INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN ACCOUNTING, FINANCE AND MANAGEMENT SCIENCES

OPEN ACCESS JOURNAL

Vol 12, Issue 3, (2023) E-ISSN: 2225-8329

Prediction on Crude Palm Oil Futures (FCPO) Price in Malaysia: An Artificial Intelligence (AI) Approach

Yong Xhin Rong[1], Mohamad Jais[2], Khairul Fikri Tamrin[3], Nurul Syuhada Zaidi[4]

Universiti Malaysia Sarawak (UNIMAS), 94300 Kota Samarahan, Sarawak, Malaysia.

E-mail: yongxhinrong@gmail.com

Abstract

To Link this Article: http://dx.doi.org/10.6007/IJARAFMS/v12-i3/19303 DOI:10.6007/IJARAFMS/v12-i3/19303

Published Online: 23 September, 2023

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. This paper aims to predict the price of Crude Palm Oil Futures (FCPO) in Malaysia by using a single-layer feed-forward neural network called Extreme Learning Machine (ELM). Using daily time series data that consists of the opening, the high, low and closing price of FCPO ranging from the first of January 2010 to the end of December 2019. The data is trained and tested against the various number of hidden neurons and different activation functions such as sine, sigmoidal, triangular basis, and radial basis. It is found that the ideal number of hidden neurons is at 2 to 4. Besides that, the main result shows that the radial basis activation function is more suitable in the prediction of FCPO price as compared to other functions such as the sine, sigmoidal and triangular basis functions. The price predicted using the radial basis function has a higher testing and training accuracy as compared with other functions. Not only that, the time taken to test and train the ELM using the radial basis function is also lower as compared to others. The predictability of FCPO prices also disputes the weak form of the Efficient Market Hypothesis (EMH) which indicates that it is nearly impossible to predict future prices of any security using historical data.

Keywords— Neural network; ELM; FCPO; Price prediction.

I. Introduction

The prediction of FCPO prices is important for investors to mitigate and reduce risks associated with uncertainties. The emergence and transformation of technology have changed the role and usage of Artificial Intelligence (AI) in our daily lives, thus allowing it to change the thinking and decision-making process of users. Besides that, the existence and accumulation of bulky financial data in this current era allow professionals to utilise it efficiently and maximize the hidden potential of AI.

Financial data are intricate and could be affected by various factors ranging from economic, political, and socioeconomic. The continuous increase in such big data creates difficulties that are complex and might be tedious to solve as it is subjected to great errors [1]. Therefore, the need to create and evolve intelligent and automated systems that could potentially resolve such complex issues has become an increasingly popular research area among researchers. In the case of commodities, real-world commodity market price prediction acts as a challenging problem. In recent years, investors tend to pay more attention to futures as it provides a higher return. Future Crude Palm Oil (FCPO) price prediction is important as it enhances investor's trading decisions and allows them to deal with uncertainties and risks in the future.

Financial market movements and price prediction has always been a hot topic among researchers and investors. Traditional price prediction usually revolves around using publicly available information or past trend and patterns. Obtaining high profits has always been a dream of all investors. In the financial market, there are many types of financial instruments that investors can choose to invest in. A few examples of it are the trading of bonds, stocks, futures, foreign currencies, commodities and many more.

In this study, FCPO will be emphasized as it is still relatively new and less popular as compared to stock trading. FCPO is a Ringgit Malaysia (RM) designated futures contract which is mainly traded in the Bursa Malaysia derivatives market. In simpler terms, it is a contract that allows a buyer or seller to trade crude palm oil at a prearranged price only to be delivered with the commodity at a fixed time in the near future. FCPO are usually traded by two types of investors, hedgers, and speculators. An oil-related businessman would enter an FCPO contract to hedge themselves against unfavourable price increases in the future. As for speculators, they are traders who trade FCPO to obtain leverage and earn through price movement and spread of palm oil.

The prediction of FCPO price is deemed to be critical as it allows palm oil-related businesses and traders to deal with unforeseen risks. In recent years, the prediction of time series data has been heavily challenged due to the emergence of AI [2]. All of these study shows that the predictability of statistical forecasting approaches especially in the context of FCPO may have a certain limit and requires deeper learning. [3] states that AI is the use of computer systems to perform tasks that could assist humans in making certain decisions. 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. The usage of AI on time series prediction has been increasing rapidly in recent years.

