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Currency Exchange Rate Prediction for United States Dollar to Malaysian Ringgit with Unscented Kalman Filter Technique

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Abstract

Currency exchange rates are crucial in international trade among countries. However, the fluctuation of exchange rates affects the gains and losses of the trading. Hence, the prediction of exchange rates is particularly needed. This paper studies the prediction of the exchange rate of the United States Dollar (USD) to the Malaysian Ringgit (MYR) using the unscented Kalman filter (UKF) technique. The UKF technique employs the unscented transform to generate a set of sigma points and to associate the prior knowledge of the probability distribution for a random variable by propagating the mean and the variance from a nonlinear function. The time prediction and output estimation in the UKF technique can handle the uncertainty shown by the exchange rates. We choose a logistic map model as the state equation, and the exchange rate data are the output observation. We measure the UKF technique's performance in predicting the currency exchange rates by a mean square error. For illustration, logistic map models with different growth rate values are studied. Simulation results show that the appropriate logistic map model gives the smallest mean square error value. Moreover, the testing results on trial models show that the prediction accuracy increases when the chaoticity of the model increases. In conclusion, the UKF technique is an efficient computational approach for currency exchange rate prediction.

1. Introduction

Currency exchange refers to exchanging one currency for another. It is commonly used in many cross-border transactions, including business and personal transactions, as well as educational, travelling or residency purposes. Exchange rates are critical determinants of economic transactions, costs, revenues and financial positions. A high exchange rate leads to high living costs and slows down the growth of the economy, while a low exchange rate influences foreign investment and creates employment [1][2][3]. From the perspective of monetary factors, exchange rates are determined by factors like interest rates, inflation, the political stability of the countries involved and the performances of the two economies.

Governments will control and administratively set foreign exchange rates with a fixed system, where an offer and demand system are called the floating system, or a mixture of both is called the managed floating system [4][5]. Correctly estimating these rates is essential for the most suitable organizational and individual financial decision-making, which will minimize any liabilities. Nonetheless, currency exchange rate prediction is still a complex research area, mainly owing to the random and nonlinear nature of the financial markets. Other factors, such as speculative trading and arbitrage opportunities, also exaggerate exchange rate changes, thus posing some degree of risk to the stakeholders [6][7].

In the past studies, the prediction of exchange rates has been well-performed. [8] suggested a hybridization model for exchange rate prediction that combines statistical and intelligent techniques inside a Kalman filter framework. They blended artificial neural networks (ANNs) with autoregressive integrated moving average (ARIMA) models to improve prediction accuracy of Europe-to-Dollar exchange rates. [9] also used ARIMA to exchange rates currency for a better result. [10] predicted the Malaysian Ringgit (MYR) exchange rate against the United States Dollar (USD) using exponential smoothing techniques.

The unscented Kalman filter (UKF), a tractable computational method for nonlinear systems, has been applied in the forecast of financial data due to its mitigation of noise and the nonlinear nature of data [11]. [12] explored the application of the UKF algorithm to multivariate financial time series data to evaluate its effectiveness in smoothing the direction of Kuala Lumpur Composite index (KLCI) stock price movements. [13] also worked on predicting stock market trends, where they used two main methods: a dynamic neural network (DNN) with a simple infinite impulse response (IIR) filter and an optimized adaptive UKF. [14] proposed a study to evaluate the prices of raw petroleum using two different algorithms: the UKF method and the KF techniques. The results show that the UKF provides better results than the traditional KF in dealing with the time series data. [15] proposed a project to enhance temperature prediction by leveraging advanced artificial neural network (ANN) techniques, particularly the long short-term memory (LSTM) model, and a unique optimization technique, and the UKF. They improved predicting accuracy by effectively addressing challenges such as handling lengthy data sequences and optimizing model parameters.

Our study predicts the exchange rate of the United States Dollar to the Malaysia Ringgit (USD / MYR) using the UKF technique. For this aim, historical data on the exchange rate of USD / MYR from 1 January 2024 to 31 October 2024 is collected. to estimate dynamic systems and predict future rates. The unscented transform generates a set of sigma points to propagate the mean and covariance through a nonlinear function and to associate the prior knowledge of probability distribution with a random variable. Then, the UKF technique applies the time and output updates to predict the exchange rates. Accordingly, the objectives of the study: (a) to predict the USD/MYR exchange rate using the UKF technique; (b) to apply a logistic map model for filtering and prediction in the UKF technique, and (c) to measure the performance of the UKF technique for the exchange rate prediction by a mean square error.

