Journal of Academia Vol. 13, Issue 2 (2025) 197 – 208

FORECASTING MALAYSIA'S UNEMPLOYMENT RATE: A COMPARATIVE STUDY OF ARIMA AND INTERRUPTED TIME SERIES WITH ARIMA MODELS

Nurul Hidayah Mohamad Azam Shah, Pauline Jin Wee Mah, Noor Fadhilah Ahmad Radi*

Faculty of Computer and Mathematical Sciences
Universiti Teknologi MARA (UiTM), Cawangan Selangor, Kampus Shah Alam, 40450 Shah Alam, Selangor, Malaysia

**Corresponding author: pauli874@uitm.edu.my*

Abstract

Malaysia, like other countries, was experiencing the effect of the outbreak of the COVID-19 pandemic on the economic sector, which led to a hike in unemployment. High unemployment could interfere with the economic progress, which may impact Malaysia's long-term performance. Hence, to maintain economic stability in the long run, the issue of unemployment should be addressed strategically. In a previous study, the ARIMA and ARFIMA models were used to model and forecast the unemployment rate in Malaysia. Since then, the outbreak of the COVID-19 pandemic which saw a sudden spike resulting in an abrupt change of trend in the unemployment rate may cause the forecast ability of existing models to be not as good. Thus, this study aimed to model Malaysia's unemployment rates using ARIMA and ARIMA interrupted time series models besides comparing the forecast performance between these two models. The monthly data obtained from of the Department of Statistics Malaysia consisted of 176 observations of Malaysia's unemployment rate from January 2010 to August 2024. The ARIMA (0,1,1) was found to be the best ARIMA model in its class for forecasting Malaysia's unemployment rate since it has the lowest BIC and AICc values. Further, the ARIMA model also gave a better forecast performance compared to the ARIMA with interrupted time series model based on the error measures of RMSE, MAE and MAPE values.

Keywords: unemployment rate, interruption, ARIMA, interrupted time series

Article History:- Received: 2 July 2025; Revised: 17 August 2025; Accepted: 18 August 2025; Published: 31 October 2025

DOI: 10.24191/joa.v13i2.7219

Introduction

The unemployment rate is the proportion of individuals who are unemployed to the total number of individuals in the labour force. It is a critical indicator of the economy's status of a country (Case et al., 2020). Department of Statistics Malaysia (DOSM) stated that in January 2024, unemployment rate stayed at 3.3% and the amount of jobless people reduced to 567,300 compared to 567,800 in December 2023. To accurately estimate monthly data, it is crucial to continuously experiment with different forecasting models (Chia & Khalid, 2022). Malaysia, like other countries, was also experiencing the impact of the COVID-19 pandemic on the economic sector. The unemployment rate rose to 5% in April 2020, with 778,800 people left jobless, a 48.8% increase from the previous year. The shutdown of most firms during the movement control order (MCO) resulted in job losses, and unemployed people struggled to find work, according to chief statistician Mohd Uzir Mahidin (Free Malaysia Today, 2020).

A previous study by Ismail et al. (2022) focused on forecasting the unemployment rate by using autoregressive integrated moving average (ARIMA) model and autoregressive fractionally integrated moving average (ARFIMA) model. Yet, these models may not be suitable if unexpected occurrences happened during that period. The occurrences including policy changes and barriers, like penalties, shocks, strikes, and unexpected repercussions are frequently impacting economic time-series as shown from Japan's Noto Peninsula earthquake tsunami (Yuhi et al., 2024), Iran's financial sanctions (Heydarian et al., 2021) and government's health guidelines (Schaffer et al., 2021). Besides unexpected events as stated, COVID-19 pandemic was also one of the major interrupting events.

An interrupted time series (ITS) analysis regarding the effectiveness of physical distancing policy was done in Europe where the study targeted to identify the turning points in 28 European countries due to the COVID-19 outbreaks and to assess the relationship between physical distance and the reported drop in the national epidemics (Vokó and Pitter, 2020). A study related to the heart failure (HF) hospitalizations in Japan during the outbreak of COVID-19 pandemic was carried out by Morishita et al. (2021) where the authors applied the ITS analysis to validate the influence of COVID-19 states of emergency of HF hospitalizations. Pirkis et al. (2021) studied the trends of suicide before and after the outbreak of COVID-19 of 21 countries using ITS analysis. These are the scenarios of interventions or interruptions in time-series (Heydarian et al., 2021). ITS is a model to forecast myriads of sudden events. Schaffer et al. (2021) conducted an interrupted time series analysis using ARIMA models as a guide for evaluating large-scale health interventions. In a previous study (Ismail et al., 2022), an interrupted time series model was recommended to analyze the impact of abrupt occurrences on future research involving time series data. An interrupted time series (ITS) is designed to collect the data before and after an interruption whether it occurs permanently or temporarily (Hays, 2021). With the outbreak of the COVID-19 pandemic and the availability of a new dataset, this study will reconsider modelling the unemployment rate using ARIMA models, this time with the updated dataset.