Due to the high level of uncertainties, this study investigates whether Artificial Neural Network (ANN) such as ELM can be used to predict the future price of FCPO to aid investors in buying and selling futures. The primary objective of this study is to apply ELM to a set of past data with different parameters to try and predict the future price of FCPO.

[4] maintained that ELM has a high precision and quick prediction speed when solving problems, especially problems that are related to real-life applications. In their study, ELM randomly assigns weightage and hidden layers to the input instead of altering the parameters manually. Due to its single-layer feed-forward network, ELM could determine the output analytically. In short, Huang et al. state that ELM provides the smallest norm of weights, thus providing a faster prediction speed. [5] also states that ELM overcomes slow training speed problems and is suitable for predicting future prices. [6] also shows that ELM has good

predicting accuracy and a rapid prediction speed. Not only that, ELM was also found to have a greater prediction performance compared to other types of neural networks such as SVM.

Besides that, [7] maintained that ELM has an above-average performance and high training and testing speed in terms of learning as compared to back-propagated models. ELM also provides a united learning platform and seldom faces problems such as overfitting and local minima issues. [8] had also used ELM as a forecasting technique in their research and have stated that ELM has a high prediction accuracy. On the other hand, [9] compared ELM with another model such as genetic programming and have found that ELM is a very fast and highly reliable model. Furthermore, [10] have also conducted a classification of time series data with ELM as the forecasting model. It was found that ELM is fast and has a higher prediction accuracy.

Furthermore, [11] defines EMH as the price of the security that contains and reflects all the information available. 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 hypotheses and have conducted research to show that fundamental and technical analysis does allow investors to buy undervalued stocks or buy stocks at the optimal timing. [12] maintains that a market might not be extremely efficient or else traders would are not motivated to trade that particular security. This is because EMH states that no excess profit could be generated through any means of prediction.

II. Material and Methods

This study uses the daily opening, high, low and closing price of FCPO in Malaysia ranging from the 1st of January 2010 to 31st December 2019. The sample data consists of approximately 9800 observations. Fig. 1 depicts the daily FCPO price movement in Malaysia. The purpose of conducting research is to predict the FCPO price in Malaysia using historical data. MATLAB version R2020a is used to generate training and testing of the data.

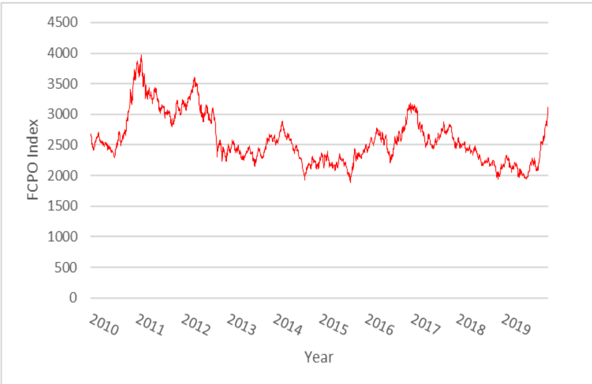

Fig. 1 FCPO Prices from 1st of January 2010 to 31st of December 2019.

A. *Extreme Learning Machine (ELM)*

ELM is a single-hidden layer forwardly fed neural network which chooses the weightage of connection randomly. Other advantages of ELM include faster training and testing speed and higher performance. The main advantage of using ELM is that the hidden layer of the algorithm still works without much tuning as it has several activation functions such as sigmoidal function, sine function, radial basis function and triangular basis function. ELM will be train 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 below:

$$\sum_{i=1}^{N}[\beta_i g(a_i, b_i, x_j)] = t_j, j = 1, \dots, N \quad (1)$$

In simpler form, the equation above can be written as $\beta H = T$. In this simpler form, H is the hidden layer output and could be express as such:

$$H(a_1, \dots, a_N; b_1, \dots, b_N; x_1, \dots, x_M) = \quad (2)$$

$$\begin{matrix} G(a_1, b_1, x_1) & . & G(a_N, b_N, x_1) \\ . & . & . \\ G(a_1, b_1, x_M) & . & G(a_N, b_N, x_M) \end{matrix} \quad (3)$$

$$\beta = [\beta_1 \beta_2 \dots \beta_n]^{\boldsymbol{T}} \text{and } T = [t_1 t_2 \dots t_n]^{\boldsymbol{T}} \quad (4)$$

