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Forecasting Exchange Rates between Malaysian Ringgit and Chinese Yuan with Neural Network

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Abstract

Forecasting exchange rates influences the investment decision-making of investors, traders and countries in international trading. This paper uses a neural network model to discuss the Malaysian Ringgit (RM) forecasting exchange rates against the Chinese Yuan (CNY). For this purpose, historical data on exchange rates from 1 January 2022 to 24 October 2023 at the Malaysia Central Bank's official website are collected and normalized. The weights are randomly chosen in the neural network model, and the bias parameter is set to one. A loss function representing the mean squares error and a sigmoid activation function is defined. The forward propagation is conducted along the input, hidden and output layers. To minimize the loss function, the backpropagation is carried out, in turn, to update the weight and bias parameters iteratively. The exchange rates are satisfactorily estimated once convergence is achieved. After this, the effect of forecasting exchange rates using different numbers of neurons on the input and hidden layers is investigated. In the end, a comparison of forecasting accuracy between the neural network model and time series methods shows that the neural network is the best model for forecasting exchange rates of RM/CNY.

1. Introduction

The exchange rate, also known as the rate of exchange, foreign exchange rate or currency exchange rate, is defined as the rate at which one currency can be converted into another [1]. In international trading, exchange rates play a crucial role because the exchange rate can influence trading costs, as evidenced by a study conducted on 12 African countries that showed the exchange rate affects international trade flows [2]. The United States dollar (USD) has dominated international trade for many decades. Still, China's rapid growth, particularly with the One Belt One Road initiative in 2013, has made the Chinese Yuan (CNY) an increasingly popular alternative. It became the fifth most traded currency in 2022 [3]. Recently, the high currency exchange rate of the USD to the Malaysian Ringgit (RM) caused investors, traders, and manufacturers to pay a higher cost in trading, causing their businesses to suffer a loss.

In contrast, the CNY to RM exchange rate is lower, and it is more advantageous for those using the CNY in trading since they can save costs. Therefore, the exchange rate between the CNY and RM is essential. Besides that, China, being Malaysia's largest trading partner, highlights the significance of the exchange rate between the two countries as it can significantly impact economic activity [4]. Therefore, forecasting exchange rates between CNY and RM is essential for investors, traders, and governments engaged in trading activities.

Forecasting is a widespread technique in various areas such as business, finance, healthcare, and engineering. It uses historical time-based data points to estimate future values [5]. Exchange rates are characterized by volatility and uncertainty, where the movement of the rates is randomly up and down, and the forecasting task is challenging due to the influence of various factors. Addressing these challenges, multiple methods are available for forecasting exchange rates, each with its techniques and level of accuracy. The neural network technique is one of the most common methods for forecasting exchange rates. A neural network is a computational model consisting of linked nodes known as neurons that work together to process and analyse data in a way inspired by the human brain [6]. There are many types of neural networks suited for exchange rate forecasting. Still, each type of neural network has advantages and disadvantages, and their performance depends on the specific characteristics of the time series data. Other previous studies were done in using forecasting method with the statistics technique in worldwide according to various fields of studies [7, 8, 9, 10].

The main aim of our study is to apply a neural network model for forecasting currency exchange rates of RM against CNY, where its computational procedure is delivered. Our analysis uses the curve fitting concept in forecasting without considering the factors influencing currency exchange rates. A single hidden layer neural network is considered for efficient computation in forecasting currency exchange rates. Therefore, there are three objectives in the study. The first objective is to design an appropriate neural network architecture, including input, hidden, and output layers with different numbers of neurons suitable for forecasting purposes depending on the dataset. The second objective is to forecast the exchange rates between the RM and the CNY using the neural network technique and historical data of exchange rates in 2022, and the third objective is to demonstrate the accuracy of the neural network technique by comparing the mean square error with the simple moving averages and exponential smoothing. Throughout this study, the neural network modelling and its computational procedure for forecasting currency exchange rates are interpreted. Hence, an efficient computational technique for predicting the currency exchange rate of RM against CNY is provided.

