INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES
Vol 12, Issue 7, (2022) E-ISSN: 2222-6990

Forecasting Unemployment Rate in Malaysia Using Box-Jenkins Methodology during Covid-19 Outbreak

Siti Sarah Januri, Noryanti Nasir, Isnewati Ab Malek & Zaitul Anna Melisa Md Yasin
Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Cawangan Negeri Sembilan, Kampus Seremban, Negeri Sembilan, Malaysia, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Shah Alam, Selangor, Malaysia
Corresponding Author Email: noryantinasir@uitm.edu.my

To Link this Article: http://dx.doi.org/10.6007/IJARBSS/v12-i7/13164 DOI:10.6007/IJARBSS/v12-i7/13164

Published Date: *11* July 2022

Abstract
The economic dimension has revealed that weak economic growth is one of the causes of unemployment and is related to GDP. Forecasting the unemployment rate is essential and is an important determinant of monetary policy decisions and needs to be addressed. This study is conducted to identify whether novel coronavirus 2019, COVID-19 affects Malaysia's unemployment rate and forecast the rate for the next two years. The Box-Jenkins approach uses the Augmented Dickey-Fuller test to stabilize the data. After reducing the trend pattern of the partial autocorrelation coefficient, the ARIMA prediction method ARIMA (2,1,2) was selected as the best model to apply to the unemployment rate time series data. As a result, the projected unemployment rate graph showed a steady increase over the next two years. For future research, it is recommended to consider factors such as inflation, growth domestic product and employment to predict this value to improve results.
Keywords: Forecasting, Unemployment Rate, COVID-19, ARIMA, Box-Jenkins's Methodology

Introduction
In December 2019, a persistent outbreak of an unspecified acute respiratory tract outbreak was reported in the city of Wuhan, China, originating from the Hunan South China Seafood (Guo, Cao, Hong, Tan, Chen, Jin, and Yan, 2020). On 12 January 2020, the World Health Organization (WHO) stated that the cause of this epidemic outbreak was a novel coronavirus reported in 2019 (2019-nCoV) or SARS-CoV-2 and named coronavirus disease 2019 (COVID-19) (WHO, 2020). As of April 17, 2020, there have been a total of 2,230,439 COVID-19 events worldwide, with 150,810 deaths and 564,210 recovered cases (Elengoe, 2020). COVID-19 symptoms typically include fever, a dry cough, and fatigue. Minor symptoms such as migraine, muscle pain, flu, sore throat, or diarrhoea may occur in any affected individuals. Some COVID-

19 patients may develop severe influenza, organ dysfunction (e.g., kidney), upper respiratory tract infection, and septic shock, which can all lead to death (Zhou et al., 2020).

According to new Unemployment Insurance (UI) estimates, approximately 25 million jobs were lost during the first month of the pandemic response, which ran from late March to mid-April 2020. According to Kanyakumari (2020), Malaysia's unemployment rate has risen to 3.9 percent, the highest in a decade, as people's livelihoods suffer due to COVID-19 and the Movement Control Order (MCO). According to data from the Department of Statistics Malaysia (DOSM), this has taken the country’s unemployment rate to its peak this year, exceeding 5.3 percent in May 2020, making the total of unemployment reaching 826,100. As joblessness hit 4.6 percent in April, DOSM announced that the situation had further deteriorated (DOSM, 2021).

The arrival of the coronavirus disease 2019 (COVID-19) has exacerbated the situation. According to Toh (2017), one of the significant issues in Malaysia is unemployment, which is influenced by factors such as GDP, inflation, and population growth. According to the Ministry of Finance (2021), Malaysia's unemployment rate is expected to be 3.5 percent, based on the country's estimated 562.6 million unemployed people versus a workforce of around 51.91 million people (Zainul, 2020). Previous research on the economic dimension has found that poor economic growth is one of the reasons for unemployment and that the unemployment rate is related to the GDP, which adds to poverty and low foreign investment (Alkatheri and Saad, 2019).

Malaysia is one of almost 200 countries and territories fighting the COVID-19 virus. A restricted lock-down technique known as the Movement Control Order (MCO) was implemented for the entire country to control the epidemic’s spread. A few macroeconomic variables are gaining in value, one of which is employment, at a time when everything appears to be dropping, whether global oil prices, the gross domestic product, or the global economy. According to the chief statistician of the Department of Statistics, 2.8 million of Malaysia's 15.23 million working population were self-employed. They were vulnerable to the possibility of unemployment and job cuts, which impacted their income during the MCO phase, partly because they were unable to work (Kanyakumari, 2020).