In the matrix, each value represents the hidden output. In this feed forward neural network, (x_i, t_i) acts as the training data and $g(a, b, x)$ acts as the hidden node output function. An example of the basic structure of ELM can be seen in Fig. 2:

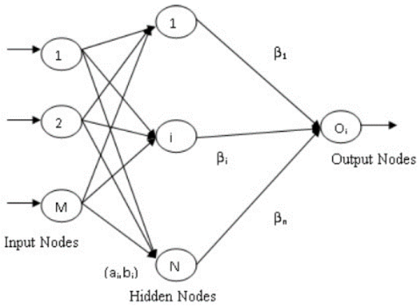

Fig. 2 Single Layer Feed Forward Network Structure

B. Research Framework

The research framework of this study is established based on the ELM approach. The proposed framework consists of a few different layers which includes the input, hidden and output layer. The daily prices of FCPO will be fed into the ELM and the output with the highest training and testing accuracy will be used. The proposed framework can be seen in Fig. 3.

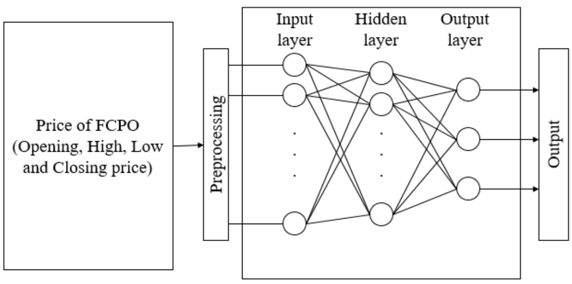

Fig. 3 Research Framework of the Study

C. Process in Price Prediction

In this section, the detailed process in predicting FCPO price using ELM will be separated into few steps which includes the collection of data, pre-processing the data, training, and testing the data using ELM and comparing the predicted price with actual price.

In the data collection step, the data of the historical prices of FCPO from the year 2010 to year 2019 is downloaded from Bursa Station and is used as the sample data. The accuracy of data collected is important as it affects the result of prediction. The raw data consists of historical opening, high, low, and closing price of FCPO.

The pre-processing step transforms the raw data into simple and understandable format by the ELM. This includes filtering data, normalizing data and checking the data. The processed data will then be separated into an 80:20 ratio. In other words, 80% of the processed data will be divided as the training data and 20% will be the testing data. The testing data also acts as the validation data to validate the predicted price. All the input attributes except for the closing price of FCPO is normalized to ensure higher data consistency.

In the training and testing of the machine step, the separated data are fed into the ELM with randomly assigned input weightage and biases generated by the machine itself. Various number of hidden neurons and activation functions will then be used to train and test the machine. Output with a higher training and testing accuracy supplemented by a lower training time is deemed to be optimal and will be chosen.

The predicted output price with the highest training and testing accuracy will be compared with the actual price of FCPO. If the price predicted by the ELM is similar to the actual value of FCPO, the ELM neural network is said to be working and could potentially be used to predict future prices.

III. Results and Discussion

In this study, the training and testing datasets are tested repeatedly against different number of hidden neurons and activation functions until the optimal result is obtained. An optimal result is deemed to have the highest training and testing accuracy accompanied by a low training time.

Table 1 depicts the testing and training accuracy result tested against different number of hidden neurons and activation function. The datasets are tested against 2 to 4 hidden neurons as any more than 4 produces output with lower accuracy. The optimum number of neurons alongside its activation function is recorded. T The comparison of the actual FCPO price against the price predicted using ELM can be seen in Fig.4, 5, 6, 7, 8 and 9.

