Enhanced Knowledge in Sciences and Technology Vol. 3 No. 2 (2023) 332-343
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EKST

Homepage: http://publisher.uthm.edu.my/periodicals/index.php/ekst
e-ISSN : 2773-6385

Covid-19 Cases in Malaysia: Time Series Forecasting and The Uncertainty

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DOI: https://doi.org/10.30880/ekst.2023.03.02.039
Received 16 January 2023; Accepted 16 February 2023; Available online 30 November 2023

Abstract: COVID-19 predictive analysis has emerged as a prominent research topic to assist healthcare services and governments in planning and controlling the development of infectious illness. Modelling and forecasting the virus's daily transmission pattern can help healthcare systems prepare for the influx of new patients. Accurate forecast of COVID-19 transmission is crucial for all parties involved. Therefore, daily new cases of COVID-19 are forecast using three different methods as ARIMA method, Holt's Linear Trend method and the Naïve method. The methods are then compared using RMSE, MAE, MAPE and the uncertainty was calculated. The ARIMA has the lowest level for all performance measurement, but the Naïve method produce the lowest uncertainty. The forecast value of COVID-19 cases from 26/07/2022 to 30/07/2022 using ARIMA (2,1,4) fluctuates from 3516 cases to 4237 cases. Cases prediction that is accurate can be used as information as it could help the government, healthcare management and citizens prepare for the wave of new cases and help for similar pandemic issues in future.

Keywords: COVID-19, Forecasting, Uncertainty, ARIMA, Holt's Linear Trend, Naïve

1. Introduction

Epidemics have evolved into something more deadly as over the last six decades, the fatality count has risen ever since the year 1980 [1]. Pandemics are less common compared to epidemics, but their outcomes are far more devastating. The globe is presently experiencing a pandemic prompted by the upsurge of a novel Coronavirus, the COVID-19 [2]. COVID-19 is a new extremely infectious virus of the Coronaviridae family. COVID-19 or SARS-CoV-2 that was first detected at a seafood market in Wuhan, China [16].

Infected individuals suffer from severe respiratory issues and might potentially develop serious illness if they have chronic disorders such as a weakened immune system or are of old age [3]. In 2020,

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Malaysia experienced an eruption of a virus known as Severe Acute Respiratory Syndrome Coronavirus 2 or COVID-19, which is contagious to the respiration, intestinal and brain systems of humans. By the end of January 2020, the virus had begun to spread rapidly in Malaysia. The first COVID-19 case recorded in Malaysia was on the 25th of January 2020 [2020]. The COVID-19 pandemic is Malaysia's worst infectious illness pandemic since the 1918 Spanish Flu that killed 1% of the country's population which is equivalent to 34,644 persons [4].

On March 19th 2020, Malaysia was officially ranked as the fourth country with the highest number of COVID-19 cases and the first in South-east Asia [5]. In regards of growth and fleets expansion, the Covid-19 epidemic is affecting global shipping firms and markets [15]. Since the effect of this virus is devastating, it is critical to be able to recognise the pattern and anticipate the transmission of confirmed cases. As of January 3rd 2020 to 19 May 2022, there were 4,481,278 reported cases of COVID-19 in Malaysia, with 35,623 deaths [6]. However, it is estimate that the actual COVID-19 cases might be higher than reported case counts which is caused by in home testing, which is excluded from official numbers, as well as mass fears of public leading some people to refuse to check at all, even if they shows symptoms or have been exposed to the virus [7]. Since, the precise and accurate number of COVID-19 cases is impossible to have knowledge on, the next best thing to do is to forecast the government recorded cases as it might help in predicting new cases that might arise in the future. This pandemic has pushed pandemic modelling to the centre of global public policy-making.

Therefore, this study aims to contribute to this growing area of research by exploring and developing a short term forecasting model using three methods to forecast the daily new cases in Malaysia for 118 days and to assess its accuracy and utility combined with analysing its uncertainty. There are three objectives for this research, first is to forecast COVID-19 new cases by using Holt's Linear Trend Method, ARIMA Method and Naïve Method, to determine the accuracy of forecasting methods between the Holt's Linear Trend Method, ARIMA Method and Naïve Method using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), evaluate the uncertainties on the forecasting results by measuring the percentage of difference of forecast values and interval. Therefore, COVID-19 predictive analysis has emerged as a prominent research topic to assist healthcare services and governments in planning and controlling the development of the infectious illness [8].