A recent study by Didiharyono and Syukri (2020) stated that forecasting is used to predict what will happen in the future so that appropriate action can be implemented. As a result, forecasting the unemployment rate due to the COVID-19 outbreak is necessary because long-term unemployment may directly impact individuals, families, and communities in a plausible way (Nichol et al., 2013). The study by Dritsakis and Klazoglou (2018) predicted the potential rate of unemployment in the United States (US) using the Box-Jenkins approach and Seasonal Autoregressive Integrated Moving Average (SARIMA) models. Another study by Tatarczak and Bouchuk (2018) used multivariate techniques as their theoretical framework to classify classes of Polish regions that share common unemployment trends among young people. Dumicic et al (2015) conducted a study to determine the most precise method of forecasting to investigate the prediction of future unemployment rate values and other forecasting techniques with trend components in selected European countries. Then, Petropoulos and Makridakis (2020) believed that forecasting future events, especially in high-risk situations, should be an essential strategic decision-making process. As a result, it is possible to conclude that the forecasting method is crucial for projecting the future unemployment rate affected by COVID-19.

A study conducted by Ramli et al (2018) examined the best approach for predicting the unemployment rate in Malaysia using Autoregressive Integrated Moving Average (ARIMA) and Holt's Exponential Smoothing (Holt's). The results demonstrate that the ARIMA(2,1,2) method is used to forecast Malaysia's unemployment rate for the next ten years. It has been discovered that the ARIMA(2,1,2) model is the preferred model for predicting unemployment because the ARIMA MSE value of 0.2623 is low when compared to Holt's MSE value of 0.3344. The Malaysian unemployment rate is expected to rise marginally between 2017 and 2026. According to this study, Malaysia's unemployment rate is significant and was not considered a serious issue within the next decade before the COVID-19 issue, but it is no longer relevant and needs to be revised. Many previous studies have shown that the Box-Jenkins methodology can predict unemployment rates in many countries. It is simple to use when compared to other methods because the Box-Jenkins methodology is simple and provides an optimal method for forecasting future value.

As a result, forecasting the unemployment rate for the following years is essential, as it has become a key determinant in recent monetary policy decisions. Indirectly, because it provides a timely signal of the general health of the labour market and consequently of aggregate economic activity, the unemployment rate has long been a primary focus of discussions about the status of the economy. Through this study, the objectives of identifying whether the virus affects the unemployment rate in Malaysia and proof it by forecasting the rate for the next two years are to be achieved.

The remainder of this paper is organized as follows. In Section 2, this paper emphasizes the methodology of the process before the forecast of the unemployment rate. The data analysis and findings are conducted in Section 3 to highlight the result of the forecast model. The best model to forecast the unemployment rate is then elected, and the result is discussed in Section 4. Finally, the conclusion is given in Section 5.

Methodology

Description of Data

Forecasting is a method that uses historical data as inputs to generate statistical forecasts to determine the course of future trends. Therefore, secondary data was used in this study. Time-series of data on the unemployment rate in Malaysia from January 2016 to December 2020 have been used to forecast the future unemployment rate in Malaysia by using the Box Jenkin methodology. The data was obtained from the Department of Statistics Malaysia (DOSM). This study forecasts the mentioned event from January 2021 until December 2022, approximately two years from the last data collected.

Stationarity Test

The main assumption of using the Box-Jenkins method is that the data series is stationary, which indicates there is no sign of growth or decline pattern. There are three methods to verify either the data series stationary or otherwise such as the Dickey-Fuller (DF) test, Phillips-Perron (PP) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. One method commonly used as a stationarity test is the Dickey-Fuller test but the augmented version

(ADF). The ADF test has been the first statistical test designed to test the null hypothesis that a unit root exists in an autoregressive model of a given time series and that the process is thus not stationary. ADF statistic is a negative number and the more negative the dismissal of the hypothesis that there is a unit root (Kang, 2017).

Most statistical forecasting techniques are built on the presumption that by using mathematical transformations, the time series can be formed nearly stationary (i.e., "stationarized"). To make it stationary, differencing in statistics is a transformation applied to time-series data. This makes it possible for the properties not to depend on observation time, eliminating trend and seasonality and stabilizing the time series mean. A stationary series is easier to predict, and the statistical features in the future are the same as they were before (Hyndman and Athanasopoulos, 2018). Through the EViews software, the stationarity test of Augmented Dickey Fuller is being conducted on the time series data of the unemployment rate.