TABLE I
TESTING AND TRAINING ACCURACY RESULT

Activation Function / Number of Hidden Neurons	Sigmoidal	Sine	Radial basis	Triangular basis
2	Testing accuracy = 88.29% Testing time = 0.016 sec Training accuracy = 94.71% Training time = 0 sec	Testing accuracy = 84.56% Testing time = 0 sec Training accuracy = 86.43% Training time = 0 sec	Testing accuracy = 98.39% Testing time = 0 sec Training accuracy = 87.0% Training time = 0 sec	Testing accuracy = 86.42 % Testing time = 0 sec Training accuracy = 96.67% Training time = 0 sec
3	Testing accuracy = 91.03% Testing time = 0 sec Training Accuracy = 86.81% Training time = 0 sec	Testing accuracy = 96.02% Testing time = 0 sec Training accuracy = 90.66% Training time = 0 sec	Testing accuracy = 91.47% Testing time = 0 sec Training accuracy = 97.85% Training time = 0 sec	Testing accuracy = 99.31% Testing time = 0 sec Training accuracy = 74.77% Training time = 0 sec
4	Testing accuracy = 24.71% Testing time = 0.016 sec Training accuracy = 25.13% Training time = 0 sec	Testing accuracy = 90.56% Testing time = 0 sec Training accuracy = 97.26% Training time = 0 sec	Testing accuracy = 96.00% Testing time = 0.016 sec Training accuracy = 94.50% Training time = 0 sec	Testing accuracy = 93.41% Testing time = 0 sec Training accuracy = 90.57% Training time = 0 sec