A high unemployment rate interferes with economic progress, which impacts Malaysia's long-term performance. To maintain economic stability in the long run, the issue of unemployment must be addressed strategically. This study could contribute to academic research on unemployment and interruption analysis. Besides, this study was intended to fill the gap in the previous literature by using the updated time series data until 2024 to forecast the unemployment rate. Policymakers, businesses, and financial institutions need to be able to predict unemployment patterns to make well-informed decisions on workforce planning, labour laws, and economic interventions. Malaysia's government can also strengthen economic resilience, improve social welfare planning, and reduce job losses by anticipating future trends in unemployment and taking prompt and necessary actions.

Methods

Data

The data were obtained from the Department of Statistics Malaysia (DOSM)'s official website. It was based on the monthly unemployment rate in Malaysia from January 2010 to August 2024 and consisted of 176 total observations.

Time Series Models

Autoregressive Integrated Moving Average (ARIMA) model is one of the basic models in forecasting time series data. The ARIMA model is usually written as ARIMA (p, d, q), where it consists of three components called the Autoregressive (AR), Integrated (I), and Moving Average (MA) (Brockwell and Davis, 2002; Lazim, 2013). The differencing in ARIMA is what distinguishes between the ARIMA and ARMA models as both models are identical to each other. When the data is not stationary, the d in ARIMA (p, d, q) represents the order of differencing to achieve stationarity in the series. Thus, it can be written as Equation (1) (Krispin, 2019):

$$y_t = \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{i=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

where,

y_t is the unemployment rate at time t;

y_{t-i} are the unemployment rate at time lags $t-i,\ i = 1, 2, \dots, p$;

$\emptyset_i$ is the estimated AR coefficient;

θ_j is the estimated moving average parameter, $j = 1, 2, \dots, q$;

ε_t is the error term at time t and assumed $\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$.

A time series may experience changes that impact its level during the observation period. It shall be assumed that such changes or interruptions occur at a known time, *T*. Thus, a transfer function-like interrupted analysis model was introduced in Equation (2).

$$Y_t = \sum_{k=0}^{\infty} \tau_k X_{t-k} + N_t \tag{2}$$

However, the input series $\{X_t\}$ is a deterministic function of *t* rather than a random series. Equation (2) is the mean of Y_t. The function $\{X_t\}$ and coefficients $\{\tau_k\}$ were selected to accurately depict the changing level of observations of $\{Y_t\}$ using the sequence $\sum_{k=0}^{\infty} \tau_k X_{t-k}$. After selecting the function $\{X_t\}$ based on data inspection, determining the coefficients $\{\tau_k\}$ became a regression issue, with errors $\{N_t\}$ representing an ARMA process. Interrupted analysis aims to assess the interruption's impact, represented by the term $\sum_{k=0}^{\infty} \tau_k X_{t-k}$, where Equation (2) was used for forecasting (Brockwell & Davis, 2002).

An interruption refers to a particular or continuous event that is expected to impact the time series models. It can be said that the impact of COVID-19 on the unemployment rate is classified as a pulse function since the time series was interrupted by a sudden and major event. Theoretically, a pulse function can be defined as an abrupt alteration that occurs momentarily following an interruption and subsequently resumes to baseline levels.

For a series $\{Y_t\}$ with $EY_t = 0$ for $t \le T$ and $EY_t \to 0$ as $t \to \infty$, a fit input series is as given by Equation (3).

$$X_t = I_t(T) = \begin{cases} 1 & \text{if } t = T, \\ 0 & \text{if } t \neq T. \end{cases} \tag{3}$$

The pulse variable is set to 1 on the interruption period and 0 otherwise (Schaffer et al., 2021). In the context of this study, the pulse function of unemployment rate was assigned the value of 0 before the sudden spike from April 2020 to March 2022 (where during this duration, the value of 1 was assigned to indicate the interruption).

Time Series Modelling Procedure

A total of 176 observations were partitioned into two parts, identified as the training and testing sets. The training set used for modelling consisted of 170 observations from January 2010 to February 2024 while the testing set used for forecast accuracy check consisted of 6 observations from March to August 2024. The data for the training set were plotted to identify the pattern and time series components in the series.