Box-Jenkins's Analysis
The Box-Jenkins method is associated with the Autoregressive Integrated Moving Average (ARIMA). ARIMA models are a set of models which can represent both stationary and non-stationary historical data and generate reliable predictions based on a review of past data of an independent condition. There are four steps to constructing ARIMA models (Manoj and Madhu, 2014). The steps are as follows:

The first step is model identification. The first step in developing an ARIMA model is determining whether the parameter prediction is stationary. The values of the variable over time differ by a constant mean and variance when using stationary means. Using the ARIMA(*p,d,q*) model where '*p*' is the order of the autoregressive part, '*d*' is the order of differencing involved, and '*q*' is the order of the moving average. The *p* helps to adjust the fitted line to series forecasting. Then, *d* refers to the number of differencing transformations required by the time series to get stationary.

ARIMA(*p,d,q*) is a variation of Autoregressive (AR) that shows that there is a relationship between current and past values, a random value, and a Moving Average (MA) model that demonstrates that the present value is determined by past residuals (Owusu-Sekyere et al., 2013).

The second is the Estimation of Parameters. Estimate the model parameter for the tentative models that have been chosen. Calculate the standard error and the AR and MA values of the specific ARIMA technique. The third step is Checking the model. The approximate model shall be tested to verify that the sequence is accurately represented. Diagnostic tests are carried out on the residuals to see whether they are randomly and normally distributed. The Ljung-Box Q statistic presents an overall checking of model adequacy. The test statistic Q is,

$$Q_m = n(n+2)\sum \frac{r_k^2(e)}{n-k} x^2_{(m-r)} \qquad (1)$$

where,
$r_k(e)$ = the residual autocorrelation at lag k

n = the number of residuals
m = the number of time lags included in the test
If the p-value is less than the significance value, the model is ineffective. Therefore, the data analyst should identify a new or modified model and the analysis should continue until a suitable model has been generated. Moreover, properties of the residuals can be checked through the following graph:

(i) Verify the normality by considering the normal probability plot or the p-value of the Kolmogorov-Smirnov One-Sample test.
(ii) Verify the randomness of the residues by considering Graph of the residual ACF and PACF.

The human residual autocorrelation should be small and usually within $\frac{\pm 2}{\sqrt{n}}$ of zero (Nochai and Nochai, 2006).

The last step is forecasting using the model. After all the three steps above, forecast the future values using the most appropriate model selected to forecast the unemployment rate in Malaysia from January 2021 until December 2022. The forecast values obtained after the modelling can help identify whether the unemployment rate in Malaysia will be high or low in the years stated earlier. To predict the trends and develop the forecast, use IBM SPSS software.

Measuring Forecast Accuracy

Measurement of precision is critical in forecasting, and it is an excellent process to evaluate the model, and the data will be matched. The analysis should consider the new data that was not used to evaluate the reliability of forecasts when evaluating the model. The dataset has been divided into two parts, known as an estimation and the evaluation data, and ratio it into 70:30, in which 70 percent is for the estimation part and another 30 percent is for the evaluation part. The key element that deserves to be undertaken is that the model that best suits the training details is not necessarily predictable. Residuals are computed in the training set, while predicted errors are computed in the test set. Residuals are based on one-step forecasts, whereas multi-step predictions contain forecasting errors (Hyndman and Athanasopoulos, 2014).

There are three stages of the widely used procedure to test the model. The first stage is splitting the data into estimation and evaluation parts. Next is estimating the model using various forms of functional relationship and variable selection in the estimation part. Lastly, the estimated model is evaluated by comparing the forecast performance against each other. As the basis for comparison to the standard model, a benchmark model is frequently used, and the model that wins is the best. The decision is made by comparing the corresponding measure of error. Based on the calculation of the out-of-sample forecast, the best model will have the smallest value of the error measured. The measurement is usually conducted based on more than one error measure to ensure the importance of the model is achieved. In conclusion, the best model to be chosen is the model with the smallest error measurement (Alias, 2011).

