Journal of New Frontiers in Education and Social Sciences

ISSN 2719- 2407 (Online)

Volume 2 (1) 2022, 1-15

Home page: www.imathm.edu.lk/publications

Modeling Consumer Price Index of Thailand

K.M.U.B. Konarasinghe
Institute of Mathematics and Management, Sri Lanka

udaya@imathm.edu.lk

ABSTRACT

The CPI attempts to quantify the overall price levels of goods and services in an economy and to measure the purchasing power of a respective country's currency unit. The CPI is used in the calculation of many key economic indicators that require country's unit of currency measures, including estimates of income, earnings, productivity, output, and poverty. Thailand's CPI shows an upward trend. This study designed to forecasts the CPI of Thailand. Monthly CPI data of Thailand for the period of May 2012 to October 2021 were obtained from the International Monitory Fund (IMF) database. Auto-Regressive Distributed Lag Model (ARDLM), Double Exponential Smoothing (DES), and Autoregressive Integrated Moving Average (ARIMA) models were tested to forecast the CPI of Thailand. Auto Correlation Function (ACF), Anderson Darling test and Ljung-Box Q (LBQ) test were applied to test the model assumptions. The relative and absolute measurements of errors were applied to assess the forecasting ability of the model. Results of the study revealed that the ARDLM with lags 1 and 2 is the most suitable model to forecast the CPI of Thailand. The future values of the CPI can be forecasted by the value of the last month and the month before. It is strongly recommended to design more studies on modeling the CPI for other countries furthermore.

Keywords: Consumer Price Index, Inflation, ARDLM, ARIMA,

1. INTRODUCTION

1.1 Background of the Study

The average change in the prices over time that consumers pay for a basket of goods and services of a specific country or a province is measured by the Consumer Price Index (CPI) (Fernando, 2021). The prices of goods and services are often changed due to the different dynamic situations within the country. The price changes depending on the effectiveness of economic policies, changes in government, national policies and various other factors, including natural disasters.

CPI indicates whether the economy of a country is experiencing inflation, deflation, or stagflation (Fernando, 2021). Inflation is a general increase in prices and a fall in the purchasing value of money. It will be further classified as Demand-Pull Inflation and Cost-Push Inflation (Hall, 2021). Demand-pull inflation, or the increase in aggregate demand, is categorized by the four sections of the macro economy: households, businesses, governments, and foreign buyers (Hall, 2021). Cost-push inflation, or the decrease in the aggregate supply of goods and services stemming from an increase in the cost of production (Hall, 2021). Deflation is a reduction of the general level of prices of goods and services in an economy and Stagflation is a situation where the rate of inflation is high, the rate of economic growth is slowing down, and unemployment remains consistently high. Changes in the CPI are used to assess price changes associated with the cost of living (Fernando, 2021).

The CPI covers a variety of individuals with different incomes, including retirees, but does not include certain populations, such as patients of mental hospitals (Fernando, 2021). The CPI attempts to quantify the overall price levels of goods and services in an economy and to measure the purchasing power of a respective country's currency unit (Fernando, 2021). The weighted average of the prices of goods and services that approximates an individual's consumption patterns is used to calculate CPI (Fernando, 2021).The CPI is used in the calculation of many key economic indicators that require country's unit of currency measures, including estimates of income, earnings, productivity, output, and poverty (Kenneth et al, 1999).

Thailand holds the 26th highest GDP in 2021 according to the IMF statistics. Its value is US$ 538.735 million. The GDP highly influences the CPI under any circumstances. Thailand's CPI shows an upward trend according to statistics from the International Monitoring Fund (IMF).

1.2 Research Problem

The increasing behavior of the CPI shows an increasing price of the basket of goods and services in Thailand. It may lead to inflation. Therefore, it is essential to predict the CPI of Thailand.

ISSN 2719-2407 (Online)

1.3 Objectives of the Study

To forecast the Consumer Price Index of Thailand

1.4 Significance of the Study

The results of the study give insight into the effectiveness of the economic policies and their performances. The findings of the study would guide the imposition or revision of monetary policies, fiscal policies, and other price controlling strategies to increase consumer confidence in Thailand. The results of the study would be a lighthouse for investment decisions of local and foreign investors, technology, and other innovations to gain optimum benefits. For example, the stock prices of the energy sector will increase due to the rise of energy prices. The share prices of the energy companies will increase due to inflation (The Investopedia Team, 2021). Homebuilding is another example of investment decisions. Further, it is a guide to increase the production, including the substitutes, and create new demand of the consumers. The results of the study would be a useful guide for financial planning in the public and private sectors. It is essential for the banking and finance sector in order to keep their investments profitable. The results of the study would be another guide for the creation and evaluation of monetary policies to protect their industries. It is another guide to calculate expenditures accurately in business and minimize the production and overhead cost to increase the profit margin. They can prepare their potential needs in wage shifts and necessary adjustments in human capital and resource, downsizing, outsourcing etc.