A Box-Cox transformation (Brockwell & Davis, 2002) is beneficial for adjusting data variability based on level. To stabilize variability linearly with level, the value of lambda should be set as zero (λ= 0) and is by Equation (4).

$$f_\lambda(y) = \begin{cases} \log(y), & \lambda = 0 \\ \dfrac{y^\lambda - 1}{\lambda}, & \lambda \neq 0 \end{cases} \tag{4}$$

A time series is stationary if the mean and variance are independent with respect to time and should not have trend or seasonality as they would influence the time series (Hyndman & Anthanasopoulos, 2018). The series is not stationary if there is a presence of a unit root. Thus, the Augmented Dickey-Fuller (ADF) test is used to conduct the unit root test in the series. Besides, an autocorrelation function (ACF) plot was also used to identify patterns and correlations in the series. A stationary series shows the ACF plot decays to zero as lag increases as there is a low correlation between observations over time, whereas a non-stationary series shows the ACF decays slowly or exhibits periodic behaviour. The trend could be removed by the process of differencing to make the series stationary.

The auto.arima () function in RStudio, based on the Hyndman – Khandakar algorithm (Hyndman & Khandakar, 2008), produced an ARIMA model by combining unit root testing, Corrected Akaike Information Criterion (AICc) minimization, and maximum likelihood estimation (MLE).

Aside from checking stationarity, the ACF and Partial Autocorrelation Function (PACF) of the residuals are observed to check whether the residuals are white noise (Lazim, 2013). The residuals that are sighted in the ACF and PACF plots ought to fall within the limits of $\pm 1.96\sqrt{n}$ approximately 95% of the time to be regarded as a suitable model (Brockwell & Davis, 2002). If the residuals are white noise, there would be no existence of significant autocorrelation coefficients. The Ljung-Box test was used to check the independence of the residuals. A model is valid for forecasting if it passes the Ljung-Box test (which indicates the residuals are independently distributed).

A similar procedure is applied for the ARIMA model with an interrupted time series model. However, in this case, pulse function was included when the interruption occurred between April 2020 to March 2022. When conducting interrupted time series analysis with an ARIMA model, a dummy variable was used to account for the interruption (COVID-19).

A forecast accuracy check was conducted to assess the forecasting ability of the time series models. The error metrics used in the study were the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) as given by Equations (5), (6) and (7) respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i-1}^{n}|x_i - \hat{x}_i| \tag{6}$$

$$MAPE = \frac{1}{n}\left(\sum_{i-1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right|\right) \times 100\% \tag{7}$$

where x_i = actual values, $\hat{x}_i$ = predicted values, n = number of predicted values (n = 6 months)

Results and Discussion

ARIMA Model

The time series data used for modelling the unemployment rate in Malaysia is as shown in Figure 1. Figure 1 shows a major upward spike in early 2020, then a decreasing trend afterwards. The spike (irregular) could be categorized as random shock due to COVID-19. There was no trend detected prior to 2020. There was also no seasonality and cyclical from the whole series.

Figure 1. Graph of Unemployment Rate in Malaysia from January 2010 to August 2024

However, the variance rose significantly and then diminished following the spike, which implied the variance was not constant. Therefore, the Box-Cox transformation was applied to stabilize the variance. The value of lambda was set to zero in the transformation since a log transformation was used. The time series plot after the Box-Cox transformation can be seen in Figure 2.

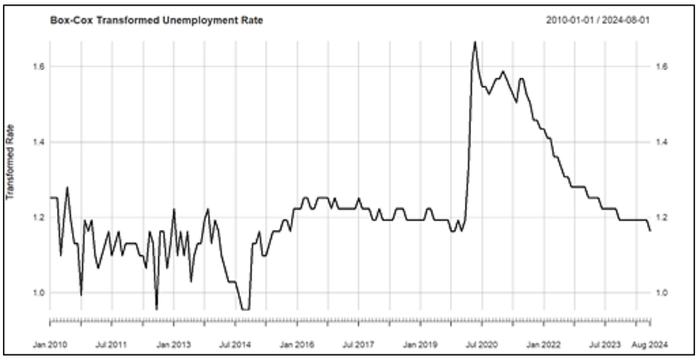

Figure 2. Box-Cox Transformed Unemployment Rate

Figure 3 shows an ACF plot with a trend in which spikes slowly decay as the lag increases, suggesting there is a high correlation between observations with respect to time. Based on the ACF plot solely, it is suggested that the series is not stationary. To confirm the stationarity, the ADF test was conducted.

