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FORECASTING EXCHANGE RATES IN SRI LANKA: A COMPARISON OF THE DOUBLE SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODELS (DSARIMA) AND SARIMA MODELS

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ABSTRACT

Exchange rates serve as a medium for currency trading in the financial market. The variations and the uncertainty movements in exchange rates have a potential effect on the performance of a country. The objective of this study is to forecast daily exchange rates in Sri Lanka using Double Seasonal Autoregressive Integrated Moving Average (DSARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) with Autoregressive Conditional Heteroscedasticity (ARCH)/ Generalized ARCH (GARCH) models. The study collected a few daily exchange rates from the Yahoo finance website in terms of LKR from 1st January 2008 to 28th February 2022. The DSARIMA and SARIMA models were incorporated with the ARCH/ GARCH specifications of normal, skew-normal, student-t and skew-t due to the accurate specification of the proper error distribution led to an increase in the accuracy of the fitted model. The model comparisons were carried out considering different performance measures. The overall results from the actual and fitted graphs and lower error values of the fitted models suggested a SARIMA model for CHF/LKR, a SARIMA model with ARCH/GARCH for USD, EURO, JPY, GBP and AUD against LKR and a DSARIMA model with ARCH/GARCH for CAD and SGD against LKR were suitable to forecast the respective exchange rate. Overall, the results from this study will support government, investors, corporate, financial and managerial sectors in their future decisions to accomplish their objectives. The originality of this study concerns the application of DSARIMA models in exchange rates due to the availability of double seasonality in data.

Keywords: Exchange rates, Double Seasonal Autoregressive Integrated Moving Average (DSARIMA), SARIMA, Autoregressive Conditional Heteroscedasticity (ARCH), Generalized ARCH (GARCH).

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INTRODUCTION

The exchange rate is the worth of a foreign nation's currency against the home nation's currency. An appropriate exchange rate value is the key to economic growth without an obstacle for developing countries such as Sri Lanka. Moreover, changes in the movements of the exchange rates have a direct impact on inflation, the balance of payment, public debts, imports and many others. Hence, predicting the extreme volatile behaviour of these rates is the main focus of many business practitioners and academic researchers.

In recent years several models were extensively developed for the purpose of forecasting variables in financial markets. For instance, Tambi (2005) described the behaviour of Special Drawing Rights (SDR), United States Dollar (USD), Pound Sterling (GBP), EURO and Japanese Yen (JPY) against the Indian rupee, Weisang & Awazu (2008) modelled USD/EURO, Appiah & Adetunde (2011) modelled the Ghana Cedi against the USD, Tlegenova (2015) modelled USD, EURO and Singapore Dollar (SGD) against Kazakh tenge and Ngan (2016) described the nature of exchange rate between Vietnam in terms of USD. All the aforementioned studies used the technique of Autoregressive Integrated Moving Average (ARIMA) models to model the respective exchange rates.

Ghysels *et al*. (2001) and Adhikari & Agrawal (2012) mentioned that over time, most of the finance and economic time series exhibit the seasonality feature in data. Seasonal Autoregressive Integrated Moving Average (SARIMA) models which is an extension of the Autoregressive Integrated Moving Average (ARIMA) models incorporating the seasonality feature, were considered by the studies of Kadilar *et al*. (2009), Etuk (2012), Etuk (2013), Etuk (2014) and Al-Gounmeein & Ismail (2020) in forecasting exchange rates. Here, Kadilar *et al*. (2009) extended the SARIMA model with Autoregressive Conditional Heteroscedasticity (ARCH) to overcome the problem of heteroscedasticity. Mustafa *et al*. (2017) applied ARIMA GARCH and ARIMA exponential GARCH to model the exchange rate of the Malaysian

Ringgit against the USD. Cerqueti *et al*. (2020) considered the specifications of Generalized ARCH (GARCH) in forecasting Bitcoin, Litecoin and Ethereum in terms of USD.