2. Materials and Methods

Consider a general dynamical system [16], as follows,

$$x_{k+1} = f(x_k) + \omega_k, \tag{1}$$

and the observation equation is

$$y_k = h(x_k) + \eta_k, \tag{2}$$

where x_k is the state variable of the system and y_k is the observed exchange rate, f is the dynamic function, and h is the measurement function. The terms ω_k and η_k are Gaussian white noises with zero mean and covariance matrices Q_ω and R_η, respectively. Here, the initial state and Gaussian white noises are statistical independent.

The UKF technique uses a set of sigma points to approximate the state distribution [17]. These sigma points are generated based on the state mean $\bar{x}$ and covariance P_{xx}, as follows:

$$\begin{aligned} \chi_0 &= \bar{x}, \\ \chi_{i+1} &= \bar{x} + \left(\sqrt{(n+\lambda)P_{xx}}\right)_i, \\ \chi_{i+n} &= \bar{x} - \left(\sqrt{(n+\lambda)P_{xx}}\right)_{i+n}, \end{aligned} \tag{3}$$

for $i = 1, \cdots, n$, where n is the state dimension, λ is a scaling parameter. These sigma points are then propagated through dynamic and measurement models to predict the state mean and covariance.

The UKF implementation [18] begins with initialization, where the initial state estimate and covariance matrix are defined. In the prediction step, the sigma points are propagated through the state equation,

$$\chi_{k+1} = f(\chi_k), \tag{4}$$

with the estimated state mean and state error covariance,

$$\hat{x}^- = \sum_{i=0}^{2n} W_i^{(m)} \chi_i, \tag{5}$$

$$P^- = \sum_{i=0}^{2n} W_i^{(c)} (\chi_i - \hat{x}^-)(\chi_i - \hat{x}^-)^{\mathrm{T}} + Q_\omega, \tag{6}$$

where $W_i^{(m)}$ and $W_i^{(c)}$ are weights for the mean and covariance, respectively. In the update step, the output of the transformed sigma points is measured by

$$\mathrm{Y}_k = \chi_k, \tag{7}$$

with the estimated observation and its error covariance,

$$\hat{y}^- = \sum_{i=0}^{2n} W_i^{(m)} \mathrm{Y}_i, \tag{8}$$

$$P_{yy} = \sum_{i=0}^{2n} W_i^{(c)} (\mathrm{Y}_i - \hat{y}^-)(\mathrm{Y}_i - \hat{y}^-)^{\mathrm{T}} + R_\eta. \tag{9}$$

The state estimate is updated by

$$\hat{x} = \hat{x}^- + K_f (y - \hat{y}^-), \tag{10}$$

with the updated state error covariance

$$P = P^- - K_f P_{yy} K_f^{\mathrm{T}}, \tag{11}$$

where

$$K_f = P_{xy} P_{yy}^{-1}, \tag{12}$$

$$P_{xy} = \sum_{i=0}^{2n} W_i^{(c)} (\chi_i - \hat{x}^-)(\mathrm{Y}_i - \hat{y}^-)^{\mathrm{T}}. \tag{13}$$

Here, K_f is the Kalman filter gain, P_{xy} is the cross-correlation matrix [6,17], and y represent the historical data on exchange rates. The output estimate is given by

$$\hat{y} = \hat{x}. \tag{14}$$

In the study, the logistic map model is used,

$$x_{k+1} = r x_k (1 - x_k), \tag{15}$$

as the dynamic model. The model's performance is evaluated through minimizing the mean square error (MSE), defined as [19, 20],

$$\mathrm{MSE} = \frac{1}{N} \sum_{k=1}^{N} (y_k - \hat{y}_k)^2 \tag{16}$$

with N is the total number of data points. Notice that a lower MSE indicates a higher accuracy of the prediction solution. By leveraging the UKF technique, this study demonstrates its effectiveness in capturing the nonlinear dynamics of currency exchange rates, providing reliable predictions that support financial decision-making and planning.

Therefore, the theoretical equations in the UKF technique as a calculation procedure as follows.

- Data — Given the exchange rates, the state mean, the state covariance, the weights and the noise covariance matrices.
- Step 1 — Generate a set of sigma points from (3) using the state mean and covariance.
- Step 2 — Calculate the estimated state mean and its error covariance from (5) and (6) based on the state equation (15).
- Step 3 — Compute the estimated observation and its error covariance from (8) and (9) with the output equation (14).
- Step 4 — Calculate the Kalman filter and the cross-correlation matrix from (12) and (13), respectively.
- Step 5 — Update the state estimate and its error covariance from (10) and (11), respectively.
- Step 6 — Evaluate the mean square error from (16).