2. Materials and Methods

2.1 COVID-19 New Cases Data

The data that is used for this research is the daily recorded COVID-19 cases on country level titled "cases_malaysia". This data is the official data on the COVID-19 pandemic in Malaysia. It was sourced from Official Github account of Malaysia's Ministry of Health (MOH) [17]. The data contains 118 rows of data and two columns. The data recorded the new cases of COVID-19 starting from 30 March 2020 to 13 July 2022.

2.2 ARIMA Method

In time series analysis, the Autoregressive Integrated Moving Average (ARIMA) is frequently utilised for any duration of data. This model was frequently employed in several fields like finance, economics and power. ARIMA, however, has the drawback of being only suitable for stationary data.

Model identification, parameter estimation and diagnostic testing are the three initiative processes that the ARIMA model typically divides into [9]. The formula for Box-Jenkins transformation approach is:

$$\boldsymbol{y(\lambda)} = \begin{cases} \frac{\boldsymbol{y^{\lambda}-1}}{\boldsymbol{\lambda}}, & \boldsymbol{if\ \lambda \neq 0} \\ \boldsymbol{log\,Y}, & \boldsymbol{if\ \lambda = 0} \end{cases}$$

Eq. 1

where $y(\lambda)$ is represents the transformed data at a time and y is denoted as actual data at time *t*.

The next step is will be to identify the data's stationarity. Stationary data has a constant variance and mean. ACF and PACF plots will also be used to check the data's stationarity. Stationarity checking can also be done by using Augmented Dickey-Fuller (ADF) test. The hypothesis of this test is $H_0: \emptyset = 0$ and the alternative is $H_1: \emptyset < 0$. ADF test statistics can be formulated as:

$$\boldsymbol{y'_t = \emptyset y_{t-1} + \beta_1 y'_{t-1} + \beta_2 y'_{t-2} + \ldots + \beta_k y'_{t-k}}$$

Eq. 2

where, y'_t is denoted as the first differenced series, $\emptyset$ is the coefficient on time trend, β is the coefficient presenting process root and k represents the number of lags.

If the *p*-value ≤0.05, reject the null hypothesis, which means the data is stationary and the process of differencing is not required [9]. When the mean is not stationary, differencing will be used until data achieve stationarity. Differencing helps to stabilise the mean of a time series. Usually, the first differencing is sufficient to achieve stationary.

After obtaining stationary data, the models can be identified by selection of the behaviour or pattern present of autoregressive (p) and moving average (q) will be performed based on the ACF and PACF plots [10]. The criteria for the model identifications are shown in Table 1:

Table 1: ACF and PACF criteria

Models	ACFs	PACFs
MA(q)	Cuts off after lag q	Decay with exponential pattern
AR(p)	Decay with exponential pattern	Cuts off after lags p
ARMA(p, q)	Decay with exponential pattern	Decay with exponential pattern
AR(p) or MA(q)	Cuts off lag q	Cuts off after lag q

After that, parameter estimation will be done to obtain the model's coefficients. ARIMA model will be generated based on the Table 1. Then, Ljung-Box test is suggested as a form of diagnostic tool for testing the fit of a time series model. If the model pass both diagnostic checking and model adequacy, the selected model will then be used to begin the forecast.

2.3 Holt's Linear Trend Method

Holt's Linear Trend method which is also known as the Holt's Trend Corrected Exponential Smoothing Method is a branch of the Simple Exponential Method family. It involves two smoothing constants which are denoted by α and γ [11]. The smoothing equation involved in this method is as follows:

$$\boldsymbol{\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1})}$$

Eq. 3

$$\boldsymbol{b_t = \gamma(\ell_t - \ell_{t-1}) + (1-\gamma)b_{t-1}}$$

Eq. 4

where, $\boldsymbol{\ell}_t$ denotes as the level estimates of the series at time *t*, b_t signify as trend estimates of the series at time *t*, α identify as smoothing constant for the level $(0 \leq \alpha \leq 1)$, γ is the constant for the trend (0 ≤ α ≤ 1), $\boldsymbol{\ell}_{t-1}$ is as the level estimate at time $t-1$ and b_{t-1} denotes trend estimate of the series at time $t-1$. The point forecast made at time *t* is denoted by:

$$\hat{\boldsymbol{y}}_{t+p}(\boldsymbol{t}) = \boldsymbol{\ell}_t + \boldsymbol{p}\boldsymbol{b}_t \qquad (\boldsymbol{p} = \mathbf{1}, \mathbf{2}, \mathbf{3}, \ldots,) \qquad Eq.\ 5$$

