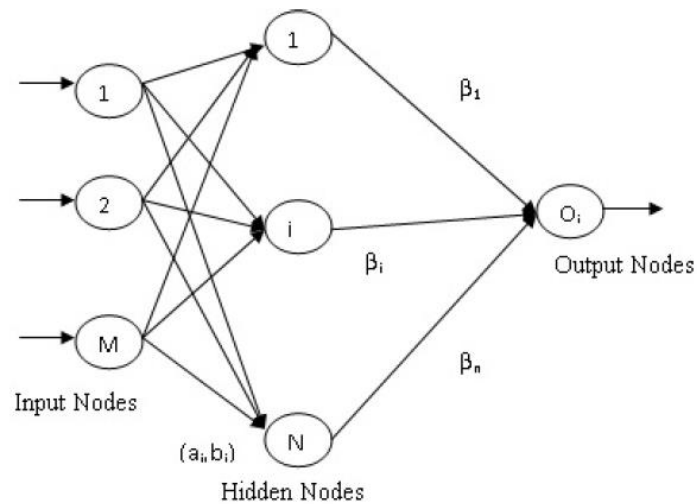


Figure 3.1: Basic Structure of ELM

Source: Sivalingam et al. (2016a)

In this study, ELM will be trained with a given set of N training datasets $D = (x_i + y_i)$, $i = 1$. x_i depicts a dimensional input whereas y_i depicts the output by a certain activation function. H will be the number of hidden neurons. The output function of ELM can be seen in Equation 3.1:

$$\sum_{i=1}^N \beta_i f(x_j; a_i, b_i) = \text{Output}, j = 1, \dots, N \quad \text{Equation 3.1}$$

In simpler form, Equation 3.1 can be written as $\beta H = T$. In this simpler form, H is the hidden layer output matrix and could be seen in Equation 3.2:

$$H(a_1, \dots, a_N; b_1, \dots, b_N; x_1, \dots, x_M) = \quad \text{Equation 3.2}$$

$$\begin{matrix} G(a_1, b_1, x_1) & \dots & G(a_N, b_N, x_1) \\ \vdots & & \vdots \\ G(a_1, b_1, x_M) & \dots & G(a_N, b_N, x_M) \end{matrix}$$

$$\beta = [\beta_1 \beta_2 \dots \beta_n]^T \text{ and } T = [t_1 t_2 \dots t_n]^T \quad \text{Equation 3.3}$$

In the matrix, each value represents the hidden output. In a Single layer feed forward network, (x_i, t_i) acts as the training data and $g(a, b, x)$ acts as the hidden node output function. Given that T is the desired output that we want to achieve, a unique solution with least squared error could be obtain through Moore-Penrose generalized inverse matrix.

3.4 Research Framework

The conceptual framework of this study is developed based on ELM. ELM is used to predict FCPO prices and to optimize the six technical indicators. This proposed system

consists of an input layer where the daily opening, high and low prices of FCPO will be fed into the ELM and the output will be tested against the testing data to ensure that the predicted output is similar to the actual output. Furthermore, the technical indicators will also be included along with the daily prices as the training data and be fed into the ELM model. The input layer will be tuned randomly with random biases and weightage.

As for the output, the predicted output will be validated against the actual output, which in this case is the actual price of FCPO. An example of the proposed framework can be seen in Figure 3.2:

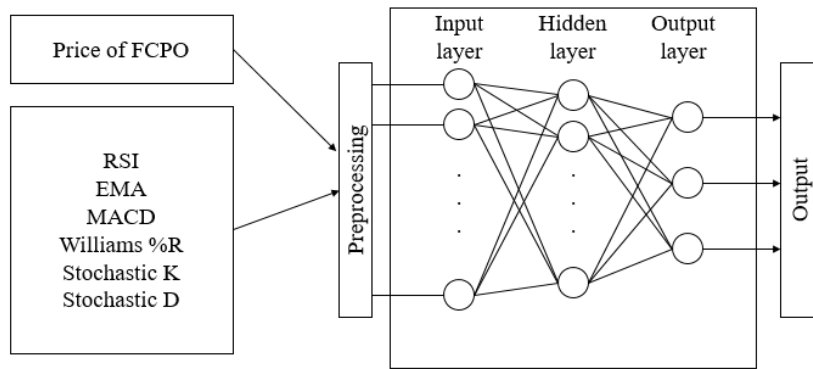


Figure 3.2: Research Framework of ELM

3.5 Detailed Steps in Trading Process

In this section, the detailed steps in predicting FCPO prices and optimizing technical indicators will be carried out using MATLAB R2019a. There are two major steps involved in the trading process and is separated and written as two parts. Part (a) is written regarding the method in predicting FCPO prices using ELM, whereas part (b) is regarding to the method in optimizing technical indicators using the identical method. The trading process

flows from the collection of data, pre-processing of data, the training and testing of ELM and comparing the predicted output with the actual data.

3.5.1 Data Collection

(a) Data collection is the first and utmost basic step towards the study. The data for historical prices of FCPO from year 2010 to year 2019 have been downloaded from Bursa Station and acts as our sample period. Data collection is important as the accuracy and credibility of the raw data could essentially affect the results of test. Our raw data mainly consists of the date, opening, high, low and closing price of FCPO throughout the sample period. All of these data are necessary for the prediction of their future prices using ELM.

(b) As for the technical indicator optimization step, the opening, high, low and closing price of FCPO is also needed. An additional step of extracting the data on technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator will be carried out. The values for all of the indicators were calculated by using Equation 2.1 to 2.7 respectively.

3.5.2 Pre-Processing of Data

Data pre-processing is an important part in data mining. This step involves transforming raw data into an understandable format for it to be trained and tested. Raw data are usually irregular and inconsistent and contains quite several errors. The data pre-processing stage consists of checking out missing values, normalizing the data, splitting approximately 80% of data set into training data and 20% into testing data. It is important to normalize inconsistent data as it reduces the redundant rate and provide higher data consistency. In this study, the normalization of raw data such as the opening, low, high and

the closing price of FCPO and the value of technical indicators which are all in continuous values are normalized into values starting from 0 to 1 using MATLAB's normalization algorithm. In short, all the input attributes except the targeted outcome should be normalized into the range of 0 to 1. The function for normalizing data can be found on MathWorks, which is the official webpage for MATLAB.

3.5.3 Training and Testing the Machine

(a) Training the machine is an important step as it feeds the data with algorithm to touch up the test data. In this step, the 80% pre-processed data which consists of the actual FCPO price, the daily opening, high and low price of FCPO are fed into the ELM with randomly assigned input weightage and biases. The 20% remaining testing data are untouched as it acts as our validation data. There are a few things to take note when categorising the data into training and testing data. The data format of the testing and training data are all in text form, each row consisting of information of one instance. An example of the training data for FCPO price prediction can be seen in Table 3.1:

Table 3.1: Example of training data set

FCPO price	Opening price	High	Low
998.022	0.86957783	0.985492529	0.623095894
988.03	0.811547947	1.000000000	0.739155665
981.04	0.666618308	0.782533004	0.579718555
980.04	0.695633251	0.753518062	0.594226026
970.05	0.652110837	0.652110837	0.492673727
966.05	0.463658784	0.492673727	0.463658784
958.06	0.376759031	0.579718555	0.318729146
937.08	0.36225156	0.449296388	0.309120984

Table 3.1 continued

FCPO price	Opening price	High	Low
969.05	0.144929639	0.536196141	0.086899753
982.04	0.855070361	0.884085304	0.666618308
946.07	0.507181198	0.536196141	0.130422167
951.07	0.159292035	0.333236617	0.159292035
960.06	0.246336863	0.449296388	0.231829392
972.05	0.405773974	0.652110837	0.405773973
969.05	0.144929639	0.536196141	0.086899753
982.04	0.855070361	0.884085304	0.666618308

During the training of ELM, various number of hidden neurons and activation function such the sigmoidal function, sine function, hard limit function, triangular basis function and radial basis function are assigned to the ELM algorithm to generate the output. In short, the training dataset will be trained repeatedly against different number of hidden neurons and activation function until an optimal output is obtained. Output with a higher training accuracy and higher testing accuracy accompanied by a low training time is deemed as optimal. Testing the data is equally important as the obtained output will be tested against the testing data to identify the testing accuracy of the algorithm.

(b) As for the optimization of technical indicators, the pre-processed data as shown in Table 3.1 are all included but with the addition of the six normalized technical indicators data. Each technical indicator will be trained and tested separately alongside with the FCPO price, opening, high and low price. Various number of hidden neurons and activation function will also be used to generate an output with high accuracy and low testing time. Six different sets of output for each technical indicator will be obtained after the training and testing of data.

3.5.4 Comparing Predicted Output with Actual Value

(a) In this step, the predicted output of FCPO price using ELM will be compared to the actual value of FCPO. The output with the highest training and testing accuracy will be used to compare with the testing dataset. If the output of the training data predicted by the ELM is similar to the actual output in the testing data. The ELM neural network is said to be effective and could be used to predict future prices.

(b) As for the optimization of technical indicators, the predicted output of FCPO price using ELM with the addition of technical indicators will be compared to the actual value of FCPO price. The six different set of optimal output represented by six different technical indicators are compared against each other to evaluate which technical indicator produces a similar output as the actual value. The graph of all six predicted FCPO price with the assistance of technical indicator will be plotted out and whichever deviates the least from the actual graph is said to be the optimal technical indicator.

3.6 Chapter Summary

This chapter contains the explanation of the research design and framework that will be carried out to predict the FCPO price and to optimize technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator. ELM is used in facilitating the prediction of FCPO price and the optimization of those technical indicators. Features of ELM such as faster training and testing speed and higher generalization performance is suitable for this study. There are a few detailed steps in predicting FCPO price and optimizing technical indicators. Such steps include data collection, pre-processing

of data, training and testing the ELM and comparing the predicted output FCPO price using ELM with the actual value of FCPO.

CHAPTER 4

EMPIRICAL FINDINGS AND DISCUSSION

4.1 Introduction

In this study, the single layer feed forward prediction method is applied to the prices of FCPO which contains the daily opening, high, low and closing price. The data is divided into 80% training data and 20% testing data. The training and testing datasets will be trained repeatedly against different parameters of number of hidden neurons and activation functions using ELM. The datasets are tested against a range of different number of hidden neurons as different number of neurons have different prediction accuracy. A test to obtain the optimal range of number of hidden neurons will also be carried out using ELM. Such process persists until an optimal parameter with a high testing and training accuracy and low training time is acquired.

This chapter includes both the accuracy test on the prediction of FCPO price without technical indicators and also the prediction of FCPO price with the chosen technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator. Furthermore, the comparison of the price predicted using ELM and the actual price will be carried out by plotting the price into a graph. Not only that, the comparison between the price predicted with the addition of technical indicators against the actual price will also be carried out. Lastly, the chapter ends with a discussion regarding the results obtained.

4.2 Testing Optimal Number of Neurons

In this section, the optimal range for the number of hidden neurons are tested using ELM. It is important to test the optimal range of number of neurons as different number of neurons could produce different results. An optimal range of number of hidden neurons could potentially produces test results with lower training and testing accuracy. The total numbers of hidden neurons tested ranges from 2 to 20. The results from testing the number of hidden neurons can be seen in Figure 4.1.