2. Materials and Methods

Consider a set of exchange rates of RM to CNY given by

$$y = \{y_1, y_2, y_n\}, \tag{1}$$

where y is $n \times 1$ vector of exchange rates, n is the number of exchange rates. Define a loss function,

$$J(\theta) = \frac{1}{n}(y - \hat{y}(\theta))^T (y - \hat{y}(\theta)), \tag{2}$$

where

$$\hat{y}(\theta) = f(\theta) \tag{3}$$

is the estimated exchange rates, f is an activation function and θ is a set of unknown weight and bias parameters.

Therefore, we aim to estimate the unknown parameters in a chosen activation function (3) for minimizing the loss function (2). In this way, the neural network model can forecast the actual exchange rates in the future.

2.1 Neural Network Computational Approach

The computational approach in a neural network is divided into three stages: forward propagation, function activation evaluation, and backpropagation [11]. In the forward propagation stage, we consider a general three-layer neural network representation, which has an input layer, a hidden layer and an output layer as shown in Figure 1. Define the input vector of the neurons in the input layer as

$$x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}, \tag{4}$$

where n is the number of neurons in the input layer. Consider the neurons in a single hidden layer that receive input x given by

$$z = Wx + b, \tag{5}$$

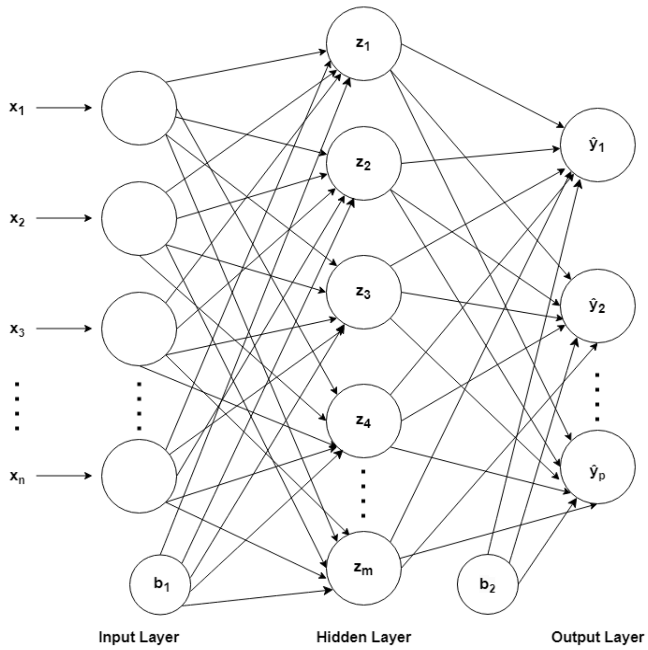

Fig. 1 *Three-layer neural network representation*

where

$$z = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{pmatrix}, \; W = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{pmatrix} \text{ and } b = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{pmatrix} \tag{6}$$

are the neuron vector in the hidden layer, the weight matrix between the input layer and the hidden layer, and the bias vector in the input layer, respectively. Here, m is the number of neurons in the hidden layer.

In a single hidden layer, the neurons (5) are transformed through an activation function to be the input neurons for the next single layer or the output layer, as follows,

$$x' = f(z), \tag{7}$$

where x' is the output neurons at the related hidden layers. In the output layer, the output neurons are formed by

$$\hat{y} = f(z') \tag{8}$$

with the input neurons

$$z' = W'x' + b', \tag{9}$$

where

$$z' = \begin{pmatrix} z'_1 \\ z'_2 \\ \vdots \\ z'_p \end{pmatrix}, \; W' = \begin{pmatrix} w'_{11} & w'_{12} & \cdots & w'_{1m} \\ w'_{21} & w'_{22} & \cdots & w'_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w'_{p1} & w'_{p2} & \cdots & w'_{pm} \end{pmatrix} \text{ and } b' = \begin{pmatrix} b'_1 \\ b'_2 \\ \vdots \\ b'_p \end{pmatrix} \tag{10}$$

are the neuron vector in the hidden layer, the weight matrix between the hidden layer and the output layer, and the bias vector in the hidden layer, respectively. Here, p is the number of neurons in the output layer.

