Supanee Harnphattananusorn

Article

Relationship between Thai Baht and oil price : a neural network model

International Journal of Energy Economics and Policy

Reference: Supanee Harnphattananusorn (2020). Relationship between Thai Baht and oil price : a neural network model. In: International Journal of Energy Economics and Policy 10 (1), S. 371 - 376.
https://www.econjournals.com/index.php/ijeep/article/download/8612/4795.
doi:10.32479/ijeep.8612.

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2020, 10(1), 371-376.

Relationship between Thai Baht and Oil Price: Artificial Neural Network Model

Supanee Harnphattananusorn*

Department of Economics, Faculty of Economics, Kasetsart University, Bangkok 10900, Thailand. *Email: hsupanee@gmail.com

Received: 22 August 2019 **Accepted:** 07 November 2019 **DOI:** https://doi.org/10.32479/ijeep.8612

ABSTRACT

The research aims to investigate the relationship between the exchange rate of Thai Baht against USD and oil price using daily data from January 1999 to March 2019. To test whether there is the long-run relationship between selected variables, the Johansen cointegration method is employed. The results indicate the evidence of long-run relationship between oil price and the Thai Baht. Then, Artificial Neural Networks (ANN) technique is employed for estimation. For ANN estimation, the results suggest that the most influential variables for the Thai Baht is gold price and oil price is the third influential variable for Thai Baht. The research applies the mean squared error, root mean square error and the mean absolute percentage error to measure the error. The results suggest that ANN estimation is more efficient than linear model in term of error estimation.

Keywords: Thai Baht, Artificial Neural Network, Cointegration
JEL Classification: A1

1. INTRODUCTION

Thailand is an oil importing country indicating by the country is highly dependent on imported energy. In 2018, Thailand crude oil import was 55.192 thousand barrels per day, increasing from 2017 by 4.9%. The total value of crude oil import was 27.799 billion U.S. dollar which was almost 8 billion U.S. dollar more than in 2017. Compared with the domestic demand, the production of crude oil from indigenous resources was about 14% of oil consumption therefore, there was a need to import crude oil at a high rate of around 86%.

An exchange rate analysis is one of the fundamental topics for macroeconomics researchers. There are many literatures about predicting exchange rate but it still has not been yet the conclusion about the theory and methodological. The prediction of exchange rate is still the challenging task in recent researches. Researchers still try to solve the mystery of exchange rate movements. In 1983, Meese et al. observed that prediction through different structural models which were based on fundamental economics and assets price did not perform better than the simple random walk (RW) model.

Crude oil prices play an important role in financial markets and the global economy. There are many literatures indicated the importance of oil prices for exchange rate movements, for examples, Fratzscher, et al. (2014), Sh and Hu (2007), Camarero and Tamarit (2002), Amano and Norden (1998a,1998b), McGuirk (1983), Krugman (1983a, 1983b), Golub (1983) and Rogoff (1991). The channels of transmission through which changes in oil prices can affect exchange rates have been described as an increase in oil prices will lead to a deterioration of the trade or current account balance and subsequently to a depreciation of the domestic currency. Additionally, oil prices can also affect exchange rates through portfolio reallocation, Golub (1983) showed that higher oil prices lead to wealth transfer from oil importers to oil exporters. Theoretically, an increase in oil prices should lead to a real appreciation of the oil exporters and real depreciation of the oil importers. The complex and dynamic relationship between exchange rate and oil prices has been attended from of the policymakers, researchers, and the general public.

Forecasting the exchange rate, there are generally two classes of estimation which are the econometric model and artificial neural network (ANN) model. For the high frequency data, autoregressive integrated moving average model, autoregressive moving average model, generalized autoregressive conditional heteroskedasticity are techniques that used for times series econometrics method. For the ANN based models, they have given consistent performance in prediction by overcoming the linearity limitations of above-mentioned models and have outperformed all the models in terms of efficiency measuring by error estimation.