Root Mean Squared Error (RMSE)

This is an error indicator used among researchers to measure the accuracy of models by comparing the prediction errors of each model. Plus, this indicator is commonly used to access a basic data series of the model's fitness and is supported by most statistical software. Its success comes in its mathematical simplicity, i.e., it is considered an excellent general-purpose error metric for numerical predictions (Neill and Hashemi, 2018).

To show the mathematical form of RMSE, assume a series $y_1, y_2, \ldots, y_n$ and the corresponding fitted values are $\underline{y}_1, \underline{y}_2, \ldots, \underline{y}_n$. The RMSE given as,

$$RMSE = \sqrt{\frac{\sum_t^n e_t^2}{n}} \qquad (2)$$

for which $e_t = y_t - \underline{y}_t$ where y_t is the actual observed value at time t and is the fitted value at time t. In other words, RMSE is the square root of the mean squared error (MSE).

Mean Absolute Percentage Error (MAPE)

This may be the most frequently used free measure for units. When determined by series, MAPE is written as,

$$MAPE = \sum_{t=1}^{n} \frac{|\left(\frac{e_t}{y_t}\right) * 100|}{n} \qquad (3)$$

where n denotes effective data points and $|\left(\frac{e_t}{y_t}\right) *100|$ is defined as the absolute percentage error calculated on the fitted values for a particular forecasting method.

Results and Discussions

Through this chapter, researchers elaborated deeper in forecasting the dataset of the unemployment rate in Malaysia. Based on figure 1, Malaysia's unemployment rate increased drastically and consistently from January 2020 until November 2020 resulting from the rapid increase of COVID-19 cases in the entire country. This behaviour is known as random shock. A brief observation implies that the series is not stationary. On the other hand, the series does not indicate the presence of a seasonal effect. Since the series does not contain the seasonal component, the general model formulation is ARIMA(p,d,q). Other than that, restriction of travel and trade with China was advised by the World Health Organization (WHO) in January 2020 to all countries. Many industries in Malaysia were affected by the announcement. Hence, resulting in the drastic increase of the unemployment rate in this country.

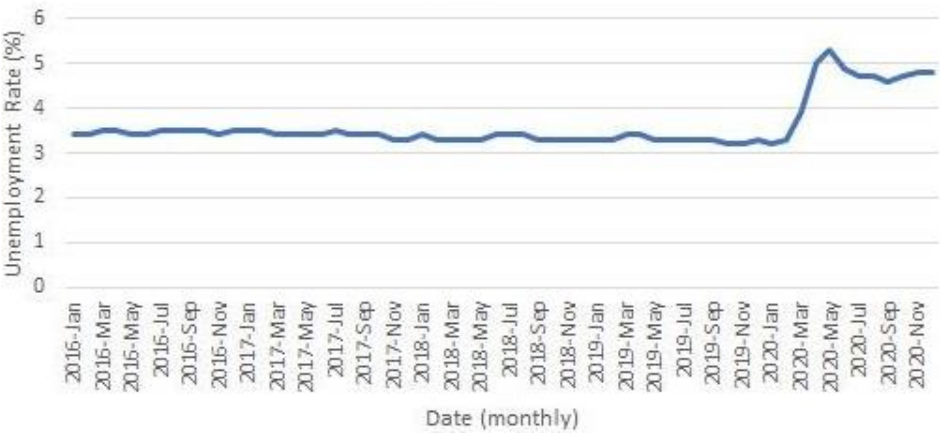


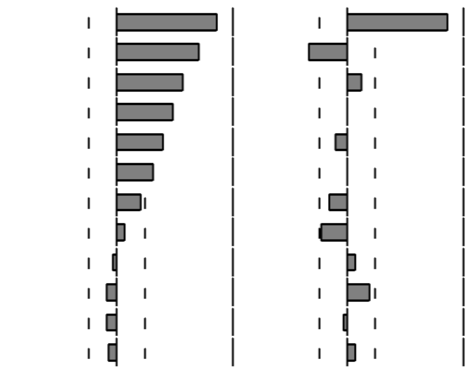
Figure 1: The time series data of unemployment rate (%) in Malaysia from January 2016 until December 2020

Several steps have been conducted, such as the stationarity test using the Augmented Dickey-Fuller and Correlogram. After achieving the stationarity of the data, proceed with choosing the best model of ARIMA to be applied as a forecasting tool on the unemployment rate in Malaysia for the next two years period. In addition, table 1 shows the unemployment rate is insignificant based on the output of the Augmented Dickey-Fuller where the p-value equals 0.8849 is greater than the significance value, 0.05.