In the function activation evaluation stage, the function f is defined as follows,

$$f(z) = \frac{1}{1+e^{-z}}, \tag{11}$$

which is known as the sigmoid function, and its derivative is

$$\frac{d}{dz} f(z) = f(z)[1 - f(z)]. \tag{12}$$

In the backpropagation stage, we denote the unknown parameter as $\theta = (W, b)$. The optimal weight W and the optimal bias b are determined by minimizing the loss function (2), where the first-order necessary conditions [12] are given as follows:

$$\frac{\partial J}{\partial W} = 0, \frac{\partial J}{\partial b} = 0, \frac{\partial J}{\partial W'} = 0, \frac{\partial J}{\partial b'} = 0. \tag{13}$$

The following gradients are calculated from

$$\frac{\partial J}{\partial W} = -\frac{2}{n}(W')^{\mathrm{T}} \times (y - \hat{y}) \times f(z')[1 - f(z')] \times f(z)[1 - f(z)] \times x^{\mathrm{T}}, \tag{14}$$

$$\frac{\partial J}{\partial b} = -\frac{2}{n}(W')^{\mathrm{T}} \times (y - \hat{y}) \times f(z')[1 - f(z')] \times f(z)[1 - f(z)], \tag{15}$$

$$\frac{\partial J}{\partial W'} = -\frac{2}{n}(y - \hat{y}) \times f(z')[1 - f(z')] \times x'^{\mathrm{T}}, \tag{16}$$

$$\frac{\partial J}{\partial b'} = -\frac{2}{n}(y - \hat{y}) \times f(z')[1 - f(z')]. \tag{17}$$

Hence, the weight and bias parameters are updated by

$$W^{(i+1)} = W^{(i)} - \alpha_1 \times \left(\frac{\partial J}{\partial W}\right)^{(i)}, \tag{18}$$

$$b^{(i+1)} = b^{(i)} - \alpha_2 \times \left(\frac{\partial J}{\partial b}\right)^{(i)}, \tag{19}$$

$$W'^{(i+1)} = W'^{(i)} - \alpha_3 \times \left(\frac{\partial J}{\partial W'}\right)^{(i)}, \tag{20}$$

$$b'^{(i+1)} = b'^{(i)} - \alpha_4 \times \left(\frac{\partial J}{\partial b'}\right)^{(i)}, \tag{21}$$

where α_1, α_2, α_3 and α_4 are learning rates ranged from 0 to 1. During the iterative procedure, the stopping criterion

$$\left| J^{(i+1)} - J^{(i)} \right| < \varepsilon \tag{22}$$

within a given tolerance, ε is employed to terminate the iteration once the convergence is reached.

2.2 Time Series Approaches

This section presents time series methods, which are simple moving averages and exponential smoothing, to forecast exchange rates.

(a) Simple moving average

The simple moving average [13] considers the arithmetic mean of a set of values within a specific period. The formula of the simple moving average of an asset over a time t is given by

$$A_t = \frac{X_1 + X_2 + \cdots X_n}{n}, \tag{23}$$

where X_1, $X_2,\ldots,$ X_n are the prices of an asset within a specific time period and n is the number of the asset's prices in a specific time period.

(b) Simple exponential smoothing

The simple exponential smoothing [14] is a time series method that assigns exponentially decreasing weights to the historical data. The formula of the simple exponential smoothing is given by

$$F_{t+1} = \alpha A_t + (1-\alpha)F_t, \tag{24}$$

where A_t is the actual data at time t, F_t is the forecast data at time t and α is the smoothing factor ranging from 0 to 1. An initial data

$$F_1 = A_1 \tag{25}$$

is required to start the forecasting process.

3. Results and Discussion

The historical data on exchange rate of Malaysian Ringgit (RM) to the Chinse Yuan (CNY) was collected from 1 January 2022 to 24 October 2023. These data were retrieved from the official website of the central bank of Malaysia. There are 441 exchange rate data points in this period and these data are divided into two different periods as shown in Table 1. Here, the exchange rates in Period I are used to estimate weight and bias parameters. While the exchange rates in Period II are used to validate the forecasting result.