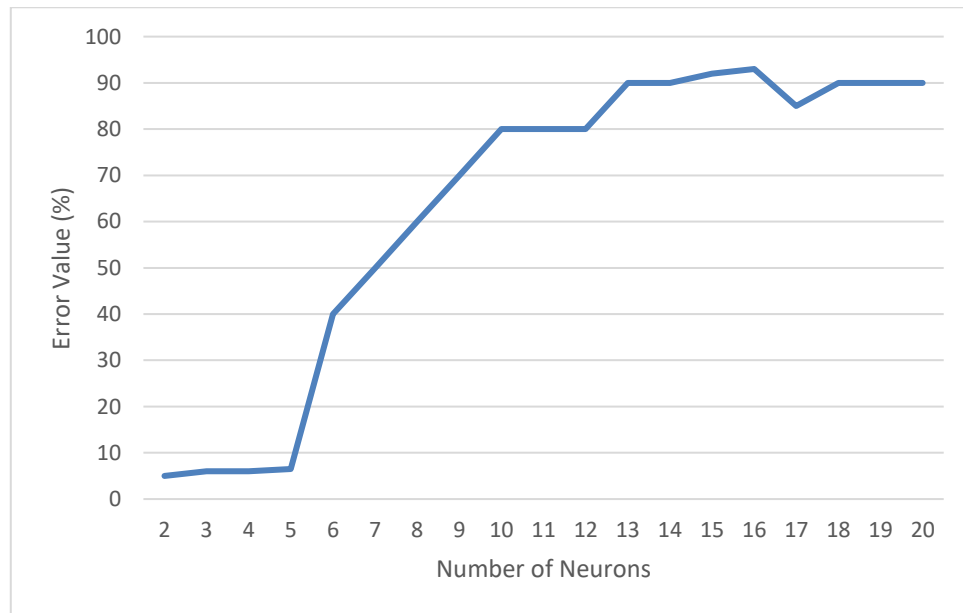


Figure 4.1: Neuron Testing Result

Figure 4.1 shows that the optimal range of number of neurons lies between 2 to 5. The error value of neurons from 2 to 5 are lower than 10%, which means that it has a high accuracy in predicting prices. According to Chang et al. (2007), the categorization of error value can be seen in Table 4.1.

Table 4.1: Error Value Criteria

Error Value	Condition
<10%	Highly Accurate
10-20%	Accurate
20-50%	Moderate
>50%	Poor

4.3 Price Prediction without Technical Indicators

In this section, the price of FCPO is predicted without the presence of any technical indicators. Data such as the daily opening, high, low and closing price are fed into the ELM to predict future prices. Table 4.2 shows the accuracy test results tested against different number of hidden neurons and activation functions.

Table 4.2: Accuracy Results without Indicators

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
2	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 87.39%	Training Accuracy = 98.82%	Training Accuracy = 92.91%	Training Accuracy = 98.36%
	Testing Accuracy = 96.08%	Testing Accuracy = 82.80%	Testing Accuracy = 94.89%	Testing Accuracy = 85.90%

Table 4.2 continued

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
3	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 99.91%	Training Accuracy = 93.48%	Training Accuracy = 91.40%	Training Accuracy = 80.52%
	Testing Accuracy = 98.58%	Testing Accuracy = 86.23%	Testing Accuracy = 90.00%	Testing Accuracy = 92.72%
4	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 65.87%	Training Accuracy = 92.96%	Training Accuracy = 90.88%	Training Accuracy = 96.46%
	Testing Accuracy = 56.87%	Testing Accuracy = 84.72%	Testing Accuracy = 95.61%	Testing Accuracy = 83.96%
5	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 20.37%	Training Accuracy = 43.39%	Training Accuracy = 88.92%	Training Accuracy = 89.64%
	Testing Accuracy = 29.43%	Testing Accuracy = 30.08%	Testing Accuracy = 81.16%	Testing Accuracy = 86.51%

As shown in Table 4.2, the prediction accuracy of FCPO for the sigmoidal function is considered to be highly accurate at 2 and 3 number of neurons, but as the number of hidden neurons increases, the prediction accuracy tends to drop to moderate and poor. This shows that as the number of hidden neurons increases, the prediction accuracy tends to decrease. Besides that, the sine function also portrays a similar result with very good accuracy at low number of hidden neurons and tends to decrease when the number of neurons increases. Furthermore, the prediction accuracy for the triangular basis function produces good results that are similar to the radial basis function. However, as the number of hidden neurons keep increasing, the radial basis function shows a higher prediction accuracy as compared to the triangular basis function.

Not only that, it can be seen that radial basis function has the highest generalization performance as the training and testing accuracy results are in the highly accurate and accurate category. As compared to other activation functions, the predicted price of FCPO using the radial basis function with 2, 3, 4 and 5 hidden neurons provides the highest testing and training accuracy accompanied with a low training and testing time (Shen et al., 2011; Kumar et al., 2012; Rout et al., 2012). This indicates that the radial basis function is more suitable in predicting FCPO prices as compared to other activation functions such as the sigmoidal, sine and triangular basis functions. The testing and training time of the prediction takes 0 seconds, which means that the results were predicted without any complex learning.

4.4 Price Prediction with RSI

In this section, the price of FCPO is predicted with the presence of the RSI indicator. This is to examine how RSI could affect the prediction results of FCPO price. Data such as the daily opening, high, low, closing price and RSI value are fed into the ELM to predict

future prices. Table 4.3 shows the accuracy test results tested against different number of hidden neurons and activation functions.

Table 4.3: Accuracy Results with RSI

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
2	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 98.07%	Training Accuracy = 89.52%	Training Accuracy = 90.32%	Training Accuracy = 72.64%
	Testing Accuracy = 98.44%	Testing Accuracy = 92.01%	Testing Accuracy = 99.59%	Testing Accuracy = 67.58%
3	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 93.68%	Training Accuracy = 93.90%	Training Accuracy = 99.93%	Training Accuracy = 90.37%
	Testing Accuracy = 95.25%	Testing Accuracy = 82.34%	Testing Accuracy = 90.17%	Testing Accuracy = 82.19%
4	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 94.36%	Training Accuracy = 92.24%	Training Accuracy = 96.56%	Training Accuracy = 97.15%

Table 4.3 continued

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
	Testing Accuracy = 89.59%	Testing Accuracy = 98.97%	Testing Accuracy = 90.53%	Testing Accuracy = 97.15%
5	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 51.17% Testing Accuracy = 56.79%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 99.28% Testing Accuracy = 80.23%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 90.55% Testing Accuracy = 92.76%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 84.98% Testing Accuracy = 98.59%

As shown in Table 4.3, the prediction accuracy with RSI for the sigmoidal function is extremely high at greater than 90% accuracy when hidden neurons used ranges from 2 to 4. However, such accuracy declines greatly to produce moderate results with an accuracy of approximately 50% when 5 number of hidden neurons were used. This shows that as the number of hidden neurons increases, the prediction accuracy decreases. As for the sine function, the prediction accuracy is consistent from 2 number of hidden neurons to 5 number of neurons. The prediction accuracy for the sine function fluctuates between 80 to 90%, which means that such activation function could be used to produce good results. As for the triangular basis function, it produces similar prediction results as the sine function, but lacks consistency. As we can see in Table 4.3, the prediction accuracy of triangular basis function at 2 number of hidden neurons records an accuracy of about 70%, as compared to other activation functions.

The radial basis function is deemed the most optimal parameter as it produces highly accurate results with great consistency across different number of hidden neurons. The error value of the price predicted using radial basis function is always lower than 10%, which fits into the criteria of highly accurate results. This means that radial basis function is more suitable in predicting FCPO prices as it produces results which are almost similar to the actual price.

4.5 Price Prediction with EMA

In this section, the price of FCPO is predicted with the presence of the EMA indicator. Data such as the daily opening, high, low, closing price and EMA value are fed into the ELM to predict future prices. Table 4.4 shows the accuracy test results tested against different number of hidden neurons and activation functions.

Table 4.4: Accuracy Results with EMA

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
2	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 96.13%	Training Accuracy = 92.96%	Training Accuracy = 98.04%	Training Accuracy = 91.85%
	Testing Accuracy = 86.42%	Testing Accuracy = 97.12%	Testing Accuracy = 83.38%	Testing Accuracy = 70.98%

Table 4.4 continued

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
3	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 95.05%	Training Accuracy = 98.31%	Training Accuracy = 90.15%	Training Accuracy = 88.57%
	Testing Accuracy = 88.54%	Testing Accuracy = 91.98%	Testing Accuracy = 99.46%	Testing Accuracy = 84.21%
4	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 65.51%	Training Accuracy = 85.86%	Training Accuracy = 86.35%	Training Accuracy = 98.65%
	Testing Accuracy = 73.50%	Testing Accuracy = 96.04%	Testing Accuracy = 95.81%	Testing Accuracy = 92.86%
5	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec
	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec	Testing Time = 0 sec
	Training Accuracy = 71.91%	Training Accuracy = 86.01%	Training Accuracy = 92.14%	Training Accuracy = 94.26%
	Testing Accuracy = 66.30%	Testing Accuracy = 76.44%	Testing Accuracy = 93.55%	Testing Accuracy = 87.32%

As shown in Table 4.4, the prediction accuracy with EMA and 2 hidden neurons for all four activation functions are considered above average as all of these functions produces similar results with an accuracy of approximately 90%. However, such accuracy declines as the number of hidden neurons increases. The sigmoidal function produced highly accurate when trained against 2 and 3 number of hidden neurons. However, the accuracy decreases greatly to around 70% as the number of hidden neurons increases to 4 and 5.

As for the sine function, the prediction accuracy is considered highly accurate when being tested against 2 to 4 number of neurons. The prediction accuracy then declines to accurate as the number of hidden neurons increases to 5. The prediction accuracy for the sine function fluctuates between 70 to 90%, which means that such activation function could potentially be used to produce results that are above average. As for the triangular basis function, it produces similar prediction results as the sine function, which also lacks consistency. As we can see in Table 4.4, the prediction accuracy of both triangular basis function and sine function fluctuates inconsistently with an accuracy of 70% to 90%.

In contrast, the radial basis function has the most optimal result as compared to other activation functions as it produces highly accurate results with greater consistency across different number of hidden neurons. The error value of the price predicted using radial basis function is always lower than 10%, which fits into the criteria of highly accurate results. As we can see in Table 4.4, the prediction accuracy for the radial basis function is consistent at approximately 90%. The highly accurate results produced by the radial basis function is also accompanied by a low training and testing time of 0 second. This indicates that the training of the ELM is carried out without any problem.

4.6 Price Prediction with MACD

In this section, the price of FCPO is predicted with the presence of the MACD indicator. Data such as the daily opening, high, low, closing price and MACD value are fed into the ELM to predict future prices. Table 4.5 shows the accuracy test results tested against different number of hidden neurons and activation functions.

Table 4.5: Accuracy Results with MACD

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
2	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 94.52% Testing Accuracy = 82.32%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 95.75% Testing Accuracy = 81.80%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 96.89% Testing Accuracy = 98.45%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 88.98% Testing Accuracy = 64.94%
3	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 94.67% Testing Accuracy = 94.99%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 84.89% Testing Accuracy = 94.95%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 92.65% Testing Accuracy = 94.54%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 85.26% Testing Accuracy = 76.34%
4	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0.0313 sec	Training Time = 0 sec

Table 4.5 continued

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
	Testing Time = 0 sec Training Accuracy = 88.76% Testing Accuracy = 82.90%	Testing Time = 0 sec Training Accuracy = 90.02% Testing Accuracy = 91.29%	Testing Time = 0 sec Training Accuracy = 98.31% Testing Accuracy = 90.92%	Testing Time = 0 sec Training Accuracy = 97.81% Testing Accuracy = 88.32%
5	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 40.17% Testing Accuracy = 47.17%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 82.81% Testing Accuracy = 88.42%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 87.99% Testing Accuracy = 97.85%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 95.65% Testing Accuracy = 72.66%

As shown in Table 4.5, the sigmoidal function to predict price with MACD produces results that are lacking in accuracy and consistency. The results produced by the sigmoidal function is seemingly accurate when the number of hidden neurons is at a range of 2 to 4. However, as it reaches 5 number of hidden neurons, the results produced drops significantly to approximately 40%, which indicates that it is poor and unreliable. As for the sine function, it produces accurate results that range from 80% and above, which stated that it is suitable to be used in predicting future price. Besides that, the triangular basis function also provides satisfactory results with an accuracy of 70% and above. This indicates that triangular basis function might also be suitable in predicting price. However, the sine function has a higher accuracy as compared to the triangular basis function based on the results obtained above.