2. LITERATURE REVIEW

The review of the study focused on CPI modeling research activities. Stochastic models and soft computing techniques have been applied for the aim.

2.1 Studies Based on Modeling CPI

Konarasinghe (2021-a) has applied Sama Circular Model (SCM), Holt-Winters' additive and multiplicative models, and Seasonal Auto-Regressive Integrated Moving Average (SARIMA) to forecast CPI of USA. Holt-Winters' additive model is the most suitable one for the aim. Djami et al (2021) have applied the Auto-Regressive Integrated Moving Average (ARIMA) model to forecast the CPI of Ambon city of Indonesia. Shinkarenko et al (2021) have applied ARIMA and Holt-Winters' to forecast the CPI of Ukraine. Konarasinghe (2021-b) has applied Double Exponential Smoothing (DES) to forecast the CPI of the USA. Purbasari et al (2020) have applied ARIMA and Artificial Neural Network (ANN) to predict the Indonesian CPI. The results of the study revealed that the ANN outperformed ARIMA. Konarasinghe (2020) has applied Auto-Regressive Distributed Lag Model (ARDLM) to forecast the CPI of Thailand. Aabeyir (2019) has applied Simple Exponential Smoothing (SES), DES, and Winters' additive and multiplicative models to forecast the CPI of Ghana. The results of this study revealed that Winters' multiplicative model performed better than other models.

ISSN 2719-2407 (Online)

Jere et al (2019) have applied Error Correction Model (ECM) and ARIMA to forecast the CPI of Zambia. The results of the study revealed that ECM is the most suitable for this purpose. Nyoni (2019-a) has applied ARIMA to forecasting the CPI of Mauritius. Konarasinghe, W.G.S. (2019-a) has applied the SCM and ARIMA on the forecasting CPI of India and found that SCM performed better than ARIMA. Nyoni (2019-b) has applied ARIMA to model the CPI of Germany. Singla et al (2019) have applied Holt-Winters' additive and SARIMA model to forecast the CPI of India. The performances of both models were satisfactory level. Sinha et al (2018) have applied Neural Network Models to forecast the CPI of India. Gjika et al (2018) have applied SARIMA and Multiple Regression model to forecast the CPI of Albania. The results revealed that SARIMA outperformed Multiple Regression. Ambukege, et al (2017) have applied Neuro-Fuzzy modeling for forecasting the CPI of Tanzania. Norbert et al (2016) have applied ARIMA to model the CPI of Rwanda. Kharimah et al (2015) has applied ARIMA to forecast CPI of Bandar Lampung City, Indonesia from 2009-2013. Adams et al (2014) have applied ARIMA to model CPI of Nigeria. Alibuhtto (2014) applied the Vector Auto-Regressive (VAR) model to predict the Colombo Consumer Price Index (CCPI) of Sri Lanka. Zhang et al (2013) have applied ARMA to forecast the CPI of China.

The ARIMA was highly applied to model CPI. Besides, SARIMA, ARDLM, ECM, DES, SCM, SES, VAR, Holt-Winters' and Multiple Regression were other stochastic models applied for the aim. Some researchers have applied soft computing approaches. ANN and the combination of ANN and fuzzy logic were a few of them. They were highly successful in forecasting CPI. The review of the study revealed that SCM, ECM, Holt-Winters' and ANN outperformed ARIMA on a few occasions. The model validation and the verification part was not clear in a few studies.

3. METHODOLOGY

Monthly data of CPI of Thailand for the period of May 2012 to October 2021 were obtained from the International Monitory Fund (IMF) database. The behavior of the data series paves the path for the model selection to forecast CPI of Thailand (Konarasinghe, 2016-a; 2016-b); and (Konarasinghe, W.G.S., & Abeynayake, 2014). The data series could be included seasonal, cyclical, trends, heavy and minor volatility within the period.(Konarasinghe, W.G.S. & Abeynayake, 2014). The data series would follow an irregular wave-like pattern with; constant amplitude, increasing amplitude, decreasing amplitude, or a mix of them due to the various behaviors (Konarasinghe, W.G.S., & Konarasinghe, 2021). The behavior of the data series is recognized by the ACF and the time series plots, as done by Konarasinghe, W.G.S., & Abeynayake (2014). As per the behavior of the data series, ARDLM, DES, and ARIMA models were tested to forecast the CPI of Thailand. ACF, Anderson Darling test, and Ljung-Box Q (LBQ) test were applied to test the model assumptions (Konarasinghe, W.G.S., et al, 2015). The forecasting ability of the model asses by three measurements of errors, as per

Konarasinghe, (2018; 2016-c; 2015-a; 2015-b).They are; Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Mean Absolute Deviation (MAD) Konarasinghe, (2018; 2016-c; 2015-a; 2015-b).