Table 1 *Datasets for forecasting*

Dataset	Number of Data	Period
I	243	1 January 2022 to 31 December 2022
II	198	1 January 2023 to 24 October 2023

At the beginning of the study, the historical data of exchange rate are normalized with the following equation,

$$\text{Normalized Exchange Rate} = \frac{\text{Actual Rate} - \text{Minimum Rate}}{\text{Maximum Rate} - \text{Minimum Rate}}. \tag{26}$$

The aim of the normalization of exchange rate is to ensure that these exchange rates are ranged from zero to one, and suitable to be managed during the calculation in neural network framework, especially in the evaluation of the activation function.

3.1 Forecasting Results

Table 2 shows the neural network configuration for forecasting in Period I. The initial condition for the weight is randomly chosen and the bias parameter is set to 1.

Table 2 *Neural network configuration for Period I forecasting*

Item	Value
Number of input neurons	3
Number of hidden neurons	5
Number of output neurons	240
Learning rate	0.01
Activation function	Sigmoid
Tolerance	1×10^{-9}

Figure 2 shows the forecasting solution of the exchange rate of RM/CNY in Period I. The forecasting points follow closely the actual exchange rates. The estimation errors for the exchange rate in Period I are shown in Figure 3, where these errors stay around zero but there are two jumps obviously occurred.