Here, remark that

(a) The unscented transformation is applied in Steps 2 and 3.
(b) The time update is conducted in Steps 2 and 5, while the output estimation is performed in Steps 3 and 4.
(c) The prediction accuracy is expressed by a mean square error in Step 6.
(d) The logistic map model as the state equation is used in Step 2.

There are many types of prediction suited for exchange rate forecasting. Still, each type of prediction has advantages and disadvantages, and their performance depends on the specific characteristics of the data. Other previous studies were done in using forecasting method with the mathematics technique in worldwide according to various fields of studies [21-23].

3. Result and Discussion

The implementation of the UKF for predicting the exchange rate between the USD and the MYR demonstrated strong accuracy and adaptability. Historical exchange rate data from January 1, 2024, to October 31, 2024, was normalized to ensure uniform scaling between 0 and 1, avoiding large variations during computation. Fig. 1 illustrates fluctuation in the exchange rates during the period, highlighting key trends such as a rapid decline around the 145$^{\text{th}}$ day and a gradual recovery after the 196th day.

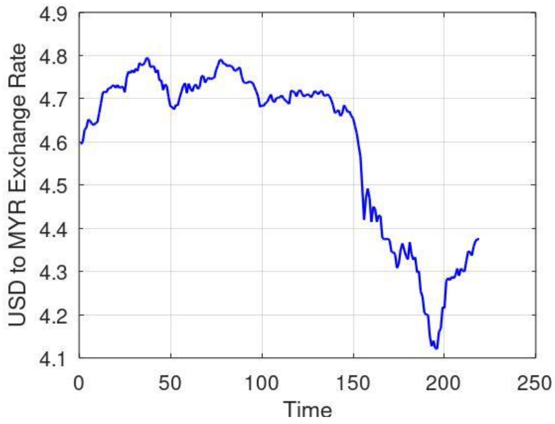

Fig. 1 Exchange rate of USD / MYR

To model system dynamics, logistic map models with different growth rates ($r = 0.5, 1.5, 2.5, 3.5$) were employed. These models incorporated random noise to simulate real-world volatility. In Fig. 2, the solution curve towards zero for the growth rate r = 0.5, and in Fig. 3, the solution curve tends to the steady state of 0.333 for the growth rate r = 1.5. When the growth rate is r = 2.5, the population goes to the steady state of 0.6 as shown in Fig. 4; however, the population presents the oscillation behaviour when the growth rate is r = 3.5 as shown in Fig. 5.