In summary, many authors in previous studies applied different statistical models to forecast exchange rates. The literature such as Mohamed *et al*. (2010), Mado *et al*. (2018) and Azka *et al*. (2020) claimed that the Double Seasonal Autoregressive Integrated Moving Average (DSARIMA) models were mainly applied in forecasting load demand and electrical power demand.

Forecasting based on time-series models relies on historical data and these methods hold the assumption that past observations and their patterns can be applied to forecast future data values. Hence, the main objective of this study is to model the behaviour of some selected exchange rates in terms of LKR using time-series models of SARIMA and DSARIMA. This study proposed DSARIMA due to the presence of weekly and annual seasonality in exchange rates of USD, EURO, JPY, GBP, Australian Dollar (AUD), Canadian Dollar (CAD), SGD and Swiss Franc (CHF) in terms of LKR. This is the first study that applies DSARIMA models to forecast exchange rates. Previous work mainly focused on weekly or annual seasonality separately, and those works did not consider both seasonality. Further, DSARIMA models were extended incorporating ARCH/GARCH employing error distributions of normal, skew-normal, student-t and skew-t to model the volatile nature of the exchange rates. With the referred literature, there is no previous study that considered DASRIMA models with ARCH/GARCH specifications in modeling the exchange rates. Hence, this study adds more value to the existing work by revealing the double seasonality nature of the exchange rates through DSARIMA models and considering several specifications of error distributions to capture the volatile nature of the data.

METHODOLOGY

The daily data for this work (eight exchange rates namely, USD, EURO, JPY, GBP, AUD, CAD, SGD and CHF in terms of LKR) were obtained from the Yahoo finance site from

1st January 2008 to 28th February 2022. Data were split non-randomly for training from 1st January 2008 to 07th January 2022 and the rest of the data for testing. The stationary of these exchange rates was checked with the unit roots tests of the Augmented Dickey-Fuller test (ADF), Phillips-Perron test (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

Augmented Dickey-Fuller test (ADF) test and Phillips-Perron test (PP) test

H_0: The series is not stationary

H_1: The series is stationary

Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

H_0: The series is stationary

H_1: The series is not stationary

Here, if the calculated *p*-value is less than a 5% significant level, the null hypothesis (H_0) is rejected at the 5% significance level indicating the series is not stationary.

Log and differencing transformations were used respectively to transform non-stationary series to stationary. Cellini & Cuccia (2011), Xu *et al.* (2021), Basnayake & Chandrasekara (2022) and Saxena et al. (2022) mentioned that the seasonality behaviours of data can be observed with different formal tests. This study used Webel-Ollech (WO), Friedman rank (FR) and Kruskal-Wallis (KW) to detect the seasonality of the data. WO test merged results from QS-test and the Kwman-test and this test identifies the seasonality in the series when the p-value of the QS-test is below 0.01 and the p-value of the Kwman-test is below 0.002. FR and KW tests detect the seasonality of the data when the calculated p-value is below 0.05 at a 5% level of significance.

ARIMA models explain the present behaviour of the variable using their past values with the linear relationships and this model consists of two main components. The first component is the integrated component (d) which indicates the number of differencing performed to make the non-stationary series to stationary. The second component is an ARMA model where the Auto Regressive (AR) portion identifies the correlation between the current value of the series and its past values, and the Moving Average (MA) portion presents the duration of the effect of an unexplained or random shock.

The general structure of the ARIMA model is in Equation 1:

$$ARIMA\ (p, d, q) \tag{1}$$

where p is the number of parameters in the AR model, d is the degree of differencing, q is the number of parameters in the MA model. ARIMA was extended to SARIMA by including the seasonality feature and the general structure of the SARIMA model is in Equation 2:

$$ARIMA\ (p, d, q)(P, D, Q)_S \tag{2}$$

where P is the number of parameters in the seasonal AR model, D is the degree of seasonal differencing, Q is the number of parameters in the seasonal MA model and S is the period of seasonality.