The non-linear, volatile and chaotic nature of exchange rate coupled with a large number of factors that affect the exchange rate makes the prediction of exchange rate a challenging and difficult task. In the recent past, ANNs have gained popularity as an effective tool for forecasting purposes and they have been successfully employed to forecast oil prices by various researchers across the world (Zhang et al. (1998). Many literatures, for examples, Nagpure (2019), predicted top traded currencies in the world using different deep learning models. The deep learning model using support vector regressor, ANN, long short-term memory, and neural network with hidden layers was applied for estimation. The result showed that the average accuracy of the predicting model exceeds 99%. Sun and Chang (2017) applied radial basis function neural network (RBFNN) to forecast exchange rates of USD/EUR, USD/CHY and JPY/USD. The results showed that RBFNN has the ability to detect the complex nonlinear relationships between dependent and independent variables. Cagatay and Demir (2017) forecasted TRY/USD exchange with different learning algorithms, activation functions, and performance measures. The results showed that backpropagation learning algorithm and tan-sigmoid activation function have the best performance for TRY/USD exchange rate forecasting. Yuxi (2017) studied on exchange rate forecasting using recurrent neural networks and found that RNN perform better than other methods. Sun (2012) utilized back propagation neural network (BPNN) for forecasting Chinese currency RMB. The RMB forecasting from BPNN is precise and efficient. Bissoondeeal et al. (2011) compared UK/US exchange rate forecasting performance of linear and nonlinear models based on monetary fundamentals, to a RW model. They concluded that the most accurate forecasts of the UK/US exchange rate are obtained with a nonlinear model. Chakradhara and Narasimhan (2007) compared the forecasting accuracy of neural network with that of linear autoregressive and RW models using Indian rupee/US dollar exchange rate. They found that neural network has superior in-sample forecast than linear autoregressive and RW models. Lisi and Schiavo (1999) have compared the performance of neural networks and chaotic models with the RW model. The monthly exchange rates of DEM, Italian lira French franc, and GBP against USD are taken for the study from 1973 to 1995. The results showed that both neural networks and chaotic models perform better than RW model and neural network perform slightly better than the chaotic model. Yao et al. (1996) applied NNR model to forecast the exchange rates of GBP, DEM, JPY, CHF, and AUD against USD from 1984 to 1995 using weekly data. They concluded that NNR models give better results.

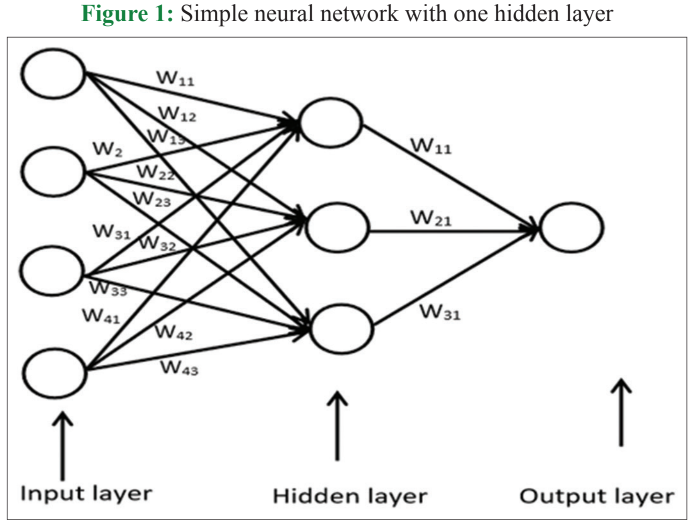
This paper intends to contribute for an empirical study of relationship between the exchange rate of Thai Baht against USD and crude oil price. We introduce crude oil price and a set of asset prices (gold price and US fixed deposits rates) together with volatility index to explain Thai Baht. We estimate models of the BAHT/USD using feed forward ANN (FANN) with BP algorithm and evaluate whether the FANN model is better than the linear model. The rest of the paper is organized as follows; the next section is the structure of the ANN model. Section 3 is the statistics of the time series data. Section 4 is the methodology of the study. Section 5 is the results of the study. The last section is the conclusion.