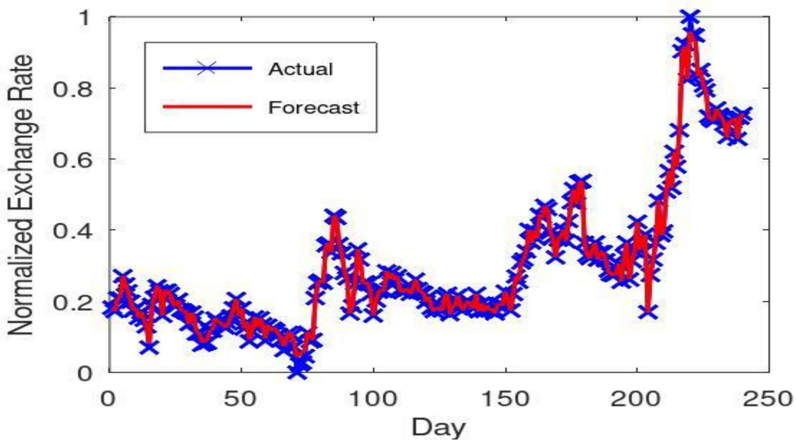

Fig. 2 *Forecasting solution of exchange rates of RM/CNY in Period I*

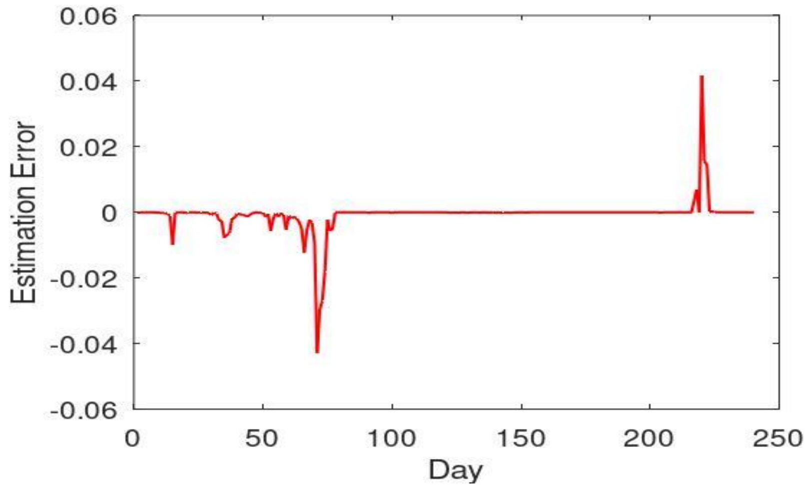

Fig. 3 *Estimation error of exchange rates of RM/CNY in Period I*

Table 3 shows the simulation results for forecasting exchange rates of RM/CNY in Period I. There are 49,180 iteration numbers to converge within 25.7 seconds. The loss function of 2.8289×10^{-5} units indicates that the forecasting result closely follows the actual exchange rates of RM/CNY and the loss function error of 9.9999×10^{-10} units present the mean square error (MSE) that measures the accuracy of output estimates and the value. Hence, the forecasting result for Period I using the neural network is satisfactorily accepted. Table 4 shows the neural network configuration for forecasting exchange rates in Period II. Only the forward propagation is conducted during the calculation procedure, where the estimated weights and biases obtained in Period I are applied in the neural network.

Table 3 *Simulation results for forecasting exchange rates*

Iteration Number	Elapsed Time (s)	Loss Function	Loss Function Error
49,180	25.74	2.8289×10^{-5}	9.9999×10^{-10}

Figure 4 shows the forecasting result of the exchange rates compared to the actual exchange rates. We observe that the forecasting result at the beginning does not follow the actual trend of the exchange rates, but the trends for 40 days to 50 days, 85 days to 110 days and after 165 days can be tracked satisfactorily. The loss function of 0.078830 is relatively large compared with the loss function of 2.8289×10^{-5} in the Period I forecasting. Figure 5 shows the estimation error for forecasting exchange rates in Period II.

Table 4 *Neural network configuration for Period II forecasting*

Item	Value
Number of input neurons	3
Number of hidden neurons	5
Number of output neurons	195
Learning rate	0.01
Activation function	Sigmoid
Tolerance	1×10^{-9}