With the availability of double seasonality, SARIMA model is extended as follows.

$$ARIMA\ (p, d, q)(P_1, D_1, Q_1)_{s_1}(P_2, D_2, Q_2)_{s_2} \tag{3}$$

where P_1, Q_1 and D_1 are the number of parameters in the seasonal AR model, the degree of seasonal differencing, and the number of parameters in the seasonal MA model respectively for the S_1 seasonal period. Similarly, P_2, Q_2 and D_2 are the number of parameters in the seasonal AR model, the degree of seasonal differencing, and the number of parameters in the seasonal MA model respectively for the S_2 seasonal period.

Three separate cases are considered under model fitting in this study: (1) Weekly seasonal differencing, (2) Annual seasonal differencing and (3) Double seasonal differencing. The seasonal pattern is modelled using Fourier terms as per the study of Iwok & Udoh (2016) by incorporating $Y_t = \sum_{k=0}^{n/2}\left[a_k cos\left(\frac{2\pi kt}{n}\right) + b_k sin\left(\frac{2\pi kt}{n}\right)\right]$ term to the ARIMA process as external regressors where $Y_1, Y_2, ..., Y_n$ are sequence of numbers such that $t = 1, 2, \dots, n$; a_k and b_k are Fourier coefficients; n is the seasonal period and k is selected such that to minimize AIC value.

The better-performed model for each exchange rate and aforementioned each case was identified with the minimum Akaike Information Criterion (AIC). Model diagnostics checking was carried out with the tests of Jarque–Bera, ARCH and Ljung-Box to check the presence of normality, heteroscedasticity and autocorrelation in the residuals, respectively.

Normality: Jarque–Bera Test

H_0: Residuals are normally distributed

H_1: Residuals are not normally distributed

Heteroscedasticity: ARCH test

H_0: There is no heteroscedasticity in the residuals

H_1: There is heteroscedasticity in the residuals

Autocorrelation: Ljung-Box Test on Residuals

H_0: There is no autocorrelation in the residuals

H_1: There is autocorrelation in the residuals

In order to deal with heteroscedasticity, ARCH and GARCH models were applied.

The ARCH(q) model can be specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{4}$$

where z_t is a sequence of independent and identically distributed random variable such that $\varepsilon_t = \sigma_t z_t$, σ_t^2 is the estimated conditional variance, ε_i is the residual return, $\alpha_0 > 0, \alpha_i \geq 0$, $i > 0$ and $i = 1, 2, \ldots, q$.

The GARCH model consists of both AR and MA components to show the heteroscedastic variance. The GARCH (p,q) model can be specified as follows:

$$\begin{aligned}\sigma_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_P \sigma_{t-P}^2 \\ &= \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{P} \beta_j \sigma_{t-j}^2 \end{aligned} \tag{5}$$

where p is the order of the GARCH terms (σ^2), q is the order of the ARCH terms (ε^2), $\alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0, i, j > 0, i = 1, 2, \ldots, q$ and $j = 1, 2, \ldots, p$.

Here, different error distributions of normal, skew-normal, student-t and skew-t were employed to model the volatile nature of the exchange rates. The appropriate error distribution was detected the through minimum AIC value. Measures of Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) were used to evaluate the forecasting performances of the fitted models.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \quad (6)$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(e_t)^2 \quad (7)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{y_t} \times 100 \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(e_t)^2} \quad (9)$$

where t is the time-period, y_t is the actual value, $\hat{y}_t$ is the fitted value and $e_t = y_t - \hat{y}_t$ is the error and n is the total number of observations.

The better-performed model among the candidate models for each exchange rate was identified with the lower forecasting performance values.

RESULTS

The main aim of this study is to model the uncertain behaviour of the exchange rates using SARIMA or DSARIMA models. This section contains the results of the analysis carried out in model fitting. Figure 1 is the time plot of the currency exchange rates and they illustrate the volatile behaviour of exchange rates over time.