As for the radial basis function, the training and testing accuracy for all number of hidden neurons are considered high and extremely accurate. The accuracy results produced by this function fluctuates above 85%, which means that it falls under the highly accurate category and is the most suitable function to be used in predicting FCPO future prices.

4.7 Price Prediction with Williams Percent Range

In this section, the price of FCPO is predicted with the presence of the Williams Percent Range indicator. Data such as the daily opening, high, low, closing price and Williams Percent Range value are fed into the ELM to predict future prices. Table 4.6 shows the accuracy test results tested against different number of hidden neurons and activation functions.

Table 4.6: Accuracy Results with Williams Percent Range

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
2	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 85.63% Testing Accuracy = 99.21%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 92.80% Testing Accuracy = 97.81%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 97.36% Testing Accuracy = 96.17%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 75.64% Testing Accuracy = 66.20%
3	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0 sec

Table 4.6 continued

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
	Testing Time = 0 sec Training Accuracy = 92.55% Testing Accuracy = 88.62%	Testing Time = 0 sec Training Accuracy = 97.95% Testing Accuracy = 93.61%	Testing Time = 0 sec Training Accuracy = 96.48% Testing Accuracy = 99.09%	Testing Time = 0 sec Training Accuracy = 79.17% Testing Accuracy = 99.86%
4	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 81.21% Testing Accuracy = 90.51%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 94.18% Testing Accuracy = 96.48%	Training Time = 0.0313 sec Testing Time = 0 sec Training Accuracy = 97.46% Testing Accuracy = 95.46%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 75.43% Testing Accuracy = 95.97%
5	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 88.69% Testing Accuracy = 85.12%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 92.29% Testing Accuracy = 96.28%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 97.22% Testing Accuracy = 96.71%	Training Time = 0 sec Testing Time = 0.0156 sec Training Accuracy = 89.50% Testing Accuracy = 91.35%

As shown in Table 4.6, the sigmoidal function produces results that are accurate which fluctuates between 80% and 100%. This shows that the results produced across the different number of hidden neurons are consistent and does not decrease suddenly, which

means that the sigmoidal function might be suitable in predicting future price. As for the sine function, the training and testing accuracy fluctuates between 90% and 100% across all level of number of neurons. This indicates that this function is highly accurate in predicting FCPO price with the presence of Williams Percent Range. As for the triangular basis function, the results produced are less accurate as compared to the other functions. As we can see in Table 4.6, the accuracy results for the triangular basis function ranges from 60% to 100%, which stated that it lacks consistency and might be accurate at some point, but also performs moderately at other times. This shows that the triangular basis function might not be suitable in predicting FCPO prices with Williams Percent Range.

The radial basis function produces the most accurate results as compared to the other three activation functions. As seen in Table 4.6, the radial basis function managed to predict future price with an accuracy of more than 95%, which is extremely accurate. This indicates that by using the radial basis function to predict FCPO price with Williams Percent Range, the results are almost identical with the actual value. However, as we can see in Table 4.6, the training time of the radial basis function at 4 number of hidden neurons takes about 0.0313 second as compared to other functions which takes 0 second, such training time is still considered extremely low as it is less than a second. In short, Table 4.6 shows that the radial basis function is the most suitable activation function to be used in predicting future price as it produces results with high accuracy and low training and testing time.

4.8 Price Prediction with Stochastic Oscillator

In this section, the price of FCPO is predicted with the presence of the Stochastic indicator. Data such as the daily opening, high, low, closing price and Stochastic value are fed into the ELM to predict future prices. Table 4.7 shows the accuracy test results tested against different number of hidden neurons and activation functions.

Table 4.7: Accuracy Results with Stochastic Oscillator

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
2	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 94.62% Testing Accuracy = 97.69%	Training Time = 0 sec Testing Time = 0.0156 sec Training Accuracy = 93.65% Testing Accuracy = 99.90%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 88.09% Testing Accuracy = 87.69%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 85.25% Testing Accuracy = 84.36%
3	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 89.31% Testing Accuracy = 99.61%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 94.91% Testing Accuracy = 90.14%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 91.25% Testing Accuracy = 95.46%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 90.84% Testing Accuracy = 92.56%
4	Training Time = 0 sec	Training Time = 0 sec	Training Time = 0.0313 sec	Training Time = 0 sec

Table 4.7 continued

Activation Function Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
	Testing Time = 0 sec Training Accuracy = 81.21% Testing Accuracy = 90.50%	Testing Time = 0 sec Training Accuracy = 91.41% Testing Accuracy = 99.77%	Testing Time = 0 sec Training Accuracy = 93.22% Testing Accuracy = 97.41%	Testing Time = 0 sec Training Accuracy = 97.45% Testing Accuracy = 89.40%
5	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 60.68% Testing Accuracy = 65.21%	Training Time = 0.0156 sec Testing Time = 0 sec Training Accuracy = 94.95% Testing Accuracy = 91.25%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 98.86% Testing Accuracy = 94.25%	Training Time = 0 sec Testing Time = 0 sec Training Accuracy = 94.93% Testing Accuracy = 97.66%

As shown in Table 4.7, the sigmoidal function has a high prediction accuracy when there are 2 to 4 number of hidden neurons. However, as the number of neurons reaches 5, the prediction accuracy drops greatly from accurate to moderate. This shows that as the number of hidden neurons increases, the prediction accuracy decreases. This also indicates that the sigmoidal function is not suitable in predicting FCPO price with the use of Stochastic Oscillator. As for the radial basis function, it produces accurate and highly accurate results that ranges from 85% to 100%, this shows that the radial basis could be used in predicting future prices as it shows good consistency and accuracy across the different number of

hidden neurons. As for the triangular basis function, it produces a similar result with the radial basis function in the price prediction of FCPO with Stochastic Oscillator.

The sine function produces highly accurate results with an error of less than 10% across all level of number of hidden neurons. An average of 93% prediction accuracy can be obtained by using the sine function to predict future price. This indicates that the sine function is the most suitable in predicting FCPO price with the presence of Stochastic Oscillator compared to other activation functions. This also shows that the presence of different technical indicators could affect the results produced by the activation function. The radial basis function is more suitable for the previous indicators, but it does not apply in the price prediction of FCPO with the presence of Stochastic Oscillator.

4.9 Comparison of Price Predicted against Actual Price without Indicators

In this section, the price predicted using ELM will be compared to the actual price to see how the radial basis function at different level number of hidden neurons could produce results that are similar to the actual value. The comparison of the actual FCPO price against the predicted price using the radial basis function can be seen in Figure 4.2 to Figure 4.5.