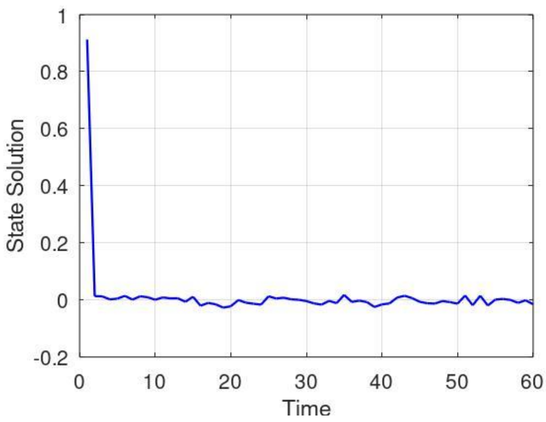

Fig. 2 Solution curve with r = 0.5

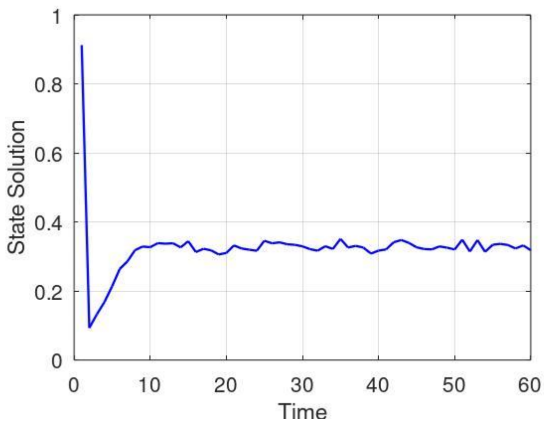

Fig. 3 Solution curve with r = 1.5

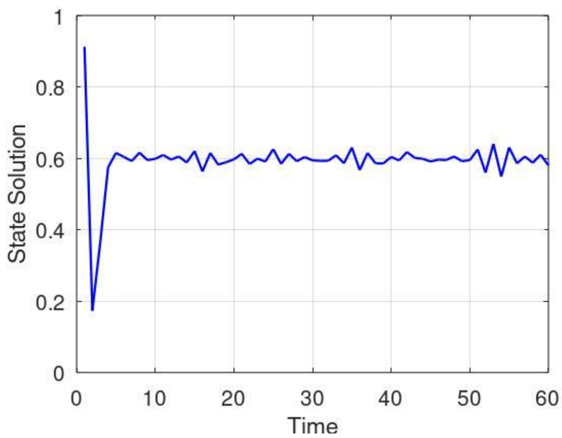

Fig. 4 Solution curve with r = 2.5

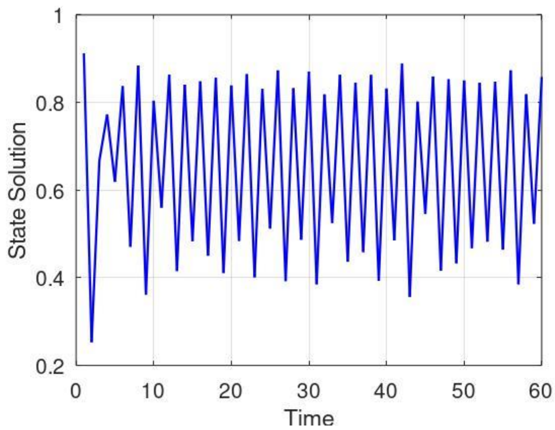

Fig. 5 Solution curve with r = 3.5

Simulation results for the model with different growth rates using the UKF technique revealed low MSE values, confirming the model's accuracy. Table 1 summarizes the MSE and elapsed computation time for the logistic map model with different growth rates. The model with $r = 3.5$ achieved the smallest MSE of 2.2544×10^{-9}, indicating superior performance.

Table 1 Simulation results for different growth rates

Growth Rate	Mean Square Error	Elapsed Time (seconds)
$r = 0.5$	1.9310×10^{-7}	0.060708
$r = 1.5$	5.2772×10^{-7}	0.068754
$r = 2.5$	6.0780×10^{-6}	0.063341
$r = 3.5$	2.2544×10^{-9}	0.066855

Graphical result comparison of the prediction solutions and estimation errors revealed a close match between actual and predicted exchange rates across all models. For instance, Fig. 6 shows the prediction solution and estimation error for the logistic map model with $r = 0.5$. Similar results were observed for other growth rates, with minimal estimation errors, as shown in Figs. 6, 7, 8, 9, 10, 11, 12 and 13. The prediction solutions are well presented, but the different estimation errors are expressed.