The ADF, PP and KPSS test results suggested that the original exchange rates were not stationary at a 5% level of significance. Table 1 includes the p-values resulted from the unit root tests for the original exchange rates. Here, all the KPSS test's p-values are less than 0.05 and p-values from ADF and PP tests are greater than 0.05. The first differed logarithmic exchange rates were stationary at a 5% level of significance. Here, the p-values from the KPSS test for transformed exchange rates were 0.1 and the p-values from ADF and PP tests were 0.01.

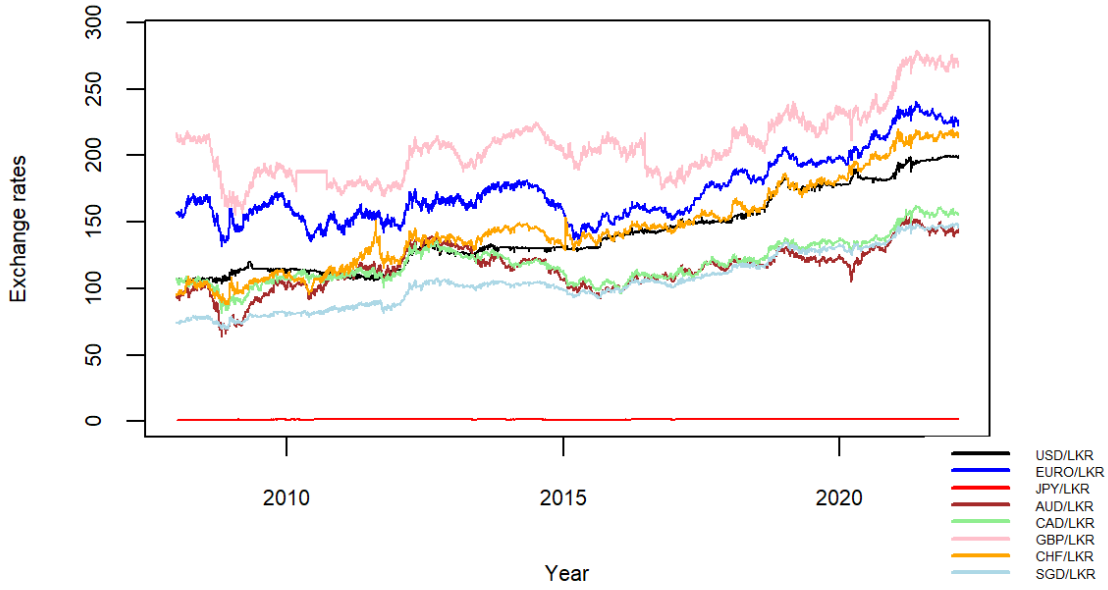


Figure 1: Time plot of currency exchange rates.

Table 1: p-value results of unit root tests for original exchange rates

Original exchange rate	KPSS test (p-value)	ADF test (p-value)	PP test (p-value)
USD/LKR	0.0100	0.7290	0.5562
EURO/LKR	0.0100	0.6143	0.5923
JPY/LKR	0.0100	0.7370	0.7223
GBP/LKR	0.0100	0.2506	0.4502
AUD/LKR	0.0100	0.5692	0.5471
CAD/LKR	0.0100	0.7494	0.6026
SGD/LKR	0.0100	0.6376	0.4286
CHF/LKR	0.0100	0.3656	0.0515

Overall, weekly and annual seasonality patterns were identified from the results of WO, FR and KW tests for all the exchange rates, except FR test results suggested there is no annual seasonality in all the considered exchange rates. Table 2 includes the p-values from the test results of seasonality tests for transformed exchange rates. Here, only the FR test p-values are greater than 0.05 in each exchange rate for the annual seasonality, which indicates there is no annual seasonality at a 5% level of significance. All other test's p-values show the weekly and annual seasonality in the transformed exchange rates.