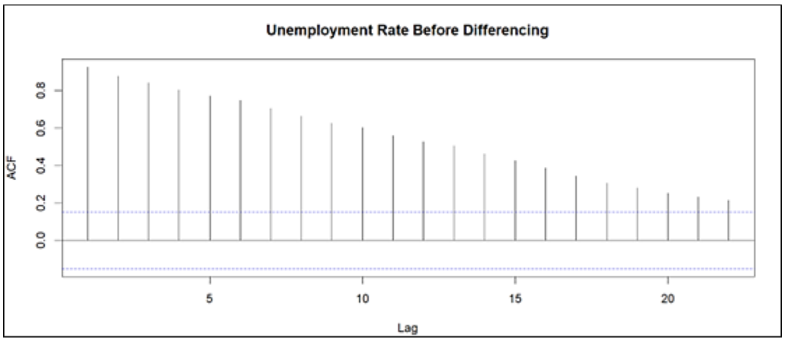

Figure 3. ACF Plot of Unemployment Rate Before Differencing

Table 1 proved that the series is not stationary as the p-value is more than the significance level of 0.05. Hence, first order differencing was applied to remove the trend. After differencing, ACF plot in Figure 4 was improved and it is further supported by PACF plot in Figure 5 which indicated the series is now stationary. Both figures show no spikes outside the significance bounds and the plots decay rapidly to zero as lag increases. Based on Table 2, the stationarity of the series is proven statistically as the *p*-value from ADF test is less than the significance level of 0.05. Figure 6 displays the time series plot after differencing which shows that stationarity is now achieved.

Table 1. ADF Test of Unemployment Rate Before Differencing

Dickey-Fuller	P-value
-2.2125	0.4876

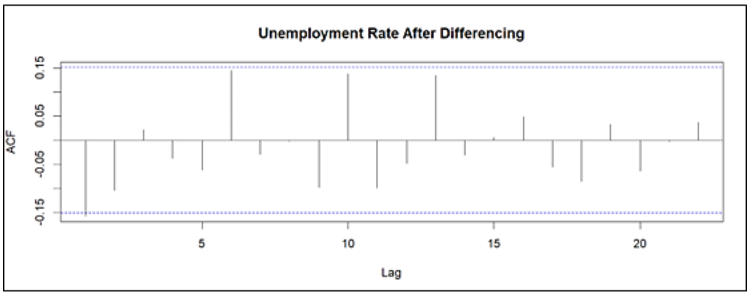

Figure 4. ACF Plot of Unemployment Rate After Differencing

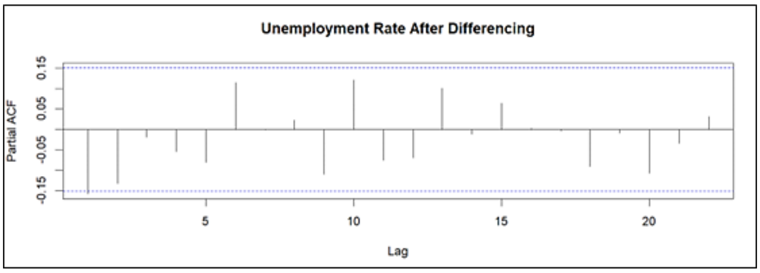

Figure 5. PACF Plot of Unemployment Rate After Differencing

Table 2. ADF Test of Unemployment Rate After Differencing

Dickey-Fuller	P-value
-5.3014	0.01

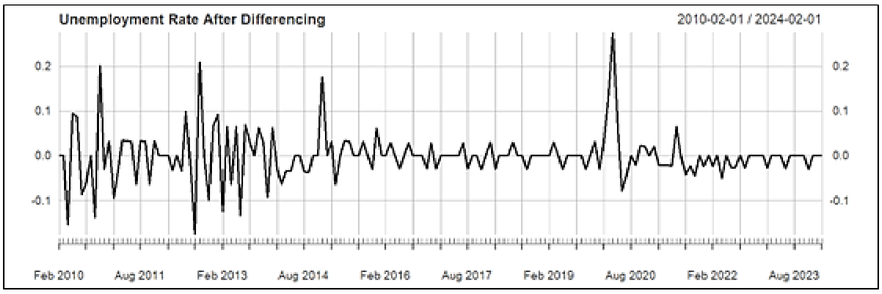

Figure 6. Plot of Unemployment Rate After Differencing

The best ARIMA model was chosen automatically using auto.arima function in RStudio. The function resulted to ARIMA (0,1,1) as the best model since it has the lowest AICc value. Table 3 summarized the estimated coefficients of MA, AIC, BIC and AICc values for ARIMA (0,1,1). It can be written as Equation (8).

Journal of Academia Vol. 13, Issue 2 (2025) 197 – 208

Table 3. The best ARIMA model using auto.arima function

	MA (1)	AIC	BIC	AICc
ARIMA (0,1,1)	-0.2042	-501.1755	-494.9157	-501.1

$$Y_t = -0.2042\varepsilon_{t-1} + \varepsilon_t \quad (8)$$

Ljung-Box test was conducted to check whether the residuals are white noise and independently distributed. Table 4 displays the result of the assumption test for ARIMA (0,1,1). The Ljung-Box test shows that the residuals are independently distributed as the p-value is more than significance level (0.05). Since ARIMA (0,1,1) passed the Ljung-Box test, the model is valid to be used as a forecasting model.