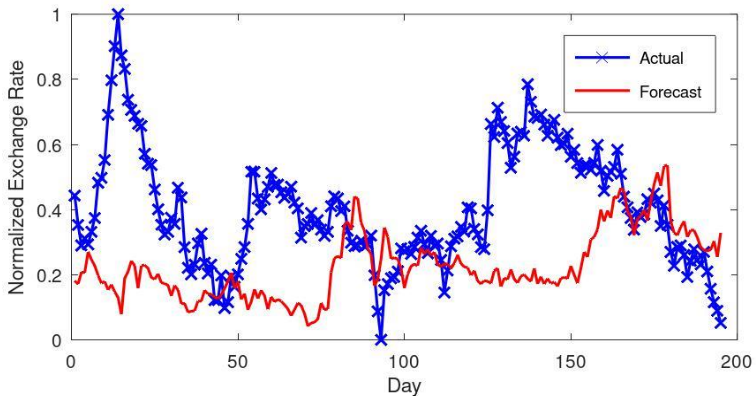

Fig. 4 *Forecasting solution of exchange rates of RM/CNY in Period II*

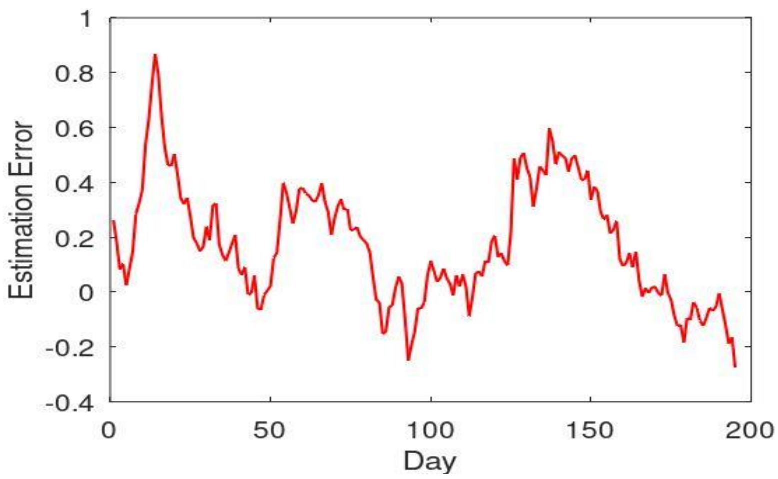

Fig. 5 *Estimation error of exchange rates of RM/CNY in Period II*

3.2 Results on Different Numbers of Neurons

This section discusses the results of using different numbers of neurons on the input and hidden layers. Table 5 shows the simulation results for the numbers of neurons in the input layer varying from 1 to 5, given that the number of neurons in the hidden layer is fixed at 10. It is noted that the increment of the input neurons requires an increasing iteration number to converge, which increases from 23,768 to 70,675. The loss function increases from 2.24×10^{-5} to 3.76×10^{-5} at a reduced rate when the number of input neurons increases.

Table 5 *Simulation results for different numbers of input neurons*

Input	Hidden	Output	Iteration	Loss Function
1	10	243	23,768	2.2468×10^{-5}
2	10	243	37,633	2.2469×10^{-5}
3	10	243	49,588	2.8152×10^{-5}
4	10	243	60,462	3.3103×10^{-5}
5	10	243	70,675	3.7567×10^{-5}

Table 6 shows the simulation results for using different numbers of neurons at the hidden layers. The number of hidden neurons varies from 3 to 15, while the number of input neurons is fixed at 10. It is noted that increasing the number of hidden neurons requires a relative increase in the respective iteration number from 112,591 to 139,876 to converge, and a constant value of the loss function of 5.62×10^{-5} is obtained.

Table 6 *Simulation results for different numbers of hidden neurons*

Input	Hidden	Output	Iteration	Loss Function
10	3	243	112,591	5.6234×10^{-5}
10	6	243	113,362	5.6243×10^{-5}
10	9	243	115,722	5.6298×10^{-5}
10	12	243	122,573	5.6326×10^{-5}
10	15	243	139,876	5.6229×10^{-5}

3.3 Performance Comparison

Table 7 shows a comparison performance measure of the forecasting accuracy using the neural network and the time series methods: a 2-day simple moving average, a 3-day simple moving average, and a simple exponential smoothing method with factors α = 0.1 and α = 0.5. The exchange rates in Period I are used for this comparison. From the loss function values, we notice that the neural network method has the smallest loss function value, which is the best model for foresting exchange rates of RM/CNY. The simple exponential smoothing with factors α = 0.1 shows the poorest performance among these methods.

Table 7 *Comparison of forecasting accuracy for exchange rate of RM/CNY*

Forecasting method	Loss Function
Neural Network Method	2.8289×10^{-5}
Two-day Simple Moving Average	2.6476×10^{-3}
Three-day Simple Moving Average	3.0545×10^{-3}
Simple Exponential Smoothing, $\alpha = 0.1$	8.5308×10^{-3}
Simple Exponential Smoothing, $\alpha = 0.5$	2.7212×10^{-3}

4. Conclusion

This paper discussed using a neural network to forecast RM/CNY exchange rates. A simple neural network representation with input, single hidden and output layers was presented, and the computational approach, including the forward propagation, activation function evaluation and error backpropagation, was explained systematically. For illustration, the historical data of exchange rates of RM/CNY was employed in the calculation procedure. The simulation results revealed that the neural network method provides an accurate forecasting result compared with time series methods. In conclusion, the efficiency of the neural network for forecasting exchange rates of RM/CNY is highly demonstrated. For future research, exploring alternative architectures of neural networks or adjusting the hyperparameters, including learning rate and activation function, is recommended to improve the forecasting results. Exploring other advanced neural network models, such as recurrent neural networks (RNNs) and long short-term memory networks, might give a better result. In addition, combining the neural network model with other forecasting methods can also offer a comprehensive and practical approach to exchange rate forecasting.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Cheong Hor Yen, Kek Sie Long;* ***data collection:*** *Cheong Hor Yen;* ***analysis and interpretation of results:*** *Cheong Hor Yen, Kek Sie Long;* ***review and editing:*** *Kek Sie Long;* ***visualization:*** *Cheong Hor Yen. All authors reviewed the results and approved the final version of the manuscript.*

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