Table 2: p-value resulted from the seasonality tests for transformed exchange rates

Transformed exchange rate	Weekly seasonality (p-value)				Annual seasonality (p-value)			
	WO test		FR test	KW test	WO test		FR test	KW test
	QS-test	Kwman-test			QS-test	Kwman-test		
USD/LKR	0.0000	0.0000	1.1546e-14	0.0000	0.0000	0.0000	0.1459	0.0000
EURO/LKR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8958	0.0000
JPY/LKR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5806	0.0000
GBP/LKR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9000	0.0000
AUD/LKR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.7777	0.0000
CAD/LKR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6744	0.0000
SGD/LKR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.3189	0.0000
CHF/LKR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.8852	0.0000

Hence, SARIMA and DSARIMA models were fitted, including weekly and annual seasonality separately and together, respectively. To determine the appropriate components of SARIMA and DSARIMA models used the respective autocorrelation function (ACF) and partial ACF (PACF) plots. The out-performed model for each case was identified with the minimum AIC. Table 3 illustrates the p-value results for tests of model diagnostics for the selected model from each exchange rate. Here, the Ljung-Box test on residuals showed there is no autocorrelation at a 5% level of significance in the residuals as p-value are greater than 0.05 and the Jarque –Bera test results exhibited that the residuals are not normally distributed at a 5% level of significance as p-values are less than 0.05. Further, all the exchange rates indicate the ARCH effect (p-values less than 0.05) at a 5% level of significance except CHF/LKR.

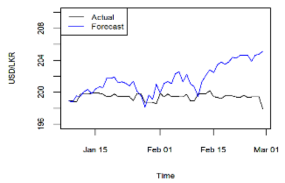
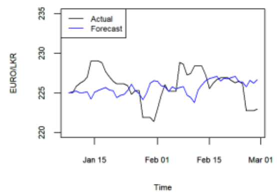
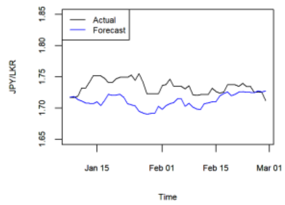
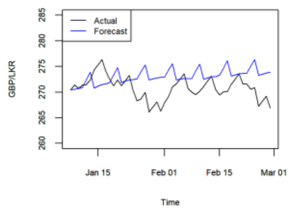
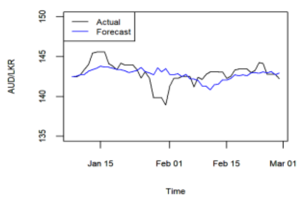
Table 3: p-values resulted from the tests of model diagnostics checking

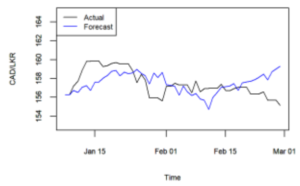
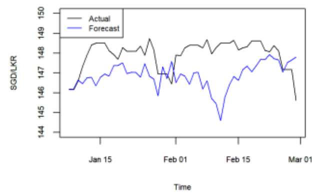
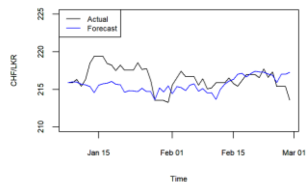
Exchange rate	Jarque-Bera test (p-value)	ARCH test (p-value)	Ljung-Box test (p-value)
USD/LKR	< 2.2000e-16	< 2.2000e-16	0.9923
EURO/LKR	< 2.2000e-16	< 2.2000e-16	0.9800
JPY/LKR	< 2.2000e-16	< 2.2000e-16	0.9894
GBP/LKR	< 2.2000e-16	< 2.2000e-16	0.7572
AUD/LKR	< 2.2000e-16	< 2.2000e-16	0.6600
CAD/LKR	< 2.2000e-16	< 2.2000e-16	0.7406
SGD/LKR	< 2.2000e-16	< 2.2000e-16	0.9985
CHF/LKR	< 2.2000e-16	0.1187	0.9951

Aryani *et al*. (2018) mentioned that due to the high volatility inside data, the normality assumption of the residuals may get violated. Further, they stated ARIMA model could be used to forecast even with this model diagnostic rule violation. Due to the presence of heteroscedasticity, each model was extended with ARCH/GARCH with different error specifications except for the exchange rate of CHF/LKR. Here, the appropriate error specification of each ARCH/GARCH model was identified with the minimum AIC. Further, the model diagnostic test results of the Ljung-Box test indicated there is no autocorrelation and the ARCH test exhibited that the ARCH/GARCH process is adequately fitted.