3.1 Auto Regressive Integrated Moving Average (ARIMA)

ARIMA modeling can be used to model many different time series, with or without trend or seasonal components, and to provide forecasts (Box & Jenkins, 1970); (Box, & Jenkins, 1976). The model is as follows;

An ARIMA model is given by:

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t$$

Where; $\phi(B) = 1-\phi_1 B-\phi_2 B^2 ....\phi_p B^p$

$$\theta(B) - 1-\theta_1 B-\theta_2 B^2 ......\theta_P B^q \qquad (1)$$

$\varepsilon_t =$ Error term

D = Differencing term

B = Backshift operator ($B^a Y_t = Y_{t-a}$)

3.2 Double Exponential Smoothing (DES) Model

This model uses a second smoothing constant, β to separately smoothly the trend DeLurgio, (1998). DES model further adjusts each smoothed value for the trend of the previous period before calculating the new smoothed value DeLurgio, (1998). DES model is implemented using the following equations:

$$S_t = \alpha Y_t + (1-\alpha)(S_{t-1} + b_{t-1}) \qquad (2\text{-}1)$$

$$b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1} \qquad (2\text{-}2)$$

$$F_{t+m} = S_t + b_t m \qquad (2\text{-}3)$$

where

α = level smoothing constant
S_t = smoothing level at end of period t
β = trend smoothing constant (called Beta)
b_t = smoothed trend in period t
m = forecast horizon

ISSN 2719-2407 (Online)

3.3 Auto-Regressive Models and Distributive Lag Model

Theoretically, distributed lags arise when any cause-effect only after a period of time between one event and another (lag) in time, so that the effect doesn't feel all at once at a single point in time but is distributed over a period of time. Chen (2010) defines that the regresses may include lagged values of the predictive variable and current and lagged values of one or many predictive variables. This type of model included the lagged values of the predictive variables.

3.3.1 Auto-Regressive (AR) Models

The lagged values of the predictive variable included in AR models. This model included one or more lagged values Chen (2010); Konarasinghe, W.G.S. (2016); DeLurgio, (1998). This type of models called Auto–Regressive Model .The Auto Regressive Process $\{Y_t\}$ of order p has the model;

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t \tag{3}$$

3.3.2 Distributed Lag (DL) Models

This type of models included the lagged values of the predictive variables. If the length of the lag is defined, it is known as 'Finite Distributed Lag Models' (Gujarati et al, 2012). If the length of the lag is undefined or unknown, then it is known as "Infinite Distributed Lag Models' (Gujarati et al, 2012).

$$Y_t = \alpha + \beta_0 X_{t-1} + \beta_1 X_{t-2} + \ldots + \beta_n X_{t-n} + U_t \tag{4}$$

3.3.3 Auto Regressive Distributed Lag Model (ARDLM)

These models included lagged values of all predictive variables (Gujarati, et al, 2012).

$$Y_t = \alpha + \beta_0 X_{t-1} + \beta_1 X_{t-2} + \ldots + \beta_n X_{t-n} + \lambda_0 X_{t-1} + \lambda_1 X_{t-2} + \ldots + \lambda_n X_{t-n} + U_t \tag{5}$$

4. RESULTS

The analysis contains two main parts:

4.1 Pattern recognition of CPI of Thailand.

4.2 Forecasting CPI of Thailand.

ISSN 2719-2407 (Online)

4.1 Pattern Recognition of CPI of Thailand

Figure 1 is the time series plot of CPI of Thailand for the period of May 2012 to October 2021. The pattern of the CPI shows increasing and declining trends with minor fluctuations. After, February 2020 there is a decade till April 2020. Thereafter, exponential growth has been observed till August 2020. An increasing trend with minor fluctuations continued afterward.

Figure 1: Time Series Plot of CPI of Thailand

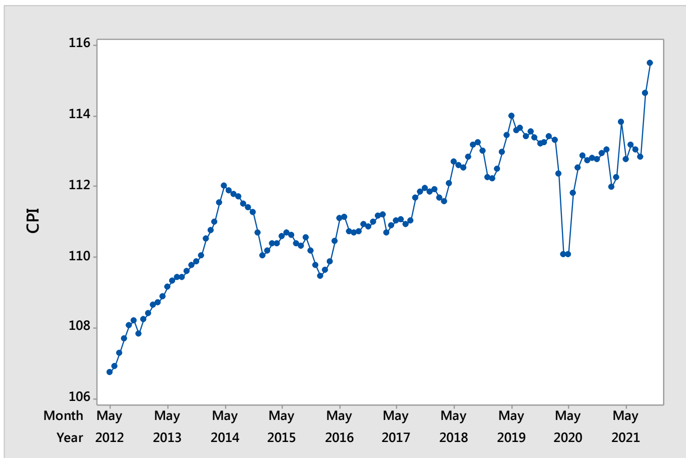


Figure 2 is the ACF of the CPI. It shows a trend but cannot identify any significant seasonal behaviors. There are few significant lags, confirmed the weak stationary of the series.