2. STRUCTURE OF A NEURAL NETWORK MODEL

The neural network model was developed by McCulloch and Pitts in 1943. The model applied working process of human brain to develop algorithms that can be used to estimate, predict and solve the optimization problems. It is a computational method. ANN has been used by many researchers in many fields, for examples, economic, engineering, and transportation etc. since the ANN has more advantage in term of non-linear and dynamic estimation than traditional linear estimation techniques. ANN can solve for complex relationship between input and output.

The structure of ANN are composed of neurons, layers, learning process algorithm and the activation function. The simple and the most popular type of neural network is multi-layer perceptron (MLP). The MLP architecture has an input layer, hidden layers (there can be more than 1) and the output layer. It is called MLP because it consists of multiple layers. It has interconnection between all neurons in a network. Each neuron in a layer is connected to all the neurons of the next layer, and the neurons in one layer are not connected among themselves. The neurons are grouped in to layers. There are different types of MLP such as recurrent networks, feed-forward networks, etc. If there is one direction information processing from the inputs toward outputs throughout the network, then the network is referred as a feed-forward neural network. If

Figure 1: Simple neural network with one hidden layer



there exists such a feedback, i.e. a synaptic connection from the outputs towards the inputs (either their own inputs or the inputs of other neurons), then the network is called a "recurrent neural network."

The simple feed forward network, with one hidden layer and three neurons, is shown in Figure 1. It can be seen that the flow of information is only one direction from inputs to outputs. Each arrow represents a connection between two neurons. Each connection has a weight, a real number, which used to controls the signal between the two neurons using learning process algorithms. The widely learning process algorithm is BP which was introduced by Werbos (1974). The BP algorithm distributed the error term back up through the layers, by modifying the weights at each node. There are many BP algorithms such as Levenberg-Marquadt, BFGS Quasi-Newton, resilient BP, scaled conjugate gradient.

Activation functions provide the non-linear mapping between input and output. The performance of ANN estimation depends on the choice of activation function. Each neuron in a network receives "weighted" information via these synaptic connections from the neurons that it is connected to and produces an output by passing the weighted sum of those input signals (either external inputs from the environment or the outputs of other neurons) through an "activation function." In summary, the activation function captures non-linear relationship between the inputs and convert the input into an output, making neural network can learn and perform complex task.

3. DATA

This research uses the daily data form January 1999 to March 2019. The exchange rate is defined as BAHT/USD, in addition, oil prices are used together with the multi-asset price which includes US time deposit (as a measure of US monetary policy and economic activity), the gold price (as a proxy for assets holding in the international system), the VIX (for global volatility) for predicting the Thai Baht exchange. The British price of oil (Brent) is used as a proxy for world oil price.

Table 1 shows basic statistics of the data including maximum and minimum values, skewness, kurtosis, mean, median, and Jarque-Bera test. Figure 2 shows time series of all variables used in the estimation. It can be seen that all variables are movement with trend. However, we need to test stationary properties for supporting the unit root properties.

Table 1: Data statistics

Statistics	BAHT	VIX	TED	GOLD	BRENT
Mean	35.77336	19.68540	0.436791	908.6768	62.20802
Median	34.45000	17.55500	0.310000	952.2500	59.70500
Maximum	45.82000	80.86000	4.580000	1895.000	145.3100
Minimum	28.60000	9.140000	0.090000	255.9500	17.50000
Standard deviation	4.567369	8.626971	0.411559	464.2007	26.91173
Skewness	0.545210	2.117516	3.765221	0.017607	0.344510
Kurtosis	1.993267	10.15321	23.35268	1.659720	2.167011

Source: Author's calculation

4. METHODOLOGY

4.1. Unit Root Test

The tests for stationary of time series that will be used in this study are unit root test, those are the augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) and KPSS (Kwiatkowski et al., 1992) For the ADF test, the null hypothesis is "series has unit root, or I(1)." If the test has a significant, it means that series is stationary and does not has a unit root test, so the null hypothesis will be rejected but alternative hypothesis will be accepted. For the KPSS, it tests the null hypothesis that the time series is stationary or I(0), which null hypotheses are defined reversely with ADF. KPSS test is based on LM test. The Johansen cointegration, then, are applied for testing long run relationship dependent and independent between variables.