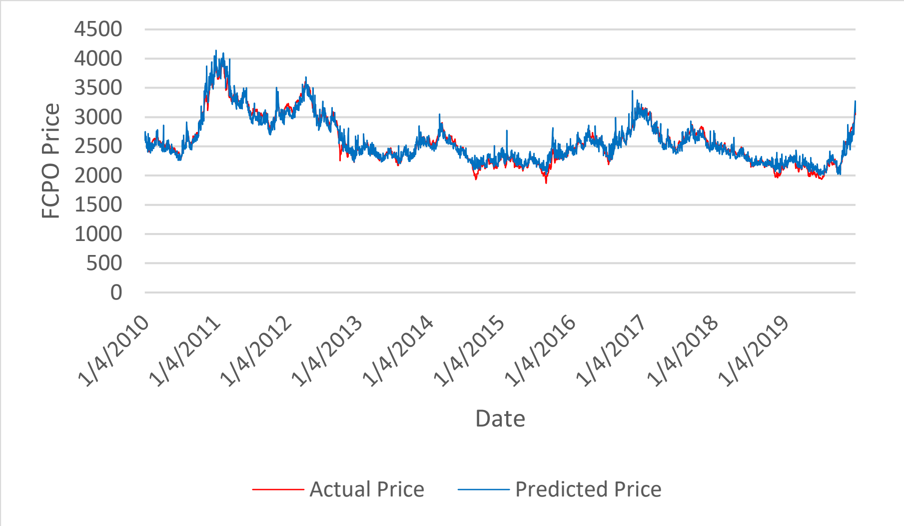

Fig. 4 Predicted Price using Sigmoidal Function with 2 Hidden Neurons

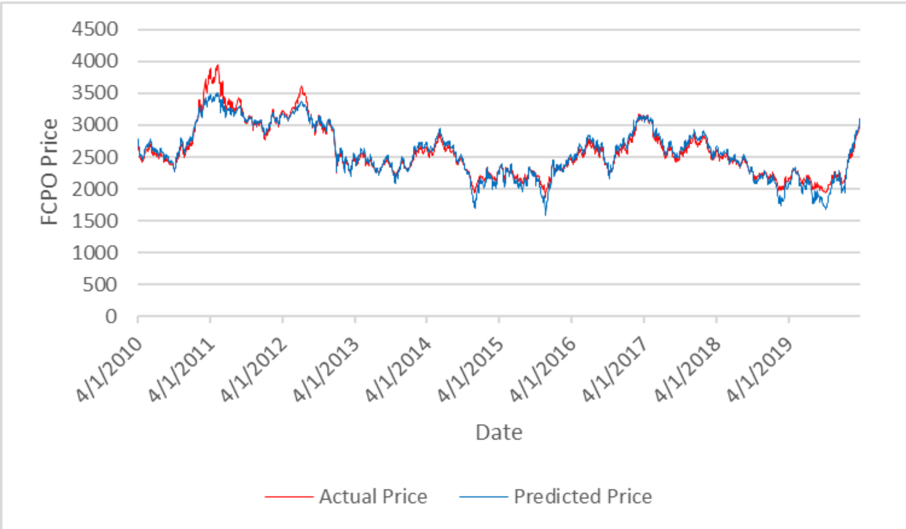

Fig. 5 Predicted Price using Radial Basis Function with 2 Hidden Neurons

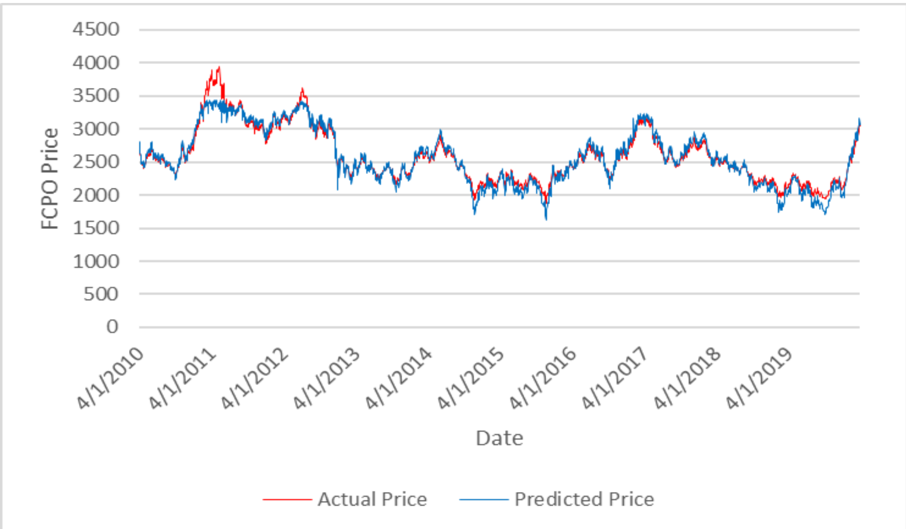

Fig. 6 Predicted Price using Sine Function with 3 Hidden Neurons

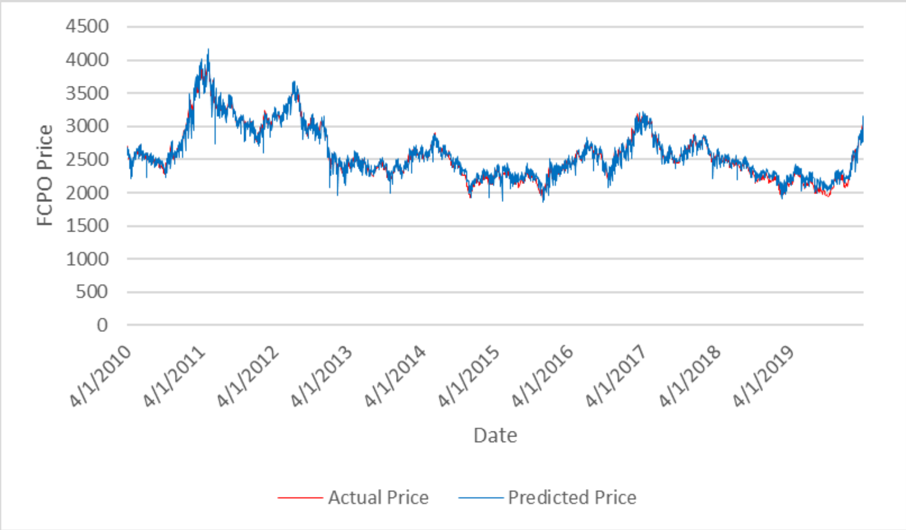

Fig. 7 Predicted Price using Radial Basis Function with 3 hidden neurons

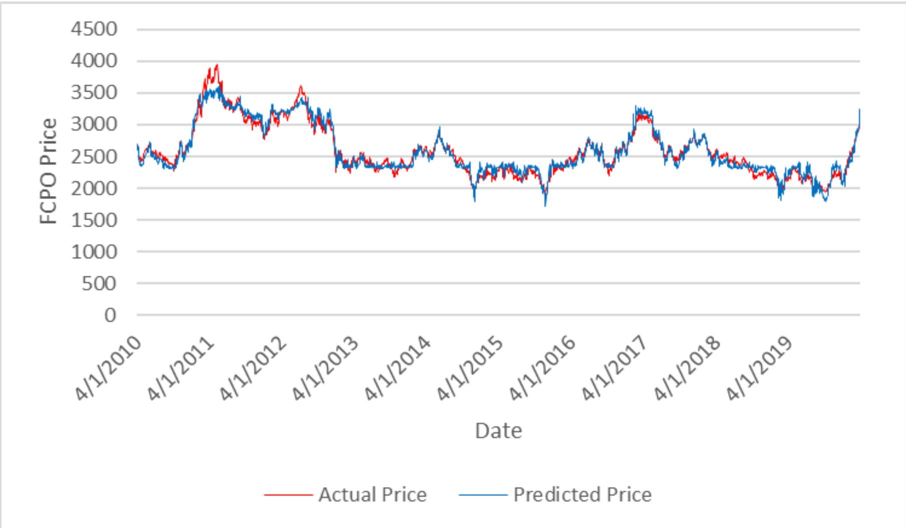

Fig. 8 Predicted Price using Triangular Basis Function with 4 Hidden Neurons

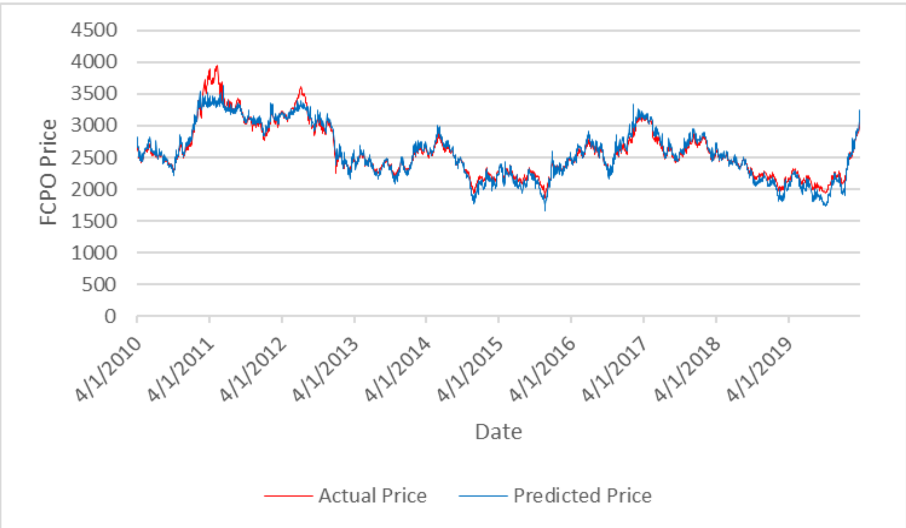

Fig.9 Predicted Price using Radial Basis Function with 4 Hidden Neurons

observed in the figures above, it is possible to predict prices of FCPO by using its historical data, thus refuting EMH [13],[14],[15]. The predicted price of FCPO using the radial basis function with 2, 3 and 4 hidden neurons provides the highest testing and training accuracy as compared to other activation functions [16],[17]. This indicates that the radial basis function is the optimal predicting parameter as compared to other activation functions such as the sigmoidal, sine and triangular basis functions. The testing and training time of it is close to 0, which means it is predicted without much problem.

IV. Conclusion

Future price prediction is important for investors and businesses to plan ahead and avoid any unnecessary risks. Therefore, this paper has proposed a neural network learning model for prediction of FCPO price. Among different numbers of hidden neuron and activation function, we seek out the optimum number of hidden