Figure 2: ACF of CPI

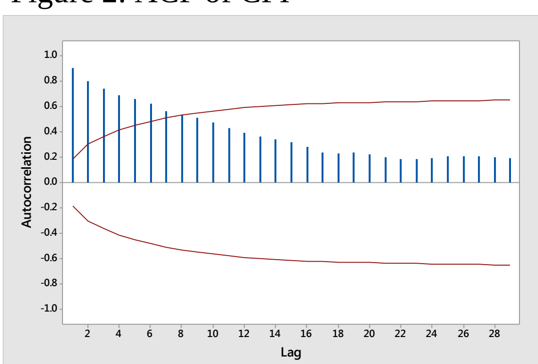


Figure 3: Plot of 1st Difference of CPI

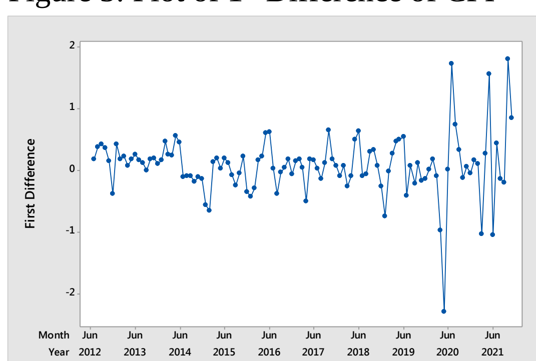


Figure 3 has shown the first difference series of CPI. Figure 2 shows the stationary along with a few significant spikes. This is suitable to pick and apply the ARDLM and ARIMA. Besides, DES is another suitable approach for the aim. Hence, ARDLM, ARIMA, and DES models were selected to forecast the CPI of Thailand by considering the behaviors of the data set.

ISSN 2719-2407 (Online)

4.2 Forecasting CPI of Thailand

The ARIMA model was tested initially. The results given in Table 1.

Table 1: Model Summary of ARIMA

Model	Model Fitting		Model Verification	
ARIMA (1,1,0)	MAPE	0.040658	MAPE	0.276614
	MSE	0.000005	MSE	0.000245
	MAD	0.001915	MAD	0.013056
	Normality	P = 0.288		
	Independence of Residuals	Yes		

ARIMA (1,1,0) satisfied all model validation criteria of normality and the independence of the residuals. This model included 1 autoregressive parameter, with one difference. It means, the future CPI values can be forecasted by past CPI values. The measurements of errors were very low under the fitting and verification. Actual vs fits of ARIMA (1,1,0) are shown in Figure 4. The fits of the CPI follow an analogous pattern of the actual series with the least deviation. Figure 5 is the actual vs. forecast of ARIMA (1,1,0). The deviation between actual and forecast is satisfactorily low. But, the forecast does not follow the pattern of the actual series.

Figure 4: Actual vs. Fits of ARIMA

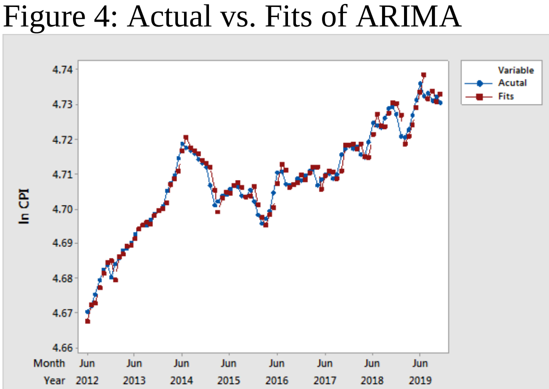
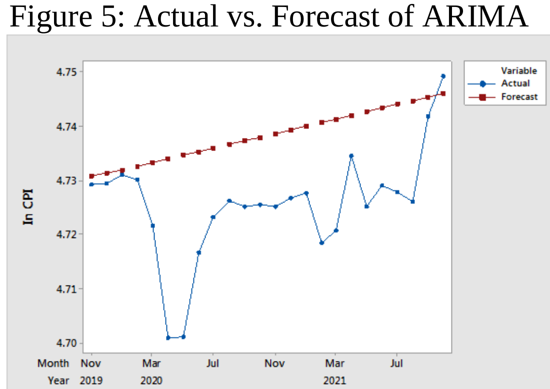


Figure 5: Actual vs. Forecast of ARIMA



DES model was tested after ARIMA with different weights bases on trial and error method. The model summary of DES is given in Table 2.