4.2. Feed Forward Neural Network Approach

For the ANN model, the number of input and output are set by the problem statement. In this paper, the most popular feed forward neural network MLP is selected. The information from four neuron of inputs flow forward to the hidden layer and finally to the single neuron of output layer. The first layer is the input layer which correspond to the independent variables (oil price: Brent, gold price: Gold, US time-deposit rate: TED, and volatility index: VIX) in the model. The second layer is hidden layer which consists of all possible connection between the input and output layers, and allows for combined impact of a multiple set of independent variables on the output layer. In this paper, two hidden layers are applied. The third layer is output layer which correspond to the dependent variables or Thai Baht exchange rate.

As shown in Figure 3, ANN model consists of a number of processing element which is called nodes or neurons. Each neuron is connected to other neurons by directed link. Each connection has an associated weight. The weights are the parameters which are used to solve a problem. In Figure 3, each neuron in the first hidden layer compute $y_j\left(j=1,2,3\right)$ by applying a sigmoid function, $y_j=\frac{1}{1+e^{-f_j}}$ where $f_j=\sum_{i=1}^{4}x_i w_{ij}$ is the sum of weighted input signals of the first hidden layer, x_i are the input variables, w_{ij} is the weight of the link from input i (input layer) to first hidden layer neuron j. The second hidden layer compute y_k (k=1) from the previous hidden layer output (y_j) as shown by $y_k=\frac{1}{1+e^{-g_k}}$, where $g_k=\sum_{j=1}^{3}y_j w_{jk}$ is the sum of weighted for the second hidden layer, w_{jk} is the weight of the link from first hidden layer neuron j to second hidden layer neuron k = 1. The output Y which is the solution of the problem in the output layer is calculated from $Y= y_k w_k$.

For learning algorithm, a feed forward neural network learns from a supervised training data to discover patterns connecting input and output variables. The BP learning algorithm gives the network the ability to form and modify its own interconnections in a way that often rapidly approaches a goodness-of-fit optimum. This paper uses resilient BP algorithm because it can combine fast convergence, stability and generally good results (Fernandes and Teixeira, 2008).