Table 4. Significance value of Ljung-Box test of ARIMA (0,1,1)

Model	***p*-value**
ARIMA (0,1,1)	0.4328

Figure 7 shows the residual time series plot for ARIMA (0,1,1). The residual fluctuates randomly at zero value with no visible pattern detected. It indicates the model is a good fit. Figure 8 displays the ACF plot of the residual for ARIMA (0,1,1). All the spikes are within the significance bounds which suggests there is no significant autocorrelation with respect to time and the model has fully captured dependencies in the data.

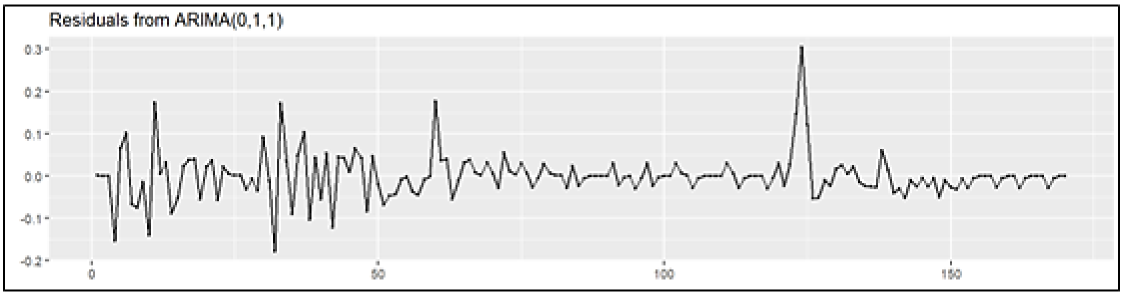

Figure 7. Residual Time Series Plot for ARIMA (0,1,1)

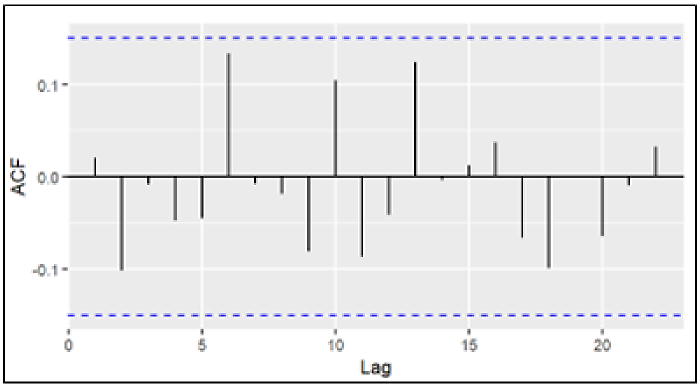

Figure 8. ACF Plot of Residual ARIMA (0,1,1)

Table 5 and Figure 9 show the actual and forecasted values, and the 95% forecast interval using ARIMA (0,1,1) model for Malaysia's unemployment rate. Based on Table 5, the actual unemployment rate from March to July 2024 is steady at 3.3% but drop slightly to 3.2% in August 2024. The forecasted values remain the same at 3.3002% for each month. The possible reason for the forecast values to remain constant at 3.3% (almost similar to be actual values) based on the ARIMA (0,1,1) could be due to the ARIMA being a short memory model which could have possibly captured the behaviour of the unemployment rate after the occurrence of COVID-19 pandemic. Figure 9 shows that the forecasted values (indicated by orange line) from March to August 2024 are within the forecast boundaries (blue and green lines).

Table 5. Actual and Forecasted Values for Unemployment Rate using ARIMA (0,1,1)

Months	Actual Unemployment Rate (y_t)	Forecasted Values (F_t)	95% Forecast Interval	
			Lower Boundary	Upper Boundary
March 2024	3.3	3.3002	2.9671	3.6706
April 2024	3.3	3.3002	2.8807	3.7808
May 2024	3.3	3.3002	2.8118	3.8734
June 2024	3.3	3.3002	2.7533	3.9556
July 2024	3.3	3.3002	2.7020	4.0307
August 2024	3.2	3.3002	2.6560	4.1006