neurons for each activation function as various numbers of hidden neurons could be troublesome for future researchers. Consistent with previous findings carried out using ELM model for prediction [18],[19],[20]. This study found that ANN trained by ELM produces accurate results with a low training time. This study also shows that the prediction of FCPO price is possible by using ELM supplemented by the historical price data as the training and testing data.

So far, minimal attention is given to the learning method of neural network. This paper focuses on improving prediction accuracy using ELM. Through this study, the results show that ELM trained with the radial basis function is suitable to predict FCPO prices as it has a high testing and training accuracy. However, this study only comprises of in-sample forecasting technique and does not take external factors into consideration. As future work, additional parameters will be included into the AI system to improve the model.

ACKNOWLEDGMENT
Financial support from Universiti Malaysia Sarawak (UNIMAS) and Digital Sarawak CoE [UHSB/B-AM2018/083] are gratefully acknowledged.

References

[1] A. K. Rout, P. K. Dash, R. Dash, and R. Bisoi, “Forecasting financial time series using a low complexity recurrent neural network and evolutionary learning approach,” *J. King Saud Univ. - Comput. Inf. Sci.*, 2017, doi: 10.1016/j.jksuci.2015.06.002.

[2] B. Samanta, “Prediction of chaotic time series using computational intelligence,” *Expert Syst. Appl.*, 2011, doi: 10.1016/j.eswa.2011.03.013.

[3] S. R. and P. Norvig, *Artificial Intelligence A Modern Approach 2nd Ed.* 2019.