Figure 2: Movement of the variables

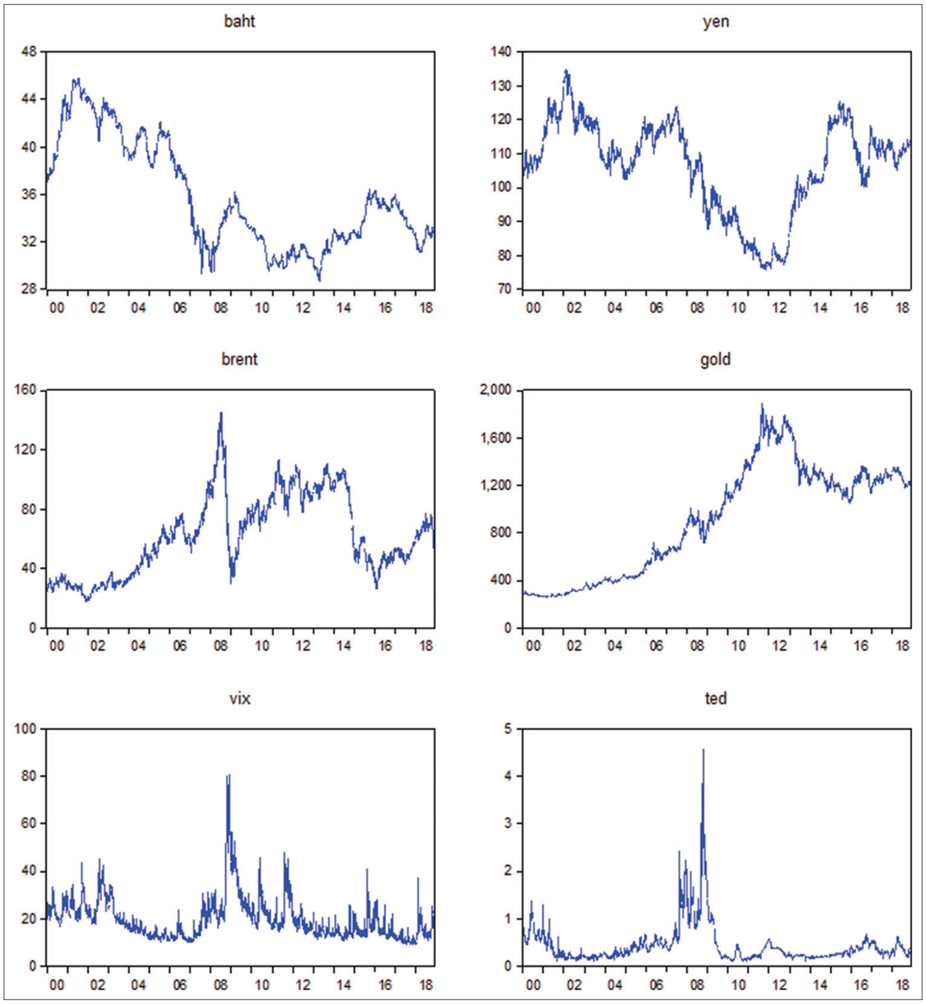
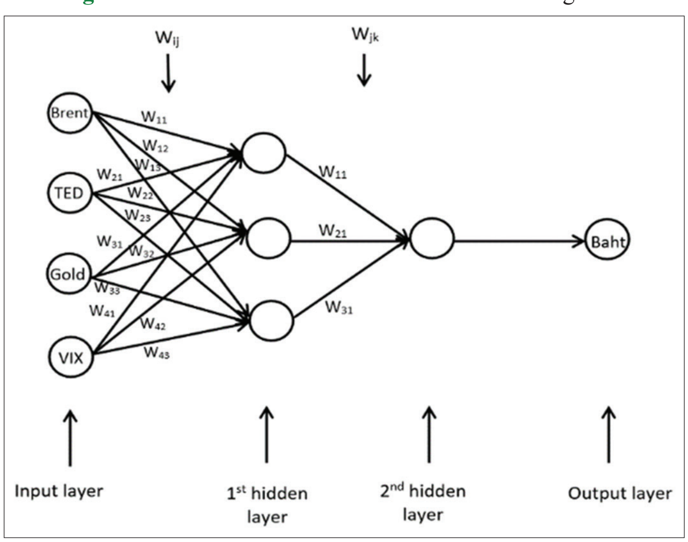


Figure 3: Artificial neural network model of exchange rate



5. RESULTS

5.1. Unit Root and Cointegration Results

The results of unit root test using both ADF and KPSS test are shown in Table 2. According to the ADF tests, we cannot reject the null hypothesis menaing that all series have order of integration at 1st difference or I(1). Next, whether or not exchange rate are cointegrated with oil prices and all explanatory variables are tested by using Johansen (1988) test. Table 3 shows the Johansen cointegration test and the results are concluded from the trace and max-eigenvalue statistics. There is one cointegrating vector of long run relationship between exchange rate and explanatory variables including oil price.

5.2. ANN Results

The parameter for ANN estimation are shown in Table 4. For the ANN estimation, the optimum network is 3 neurons for the first hidden layer and 1 neurons for the second hidden layer as shown in the Figure 4. Each line in Figure 4 shows the weights connecting the independent variables or inputs layer to first and second hidden layer and the weights connecting second hidden layer and output. The weights are calculated using the resilient BP algorithm.