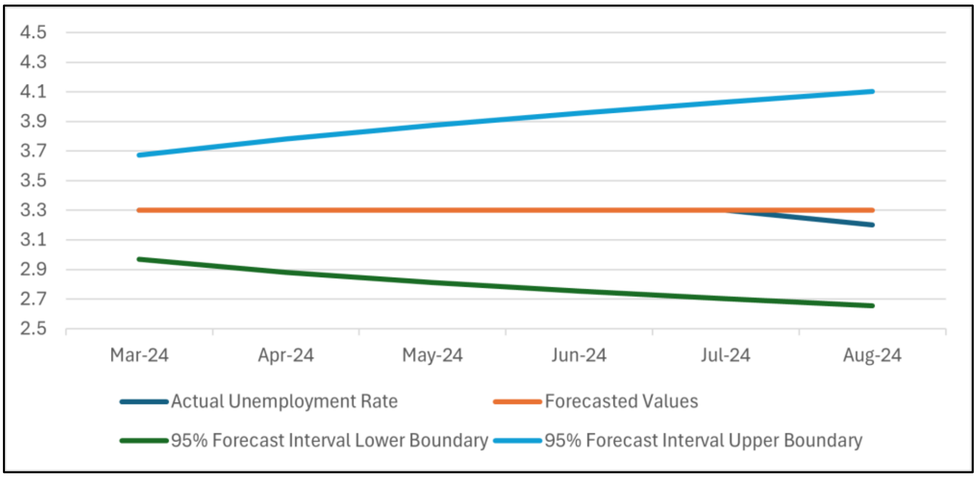

Figure 9. Actual, Forecast and 95% Forecast Interval of ARIMA (0,1,1) for Unemployment Rate from March 2024 to August 2024

ARIMA with Interrupted Time Series

ARIMA with interrupted time series was applied to the data of the unemployment rate in Malaysia. Due to the outbreak of the COVID-19 pandemic, a sudden spike in the time series was observed between April 2020 to March 2022 as could be seen in Figure 1. To capture the impact of the sudden interruption, pulse function was applied in the best model, ARIMA (0,1,1). A dummy variable with the values of 1 and 0 were introduced to show the presence and absence of interruption, respectively.

Table 6 presents the estimated coefficients and assumption checking for ARIMA (0,1,1) with interrupted model. The estimated coefficient for MA (1) is -0.3840 while the coefficient of external regressor (interruption) is 0.2001 which indicates that a unit increase in the outbreak of COVID-19, the unemployment rate would increase by 0.2001%. The values of AIC, BIC, and AICc are -528.4346, -519.0449 and -528.2892, respectively. The Ljung Box test indicates that the residuals are independently distributed.

Table 6. ARIMA (0,1,1) Interruption Model of Unemployment Rate

	Values
MA (1) coefficient, θ_1	-0.3840
External Regressor, τ_1	0.2001
AIC	-528.4346
BIC	-519.0449
AICc	-528.2892
p-value of Ljung-Box test	0.2218

ARIMA (0,1,1) with interruption can be written as Equation (9):

$$Y_t = (1 - 0.3840B)\varepsilon_t + 0.2001X_{t,1} \quad (9)$$

Figure 10 shows the residual time series plot for ARIMA (0,1,1) with interruption. The residual fluctuates randomly at zero value with no visible pattern detected. It indicates the model is a good fit. Figure 11 displays the ACF plot of the residual for ARIMA (0,1,1) with interruption. All the spikes are within the significance bounds, which suggests there is no significant autocorrelation concerning time and the model has fully captured dependencies in the data.