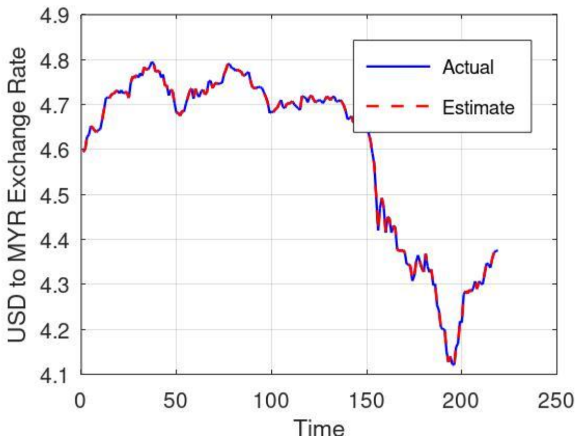

Fig. 6 Prediction solution for r = 0.5

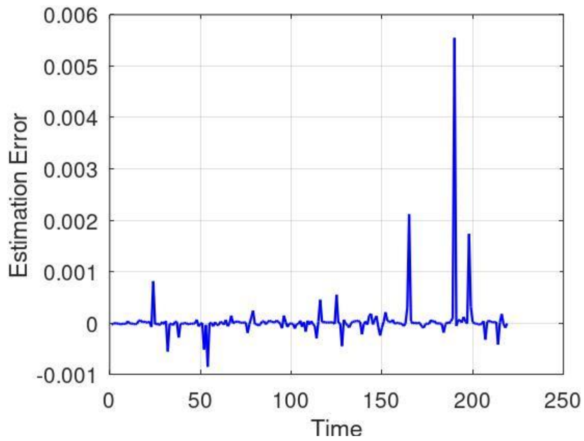

Fig. 7 Estimation error for r = 0.5

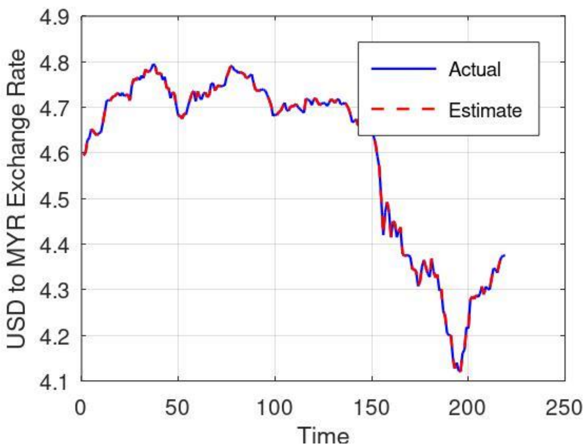

Fig. 8 Prediction solution for r = 1.5

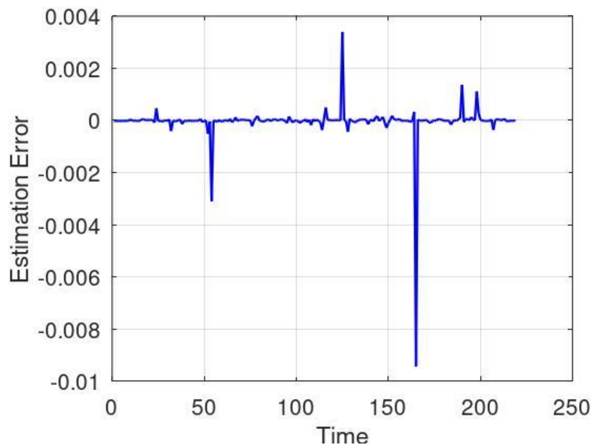

Fig. 9 Estimation error for r = 1.5

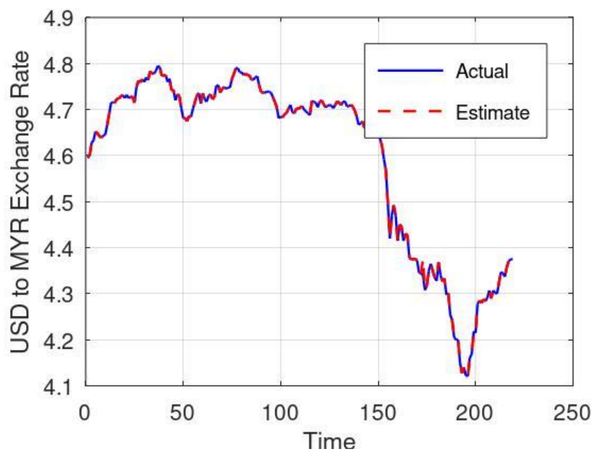

Fig. 10 Prediction solution for r = 2.5

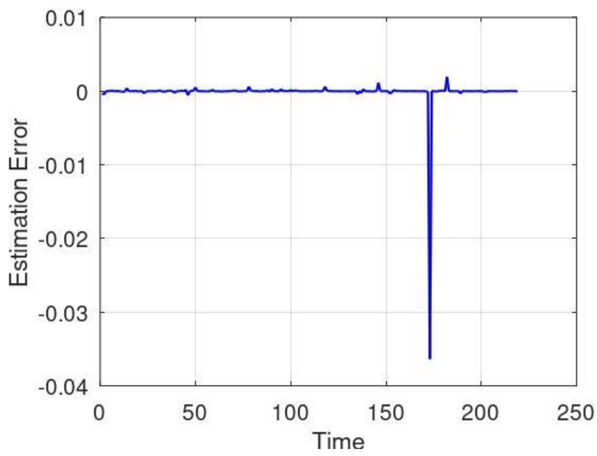

Fig. 11 Estimation error for r = 2.5

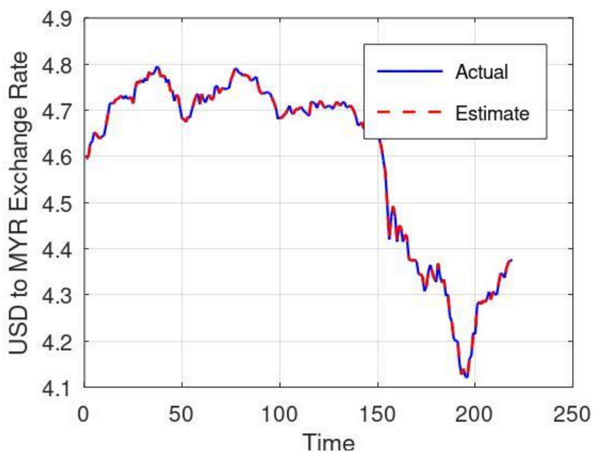

Fig. 12 Prediction solution for r = 3.5

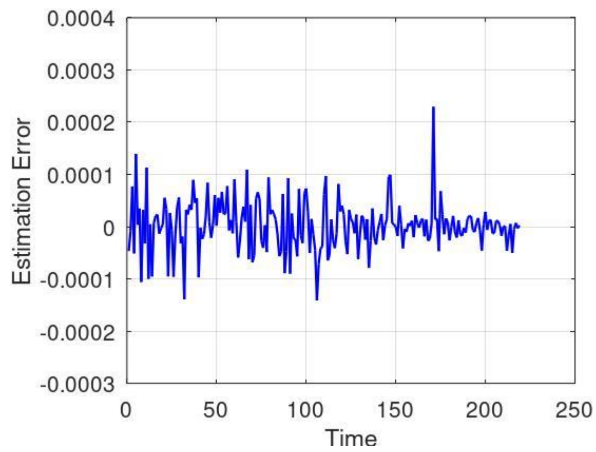

Fig. 13 Estimation error for r = 3.5

To examine better predictions further, trial models with r values from 3.1 to 3.9 were evaluated. Table 2 shows the testing results of these trial models, highlighting the impact of growth rate tuning. The model with $r = 3.1$ achieved the lowest MSE value of 1.9306×10^{-7}, outperforming the baseline model with $r = 3.5$. The dynamic models generated prediction solution curves that aligned closely with historical exchange rate data, validating the model's robustness. Further testing of growth rate values revealed that the logistic map model with $r = 3.2$ yielded the largest MSE value of 1.6152×10^{-7}, demonstrating the importance of parameter tuning in enhancing model performance. It is summarized that the prediction accuracy increases when the chaoticity of the logistic map model increases.

Table 2 Simulation results of trial models

Value of r	Mean Square Error	Elapsed Time (seconds)
3.1	1.9306×10^{-9}	0.068374
3.2	1.6152×10^{-7}	0.061219
3.3	6.8902×10^{-8}	0.064086
3.4	8.8534×10^{-8}	0.068104
3.5	2.2544×10^{-9}	0.066855
3.6	3.9097×10^{-9}	0.066328
3.7	4.7886×10^{-9}	0.064967
3.8	7.1995×10^{-9}	0.062488
3.9	8.1136×10^{-9}	0.068162