Figure 5 shows the relative important of the variables, the important variables that affecting Thai Baht are ranked from highest to lowest as following; gold price, time deposits rate, oil price, and volatility index. According to the results of relative important variables, oil price has positive impact on exchange rate of BAHT/USD. An increase in oil price leads to an increase in exchange rate or Baht devaluation.

Table 2: Unit root test

Series	Augmented Dickey-Fuller test (At Level)				KPSS test (At Level)	
	None	Intercept	Intercept and trend	Lag	Constant and trend	Constant
	(P-value)				KPSS_stat.	
BAHT	0.7162	0.3129	0.5956	11	2.1802	9.3154
BRENT	0.5772	0.3986	0.7055	5	2.1148	4.9210
GOLD	0.5907	0.5045	0.8274	0	1.9718	11.751
VIX	0.0608	0.0189	0.1149	10	0.5371	1.7876
TED	0.9919	0.9996	1.0000	8	0.6712	0.9414

Source: Author's calculation

Table 3: Long run cointegration results

Test type	No intercept no trend	Intercept no trend	Intercept no trend (Linear)	Intercept trend (Linear)	Intercept trend (Quadartic)
Trace	1	1	1	1	1
Max-Eig.	1	1	1	1	1

Source: Author's calculation

Table 4: Parameter for artificial neural network estimation

Items	Specification in the model
Training data	Random 80%
Testing data	Random 20%
Algorithm	Resilient back propagation
Activation function	Tan sigmoid function
Number of input	Four
Input hidden layer	Two hidden layers with three neurons (J=1,2,3) at first hidden layer and one neuron (k=1) at the second layer
Error function	Sum square error function

Table 5: Efficiency of the model

Measurement Error	LM	NN
MSE	3.1653	1.4652
MAE	1.4066	0.9032
RMSE	1.7791	1.2104

Figure 6 is the scatter plot between predicted value and actual value for both ANN and linear model for the testing set of value. The closer prediction alignment with the straight line the more efficient prediction of ANN. If all the prediction are on the line, it means error is zero. We can see that the predictions made by the neural network (left panel) are more alignment around the line than the linear model (right panel). The results indicate that selected ANN model dominates linear model and produced better out-of-sample forecasts, since ANN is able to capture any non-linear as well as linear functional dependencies of the variables.

Figure 4: Weight of independent variables

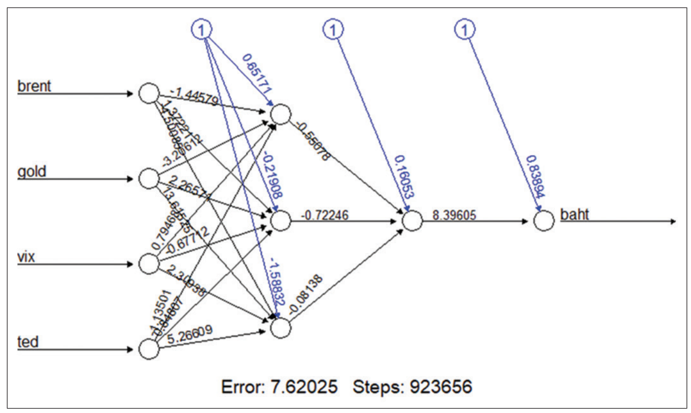
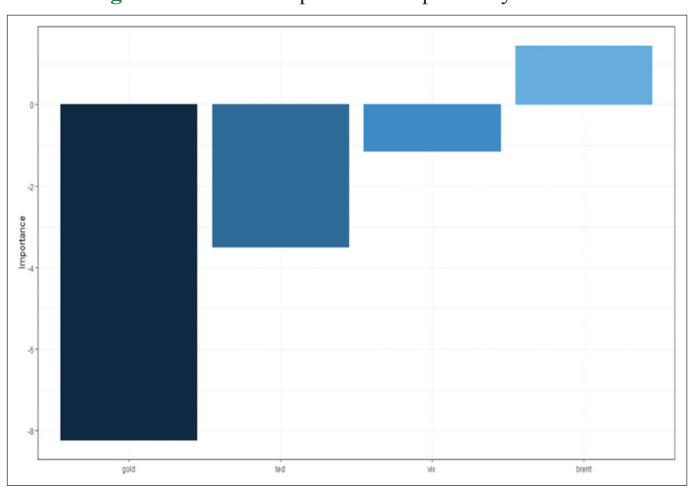