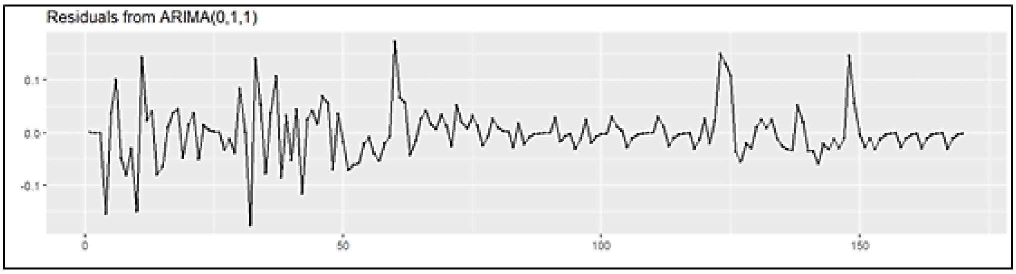

Figure 10. Residual Time Series Plot ARIMA (0,1,1) Interruption

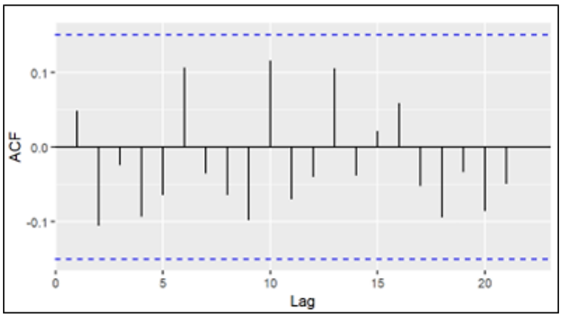

Figure 11. ACF Plot of Residual ARIMA (0,1,1) Interruption

Table 7 and Figure 12 show the forecasted values and their forecast interval using ARIMA (0,1,1) with interruption. The forecasted values remained at 3.3021% for each month. These forecasted values are the same those forecasted by ARIMA (0,1,1) model given in Table 5. It is clear that in this study, the outbreak of COVID-19 pandemic did not statistical effect the unemployment rate. Figure 12 shows that the forecasted values (indicated by orange line) from March to August 2024 are within the forecast boundaries (blue and green lines).

Table 7. Actual and Forecasted Values for Unemployment Rate using ARIMA (0,1,1) with interruption

Months	Actual Unemployment Rate (y_t)	Forecasted Values (F_t)	95% Forecast Interval	
			Lower Boundary	Upper Boundary
March 2024	3.3	3.3021	2.9953	3.6404
April 2024	3.3	3.3021	2.9448	3.7029
May 2024	3.3	3.3021	2.9015	3.7581
June 2024	3.3	3.3021	2.8633	3.8083
July 2024	3.3	3.3021	2.8287	3.8548
August 2024	3.2	3.3021	2.7971	3.8984

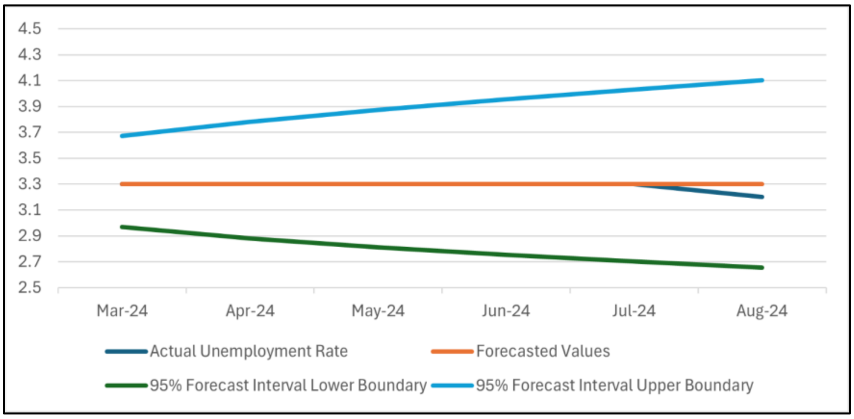

Figure 12. Actual, Forecast and 95% Forecast Interval of ARIMA (0,1,1) with interruption for Unemployment Rate from March 2024 to August 2024

Comparison Between ARIMA and ARIMA Interruption Models

ARIMA (0,1,1) and ARIMA (0,1,1) with interrupted models were compared based on the RMSE, MAE, and MAPE values as shown in Table 8. ARIMA (0,1,1) is a better model and performs better in forecasting Malaysia's unemployment rate as the values of RMSE, MAE and MAPE are lower than ARIMA (0,1,1) with intervention.

Table 8. Out-of-Sample Model Evaluation

Models	**RMSE**	**MAE**	**MAPE**
ARIMA (0,1,1)	0.0409	0.0168	0.5261%
ARIMA (0,1,1) Interruption	0.0418	0.0188	0.5867%

Conclusion

Malaysia's unemployment rate was said to have been impacted by COVID-19 pandemic. The sudden change in the trend may suggest the application of interrupted time series model to fully capture the trend. The study aimed to model the unemployment rate using ARIMA and ARIMA interrupted time series for the updated dataset. ARIMA (0,1,1) was found to be the best ARIMA model for forecasting Malaysia's unemployment rate from March 2024 to August 2024 since it has the lowest AICc values. The findings revealed that the ARIMA model gave a better forecast performance compared to the ARIMA with interruption when comparing the forecast performance between the two time series models. Although there was an interruption (the sudden outbreak of the COVID-19 pandemic) in the unemployment rate, the ARIMA model was still able to forecast the unemployment with slightly lower forecast errors compared to the ARIMA with interruption. It can be concluded that the impact of COVID-19 (sudden interruption) may not be significant enough to impact the unemployment trend. Hence, the ARIMA model is a suitable forecast model as it can solely capture information in the unemployment trend without any external regressors added to the model. The forecasts from ARIMA model did not show varying values as it could be due to ARIMA being a short memory model. Considering the long memory characteristics in economic data, future studies may apply Long Short-Term Memory (LSTM) model to capture such patterns in Malaysia's unemployment rate. Besides univariate time series models, multiple time series can be included for future study by considering more variables that would affect the unemployment rate.