Table 1
The output of the Augmented Dickey-Fuller test on the unemployment rate dataset

		t-Statistic	Prob
Augmented Dickey-Fuller test statistic		-0.4912	0.8849
Test critical values:	**1% level**	-3.5504	
	5% level	-2.9135	
	10% level	-2.5945	

The time-series data of the unemployment rate in Malaysia from January 2016 until December 2020 shows there is a decaying pattern on the Autocorrelation Function (ACF) and the presence of trend indicating the dataset is non-stationary after undergoing the Correlogram Test as shown in figure 2. The slow decline in the values of the ACF of the original series suggests that the unemployment rate is not stationary. Plus, the Partial Autocorrelation Function (PACF) has one significant spike.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.896	0.896	50.631	0.000
		2	0.736	-0.339	85.397	0.000
		3	0.602	0.128	109.05	0.000
		4	0.501	0.003	125.73	0.000
		5	0.404	-0.103	136.75	0.000
		6	0.312	0.008	143.45	0.000
		7	0.209	-0.161	146.53	0.000
		8	0.074	-0.230	146.92	0.000
		9	-0.046	0.072	147.07	0.000
		10	-0.092	0.201	147.70	0.000
		11	-0.092	-0.025	148.35	0.000
		12	-0.080	0.076	148.85	0.000

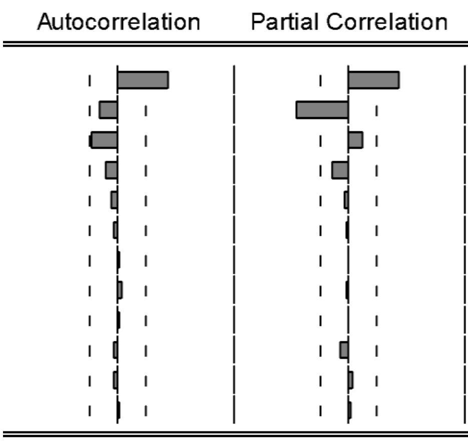
Figure 2: The output of correlogram test, autocorrelation, and partial autocorrelation function

To achieve the stationarity of the dataset, the Augmented Dickey-Fuller test first-order differencing was applied where it stabilized the time series data by reducing the trend and seasonality shown in table 2. This results in the significance of the unemployment rate data as the p-value equal zero is less than the significance value, 0.05.

Table 2
The output of first-order differencing Augmented Dickey-Fuller test on the unemployment rate

		t-Statistic	Prob
Augmented Dickey-Fuller test statistic		-6.3516	0.0000
Test critical values:	**1% level**	-3.5504	
	5% level	-2.9135	
	10% level	-2.5945	

The Correlogram is then being tested on the first-order differencing dataset, resulting in figure 3. There are two significant spikes on lag 1 and lag 2 in the Partial Correlation Function (PACF) indicating the order of the AR(p) is AR(2). On the other hand, the Autocorrelation Function (ACF) shows there is one significant spike on lag 1 and possible significant spike on lag 3, which concluded that it is possible for the order of MA(q) to be either MA(1) or MA(2). However, to obtain more conclusive evidence of the best model form, four models ARIMA(2,1,1), ARIMA(1,1,1), ARIMA(2,1,2) and ARIMA(1,1,2) are estimated.



	AC	PAC	Q-Stat	Prob
1	0.453	0.453	12.707	0.000
2	-0.161	-0.460	14.344	0.001
3	-0.233	0.129	17.846	0.000
4	-0.114	-0.150	18.695	0.001
5	-0.065	-0.036	18.979	0.002
6	-0.033	-0.014	19.051	0.004
7	0.016	-0.007	19.069	0.008
8	0.029	-0.015	19.130	0.014
9	0.012	-0.001	19.141	0.024
10	-0.036	-0.066	19.235	0.037
11	-0.039	0.025	19.347	0.055
12	0.014	0.008	19.361	0.080

Figure 3: The output of first-order differencing correlogram test, autocorrelation, and partial autocorrelation function

This is the summary of the output for Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Ljung-Box Q for all ARIMA models. The ARIMA models above have similar residual values as can be seen on the value of MSE, MAPE, MAE, and Ljung-Box Q, presented in table 3. It is difficult to only point out one best model based on these values as all models might have similar outcomes. Additionally, the p-value of Ljung-Box for all models shows the values are more than the significance value, 0.05, indicating that the models are all fit to conduct forecasting on the unemployment rate dataset.