Table 5 includes the final selected better-performed model for each exchange rate with their forecasting performances and graphs of actual vs fitted values.

Table 5: Better-performed models for the exchange rates

Exchange rate	Better-performed model	Actual vs fitted graph	Forecasting performances
USD/LKR	SARIMA with seasonal period 7 + GARCH(1,3) in skew-normal distribution with skewness parameter of 0.7836		MAE = 2.2751 MSE = 8.4040 MAPE = 0.0114 RMSE = 2.8990
EURO/LKR	SARIMA with seasonal period 7 + GARCH(1,2) in skew-normal distribution with skewness parameter of 0.9843		MAE = 1.8080 MSE = 5.4690 MAPE = 0.0080 RMSE = 2.3386
JPY/LKR	SARIMA with seasonal period 365 + ARCH(1) in normal distribution		MAE = 0.0232 MSE = 0.0007 MAPE = 0.0133 RMSE = 0.0273
GBP/LKR	SARIMA with seasonal period 7 + ARCH(1) in skew-t distribution with skew skewness parameter of 1.0229 and shape parameter of 2.0100		MAE = 2.9896 MSE = 13.5009 MAPE = 0.0111 RMSE = 3.6744
AUD/LKR	SARIMA with seasonal period 365 + GARCH(2,3) in normal distribution		MAE = 0.9767 MSE = 1.9149 MAPE =0.0069 RMSE = 1.3838
CAD/LKR			MAE = 1.2356 MSE = 2.4968

	DSARIMA + GARCH(1,2) in normal distribution		MAPE = 0.0079
			RMSE = 1.5801
SGD/LKR	DSARIMA + ARCH(1) in normal distribution		MAE = 1.2298
			MSE = 2.1540
			MAPE = 0.0083
			RMSE = 1.4677
CHF/LKR	SARIMA with seasonal period 7		MAE = 1.5302
			MSE = 3.7596
			MAPE = 0.0070
			RMSE = 1.9390

Orderly, Equations (10) to (17) represent the final equations of the selected forecasting models for USD, EURO, JPY, GBP, AUD, CAD, SGD and CHF in terms of LKR respectively.

- $y_t = 0.0001 - 0.2542y_{t-1} + \varepsilon_t + 0.1940\varepsilon_{t-1} + 0.1643\varepsilon_{t-2} + 0.1079\varepsilon_{t-3} + 0.0009\sin\left(\frac{2\pi t}{7}\right) + 0.0005\cos\left(\frac{2\pi t}{7}\right) + 0.0012\sin\left(\frac{4\pi t}{7}\right) + 0.0014\cos\left(\frac{4\pi t}{7}\right) + +0.0006\sin\left(\frac{6\pi t}{7}\right) + 0.0019\cos\left(\frac{6\pi t}{7}\right) + 0.2148\varepsilon_{t-1}^2 + +0.1509\sigma_{t-2}^2 + 0.6148\sigma_{t-3}^2$ where $\varepsilon_t \sim SN(0.7836)$ (10)
- $y_t = 0.0001 - 0.4457y_{t-1} - 0.9976y_{t-2} + \varepsilon_t - 0.2427\varepsilon_{t-1} - 0.8923\varepsilon_{t-2} + 0.2045\varepsilon_{t-3} + 0.0011\sin\left(\frac{2\pi t}{7}\right) + 0.0006\cos\left(\frac{2\pi t}{7}\right) + 0.0014\sin\left(\frac{4\pi t}{7}\right) + 0.0015\cos\left(\frac{4\pi t}{7}\right) + +0.0008\sin\left(\frac{6\pi t}{7}\right) + 0.0020\cos\left(\frac{6\pi t}{7}\right) + 0.0400\varepsilon_{t-1}^2 + 0.1481\sigma_{t-1}^2 + 0.8102\sigma_{t-2}^2$ where $\varepsilon_t \sim SN(0.9843)$ (11)
- $y_t = 0.0001 + 0.3297y_{t-1} + 0.0702y_{t-2} + \varepsilon_t + 0.6516\varepsilon_{t-1} - 0.0004\cos\left(\frac{2\pi t}{365}\right) + 0.9998\varepsilon_{t-1}^2$ where $\varepsilon_t \sim N(0,1)$ (12)