Acknowledgement/Funding

The authors would like to thank Universiti Teknologi MARA Shah Alam for their support in the completion of this study. The authors received no financial support for the work.

Author Contribution

NH Mohamad Azam Shah – data collection, analysis of data, writing the manuscript; PJW Mah – Supervision writing – review and editing; NF Ahmad Radi – writing – review and editing.

Conflict of Interest

Authors declare no conflict of interest.

References

Brockwell, P. J. & Davis, R. A. (2002). *Introduction to Time Series and Forecasting*. Springer, New York, United States. 2(1): pp. 82 – 332.

Case, K. E., Fair, R. C., & Oster, S. M. (2020). *Principles of Macroeconomics*. Pearson Education Limited, United Kingdom. 13(1): pp. 121.

Chia, X. Y. & Khalid, K. (2022). Forecasting Analysis of Unemployment Rate in Malaysia based on the Naive, Holt's Linear Trend and Box-Jenkins Models. *Enhanced Knowledge in Sciences and Technology*, *2*(2), 11 - 20.

Department of Statistics Malaysia. (2024). Monthly Principal Labour Force Statistics. https://open.dosm.gov.my/data-catalogue/lfs_month. [Access online 4 April 2024].

Free Malaysia Today. (2020, June 15). *Malaysia's unemployment rate rises to 5% in April as Covid-19 takes toll*. https://www.freemalaysiatoday.com/category/nation/2020/06/15/malaysias-unemployment-rate-rises-to-5-in-april-as-covid-19-takes-toll/. [Assess online 5 May 2024].

Hays, J. C. (2021). Time Series Analysis Intervention Models and Transfer Functions. https://sites.pitt.edu/~jch61/PS2740/Notes_and_Slides/supplemental.pdf. [Access online 4 May 2024].

Heydarian, S., Pahlavani, M., & Mirjalili, S. H. (2021). Financial Sanctions and Economic Growth: An Intervention Time-series Approach. *International Economics Studies*, *51*(1), 1-14.

Hyndman, R.J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice*. 2nd edition, OTexts, Melbourne, Australia. 2(1): pp. 63 – 78.

Ismail, N. A., Ramzi, N. A., & Mah, P. J. W. (2022). Forecasting The Unemployment Rate In Malaysia During Covid-19 Pandemic Using ARIMA And ARFIMA Models. *Malaysian Journal of Computing* (MJoC), *7*(1), 982-994.

Krispin, R. (2019). *Hands-on time series analysis with R : Perform time series analysis and forecasting using R*. Packt Publishing, Limited, United Kingdom. 1(1): pp. 352 – 353.

Lazim, M. A. (2013). *Introductory Business Forecasting: A Practical Approach*. UPENA, UiTM, Malaysia. 3(1): pp. 223 – 274. ISBN:978-983-3643

Morishita, T., Takada, D., Shin, J. H., Higuchi, T., Kunisawa, S., Fushimi, K., & Imanaka, Y. (2021). Effects of the COVID-19 pandemic on heart failure hospitalizations in Japan: interrupted time series analysis. *ESC Heart Failure*, *9*(1), 31–38.

Pirkis, J., John, A., Shin, S., DelPozo-Banos, M., Arya, V., Analuisa-Aguilar, P., Appleby, L., Arensman, E., Bantjes, J., Baran, A., Bertolote, J. M., Borges, G., Brečić, P., Caine, E., Castelpietra, G., Chang, S. S., Colchester, D., Crompton, D., Curkovic, M., Deisenhammer, E. A., … Spittal, M. J. (2021). Suicide trends in the early months of the COVID-19 pandemic: an interrupted time-series analysis of preliminary data from 21 countries. *The Lancet Psychiatry*, *8*(7), 579–588.

Schaffer, A. L., Dobbins, T. A., & Pearson, S. A. (2021). Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: a guide for evaluating large-scale health interventions. *BMC Medical Research Methodology*, *21*(1), 58.

Vokó, Z., & Pitter, J. G. (2020). The effect of social distance measures on COVID-19 epidemics in Europe: An interrupted time series analysis. *GeroScience*, *42*(4), 1075–1082.

Yuhi, M., Umeda, S., Arita, M., Ninomiya, J., Gokon, H., Arikawa, T., Baba T., Imamura F., Kawai A., Kumagai K., Kure S., Miyashita T., Suppasri A., Nobuoka H., Shibayama T., Koshimura S., & Mori, N. (2024). Post-event survey of the 2024 Noto Peninsula earthquake tsunami in Japan. *Coastal Engineering Journal*, *66*(3), 405–418.