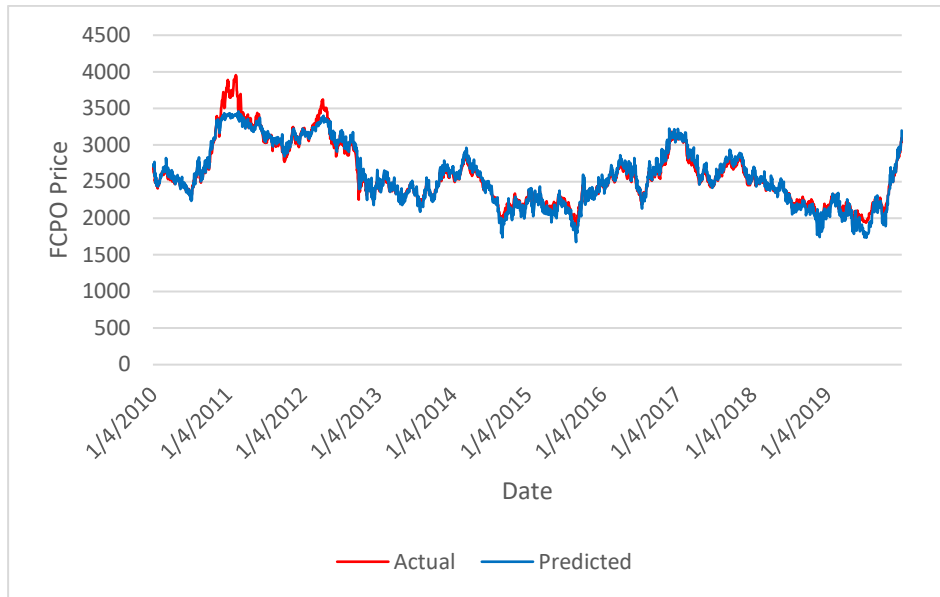


Figure 4.2: Price Predicted using Radial Basis Function with 2 Hidden Neurons

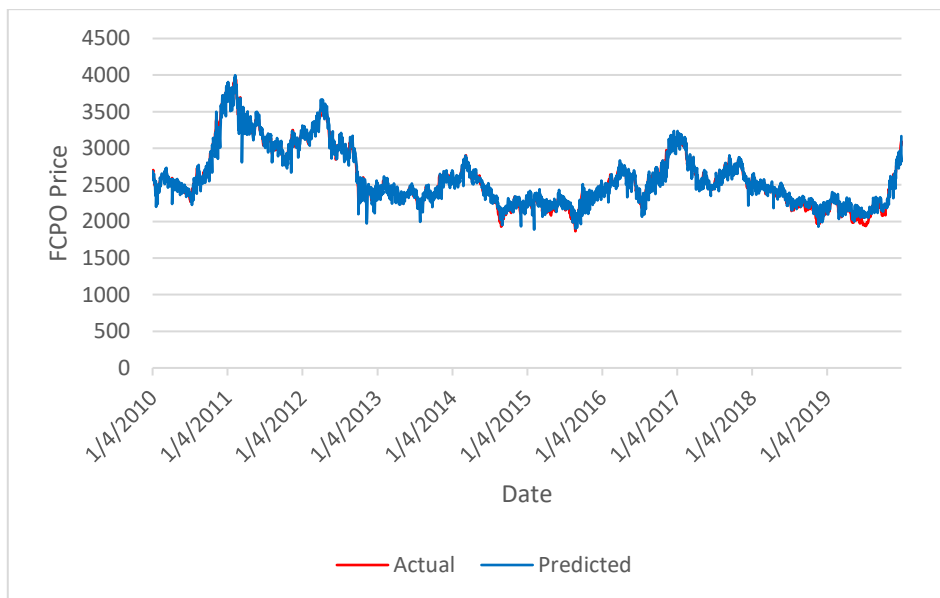


Figure 4.3: Price Predicted using Radial Basis Function with 3 Hidden Neurons

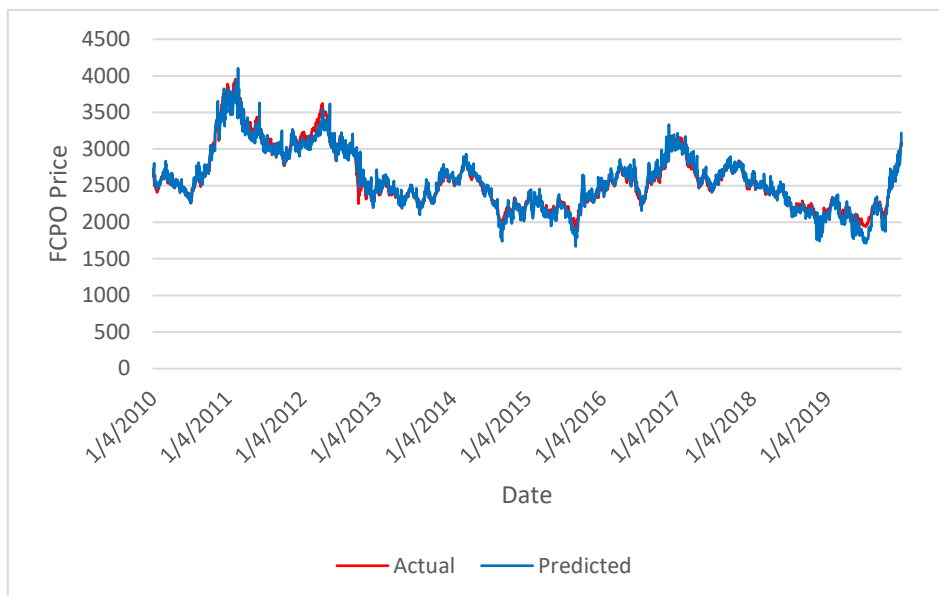


Figure 4.4: Price Predicted using Radial Basis Function with 4 Hidden Neurons

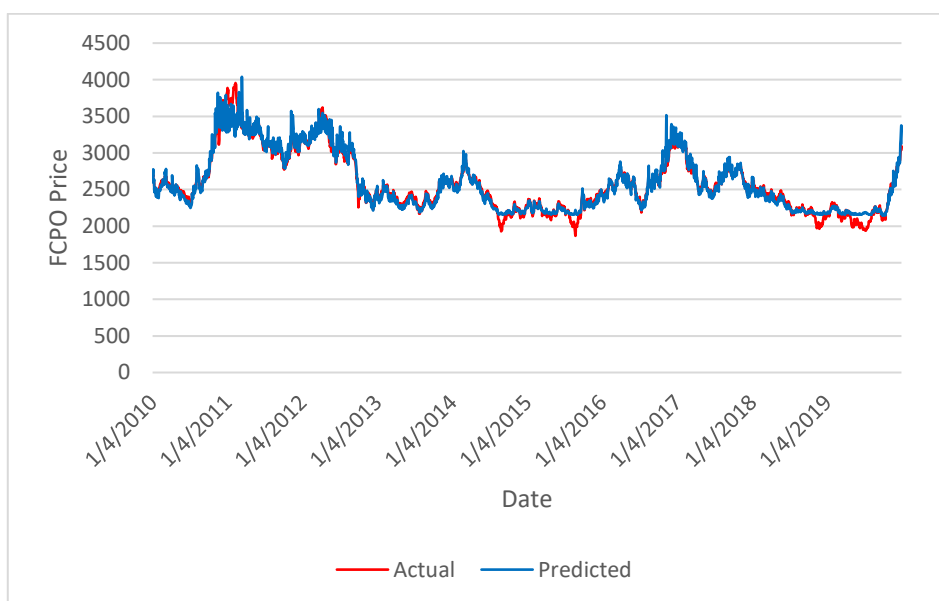


Figure 4.5: Price Predicted using Radial Basis Function with 5 Hidden Neurons

As shown in the figures above, the radial basis function produces similar results as compared to the actual FCPO price. Based on the accuracy results, the price predicted using radial basis function with 2 hidden neurons produces the most accurate result at approximately 93% similarity. The radial basis function is chosen due to its higher generalization performance with high accuracy and consistency across all levels of number of hidden neurons.

4.10 Comparison of Price Predicted against Actual Price with Indicators

In this section, the price predicted using ELM alongside with technical indicators will be compared to the actual price to examine which technical indicator is more suitable in predicting the future FCPO price. The comparison of the actual FCPO price against the price predicted with the technical indicators can be seen in Figure 4.6 to Figure 4.10.

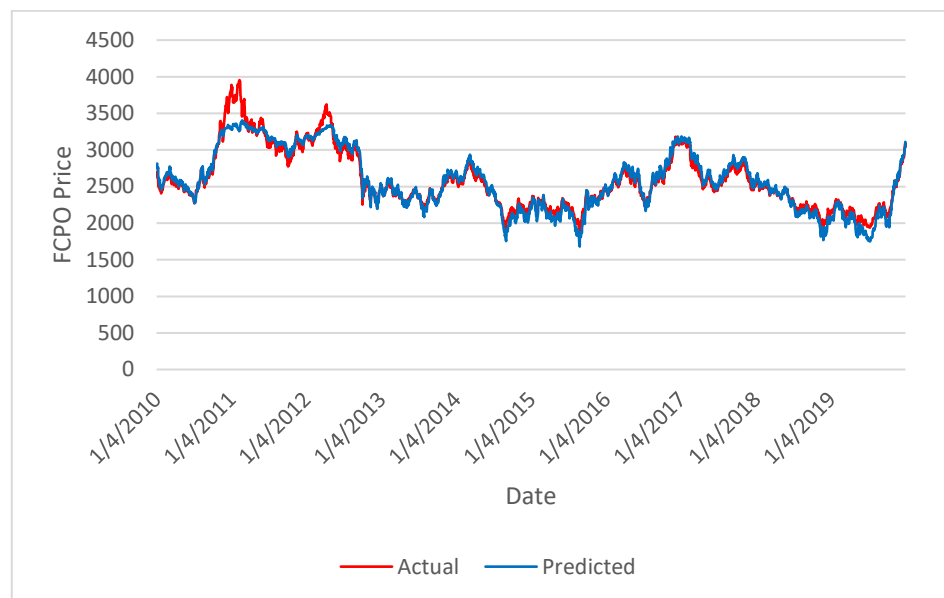


Figure 4.6: Price Predicted with RSI using Radial Basis Function with 3 Hidden Neurons

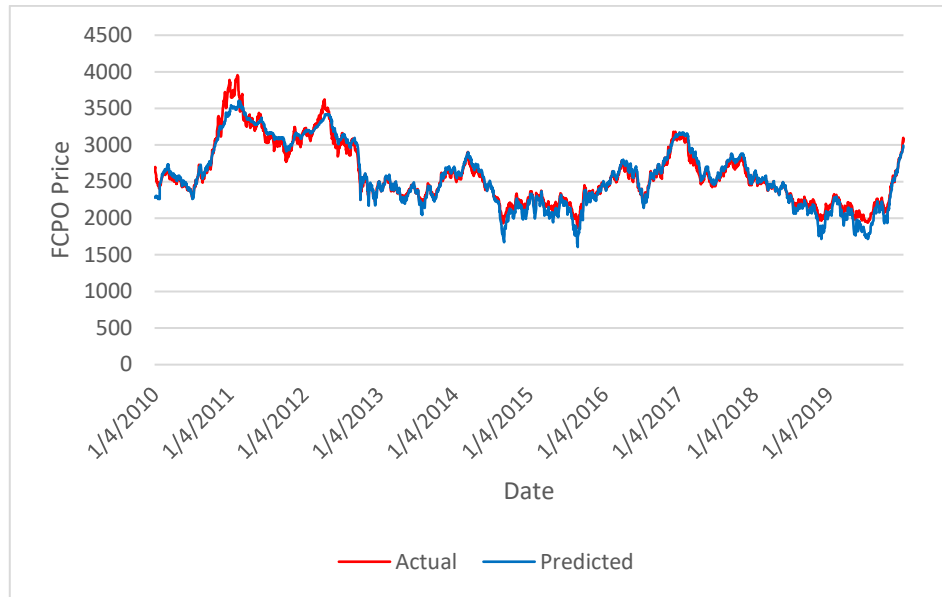


Figure 4.7: Price Predicted with EMA using Radial Basis Function with 3 Hidden Neurons

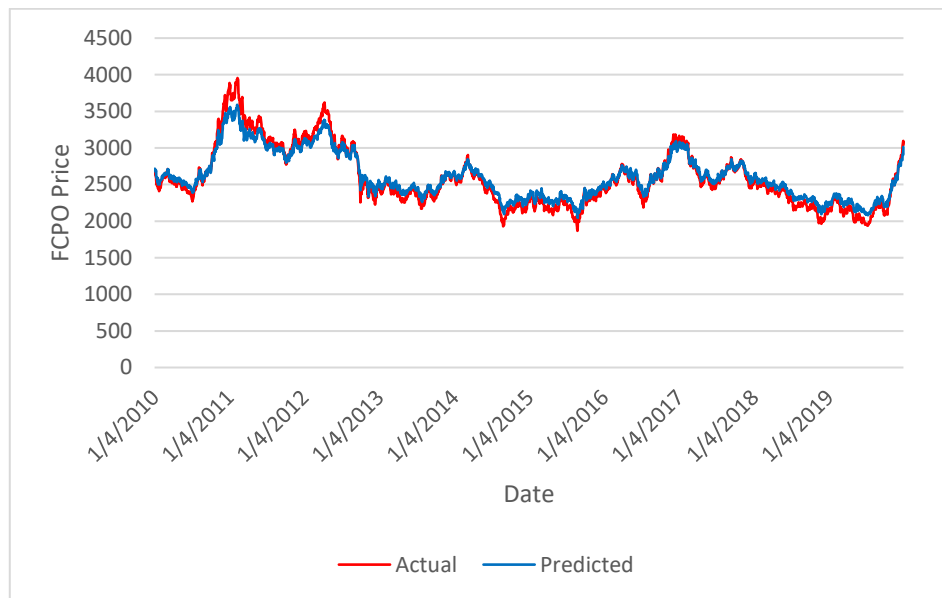


Figure 4.8: Price Predicted with MACD using Radial Basis Function with 2 Hidden Neurons

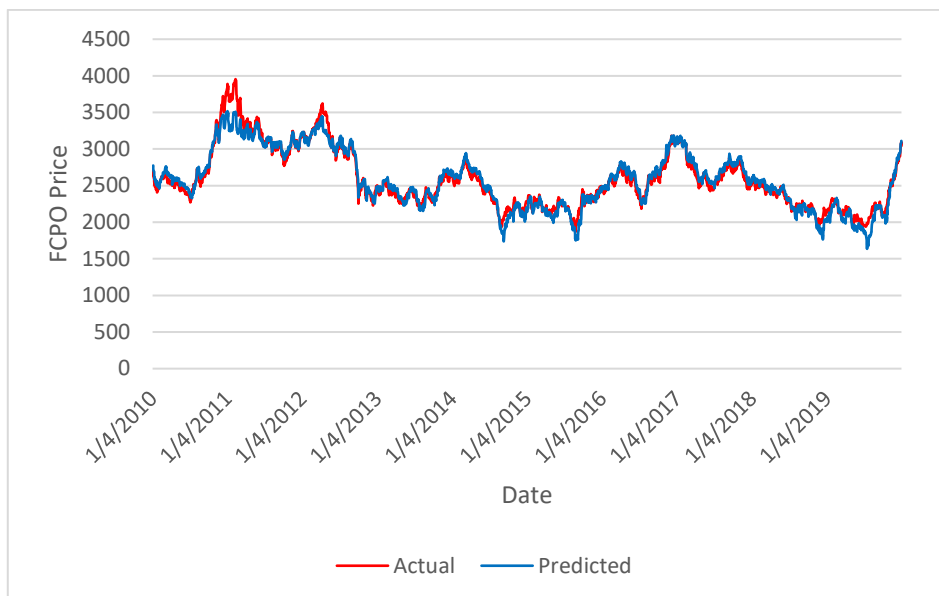


Figure 4.9: Price Predicted with Williams Percent Range using Radial Basis Function with 3 Hidden Neurons

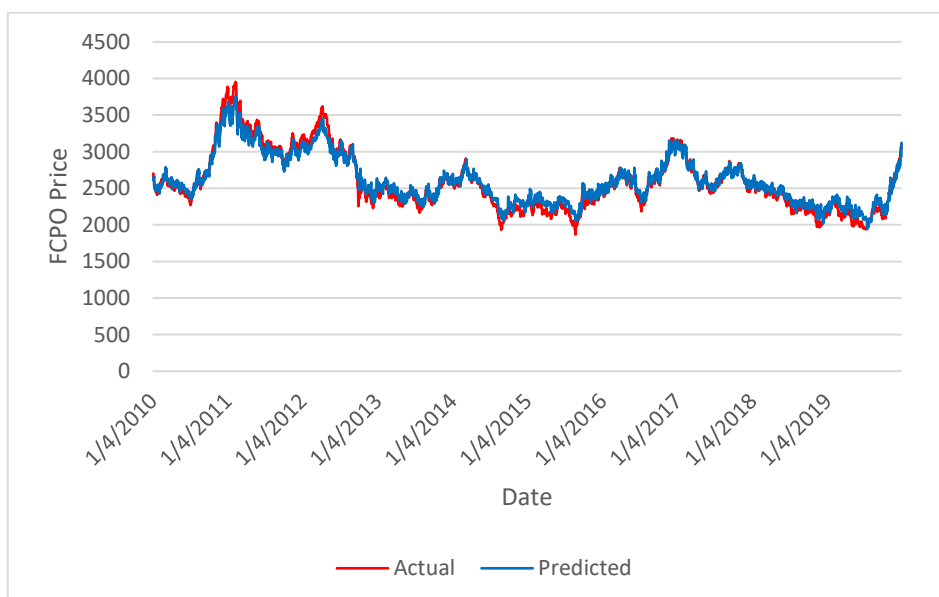


Figure 4.10: Price Predicted with Stochastic Oscillator using Sine Function with 2 Hidden Neurons

Based on the figures above, the most accurate results for each technical indicator is chosen to be compared against the actual price of FCPO. As shown in Figure 4.6, the price predicted with RSI against 3 hidden neurons using the radial basis function has a training accuracy of 99.93% and a testing accuracy of 90.17%, which falls under the highly accurate category. Besides that, the time taken to conduct both training and testing is 0 second, which indicates that the prediction results is generated without any problem.