- $y_t = 0.0629y_{t-1} - 0.0805y_{t-2} + 0.6180y_{t-3} + \varepsilon_t + 0.0935\varepsilon_{t-1} - 0.0777\varepsilon_{t-2} + 0.6746\varepsilon_{t-3} + 0.0008\sin\left(\frac{2\pi t}{7}\right) - 0.0034\cos\left(\frac{2\pi t}{7}\right) + 0.0049\sin\left(\frac{4\pi t}{7}\right) + 0.0005\cos\left(\frac{4\pi t}{7}\right) + 0.0013\sin\left(\frac{6\pi t}{7}\right) + 0.0035\cos\left(\frac{6\pi t}{7}\right) + 0.9235\varepsilon_{t-1}^2$ where $\varepsilon_t \sim SSTD(1.0229, 2.0100)$ (13)
- $y_t = 0.0001 - 1.4077y_{t-1} - 0.2958y_{t-2} + 0.3873y_{t-3} + \varepsilon_t - 1.2566\varepsilon_{t-1} - 0.0494\varepsilon_{t-2} + 0.5112\varepsilon_{t-3} + 0.0002\sin\left(\frac{2\pi t}{365}\right) + 0.0001\cos\left(\frac{2\pi t}{365}\right) + 0.1156\varepsilon_{t-1}^2 + 0.2464\sigma_{t-2}^2 + 0.6151\sigma_{t-3}^2$ where $\varepsilon_t \sim N(0,1)$ (14)
- $y_t = 0.0001 - 1.4059y_{t-1} - 0.2963y_{t-2} + 0.3857y_{t-3} + \varepsilon_t - 1.2068\varepsilon_{t-1} + 0.0323\varepsilon_{t-2} + 0.5525\varepsilon_{t-3} + 0.0010\sin\left(\frac{2\pi t}{7}\right) + 0.0005\cos\left(\frac{2\pi t}{7}\right) + 0.0012\sin\left(\frac{4\pi t}{7}\right) + 0.0014\cos\left(\frac{4\pi t}{7}\right) + 0.0006\sin\left(\frac{6\pi t}{7}\right) + 0.0020\cos\left(\frac{6\pi t}{7}\right) + 0.0001\sin\left(\frac{2\pi t}{365}\right) + 0.0673\varepsilon_{t-1}^2 + 0.1190\sigma_{t-1}^2 + 0.8053\sigma_{t-2}^2$ where $\varepsilon_t \sim N(0,1)$ (15)
- $y_t = 0.0001 - 0.2500y_{t-1} + \varepsilon_t + 0.0883\varepsilon_{t-1} + 0.1225\varepsilon_{t-2} + 0.0917\varepsilon_{t-3} + 0.0010\sin\left(\frac{2\pi t}{7}\right) + 0.0005\cos\left(\frac{2\pi t}{7}\right) + 0.0012\sin\left(\frac{4\pi t}{7}\right) + 0.0014\cos\left(\frac{4\pi t}{7}\right) + 0.0007\sin\left(\frac{6\pi t}{7}\right) + 0.0018\cos\left(\frac{6\pi t}{7}\right) + 0.0001\sin\left(\frac{2\pi t}{365}\right) + 0.0001\cos\left(\frac{2\pi t}{365}\right) + 0.9000\varepsilon_{t-1}^2$ where $\varepsilon_t \sim N(0,1)$ (16)
- $y_t = 0.0002 + 0.1039y_{t-1} - 0.0066y_{t-2} - 0.0775y_{t-3} + \varepsilon_t + 0.2812\varepsilon_{t-1} + 0.0030\sin\left(\frac{2\pi t}{7}\right) - 0.0004\cos\left(\frac{2\pi t}{7}\right) + 0.0011\sin\left(\frac{4\pi t}{7}\right) + 0.0015\cos\left(\frac{4\pi t}{7}\right) + 0.0008\sin\left(\frac{6\pi t}{7}\right) + 0.0018\cos\left(\frac{6\pi t}{7}\right)$ (17)