Table 3
The summary of results RMSE, MAPE, MAE and Ljung-Box Q

Unemployment Rate				
Statistics	**Model**			
	ARIMA(2,1,1)	ARIMA(1,1,1)	ARIMA(2,1,2)	ARIMA(1,1,2)
RMSE	0.055	0.055	0.054	0.054
MAPE	1.24	1.256	1.216	1.251
MAE	0.042	0.043	0.041	0.043
LJUNG-BOX Q	18.357	17.502	16.236	18.174

Table 3 shows the comparison statistic values of the unemployment rate in Malaysia, such as the Root Mean Squared Error, Mean Absolute Percentage Error, Mean Absolute Error, and Ljung-Box Q. These statistic values helped in narrowing down the best model in order to conduct the forecasting method on the unemployment rate in Malaysia for the next two years.

Based on the RMSE, MAPE, MAE, and Ljung-Box Q values in table 3, ARIMA(2,1,2) is the best model compared to the other as this model possessed the lowest values for all the statistic values such as 0.054, 1.216, 0.041 and 16.236, respectively. It is further proved to be the best fit model as in the Correlogram graph. The PACF shows two spikes which recommend the AR(p) is AR(2). Therefore, by considering all the tests done above, this study proceeded to forecast the unemployment rate in Malaysia using the ARIMA(2,1,2) model.

Forecasting Unemployment Rate Using The Best Model (Arima 2,1,2)

This section shows the forecasting values of the unemployment rate in Malaysia for the next two years. Using the chosen model, ARIMA(2,1,2), it is forecasted that the unemployment rate in Malaysia will have an upward trend from January 2021 until December 2022.

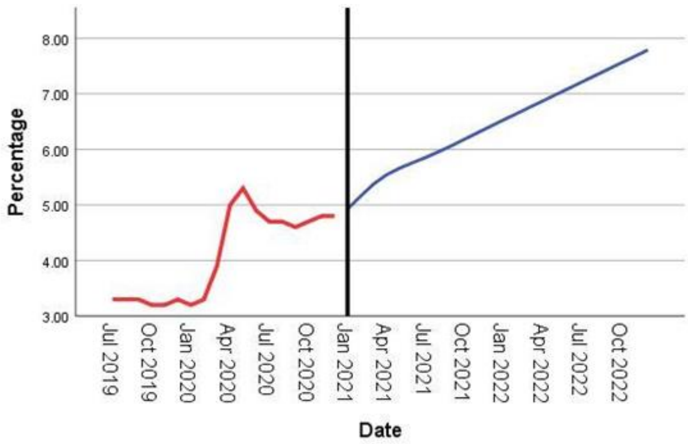


Figure 4: The forecast graph on the unemployment rate in Malaysia

Based on figure 4, the unemployment rate is forecasted to show an upward trend starting January 2021 to end of year 2022. The unemployment rate increases rapidly from the first quartile to the third quartile in 2020 due to the movement control order (MCO). While the point forecasts trend upwards, the prediction intervals allow for the data trend to trend downwards during the forecast period.

Conclusion

This research used the study of time series forecasting. The data gathered is the Malaysian unemployment rate from January 2016 to December 2020, where a forecast of two years from January 2021 until December 2022 has been made. The first objective is to identify if COVID-19 is affecting the unemployment rate in Malaysia is achieved. The descriptive analysis has been carried out to check the difference in the unemployment rate before and after the outbreak of COVID-19. For the second aim of forecasting the unemployment rate for the next two years, this study used the Box-Jenkins methodology.

Before conducting the forecast on the dataset, researchers first test the stationarity by using Augmented Dickey-Fuller and Correlogram test. The data is insignificant as the p-value is more than the significant value and there is a decaying pattern on the Autocorrelation function (ACF). Therefore, researchers apply both Augmented Dickey-Fuller and Correlogram once again with the first-order differencing. Then, the stationary and significant dataset are achieved.

Next, the process of choosing the best model of ARIMA is conducted by comparing the value of Root Mean Squared Error, Mean Absolute Percentage Error, Mean Absolute Error, and Ljung-Box Q. Finally, the ARIMA(2,1,2) model is chosen to be used as the model to forecast the unemployment rate in Malaysia for the next two years due to the model possessed the lowest error values compared to the other models. This model shows the unemployment rate in Malaysia is predicted to continuously increase, which is influenced by the COVID-19 outbreak in the country.