Furthermore, Figure 4.7 shows the price predicted with EMA against 3 hidden neurons using radial basis function has a training accuracy of 90.15% and a testing accuracy of 99.49%, which also falls under the highly accurate category. The time taken for the prediction is also 0 second.

As for Figure 4.8, the price predicted with MACD against 2 hidden neurons using the radial basis function has a training accuracy of 96.89% and a testing accuracy of 98.45%. This shows that the prediction accuracy for this function is extremely high. The time taken for the prediction process is 0 second.

Besides that, Figure 4.9 shows the price predicted with Williams Percent Range against 3 hidden neurons using the radial basis function. The predicted results have a training accuracy of 96.48% and a testing accuracy of 99.09%. This also shows that the predicted results are extremely accurate and is similar to the actual price. On top of that, the time taken for the training process is at 0 second whereas the time taken for the testing process is 0.0156 second. This is considered to be extremely fast as it takes less than a second to test the data.

As for Figure 4.10, it shows the price predicted with Stochastic Oscillator against 2 hidden neurons using the sine function. The prediction of FCPO price with Stochastic indicator is different from the prediction with other technical indicators as the sine function

produces the most accurate results. The radial basis function seems to produce the most accurate results for other technical indicators such as RSI, EMA, MACD and Williams Percent Range. The predicted results using the sine function on the price of FCPO with Stochastic indicator has a training accuracy of 93.65% and a testing accuracy of 99.90%. This indicates that the predicted price is highly accurate and is close to the actual price of FCPO. The training and testing time used to produce the results are at 0 second and 0.0156 seconds respectively.

As we compare all the predictive accuracy of the technical indicators above, the prediction result of Williams Percent Range with 3 hidden neurons using the radial basis function has the highest average accuracy at 97.79% as compared to the others. The second indicator is the MACD indicator with an average prediction accuracy of 97.67%. As we can see, the prediction accuracy of both the Williams Percent Range and MACD indicator are very similar. This indicates that both of this technical indicator are more suitable in predicting the future price of FCPO as compared to the other indicators. As for the Stochastic Oscillator indicator, it shows an average prediction accuracy of 96.78%, which also shows that it is also suitable in predicting FCPO prices. Besides that, the price predicted with RSI and EMA indicator has an average accuracy of 95.05% and 94.81% respectively.

Based on the results obtained, the Williams Percent Range indicator is deemed the most optimal technical indicator to be used in predicting future FCPO prices as it produces the most consistent and accurate results as compared to other indicators. This is followed by indicators such as MACD, Stochastic Oscillator, RSI and EMA.

CHAPTER 5

CONCLUSION AND POLICY IMPLICATIONS

5.1 Introduction

The main objectives of this study are to predict the future price of FCPO using historical data and also to optimize various technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator using ELM. Besides that, this study also compares the predicted results against the actual value to show the difference in accuracy of different technical indicators. This chapter consists of different sections such as the conclusion of the study, significance of study, limitations and recommendation for future studies.

5.2 Conclusion

This study aims to predict the future price of FCPO by using ELM and also to optimize various technical indicators through training and testing of the machine. The scope of this study is the daily opening, high, low and closing price of FCPO ranging from the year 2010 to year 2019. Not only that, the daily value of each technical indicators such as the RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator is calculated using the respective equation and is recorded together with the daily price of FCPO. In short, this study focuses on using Extreme Learning Machine (ELM) to predict future prices of FCPO and to optimize prominent technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator.

The research framework of this study is built under the presumption of Dow Theory and might refute the weak form of EMH, which stated that it is impossible to predict future price using historical data. Dow Theory has stated that the predicted price of FCPO has various trends, which includes uptrend and downtrend. This can be seen from the results produced through the use of ELM. The research framework of this study was made referring to past studies conducted by (Karia et al., 2012b; Sivalingam et al., 2016b; Das et al., 2020). The daily prices of FCPO and also the daily value of the chosen technical indicators is normalized and recorded at the pre-processing stage. These data are then fed into the ELM network to be trained and tested against different number of hidden neurons and activation functions. This is to identify at which number of hidden neurons and what activation function is more suitable to be used in predicting future price of FCPO. The more suitable parameter will produce results with high accuracy and low training time. Besides that, it is also important to identify the optimal number of hidden neurons while predicting, as some number of hidden neurons could produce overfitting results, thus affecting the accuracy of the prediction.

The result of this study shows that it is possible to predict price using historical data. The radial basis function is suitable in predicting FCPO price with or without the presence of technical indicators. This finding is supported by various researchers such as Lei et al. (2014), Havaluddin and Tahyudin (2015) and Edwards (2018). All of these studies have shown the superiority of the radial basis function over other functions as it has a significantly faster learning rate with a high accuracy. Besides that, the results have shown that Williams Percent Range with 3 hidden neurons using the radial basis function has the highest average accuracy as compared to other technical indicators such as RSI, EMA, MACD and Stochastic Oscillator at 97.79%. Furthermore, the results also shown that the MACD

indicator has a similar prediction accuracy with the Williams Percent Range, which is approximately at 97.67%. This indicates that the Williams Percent Range and MACD technical indicator are more suitable in predicting the future price of FCPO as compared to others tested in this study. As for the Stochastic Oscillator indicator, it shows an average prediction accuracy of 96.78%. Besides that, the price predicted with the RSI and EMA indicator are less accurate as compared to other indicators but still falls under the highly accurate category. The predicted results of the two indicators have an average accuracy of 95.05% and 94.81% respectively.

In this study, the main and specific research objective is fulfilled, which is to validate FCPO prices and optimize various technical indicators through the implementation of AI. The historical price of FCPO is split to 80 and 20 percent, being 20 percent of the data acting as the testing data. FCPO prices is predicted using the ELM model with the remaining 80 percent of data as the training data. The predicted output is then validated against the actual output, and based on the results obtained, the accuracy of the predicted results is higher than 90 percent. Besides that, the specific objectives such as to determine the optimal parameters for technical indicators price prediction on FCPO using ELM has also been achieved. Based on the results obtained, the optimal parameter for technical indicators price prediction is by the radial basis function accompanied with 2 to 5 number of hidden neurons. As for the last specific objective, which is to identify the optimal technical indicator on price of FCPO using ELM, the Williams Percent Range and MACD is seen to be the more effective technical indicators used to predict FCPO price. This study shows that both of these technical indicators provides a higher prediction accuracy as compared to other indicators used such as RSI, EMA and stochastic oscillator.

5.3 Contribution to Body of Knowledge

This study contributes to the body of knowledge through the use of two theories. The theories used are Dow theory and Efficient Market Hypothesis theory.

Dow Theory acts as the basis for modern technical analysis and comprises of various principles. Such principles include the market averages discounts all information, the market has three trends which are the primary, secondary, and minor trends. Not only that, a trend is said to be continuous until an obvious reversal pattern occurs. Modern technical analyst is said to follow these principles in identifying historical prices and changes in price trend to predict future price movement. In short, Dow Theory's main idea is the market consists of various trends and such trend could be predicted using the Dow Jones Industrial Average and Dow Jones Transportation Average. These two averages have led to the emergence of various other technical indicators. As shown in the results, the predicted price of FCPO does reflect the principles of Dow Theory where the price movement consists of various phases and each movement is followed by a small pullback before the trend continues in its certain trend.

The next theory applied in this study is the Efficient Market Hypothesis theory. The weak form of EMH theory stated that it is nearly impossible to predict future prices based on historical prices. However, the results obtained from the prediction of FCPO price using ELM shows that it is possible to predict future prices using only the historical data. Many studies have been conducted by past researchers on how a neural network could refute the EMH theory. The weak form of EMH stated that the market's price trend could not be predicted or determined based on past prices. Henrique et al. (2018) have used a support vector regression method to predict future price and have managed to predict a price trend

based on historical price, thus refuting the weak form of EMH. On the other hand, Heo and Yang (2016b) have tried to use fundamental analysis with the help of SVM model and have found that the predictive power decreases over time, thus unable to refute the EMH theory. However, in this study, a simple single layer feed forward neural network have been implemented and we have managed to predict and validate the FCPO prices. This means that the SLFN model could potentially be used to predict future prices and refute the weak form of EMH.

Furthermore, this paper has incorporated the optimization of technical indicators onto the prediction of FCPO price using ELM. Whereas other researchers have mainly focused solely on the price prediction of FCPO (Karia & Bujang, 2011; Karia et al., 2012c; Basheer and Khamis, 2017). This study has also trained and tested the historical data against different number of hidden neurons and activation functions. The individual results of different number of hidden neurons and activation functions have also been recorded to provide a more comprehensive study. Moreover, opposing to the general perception of researchers that all the parameters of a feed forward network should be trained, ELM used in this study generates biases and weights randomly and regulates the output analytically. The main contribution of this study is adapting the ELM system onto the price prediction of FCPO, which is important for the upbringing of the country. Khalid et al. (2018c) also mentioned that if fluctuating price trends raises concerns for those involved in the palm oil business. These uncertainties may harm the income of small market players and will further tarnish the revenue of the country. An example of the fall in price of Malaysia's crude palm oil can be seen in year 1986. CPO price falls to RM500 per tonne in year 1986 as compared to RM2000 per tonne in year 1983. The proposed approach has been applied onto the

Malaysia's FCPO daily data, and the results have been compared to the actual price of FCPO to appraise the effectiveness of the approach.

5.4 Implication to industry/ policy makers

The objective of this study is to predict the future price of FCPO and to optimize various technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator. This study can contribute to businesses in the agricultural sectors, investment firms and industry speculators in predicting future prices to hedge against unforeseen risks and to speculate future price movement. The prediction of future price could be carried out in a similar approach by testing the ELM model against different sets of number of neurons and activation functions. In this study, the number of hidden neurons from 2 to 5 and the radial basis function acts as the optimal parameter for the prediction of future price. The predicted results are reliable as it achieves a training and testing accuracy of greater than 90%, which shows that it is almost identical to the actual price.