where y_t is the present value of the time series, y_{t-i} is the value of the time series at $t-i$, ε_t is the value of the error term at time t, ε_{t-i} is the value of error term at time $t-i$, σ_{t-i}^2 is the conditional variance at time $t-i$ and $i = 1, 2, 3, \ldots$

DISCUSSION

Forecasting performance values were lower in every exchange rate, whereas a supportive idea was presented by Lewis (1982) labelling MAPE values less than 0.01 as high accuracy. Further, graphs of actual vs fitted indicated a similar idea for some exchange rates. Actual values of USD/LKR fluctuated around 200 and its forecasted values were similar to the real values at the beginning. Later, forecasted values have an upward trend with two downward shifts where these shifts were similar to the actual values. Actual values of EURO/LKR fluctuated between 220 and 230, where the forecasted values were unable to capture the unusual fluctuations. However, in the beginning and at three places in the middle, true volatility was captured by the fitted values. The actual values of JPY/LKR were slightly higher compared to fitted values whereas they have similar patterns. Forecasted values of GBP/LKR were unable to identify the trend of the test set while they captured the seasonal pattern very well. Actual and fitted values were slightly similar in AUD/LKR. In CAD/LKR, the initial downward trend was captured by the fitted line while the values at the end of February are not close. Actual and fitted lines of SGD/LKR are alike and on February 15, the forecasted line had a huge drop which was not observed truly. Real and fitted values are almost similar after February but not in January month in CHF/LKR.

The traditional statistical models were developed in the static framework where new observations are not utilized to automatically update the parameters of the models. Hence, a major disadvantage of these models is the requirement to re-estimate the periodic parameters at all needed forecast locations. Further, these models are relying on many assumptions such as stationarity and linearity where these assumptions are not satisfied by data in many situations. To overcome this issue, many past studies such as Kohara *et al.* (1997), Giles *et al.* (2001), Binner *et al.* (2005) and Chandrasekara & Tilakaratne (2009) suggested building neural network models that are capable of performing well compared to traditional time-series models.

CONCLUSIONS

The exchange rate is a principal factor in a dynamic global economy where accuracy in predicting the exchange rates is an important task for future investments. In this respect, the behaviour or the changes in the exchange rates have a direct impact on inflation, the balance of payments, imports, external trade and many others. However, the volatile and chaotic characteristics of the exchange rates may not be perfectly predictable all the time. For this reason, this study concerned estimating the movements of the exchange rates from DSARIMA models, which was not applied by previous related studies.

In conclusion, a SARIMA model favoured CHF/LKR, a SARIMA model with ARCH/GARCH for USD, EURO, JPY, GBP, AUD in terms of LKR and a DSARIMA model with ARCH/GARCH models for CAD, SGD in terms of LKR. Overall, predicted values captured the behaviour of the exchange rates. However, a considerable number of volatile and noisy movements of the foreign exchange rates were not very well captured, and graphs in Table 5 illustrate the idea. Therefore, as future work, this study recommends in building suitable neural network models in forecasting exchange rates.

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