ISSN 2719-2407 (Online)

Table 2: Model Summary of DES

Model		Model Fitting		Model Verification	
α (level) γ (trend)	0.904 0.358	MAPE	0.054018	MAPE	0.151509
		MAD	0.002542	MAD	0.007157
		MSE	0.000012	MSE	0.000129
		Normality	P= 0.129		
		Independence of Residuals	Yes		

The fitted DES model of α :0.904 and γ :0.358 model satisfied the model validation criterion of normality and independence of residuals. The model performances are quite similar to ARIMA model. Actual vs fits of fitted DES are shown in Figure 6. An analogous pattern of the actual series and fits has been observed with the least deviation. Figure 7 is the actual vs. forecast of the DES model. The pattern of the forecast does not follow the pattern of the actual series. But the deviation is less. The behavior of DES and ARIMA is similar in forecasting the CPI of Thailand.

Figure 6: Actual vs. Fits (DES)

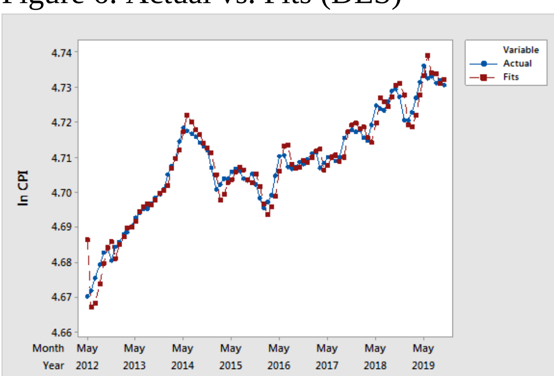
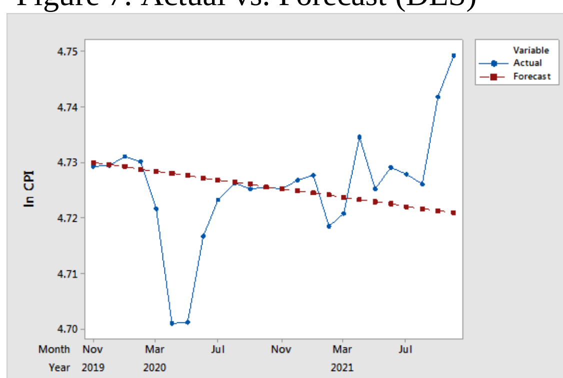


Figure 7: Actual vs. Forecast (DES)



The ARDLM runs with 7 lags. The number of lags is decided from the significant spikes from ACF in Figure 2. Two lags were significant at the end of the fitting process. The model summary of ARDLM with lag 1 and 2 is given in Table 3. The fitted ARDLM has satisfied all validation criterion. The residuals of the model have confirmed the normality and the independence. The forecasting ability of ARDLM is extremely high. The measurement of errors was very low under the fitting and verification.

ISSN 2719-2407 (Online)

Table 3: Model Summary of ARDLM

Model	Model Fitting		Model Verification	
$Y_t = 0.227 + 1.325Y_{t-1} - 0.373Y_{t-2}$	MAPE	0.038844	MAPE	0.112304
	MAD	0.001830	MAD	0.005303
	MSE	0.000005	MSE	0.000059
	Normality	P= 0.216		
	Independence of Residuals	Yes		

The behavior of the actual CPI values vs fits of ARDLM is shown in Figure 8 and the actual vs forecast in Figure 9. The pattern of the fits and actual follow an analogous pattern with the very least deviation. Figure 9 is the actual vs. forecast of ARDLM. The deviation between actual and forecast is highly satisfactory. An analogous behavior has been observed between the actual and forecast in Figure 9. The deviation is extremely low.

Figure 8: Actual vs. Fits (ARDLM)

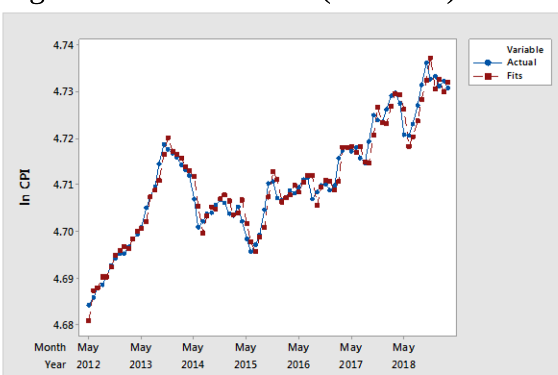
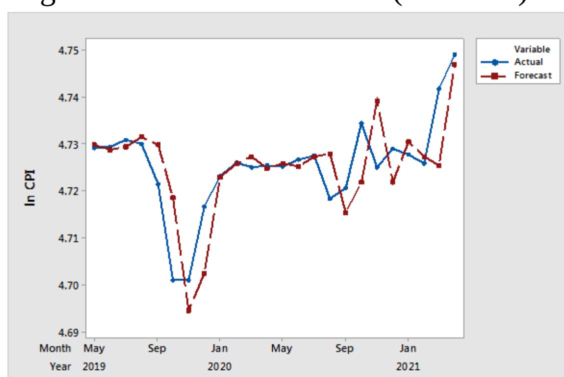