Furthermore, this study can also contribute to investment related businesses and technical analyst. In this study, different technical indicators have been tested using the ELM and the predictive accuracy of every technical indicators have been recorded. The Williams Percent Range and MACD indicators shows the highest prediction accuracy at approximately 97% which indicates both of these indicators have a greater impact on the prediction of FCPO price. The large variations of different technical indicators might be troublesome and time consuming for investors to learnt and implement each and every one. The identification of effective technical indicators usually requires plenty of experience and knowledge. In this study, ELM is used to train and test various technical indicators and the predicted price of each indicator alongside its predictive accuracy will be compared to obtain

the optimal technical indicator. This requires less knowledge and experience as compared to choosing the technical indicator individually.

Besides that, this study also contributes to policy makers in understanding more about the prediction of FCPO prices. The ELM model seems to be suitable to be used in predicting Malaysia's FCPO price. Having an appropriate model to predict and validate FCPO price could be beneficial to policy makers as it provides clearer direction to them. The ability to predict and validate price might also allow policy makers to make strategic decisions in controlling domestic palm oil output in order to maintain the price. The ELM model used to predict FCPO price also indicate that the predicted price depends greatly on the number of hidden neurons and activation function used. Thus, it is important for policy makers to consider the relationship between the parameters of the neural network and the accuracy of the results predicted. This is particularly important for policy makers in order to design a practical solution to predict future FCPO price with high accuracy.

5.5 Limitations of Study

Price prediction using neural network especially using ELM requires an activation function to produce better results with greater generalization performance. This is because activation function connects a node's input to its output, it is used to increase the linearity of the function. However, this study is limited to certain activation functions such as the sigmoidal, sine, radial basis and triangular basis function. Other activation functions such as hyperbolic, cosine and hard limit are excluded in this study.

Not only that, this study only focuses in optimizing various technical indicators such as RSI, EMA, MACD, Williams Percent Range and Stochastic Oscillator in the prediction of FCPO price. Other than this, there are still a large number of technical indicators which shows the trend, oscillator, momentum, and volume of the FCPO price. The few chosen technical indicators in this study are few of the most traditional and highly used indicators.

Furthermore, this study focuses on predicting the future FCPO price and optimizing technical indicators using ELM. ELM is a single layer feed forward neural network that provides fast training speed and satisfactory generalization performance. The nature of ELM that generates weights and biases randomly and automatically also allows the prediction to occur without the need of parameters fine tuning. This indicates that the machine learning process could still be undergone without the need for users to tune the parameter manually.

5.6 Direction of Future Study

Neural networks have been increasingly popular in the context of price prediction and technical indicator optimization. Such method to forecast future prices will be a continuing area of research as the technology era have been increasingly important. The motivation to outperform the market and obtain higher returns have also motivated researchers to conduct such studies. Few suggestions have been given for future studies in order to conduct a more comprehensive research.

Future study can include additional activation functions to predict the future price of FCPO and to optimize technical indicators. After including different activation functions, the results of the research could be different due to the nature of the different function. Besides that, future studies can predict the future price of other securities that have a

significant contribution towards the wellbeing of the country. Since Malaysia is a developing in Southeast Asia, future studies can focus on other developing countries such as Indonesia, Thailand and many more. For example, researchers could conduct similar research but in the context of Indonesia, as Indonesia acts as the largest exporter of palm oil in the world.

Not only that, future studies can include different technical indicators for optimization such as Simple Moving Average, Bollinger Bands, and many more. This is to identify more types of technical indicators and how such indicator could potentially affect the prediction accuracy. The optimal technical indicator might change after testing with different indicators.

This study also focuses on predicting FCPO price and optimizing technical indicators using the neural network called ELM. Future studies can predict future price or optimize technical indicator using other type of neural networks. The common type of neural networks used for predictions are Support Vector Machine, Back Propagated Neural Network, Regression Neural Network and many more. Different neural networks have different formula and different approach on predicting future prices and optimizing indicators. Some requires the user to tune the parameters manually whereas some are automated.

Besides that, future studies can also employ this method to other instruments or commodities such as exchange rate, white metal prices, other agricultural products and many more. The commodity chosen could vary depending on its importance towards the country's economy. For example for small open economies countries like Canada, New Zealand, Australia and others, fluctuations in commodity prices are sufficient for the design of new economic policies in order for central banks to adjust their commodity price indices to reflect the commodities they produce locally.

REFERENCES

- Abbey, B. S., & Doukas, J. A. (2012). Is technical analysis profitable for individual currency traders? *The Journal of Portfolio Management*, 39(1), 142-150.
- Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, 2014(1), 1-7.
- Ahmad, N. (2010). Impact of automated trading in the crude palm oil futures market on its underlying spot market. *International Research Journal of Finance and Economics*, 36(1), 46-58.
- Aini, H., & Havaluddin, H. (2019). Crude Palm Oil Prediction Based on Backpropagation Neural Network Approach. *Knowledge Engineering and Data Science*, 2(1), 1-9.
- Andrada-Félix, J., & Fernández-Rodríguez, F. (2008). Improving moving average trading rules with boosting and statistical learning methods. *Journal of Forecasting*, 27(5), 433-449.
- Ashour, M. A. H., Jamal, A., & Helmi, R. A. A. (2018). Effectiveness of artificial neural networks in solving financial time series. *International Journal of Engineering & Technology*, 7(4.11), 99-105.
- Assaleh, K., El-Baz, H., & Al-Salkhadi, S. (2011). Predicting stock prices using polynomial classifiers: The case of Dubai financial market. *Journal of Intelligent Learning Systems and Applications*, 3(2), 82-83.

- Barla, M., & Prasad, A. M. (2021). Evaluating Stock Performance Using Technical Analysis: A Case Study of TCS Ltd. *IUP Journal of Accounting Research & Audit Practices*, 20(1), 7-14.
- Basheer, H., & Khamis, A. (2017). Forecasting of crude palm oil price using hybridizing wavelet and group method of data handling model. *Malaysian Journal of Fundamental and Applied Sciences*, 13(4), 642-648.
- Beaton, C. (2017). *Humans are bad at predicting futures that don't benefit them*. [online] Available at: <https://www.theatlantic.com/science/archive/2017/11/11/hu> [Assessed on 7 June 2020]
- Bloomfield, J., & Fisher, M. J. (2019). Quantitative research design. *Journal of the Australasian Rehabilitation Nurses Association*, 22(2), 27-30.
- Boobalan, C. (2014). Technical analysis in select stocks of Indian companies. *International Journal of Business and Administration Research Review*, 2(4), 26-36.
- Boulton, T. J., & Braga-Alves, M. V. (2012). Naked short selling and market returns. *The Journal of Portfolio Management*, 38(3), 133-142.
- Braga, R., De Sousa, E. P., & Brugni, T. V. (2015). Stock market in Brazil: Portfolio based on dividend payout or technical analysis based on MACD? *International Journal of Advances in Management and Economics*, 4(3), 105-114.
- Brown, S. J., Goetzmann, W. N., & Kumar, A. (2002). The Dow theory: William Peter Hamilton's track record reconsidered. *The Journal of Finance*, 53(4), 1311-1333.
- Bursa Malaysia. (n.d). *Crude Palm Oil Futures (FCPO)*. [online] Available at: https://www.bursamalaysia.com/trade/our_products_services/derivatives/commodity_derivatives/crude_palm_oil_futures [Assessed on 10 December 2021]

- Butler, C. (2012). *Naked options expose you to risk*. [online] Available at: <https://www.investopedia.com/articles/optioninvestor/08/naked-options.asp>
[Assessed on 3 June 2020]
- Cervelló-Royo, R., Guijarro, F., & Michniuk, K. (2015). Stock market trading rule based on pattern recognition and technical analysis: Forecasting the DJIA index with intraday data. *Expert Systems with Applications*, 42(14), 5963-5975.
- Chang, P. C., Wang, Y. W., & Liu, C. H. (2007). The development of a weighted evolving fuzzy neural network for PCB sales forecasting. *Expert Systems with Applications*, 32(1), 86-96.
- Chisambara, P. (2019). Analytics and AI: *Humans and machines are good at different aspects of prediction*. [online] Available at: <https://erpminsights.com/analytics-and-ai-humans-and-machines-are-good-at-different-aspects-of-prediction/> [Assessed on 31 May 2020]
- Chong, T. T. L., & Ng, W. K. (2008). Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30. *Applied Economics Letters*, 15(14), 1111-1114.
- Chong, T. T. L., Li, C., & Yu, H. T. (2008). Structural change in the stock market efficiency after the millennium: the MACD approach. *Economics Bulletin*, 7(12), 1-6.
- Chong, T. T. L., Ng, W. K., & Liew, V. K. S. (2014). Revisiting the performance of MACD and RSI oscillators. *Journal of Risk and Financial Management*, 7(1), 1-12.
- Chung, H., & Shin, K. S. (2018). Genetic algorithm-optimized long short-term memory network for stock market prediction. *Sustainability*, 10(10), 3765.

- Coccia, M. (2020). Deep learning technology for improving cancer care in society: New directions in cancer imaging driven by artificial intelligence. *Technology in Society*, 60(1), 101198.
- Coe, T. S., & Laosethakul, K. (2010). Should individual investors use technical trading rules to attempt to beat the market? *American Journal of Economics and Business Administration*, 2(3), 201-209.
- Cohen, G., & Cabiri, E. (2015). Can technical oscillators outperform the buy and hold strategy? *Applied Economics*, 47(30), 3189-3197.
- Das, S. R., Mishra, D., & Rout, M. (2020). A hybridized ELM-Jaya forecasting model for currency exchange prediction. *Journal of King Saud University-Computer and Information Sciences*, 32(3), 345-366.
- Dash, R., & Dash, P. K. (2016). A hybrid stock trading framework integrating technical analysis with machine learning techniques. *The Journal of Finance and Data Science*, 2(1), 42-57.
- Delcey, T. (2019). Samuelson vs fama on the efficient market hypothesis: The point of view of expertise. *Æconomia. History, Methodology, Philosophy*, 9(1), 37-58.
- DeMatthews, D. E., Mungal, A. S., & Carrola, P. A. (2015). Despite best intentions: A critical analysis of social justice leadership and decision making. *Administrative Issues Journal*, 5(2), 3.
- Deng, S., Yoshiyama, K., Mitsubuchi, T., & Sakurai, A. (2015). Hybrid method of multiple kernel learning and genetic algorithm for forecasting short-term foreign exchange rates. *Computational Economics*, 45(1), 49-89.