[4] M. A. A. Albadr and S. Tiun, “Extreme learning machine: A review,” *International Journal of Applied Engineering Research*. 2017.

[5] B. Yadav, S. Ch, S. Mathur, and J. Adamowski, “Assessing the suitability of extreme learning machines (ELM) for groundwater level prediction,” *J. Water L. Dev.*, 2017, doi: 10.1515/jwld-2017-0012.

[6] M. Fatih Aslan, K. Sabancı, and A. Durdu, “Different Wheat Species Classifier Application of ANN and ELM,” 2017.

[7] P. Paik and B. Kumari, “Stock Market Prediction Using ANN, SVM, ELM: A Review,” *Ijettcs*, 2017.

[8] J. Fan *et al.*, “Evaluation of SVM, ELM and four tree-based ensemble models for predicting daily reference evapotranspiration using limited meteorological data in

different climates of China," *Agric. For. Meteorol.*, 2018, doi: 10.1016/j.agrformet.2018.08.019.

[9] M. Shariati *et al.*, "Application of Extreme Learning Machine (ELM) and Genetic Programming (GP) to design steel-concrete composite floor systems at elevated temperatures," *Steel Compos. Struct.*, 2019, doi: 10.12989/scs.2019.33.3.319.

[10] K. Yan, Z. Ji, H. Lu, J. Huang, W. Shen, and Y. Xue, "Fast and accurate classification of time series data using extended elm: Application in fault diagnosis of air handling units," *IEEE Trans. Syst. Man, Cybern. Syst.*, 2019, doi: 10.1109/TSMC.2017.2691774.

[11] M. Rossi and A. Gunardi, "Efficient market hypothesis and stock market anomalies: Empirical evidence in four European countries," *J. Appl. Bus. Res.*, 2018, doi: 10.19030/jabr.v34i1.10111.

[12] Y. Kurihara and A. Fukushima, "The Market Efficiency of Bitcoin: A Weekly Anomaly Perspective," *J. Appl. Financ. Bank.*, 2017.

[13] D. Peón, M. Antelo, and A. Calvo, "A guide on empirical tests of the EMH," *Review of Accounting and Finance*. 2019, doi: 10.1108/RAF-02-2016-0031.

[14] D. Aggarwal, S. Chandrasekaran, and B. Annamalai, "A complete empirical ensemble mode decomposition and support vector machine-based approach to predict Bitcoin prices," *J. Behav. Exp. Financ.*, 2020, doi: 10.1016/j.jbef.2020.100335.

[15] M. Kashif, S. Saad, I. U. Chhapra, and F. Ahmed, "An empirical evidence of over reaction hypothesis on Karachi stock exchange (KSE)," *Asian Econ. Financ. Rev.*, 2018, doi: 10.18488/journal.aefr.2018.84.449.465.

[16] B. T. Pham, A. Shirzadi, D. Tien Bui, I. Prakash, and M. B. Dholakia, "A hybrid machine learning ensemble approach based on a Radial Basis Function neural network and Rotation Forest for landslide susceptibility modeling: A case study in the Himalayan area, India," *Int. J. Sediment Res.*, 2018, doi: 10.1016/j.ijsrc.2017.09.008.

[17] H. G. Han, Y. N. Guo, and J. F. Qiao, "Nonlinear system modeling using a self-organizing recurrent radial basis function neural network," *Appl. Soft Comput. J.*, 2018, doi: 10.1016/j.asoc.2017.10.030.

[18] F. Qiao, B. Li, Y. Zhang, H. Guo, W. Li, and S. Zhou, "A fast and accurate recognition of ECG signals based on ELM-LRF and BLSTM algorithm," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.2987930.

[19] M. R. Chen, G. Q. Zeng, K. Di Lu, and J. Weng, "A Two-Layer Nonlinear Combination Method for Short-Term Wind Speed Prediction Based on ELM, ENN, and LSTM," *IEEE Internet Things J.*, 2019, doi: 10.1109/JIOT.2019.2913176.

[20] W. Fu, K. Wang, C. Li, and J. Tan, "Multi-step short-term wind speed forecasting approach based on multi-scale dominant ingredient chaotic analysis, improved hybrid GWO-SCA optimization and ELM," *Energy Convers. Manag.*, 2019, doi: 10.1016/j.enconman.2019.02.086.