Figure 9: Actual vs. Forecast (ARDLM)



The model performances of Tables 1, 2, and 3 along with Figures 4,5,6,7,8, and 9 are good pieces of evidence to suggest ARDLM is more accurate than ARIMA and DES. The fitted model given below (6). The future behavior of the CPI of Thailand can be forecast by the value of last month and before.

$$Y_t = 0.227 + 1.325Y_{t-1} - 0.373Y_{t-2} \tag{6}$$

Model comparison of ARDLM, ARIMA and DES is shown in Figure 10. The model comparison is another solid evidence to select ARDLM for forecasting CPI of Thailand.

ISSN 2719-2407 (Online)

Figure 10: Model Comparison (ARIMA, ARDLM and DES)

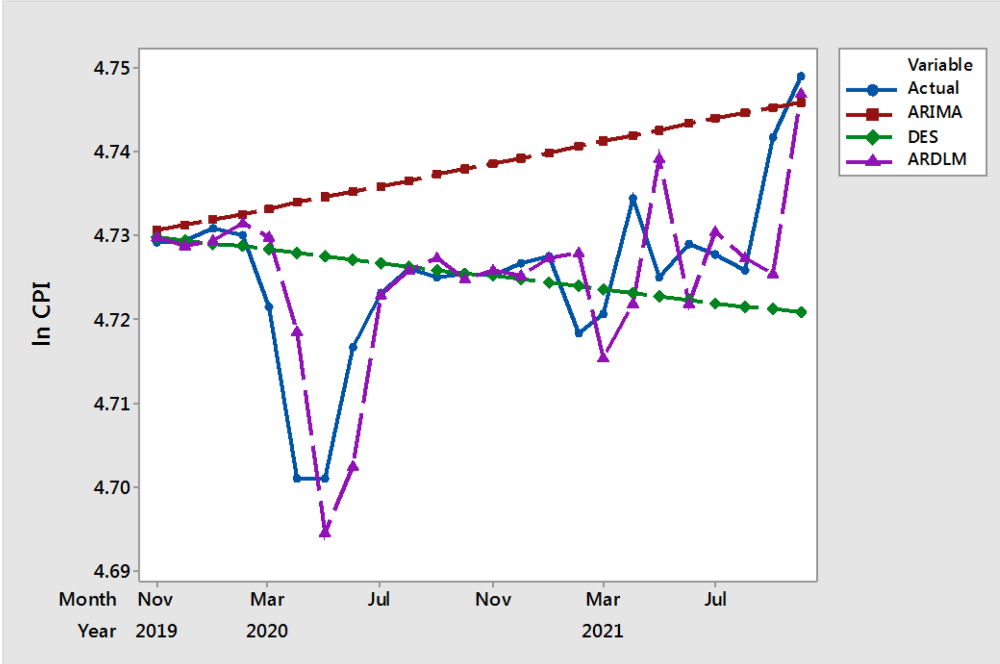


Figure 10 confirmed the accuracy of the ARDLM than ARIMA and DES. ARIMA shows an over-estimation behavior, whereas DES shows dissimilar behavior with ARIMA. Hence, ARDLM is the most suitable model to forecast the CPI of Thailand.

5. CONCLUSION AND RECOMMANDATIONS

The study has tested ARIMA, DES, and ARDLM to forecast the CPI of Thailand. These models were selected by analyzing the past behavior of the CPI. The performances of all three models were satisfactory. But, the performance of ARDLM was extremely high. It was concluded that the ARDLM is the most suitable model to forecast the CPI of Thailand.

The results of the study were similar to the previous study conducted by Konarasinghe, (2020). The present behavior of the data series is not supporting to capture the seasonal or the cyclical behaviors of the CPI of Thailand at this stage. It is recommended to conduct another study later and capture any seasonal or cyclical behaviors. According to the literature, ARIMA is the most popular and widely applied model to forecast CPI. But, in forecasting ARIMA provides a straight line that is not capable to capture the wave-like pattern of the actual series. Hence, it is recommended to test many techniques and pick up the most suitable one for the aim. Finally, it is strongly recommended to design more studies on modeling the CPI of other countries furthermore.

ISSN 2719-2407 (Online)

REFERENCES

Aabeyir, B. (2019).*Forecasting the Consumer Price Index of Ghana using Exponential Smoothing Methods.* Mathematical Theory and Modeling, 9(3). doi: 10.7176/MTM.