- Devadoss, A. V., & Ligor, T. A. A. (2013). Stock prediction using artificial neural networks. *International Journal of Data Mining Techniques and Applications*, 2(1), 283-291.
- Devos, E., McInish, T., McKenzie, M., & Upson, J. (2014). Naked Short Selling and the Market Impact of Fails-to-Deliver: Evidence from the Trading of Real Estate Investment Trusts. *The Journal of Real Estate Finance and Economics*, 49(4), 454-476.
- Di Persio, L., & Honchar, O. (2016). Artificial neural networks architectures for stock price prediction: Comparisons and applications. *International Journal of Circuits, Systems and Signal Processing*, 10(2016), 403-413.
- DOSM. (2020). *Malaysia External Trade Statistics February 2020*. [online] Available at: https://www.dosm.gov.my/v1/index.php?r=column/cthemByCat&cat=139&bul_id=bUZDUHppYjFTWGhBMldQWEhhUGRyZz09&menu_id=azJjRWpYL0VBYU90TVhpclByWjdMQT09 [Assessed on 8 February 2022]
- Dourra, H., & Siy, P. (2002). Investment using technical analysis and fuzzy logic. *Fuzzy Sets and Systems*, 127(2), 221-240.
- Dzikevičius, A., & Šaranda, S. (2010). EMA Versus SMA usage to forecast stock markets: the case of S&P 500 and OMX Baltic benchmark. *Business: Theory and Practice*, 11(3), 248-255.
- Edwards, D. (2018). *AI stock market prediction: Radial basis vs LSTM network*. [online] Available at: <https://medium.com/@davidwillamedwards2/ai-stock-market-prediction-radial-basis-function-vs-lstm-network-78cca226d4fa> [Assessed on 7 June 2020]

- Fayek, M. B., El-Boghdadi, H. M., & Omran, S. M. (2013). Multi-objective optimization of technical stock market indicators using gas. *International Journal of Computer Applications*, 68(20), 41-48.
- Fernández-Blanco, P., Bodas-Sagi, D. J., Soltero, F. J., & Hidalgo, J. I. (2008). Technical market indicators optimization using evolutionary algorithms. In: Keijzer, M. (Ed.), *Proceedings of the 10th annual conference companion on Genetic and evolutionary computation*, Atlanta, Georgia, 12-16 July 2008. Association of Computing Machinery.
- Fernandez-Rodríguez, F., Gonzalez-Martel, C., & Sosvilla-Rivero, S. (2000). On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market. *Economics Letters*, 69(1), 89-94.
- Frances-Villora, J. V., Rosado-Muñoz, A., Bataller-Mompean, M., Barrios-Aviles, J., & Guerrero-Martinez, J. F. (2018). Moving learning machine towards fast real-time applications: A high-speed FPGA-based implementation of the OS-ELM training algorithm. *Electronics*, 7(11), 308.
- Gan, P. Y., & Li, Z. D. (2014). Econometric study on Malaysia's palm oil position in the world market to 2035. *Renewable and Sustainable Energy Reviews*, 39(1), 740-747.
- Gehrig, T., & Menkhoff, L. (2006). Extended evidence on the use of technical analysis in foreign exchange. *International Journal of Finance & Economics*, 11(4), 327-338.
- Ghobadi, M. (2014). Profitability of technical analysis indicators to earn abnormal returns in international exchange markets. *Journal of Economics Finance and Accounting*, 1(4), 334-346.

- Gigerenzer, G., & Selten, R. (2002). *Bounded rationality: The adaptive toolbox*, Cambridge: MIT Press.
- Goldstein, D. G., & Gigerenzer, G. (2009). Fast and frugal forecasting. *International Journal of Forecasting*, 25(4), 760-772.
- Gorgulho, A., Neves, R., & Horta, N. (2009). Using GAs to balance technical indicators on stock picking for financial portfolio composition. In: ACM, *Proceedings of the 11th Annual Conference Companion on Genetic and Evolutionary Computation Conference: Late Breaking Papers*, Montreal, Canada, July 2009. Association for Computing Machinery.
- Gumparthi, S. (2017). Relative strength index for developing effective trading strategies in constructing optimal portfolio. *International Journal of Applied Engineering Research*, 12(19), 8926-8936.
- Gupta, N., & Nigam, S. (2020). Crude oil price prediction using artificial neural network. *Procedia Computer Science*, 170(1), 642-647.
- Güth, W., & Kliemt, H. (2004). Bounded rationality and theory absorption. *Homo Oeconomicus*, 21(1), 521-541.
- Halilbegovic, S., Celebic, N., & Kulovic, D. (2018). Analysis of a Standalone Usage and Limitations of Relative Strength Index Indicator in Stock Trading. *Ecoforum Journal*, 7(1), 1-10.
- Harrou, F., & Nounou, M. N. (2014). Monitoring linear antenna arrays using an exponentially weighted moving average-based fault detection scheme. *Systems Science & Control Engineering: An Open Access Journal*, 2(1), 433-443.

- Haviluddin, H., & Tahyudin, I. (2015). Time Series Prediction Using Radial Basis Function Neural Network. *International Journal of Electrical and Computer Engineering*, 5(4), 765-766.
- Hayes, A. (2019). *Moving average convergence divergence*. [online] Available at: <https://www.investopedia.com/terms/m/macd.asp> [Assessed on 7 June 2020]
- Hayes, A. (2021). *Technical analysis*. [online] Available at: <https://www.investopedia.com/terms/t/technicalanalysis.asp> [Assessed on 11 December 2021]
- Hejase, A. J., Srour, R. M., Hejase, H. J., & Younis, J. (2017). Technical analysis: Exploring MACD in the Lebanese stock market. *Journal of Research in Business, Economics and Management*, 8(4), 1493-1502.
- Heng, P., & Niblock, S. J. (2014). Trading with tigers: a technical analysis of Southeast Asian stock index futures. *International Economic Journal*, 28(4), 679-692.
- Henrique, B. M., Sobreiro, V. A., & Kimura, H. (2018). Stock price prediction using support vector regression on daily and up to the minute prices. *The Journal of Finance and Data Science*, 4(3), 183-201.
- Heo, J., & Yang, J. Y. (2016). Stock price prediction based on financial statements using SVM. *International Journal of Hybrid Information Technology*, 9(2), 57-66.
- Heyman, D., Inghelbrecht, K., & Pauwels, S. (2011). Technical trading rules in emerging stock markets. *World Academy of Science, Engineering and Technology*, 59(1), 2241-2264.

- Hodnett, K., & Hsieh, H. H. (2012). Capital market theories: Market efficiency versus investor prospects. *The International Business & Economics Research Journal*, 11(8), 849-850.
- Hu, Z., Liu, W., Bian, J., Liu, X., & Liu, T. Y. (2018). Listening to chaotic whispers: A deep learning framework for news-oriented stock trend prediction. In *Proceedings of the eleventh ACM international conference on web search and data mining* (pp. 261-269).
- Huang, C. J., Chen, P. W., & Pan, W. T. (2012). Using multi-stage data mining technique to build forecast model for Taiwan stocks. *Neural Computing and Applications*, 21(8), 2057-2063.
- Huang, C. J., Yang, D. X., & Chuang, Y. T. (2008). Application of wrapper approach and composite classifier to the stock trend prediction. *Expert Systems with Applications*, 34(4), 2870-2878.
- Huang, G. B., Zhu, Q. Y., & Siew, C. K. (2006). Extreme learning machine: theory and applications. *Neurocomputing*, 70(1-3), 489-501.
- Hwa, N. E. (2007). *Trading Strategies using Stochastic*. [online] Available at: https://www.chartnexus.com/learning/static/pulses_jun2007.pdf [Assessed on 7 June 2020]
- Ijegwa, A. D., Rebecca, V. O., Olusegun, F., & Isaac, O. O. (2014). A predictive stock market technical analysis using fuzzy logic. *Computer and Information Science*, 7(3), 1-17.
- Jawade, A. A., Naidu, K., & Agrawal, A. (2015). Performance of oscillators: Index futures. *SCMS Journal of Indian Management*, 12(1), 51.

- Jin, X., Wah, B. W., Cheng, X., & Wang, Y. (2015). Significance and challenges of big data research. *Big Data Research*, 2(2), 59-64.
- Karia, A. A., & Bujang, I. (2011). Progress accuracy of CPO price prediction: Evidence from ARMA family and artificial neural network approach. *International Research Journal of Finance and Economics*, 64(1), 66-79.
- Karia, A. A., Bujang, I., & Ahmad, I. (2012). Forecasting on crude palm oil prices using artificial intelligence approaches. *The Business & Management Review*, 3(1), 355.
- Kayyumi, S. (2018). *Technical classroom: Six basic tenets of dow theory for market timing*. [online] Available at: <https://www.moneycontrol.com/news/business/markets/technical-classroom-six-basic-tenets-of-dow-theory-for-market-timing-2880721.html> [Assessed on 7 June 2020]
- Khalid, N., Hamidi, H. N. A., Thinagar, S., & Marwan, N. F. (2018). Crude palm oil price forecasting in Malaysia: An econometric approach. *Jurnal Ekonomi Malaysia*, 52(3), 247-259.
- Khuntia, S., & Pattanayak, J. K. (2018). Adaptive market hypothesis and evolving predictability of bitcoin. *Economics Letters*, 167(1), 26-28.
- Kilgore, T. (2018). *Don't dis the dow theory just because it's over 100 years old*. [online] Available at: <https://www.marketwatch.com/story/dont-dis-the-dow-theory-just-because-its-over-100-years-old-2018-03-27> [Assessed on 7 June 2020]
- Kim, T., & Kim, H. Y. (2019). Forecasting stock prices with a feature fusion LSTM-CNN model using different representations of the same data, *PloS one*, 14(2), 1-23.

- Kim, Y., Seo, K., Harrington, R. J., Lee, Y., Kim, H., & Kim, S. (2020). High accuracy modeling for solar PV power generation using Noble BD-LSTM-based neural networks with EMA. *Applied Sciences*, 10(20), 7339.
- Kirkpatrick II, F. C. D., & Julie, R. (2022). Dow Theory. CMT Curriculum Level I 2022: An Introduction to Technical Analysis.
- Koedel, U., & Dietrich, P. (2020, May). Going beyond FAIR to increase data reliability. In *EGU General Assembly Conference Abstracts* (p. 11117).
- Kolarik, T., & Rudorfer, G. (1994). Time series forecasting using neural networks. *ACM Sigapl Apl Quote Quad*, 25(1), 86-94.
- Kukreja, H., Bharath, N., Siddesh, C. S., & Kuldeep, S. (2016). An introduction to artificial neural network. *Int J Adv Res Innov Ideas Educ*, 1(1), 27-30.
- Kumar, S., Srinivasa Pai, P., & Shrinivasa Rao, B. R. (2012). Radial basis function network-based prediction of performance and emission characteristics in a bio diesel engine run on WCO ester. *Advances in Artificial intelligence*, 2012(2), 1-7.
- Lahmiri, S. (2020). A predictive system integrating intrinsic mode functions, artificial neural networks, and genetic algorithms for forecasting S&P500 intraday data. *Intelligent Systems in Accounting, Finance and Management*, 27(2), 55-65.
- Lei, Y., Ding, L., & Zhang, W. (2014). Generalization performance of radial basis function networks. *IEEE Transactions on Neural Networks and Learning Systems*, 26(3), 551-564.
- Li, A. W., & Bastos, G. S. (2020). Stock market forecasting using deep learning and technical analysis: a systematic review. *IEEE Access*, 8(1), 185232-185242.

- Lin, Y. C. (2016). *Predicting the stock market and defeating the efficient market hypothesis*.
[online] Available at: <https://seekingalpha.com/article/3877416-predicting-stock-market-defeating-efficient-market-hypothesis-part> [Assessed on 6 June 2020]
- Lo, A. W. (2004). The adaptive markets hypothesis. *The Journal of Portfolio Management*, 30(5), 15-29.
- Loh, E. Y. (2007). An alternative test for weak form efficiency based on technical analysis. *Applied Financial Economics*, 17(12), 1003-1012.
- Ma, Q. (2020). Comparison of ARIMA, ANN and LSTM for stock price prediction. In *E3S Web of Conferences* (Vol. 218, p. 01026). EDP Sciences.
- Mandelbrot, B., & Hudson, R. L. (2004). *A fractal view of risk, ruin and reward*, New York: Basic Books.
- Masry, M. (2016). The dealer's characteristics and their impact on their investment decisions efficiency in Egyptian stock exchange. *International Journal of Recent Scientific Research*, 7(1), 8294-8301.
- Masry, M. (2017). The impact of technical analysis on stock returns in an emerging capital markets (ECM's) country: Theoretical and empirical Study. *International Journal of Economics and Finance*, 9(3), 91-107.
- McMillan, D., Speight, A., & Apgwilym, O. (2000). Forecasting UK stock market volatility. *Applied Financial Economics*, 10(4), 435-448.
- Metghalchi, M., Marcucci, J., & Chang, Y. H. (2012). Are moving average trading rules profitable? Evidence from the European stock markets. *Applied Economics*, 44(12), 1539-1559.