Figure 5: Relative important of explanatory variables



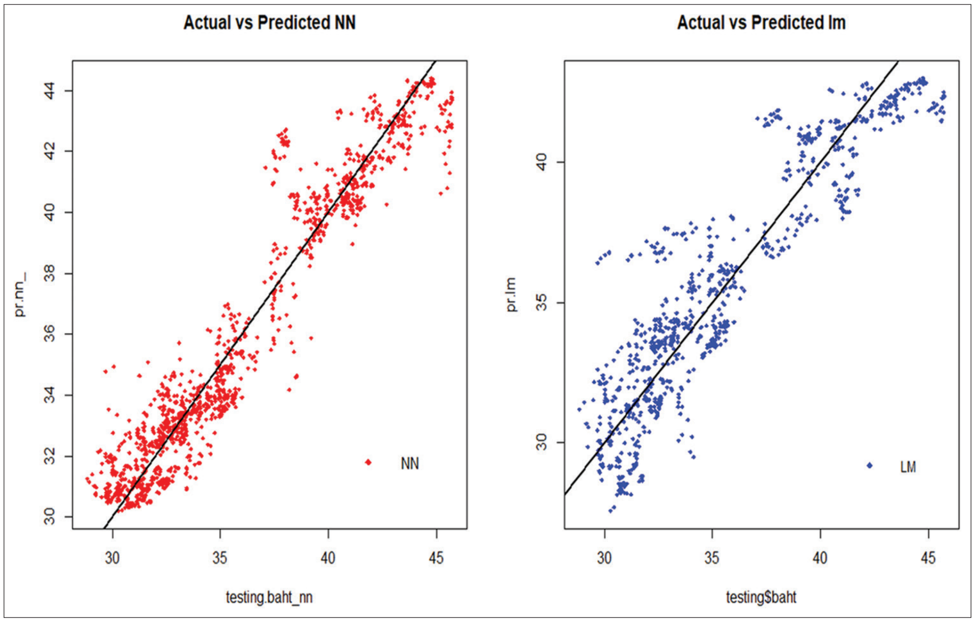
5.3. Efficiency of the Model

For assessments the efficiency of the model, this research applies the mean squared error (MSE), the root mean square error (RMSE), and the mean absolute percentage error (MAPE) to measure the error estimation. Those are the difference between the forecasted value and actual value. MSE is one of many ways to quantify the amount by which a value of estimator differs from the actual value, as shown in Table 5. MSE measures the average of the square of the error and RMSE is square root of MSE. MAPE is the value that indicates the error in absolute term.

6. CONCLUSION

The research aims to investigate the relationship between the Thai Baht exchange rate and world oil price using multi-assets approach

Figure 6: Scatter plot of predicted versus actual value



for set up the model. The daily data from January 1999 to March 2019 are used for estimation. The results show that there is one cointegrating vector indicating that there is a long-run linkage between Thai Baht exchange, oil price and selected asset prices. Then, we use ANN for estimation and prediction. The results show that the relative important variables that affecting the Thai Baht is gold price, oil price, volatility and US deposit rate respectively. RMSE, MAE, and MSE are used for efficiency evaluation. The results show that the ANN model performs better than the linear model. According to the results, multi–assets prices have relationship with the Thai Baht, the policy makers should strongly prepare for the impact of global uncertainty on the internationally traded assets prices alongside with the macroeconomic real variables.