Ambukege, G., Justo, G.,& Mushi, J.(2017). Neuro Fuzzy Modelling for Prediction of Consumer Price Index. *International Journal of Artificial Intelligence and Applications* (IJAIA),8(5).doi : 10.5121/ijaia.2017.8503 33.

Adams, S.,O., Awujola, A., & Alumgudu, A.I. (2014). Modeling Nigeria's Consumer Price index using ARIMA model. *International Journal of Development and Economic Sustainability*, 2(2):37-47.

Alibuhtto, M.C.(2014).*Modeling Colombo Consumer Price Index: A Vector Auto Regressive Approach*. Journal of Management, 11(1): 74-81.

Box, G. E., & Jenkins, G. M. (1976). Time series analysis: forecasting and control. Taiwan, Republic of China: Holden-Day.

Box, G.E.P. & Jenkins, G.M. (1970). Time Series Analysis: Forecasting and Control. *Holden-Day*, San Francisco.

Chen, Y. (2010).*Autoregressive Distributed Lag (ADL) Model*. URL:http://mail.tku.edu.tw/chenyiyi/ADL.pdf Accessed 10.04.2015.

Djami, R.J., Radjabaycolle, J.E.T., & Haumahu, G. (2021). Forecasting the Ambon City Consumer Price Index Using Arima Box-Jenkins. *TENSOR Pure and Applied Mathematics Journal*, 2(2):87-96.

DeLurgio, S.A. (1998). *Forecasting Principles and Applications*. Tom Casson. Irwin/McGraw-Hill Companies, Inc. ISBN 0-256-13433-2.

Fernando, J. (2021).*Consumer Price Index (CPI)*. Investopedia. https://www.investopedia.com/terms/c/consumerpriceindex.asp.

Gjika, E.D., Puka,L., & Zaçaj, O.(2018). Forecasting Consumer Price Index (CPI) using Time Series Models and Multi Regression Models (Albania case study). *10th International Scientific Conference "Business and Management 2018"*.doi: 10.3846/bm.2018.51.

Gujarati, D.N., Porter, D.C., & Gunasekar, S. (2012*). Basic Econometrics*. McGraw Hill Education. 5th Edition, ISBN -13:978-0-07-133345-0.

ISSN 2719-2407 (Online)

Hall, M. (2021). *Cost-Push Inflation vs Demand-Pull Inflation: An Overview*. Investopedia**.** https://www.investopedia.com/articles/05/012005.asp.

Jere, S., Banda, A.,Chilyabanyama, R. & Moyo, E. (2019). Modeling Consumer Price Index in Zambia: A Comparative Study between Multicointegration and ARIMA Approach. *Open Journal of Statistics*, 9, 245-257. doi.org/10.4236/ojs.2019.92018.

Konarasinghe, W.G.S., & Konarasinghe, K.M.U.B.(2021). Model Development for Damped and Forced Type of Oscillations in Time Series. *Journal of New Frontiers in Mathematics and Statistics*, 2 (2)20-35.

Konarasinghe, K.M.UB. (2021-a). *Modeling Wave-Like Patterns of Consumer Price Index of the USA*. Journal of New Frontiers in Education and Social Sciences, 1(1), 14-29.

Konarasinghe, K.M.UB. (2021-b). *Modeling Consumer Price Index in USA under the COVID -19 Pandemic.* Conference Proceedings of Institute of Mathematics and Management Conference on Management & Social Sciences (IMMCMSS) 2021. Canberra, Australia, 1 (1) 9.ISSN:2756-9128 (Online). https://ssrn.com/abstract=3953487 or http://dx.doi.org/10.2139/ssrn.3953487.

Konarasinghe, K.M.UB. (2020). *Forecasting Consumer Price Index in Thailand under the COVID -19 Pandemic.* Conference Proceedings of Institute of Mathematics and Management Conference on Management & Social Sciences (IMMCMSS) 2020. Melbourne, Australia.p11.ISSN:2756-9128 (Online). https://ssrn.com/abstract=3953456.

Konarasinghe W. G. S. (2019-a). *Sama Circular Model and ARIMA on Forecasting Consumer Price Index of India*. International Conference on Advances in Mathematics, Statistics and Computer Science- Andhra Loyola 2019, Andhra Loyola College (Autonomus), Andhra Pradesh, India. https://ssrn.com/abstract=3482371.

Konarasinghe K.M.U.B. (2018). *Forecasting Foreign Guest Nights in Hill Country of Sri Lanka.* Review of Integrative Business and Economics Research, 7(4):41-56.

Konarasinghe, W.G.S.(2016). *Model Development for Stock Returns*. Doctor of Philosophy Thesis, University of Peradeniya, Sri Lanka.

Konarasinghe K.M.U.B. (2016-a). *Patterns of tourist arrivals to Sri Lanka from Asian countries.* International Journal of Research and Review, 3(11), 69-79.