- Mirzaee Ghazani, M., & Jafari, M. A. (2021). The efficiency of CO2 market in the phase III EU ETS: analyzing in the context of a dynamic approach. *Environmental Science and Pollution Research*, 28(43), 61080-61095.
- M'ng, J. C. P., & Aziz, A. A. (2016). Using neural networks to enhance technical trading rule returns: A case with KLCI. *Athens Journal of Business and Economics*, 2(1), 63-70.
- M'ng, J. P., Aziz, A. A., & Ismail, K. (2017). Returns from neural network enhanced technical analysis indicator: A study on crude oil futures. *International Journal of Advanced and Applied Sciences*, 4(4), 7-13.
- Moghaddam, A. H., Moghaddam, M. H., & Esfandyari, M. (2016). Stock market index prediction using artificial neural network. *Journal of Economics, Finance and Administrative Science*, 21(41), 89-93.
- Nakano, M., Takahashi, A., & Takahashi, S. (2017). Generalized exponential moving average (EMA) model with particle filtering and anomaly detection. *Expert Systems with Applications*, 73(1), 187-200.
- Nambiappan, B., Ismail, A., Hashim, N., Ismail, N., Shahari, D. N., Idris, N. A. N., ... & Kushairi, A. (2018). Malaysia: 100 years of resilient palm oil economic performance. *Journal of Oil Palm Research*, 30(1), 13-25.
- Nguyen, D. (2018). Comparing automatic and human evaluation of local explanations for text classification. In: Walker, H., Stent, A., and Ji, H. (Eds.), *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, New Orleans, Louisiana, 1-6 June 2018. Association for Computational Linguistics.

- Ni, Y., Liao, Y. C., & Huang, P. (2015). Momentum in the Chinese stock market: Evidence from stochastic oscillator indicators. *Emerging Markets Finance and Trade*, 51(1), 99-110.
- Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). Efficient stock-market prediction using ensemble support vector machine. *Open Computer Science*, 10(1), 153-163.
- Norhidayu, A., Nur-Syazwani, M., Radzil, R., Amin, I., & Balu, N. (2017). The production of crude palm oil in Malaysia. *International Journal of Economics and Management*, 11(3), 591-606.
- Oyemade, D. A., & Ojugo, A. A. (2020). A property oriented pandemic surviving trading model. *International Journal of Advanced Trends in Computer Science and Engineering*, 9(5), 7397-7404.
- Park, C. H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys*, 21(4), 786-826.
- Patalay, S., & MadhusudhanRao, B. (2019). Design of a financial decision support system based on artificial neural networks for stock price prediction. *Journal of Mechanics of Continua and Mathematical Sciences*, 14(5), 757-766.
- Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. *Expert Systems with Applications*, 42(1), 259-268.
- Petrusheva, N., & Jordanoski, I. (2016). Comparative analysis between the fundamental and technical analysis of stocks. *Journal of Process Management - New Technologies*, 4(2), 26-31.

- Politis, A., Doka, K., & Koziris, N. (2021). Ether price prediction using advanced deep learning models. In 2021 IEEE International Conference on Blockchain and Cryptocurrency (ICBC) (pp. 1-3). IEEE.
- Rahim, N. F., Othman, M., Sokkalingam, R., & Kadir, E. A. (2018). Forecasting crude palm oil prices using fuzzy rule-based time series method. *IEEE Access*, 6(1), 32216-32224.
- Rapach, D., & Zhou, G. (2013). Forecasting stock returns. *Handbook of Economic Forecasting*, 2(1), 328-383.
- Rather, A. M., Agarwal, A., & Sastry, V. N. (2015). Recurrent neural network and a hybrid model for prediction of stock returns. *Expert Systems with Applications*, 42(6), 3234-3241.
- Rodríguez-González, A., García-Crespo, Á., Colomo-Palacios, R., Iglesias, F. G., & Gómez-Berbís, J. M. (2011). CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator. *Expert Systems with Applications*, 38(9), 11489-11500.
- Rout, M., Majhi, B., Mohapatra, U. M., & Mahapatra, R. (2012). Stock indices prediction using radial basis function neural network. In: Panigrahi, B. K., and Das, S. (Eds.), *International Conference on Swarm, Evolutionary, and Memetic Computing*, Berlin, Heidelberg, December 2012. Association for Computing Machinery.
- Sahin, U., & Ozbayoglu, A. M. (2014). TN-RSI: Trend-normalized RSI indicator for stock trading systems with evolutionary computation. *Procedia Computer Science*, 36(1), 240-245.

- Sairamya, N. J., Susmitha, L., George, S. T., & Subathra, M. S. P. (2019). Hybrid approach for classification of electroencephalographic signals using time–frequency images with wavelets and texture features. *Intelligent Data Analysis for Biomedical Applications*, 12(1), 253-273
- Salami, M. A., & Haron, R. (2018). Long-term relationship of crude palm oil commodity pricing under structural break. *Journal of Capital Markets Studies*, 2(2), 162-174.
- Sedighi, M., Jahangirnia, H., Gharakhani, M., & Farahani Fard, S. (2019). A Novel Hybrid Model for Stock Price Forecasting Based on Metaheuristics and Support Vector Machine. *Data*, 4(2), 75-76.
- Selvin, S., Vinayakumar, R., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P. (2017). Stock price prediction using LSTM, RNN and CNN-sliding window model. In 2017 international conference on advances in computing, communications and informatics (icacci) (pp. 1643-1647). IEEE.
- Sen, J., & Chaudhuri, T. D. (2018). Stock price prediction using machine learning and deep learning frameworks. In *Proceedings of the 6th International Conference on Business Analytics and Intelligence*, Bangalore, India.
- Sezer, O. B., Ozbayoglu, A. M., & Dogdu, E. (2017). An artificial neural network-based stock trading system using technical analysis and big data framework. In: ACM, *Proceedings of the SouthEast Conference*, Kennesaw, Georgia. Association for Computing Machinery.
- Shah, S. A. A., & Shah, A. M. (2020). The Predictability and profitability of Trading Range Break-out Trading Rules: Evidence from Pakistan Stock Exchange. *Journal of Business & Tourism*, 6(1), 209-215.

- Shambora, W. E., & Rossiter, R. (2007). Are there exploitable inefficiencies in the futures market for oil? *Energy Economics*, 29(1), 18-27.
- Sharma, D. K., Hota, H. S., Brown, K., & Handa, R. (2021). Integration of genetic algorithm with artificial neural network for stock market forecasting. *International Journal of System Assurance Engineering and Management*, 15(1), 1-14.
- Shastri, M., Roy, S., & Mittal, M. (2019). Stock price prediction using artificial neural model: an application of big data. *EAI Endorsed Transactions on Scalable Information Systems*, 6(20), 1-8.
- Shen, W., Guo, X., Wu, C., & Wu, D. (2011). Forecasting stock indices using radial basis function neural networks optimized by artificial fish swarm algorithm. *Knowledge-Based Systems*, 24(3), 378-385.
- Sin, E., & Wang, L. (2017). Bitcoin price prediction using ensembles of neural networks. In *2017 13th International conference on natural computation, fuzzy systems and knowledge discovery* (pp. 666-671). IEEE.
- Singh, J., & Khushi, M. (2021). Feature Learning for Stock Price Prediction Shows a Significant Role of Analyst Rating. *Applied System Innovation*, 4(1), 17.
- Širůček, M., & Šíma, K. (2016). Optimized indicators of technical analysis on the New York stock exchange. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, 64(6), 2123-2131.
- Sivalingam, K. C., Mahendran, S., & Natarajan, S. (2016). Forecasting gold prices based on extreme learning machine. *International Journal of Computers Communications & Control*, 11(3), 372-380.

- Soon, G. K., On, C. K., Rayner, A., Patricia, A., & Teo, J. (2018). A CIMB Stock Price Prediction Case Study with Feedforward Neural Network and Recurrent Neural Network. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, 10(3-2), 89-94.
- Subramanian, V., & Balakrishnan, K. P. (2014). Efficacy of refined MACD indicators: Evidence from Indian stock markets. *IUP Journal of Applied Finance*, 20(1), 76-91.
- Sundlöf, C., & Krantz, G. (2016). A comparative study of technical indicator performances by stock sector: RSI, MACD, and Larry Williams% R applied to the Information Technology, Utilities, and Consumer Staples sectors.
- Tahar, S. H. M., Yaakob, S. B., & Ahmed, A. (2017). An improved Boltzmann machine for strategic investment planning in power system environment. *Indones J Electr Eng Comput Sci*, 6(1), 259-267.
- Taran-Morosan, A. (2011). The relative strength index revisited. *African Journal of Business Management*, 5(14), 5855-5856.
- Taylor, N. (2014). The rise and fall of technical trading rule success. *Journal of Banking & Finance*, 40(1), 286-302.
- Timmermann, A. (2008). Elusive return predictability. *International Journal of Forecasting*, 24(1), 1-18.
- Todea, A., Ulici, M., & Silaghi, S. (2009). Adaptive markets hypothesis: Evidence from Asia-Pacific financial markets. *The Review of Finance and Banking*, 1(1), 7-13.
- Uyar, U., Kelten, G. S., & Moral, T. (2020). Technical analysis for investors: Bitcoin and ethereum applications. *Journal of Financial Research and Studies*, 12(23), 653-671.

- Vezeris, D. T., & Schinas, C. J. (2018). Performance comparison of three automated trading systems (MACD, PIVOT and SMA) by means of the d-backtest ps implementation. *International Journal of Trade, Economics and Finance*, 9(4), 170-173.
- Wafi, A. S., Hassan, H., & Mabrouk, A. (2015). Fundamental analysis vs technical analysis in the Egyptian stock exchange – Empirical study. *International Journal of Business and Management Study*, 2(2), 212-218.
- Wagman, L. (2003). Stock portfolio evaluation: An application of genetic-programming-based technical analysis. *Genetic Algorithms and Genetic Programming at Stanford*, 3(1), 213-220.
- Wang, J., Lu, S., Wang, S. H., & Zhang, Y. D. (2021). A review on extreme learning machine. *Multimedia Tools and Applications*, 1181(1), 1-50.
- Wang, L., You, Z. H., Huang, D. S., & Zhou, F. (2018). Combining high speed ELM learning with a deep convolutional neural network feature encoding for predicting protein-RNA interactions. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 17(3), 972-980.
- Wang, T., Pouyanfar, S., Tian, H., Tao, Y., Alonso, M., Luis, S., & Chen, S. C. (2019). A framework for airfare price prediction: a machine learning approach. In: California University, 2019 IEEE 20th international conference on information reuse and integration for data science (IRI), Los Angeles, California, 30-1 August 2019. IEEE.
- Wong, W. K., Manzur, M., & Chew, B. K. (2003). How rewarding is technical analysis? Evidence from Singapore stock market. *Applied Financial Economics*, 13(7), 543-551.

- Xavier, G. G., Massoud, M., & Chien, C. (2010). Technical analysis: Evidence from the Mexican stock market. *The Business Review*, 15(2), 49-54.
- Xie, W., Yu, L., Xu, S., & Wang, S. (2006). A new method for crude oil price forecasting based on support vector machines. *International Conference on Computational Science*, 4(6), 444-451.
- Yan, W., Sewell, M. V., & Clack, C. D. (2008). Learning to optimize profits beats predicting returns-: comparing techniques for financial portfolio optimisation. In: Keijzer, M., *Proceedings of the 10th annual conference on Genetic and evolutionary computation*, Atlanta, Georgia, July 2008. Association for Computing Machinery.
- Yan, X., & Zheng, L. (2017). Fundamental analysis and the cross-section of stock returns: A data-mining approach. *The Review of Financial Studies*, 30(4), 1382-1423.
- Yildiz, B., & Yezegel, A. (2010). Fundamental analysis with artificial neural network. *The International Journal of Business and Finance Research*, 4(1), 149-158.
- Zhu, Q. Y., Qin, A. K., Suganthan, P. N., & Huang, G. B. (2005). Evolutionary extreme learning machine. *Pattern Recognition*, 38(10), 1759-1763.