REFERENCES

Amano, R., Norden, S. (1998b), Oil prices and the rise and fall of the US real exchange rate. Journal of International Money and Finance, 17(2), 299-316.

Amano, R.A., Norden, S. (1998a), Exchange rates and oil prices. Review of International Economics, 6(4), 683-694.

Bissoondeeal, R.K., Karoglou, M., Gazely, A.M. (2011), Forecasting the UK/US exchange rate with divisia monetary models and neural networks. Scottish Journal of Political Economy, 58, 127-152.

Cagatay, B., Demir, S. (2017), Forecasting TRY/USD exchange rate with various artificial neural network models. TEM Journal, 6(1), 11-16.

Camarero, M., Tamarit, C. (2002), Oil prices and Spanish competitiveness: A cointegrated panel analysis. Journal of Policy Modeling, 24(6), 591-605.

Chakradhara, P., Narasimhan, V. (2007), Forecasting exchange rate better with artificial neural network. Journal of Policy Modeling, 29(2), 227-236.

Dickey, D., Fuller, W. (1981), Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49, 1057-1072.

Fernandes, P.O., Teixeira, J.P. (2008), Prediction Tourism Demand Using Artificial Neural Networks, International Conference in European Union's History, Culture and Citizenship, Pitesti.

Fratzscher, M., Schneider, D., Van Robays, I. (2014), Oil Prices, Exchange Rates and Asset Prices. European Central Bank. Working Paper Series No 1689.

Golub, S.S. (1983), Oil prices and exchange rates. Economic Journal, 93, 576-593.

Johansen, S. (1988), Statistical analysis of co-integration vectors. Journal of Economic Dynamics and Control, 12, 231-254.

Krugman, P. (1983a), Oil and the dollar. In: Economic Interdependence and Flexible Exchange Rates. Cambridge: MIT Press.

Krugman, P. (1983b), Oil shocks and exchange rate dynamics. In: Frankel, J.A., editor. Exchange Rates and International Macroeconomics. Chicago: University of Chicago Press.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y. (1992), Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics, 54, 159-178.

Lisi, F., Schiavo, R.A. (1999), A comparison between neural networks and chaotic models for exchange rate prediction. Computational Statistics and Data Analysis, 30(1), 87-102.

McGuirk, A. (1983), Oil price changes and real exchange rates movements among industrial countries. IMF Staff Papers, 30, 843-883.

Nagpure, A.R. (2019), Prediction of multi-currency exchange rates using deep learning. International Journal of Innovative Technology and Exploring Engineering, 8(6), 316-322.

Rogoff, K. (1991), Oil, Productivity, Government Spending and the Real Yen-Dollar Exchange Rate. San Francisco, CA: Federal Reserve Bank of San Francisco Working Paper.

Sh, C., Hu, C. (2007), Oil prices and real exchange rates. Energy Economics, 29, 390-404.

Sun, A., Chang, J.F. (2017), Application of radial basis function neural network to predict exchange rate with financial time series. International Journal on Smart Sensing and Intelligent Systems, 10(2), 308-326.

Sun, Y. (2012), RMB exchange rate forecast approach based on BP neural network. Physics Procedia, 33, 287-293.

Werbos, P.J. (1974), Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences. Ph.D. Thesis, Harvard University.

Yao, J.T., Poh, H.L., Jasic, T. (1996), Foreign exchange rates forecasting with neural networks, In: Proceedings of the International Conference on Neural Information Processing, Hong Kong: J. and Tan, C. L. p754-759.

Yuxi, Y. (2017), Study on exchange rate forecasting using recurrent neural networks. International Journal of Economics, Finance and Management Sciences, 5(6), 300-303.

Zhang, G.P., Patuwo, E.B., Hu, M.Y. (1998), Forecasting with artificial neural network: The state of the art. International Journal Forecasting, 115, 35-62.