Konarasinghe, K.M.U.B. (2016-b). *Time Series Patterns of Tourist Arrivals to Sri Lanka.* Review of Integrative Business and Economics Research, 5(3): 161-172.

ISSN 2719-2407 (Online)

Konarasinghe, K.M.U.B. (2016-c). *Decomposition Techniques on Forecasting Tourist Arrivals from Western European Countries to Sri Lanka.* Conference Proceedings of the 13th International Research Conference on Business Management (ICBM) – 2016, Faculty of Management Studies and Commerce, University of Sri Jayawardanapura, Sri Lanka. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2910291.

Konarasinghe, W.G.S., Abeynayake, N.R., & Gunaratne, L.H.P. (2015). Forecasting Share Prices of Banks of Colombo Stock Exchange. *International Journal of Research & Review,* 2(6), 372-378.

Konarasinghe, K.M.U.B. (2015-a). *Trend Analysis of Direct Employment in Tourism Industry of Sri Lanka*. Conference Proceedings of the 4th International Conference of the Sri Lankan Forum of University Economists, 31. ISSN: 2279 - 2406.

Konarasinghe, K.M.U.B. (2015-b). *Lin-Log Model for Forecasting International Tourism Income in Sri Lanka: Post-War Period.*12th International Conference on Business Management (ICBM) 2015. https://ssrn.com/abstract=2699689, http://dx.doi.org/10.2139/ssrn.2699689.

Konarasinghe, W .G. S., & Abeynayake, N. R. (2014). Time series patterns of Sri Lankan stock returns. *Proceedings of the 11th International Conference on Business Management*, *Phd Consortium*, Faculty of management studies and commerce, University of Sri Jayewardenepura, 78-95.

Kharimah, F., Usman, M., Widiarti, W., & Elfaki, F. A. M. (2015). Time Series Modeling and Forecasting of the Consumer Price Index Bandar Lampug, *Science International (Lahore), 27*(5): 4619-4624.

Kenneth, J., Stewart & Reed, S. B. (1999). Consumer Price Index research series using current methods, 1978-98. *CPI Research Series*, *Monthly Labor Review*, 29-38.

Nyoni, T. (2019-a). *Modeling and forecasting CPI in Mauritius.* Munich Personal RePEc Archive. https://mpra.ub.uni-muenchen.de/id/eprint/92423.

Nyoni, T. (2019-b). *ARIMA modeling and forecasting of Consumer Price Index (CPI) in Germany*. Munich Personal RePEc Archive. https://mpra.ub.uni-muenchen.de/92442/.

Norbert, H., Wanjoya, A., & Waititu, A.(2016). Modeling and Forecasting Consumer Price Index (Case of Rwanda). *American Journal of Theoretical and Applied Statistics*, 5(3): 101-107. doi: 10.11648/j.ajtas.20160503.14.

ISSN 2719-2407 (Online)

Purbasari,I.Y., Anggraeny,F.T., & Ardiningrum, N.A.(2020).Time-series Modeling for Consumer Price Index Forecasting using Comparison Analysis of Autoregressive Integrated Moving Average and Artificial Neural Network. *In Proceedings of the International Conference on Culture Heritage, Education, Sustainable Tourism, and Innovation Technologies (CESIT 2020)*, 599-604. doi: 10.5220/0010369205990604.

Shinkarenko, V.,Hostryk, A.,Shynkarenk, L.,& Dolinskyi,L.(2021). A forecasting the consumer price index using time series model. *SHS Web of Conferences*, 107, 10002. doi.org/10.1051/shsconf/202110710002.

Singla, C., Sarangi, P.K.,Singh,S., & Sahoo, A.K.(2019). Modeling Consumer Price Index: An Empirical Analysis Using Expert Modeler. *Journal of Technology Management for Growing Economies*, 10(1):43-50. doi: 10.15415/jtmge.2019.101004.

Sinha, D, Sarangi, P., Sinha, S., & Sharma, M. (2018). Forecasting Consumer Price Index using Neural Network Models. *3rd Conference on Innovative Practices in Operations Management & Information technology, Published in book of proceedings,* ISBN 978-93- 84562-11-3:84-93.

The Investopedia Team. (2021). What Causes Inflation and Who Profits from It? *Investopedia*. https://www.investopedia.com/ask/answers/111314/what-causes-inflation-and-does-anyone-gain-it.asp.

Zhang, F., Che, W., Xu, B., & Xu, J. (2013). The Research of ARMA Model in CPI Time Series. *Proceedings of the 2nd International Symposium on Computer, Communication, Control and Automation (ISCCCA-13),* Atlantis Press, Paris, France. doi.org/10.2991/isccca.2013.8.

ISSN 2719-2407 (Online)