Overall, the UKF combined with logistic map modelling demonstrated exceptional accuracy in predicting USD/MYR exchange rates. Its ability to adapt to dynamic conditions, combined with parameter tuning, ensured robust performance. These findings validate the UKF's suitability for real-world financial forecasting, highlighting its potential for broader applications in financial modelling and decision-making.

4. Conclusion

This study successfully applied the UKF technique to predict the USD exchange rate to the MYR between January and October 2024. The UKF methodology, comprising filtering and prediction stages, effectively modelled the nonlinear dynamics of exchange rate fluctuations. The findings were presented in tables and graphical formats, illustrating the accuracy and reliability of the UKF. Consequently, the study achieved its primary objective of developing a robust model for predicting USD/MYR exchange rates. In conclusion, this study demonstrated the efficacy of the UKF in predicting exchange rates, achieving its objectives, and contributing to the field of financial modelling. The findings highlight UKF's potential for broader applications and provide a foundation for future research in predictive analytics and economic forecasting.

The study is solely on USD/MYR exchange rates. Other computational techniques, such as machine learning models, are not considered. Thus, future research should explore applying the UKF technique to more complex financial datasets with high volatility and uncertainty. Moreover, integrating adaptive filtering techniques and advanced computational methods, such as machine learning or generative artificial intelligence, could enhance the model's performance in handling large and dynamic datasets.

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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:*** *Cleon Chua, Kek Sie Long;* ***data collection:*** *Cleon Chua;* ***analysis and interpretation of results:*** *Cleon Chua;* ***draft manuscript preparation:*** *Cleon Chua, Kek Sie Long. All authors reviewed the results and approved the final version of the manuscript.*

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