References

Guo, Y. R., Cao, Q. D., Hong, Z. S., Tan, Y. Y., Chen, S. D., Jin, H. J., ... & Yan, Y. (2020). The origin, transmission and clinical therapies on coronavirus disease 2019 (COVID-19) outbreak–an update on the status. *Military Medical Research*, 7(1), 1-10.

World Health Organization (WHO). (2020). *Recommendations for international traffic in relation to COVID-19 outbreak*. Retrieved September 20, 2021, from https://www.who.int.

Elengoe, A. (2020). COVID-19 Outbreak in Malaysia. *Osong Public Health and Research Perspectives,* 11 (3), 93–100.

Zhou, F., Yu, T., Du, R., Fan, G., Liu, Y., Liu, Z., & Cao, B. (2020). Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study. *The Lancet*, 395(10229), 1054-1062.

Kanyakumari, D. (2020). *Malaysia's unemployment rate at highest in a decade: Statistics department.* Retrieved September 20, 2021, from https://www.channelnewsasia.com.

Department of Statistics Malaysia (DOSM). (2021). *Key statistics of Labour force in Malaysia.* Press Release.

Toh, B. (2017). *Youth unemployment a 'serious issue', says MIER* Edge Financial Daily, 1–9. Retrieved September 22, 2021, from https://www.theedgemarkets.com.

Zainul E. (2020). *Malaysia's 2021 unemployment rate seen improving to 3.5%*. Retrieved September 22, 2021, from https://www.theedgemarkets.com.

Alkatheri, S., & AL-Ghamdi, A. S. A. M. (2019). A Systematic Literature Review and Analysis of Unemployment Problem and Potential Solutions. *International Journal of Computer Applications,* 182(44), 27.

Didiharyono, D., & Syukri, M. (2020). Forecasting with ARIMA model in anticipating open unemployment rates in south Sulawesi. *International Journal of Scientific and Technology Research,* 9(3), 3838-3841.

Nichols, A., Mitchell, J., & Lindner, S. (2013). *Consequences of long-term unemployment.* Washington, DC: The Urban Institute.

Dritsakis, N., & Klazoglou, P. (2018). Forecasting unemployment rates in USA using Box-Jenkins methodology. *International Journal of Economics and Financial Issues*, 8(1), 9–20.

Tatarczak, A., & Boichuk, O. (2018). The multivariate techniques in evaluation of unemployment analysis of Polish regions. *Oeconomia Copernicana*, 9(3), 361-380.

Dumicic, K., Ceh Casni, A., & Zmuk, B. (2015). Forecasting unemployment rate in selected European countries using smoothing methods. *World Academy of Science, Engineering and Technology: International Journal of Social, Education, Economics and Management Engineering*, 9, 1073.

Petropoulos, F., & Makridakis, S. (2020). Forecasting the novel coronavirus COVID-19. *PloS One*, 15(3), e0231236.

Ramli, S. F., Firdaus, M., Uzair, H., Khairi, M., & Zharif, A. (2018). Prediction of the unemployment rate in Malaysia. *International Journal of Modern Trends in Social Sciences,* 1(4), 38-44.

Kang, E. (2017). *Time Series: ARIMA Model.* Retrieved September 24, 2021, from https://medium.com/@kangeugine/time-series-arima-model-11140bc08c6.

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: principles and practice*. OTexts: Melbourne, Australia.

Kumar, M., & Anand, M. (2014). An application of time series ARIMA forecasting model for predicting sugarcane production in India. *Studies in Business and Economics*, 9(1), 81-94.

Owusu-Sekyere, E., Harris, E., & Bonyah, E. (2013). Forecasting and planning for solid waste generation in the Kumasi metropolitan area of Ghana: An ARIMA time series approach, *International Journal of Sciences*, 2, 69–83.

Nochai, R., & Nochai, T. (2006). ARIMA model for forecasting oil palm price. *In Proceedings of the 2nd IMT-GT Regional Conference on Mathematics, Statistics and applications (pp. 1–7).*

Alias, M. L. (2011). *Introductory Business Forecasting a practical approach*, 3rd edition. Penerbit Press, UiTM.

Neill, S. P., & Hashemi, M. R. (2018). *Fundamentals of ocean renewable energy: generating electricity from the sea.* Academic Press.