2.4 Naïve Method

For Naïve method forecasts, the forecast is set to be the last observation value [9]. This method works with unpredictable data. If data has a seasonal pattern, Seasonal Naïve method is the most suitable method. The following is a formula of the Naïve method:

$$\hat{\boldsymbol{y}}_{t+h} = \boldsymbol{y}_t \qquad Eq.\ 6$$

where, $\hat{y}_{t+h}$ denotes as forecast value for period of *t* and y_t denotes as the actual value for period before forecast.

2.5 Uncertainty

Uncertainty is a concept that is underrated by both statistical and judgemental forecasters with the exception of the weather forecasters [20]. Uncertainty use the standard error to derive a range in which the true value is likely to lie and helps to decide how precise a forecast is.The calculation for uncertainty denotes as [12]:

$$\boldsymbol{Z}_t = \frac{\hat{u}_t - \hat{Y}_t}{\hat{Y}_t} \qquad Eq.\ 7$$

where, Z_t denotes as uncertainty of the point forecast, $\hat{u}_t$ denotes as the 95% upper prediction interval in the furthest horizon and $\hat{Y}_t$ denotes as the point forecast.

2.6 Model Performance

The performance evaluation of each model will be conducted by applying some of the error measurements. Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RSME) will be applied to compare the accuracy of the ARIMA method, Holt's Linear Trend method and Naïve method. Each performance evaluation is useful in determining the performance of a forecasting model regardless whether it is reliable or not [18].

MAE is the absolute difference of the actual value and the forecast value [13]. With purpose is to allow researchers to know how big an error is from the forecast on an average. MAE can be written as:

$$MAE = \frac{\sum_{t=1}^{n} |Y_t - \hat{Y}_t|}{n} \qquad Eq.\ 8$$

MAPE is calculated average absolute percent error for every time period minus the actual value and divided by the actual values. MAPE produce the measure of the distance of the forecast and actual value [14]. The formula of MAPE is shown:

$$MAPE = \frac{\sum_{t=1}^{n} \left|\frac{Y_t - \hat{Y}_t}{Y_t}\right|}{n} \qquad Eq.\ 9$$

According to [12], RMSE is the standard deviation of the prediction errors which measure the spread of the errors. The formula of RMSE is shown:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n}} \qquad Eq.\ 10$$

where, for MAE, MAPE and RMSE, Y_t denotes as actual value at period t, $\hat{Y}_t$ represents as forecast value at period t and n is number of observations. Any model that has the lowest value of MAE, MAPE, RMSE will be considered as best model.

3. Results and Discussion

To determine whether the data has a trend or seasonality, a time series plot of daily new COVID-19 cases in Malaysia from 30/3/2022 to 27/7/2022 was created. The data's time series plot is shown below. According to the time series plot in Figure 1, the daily COVID-19 cases have no seasonality and a downward trend. The data analysed using the ARIMA, Holt's Linear Trend and Naïve method to determine the new COVID-19 cases.

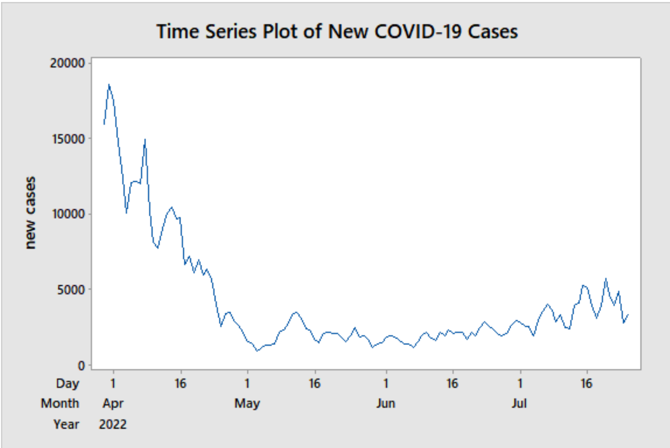

Figure 1: Time series plot for COVID-19 cases

3.1 ARIMA Method

In order to determine whether the variance is stable, and the mean is stationary, the Box-Cox plot, Augmented Dickey–Fuller test (ADF), ACF plot and PACF plot was conducted. The result from Box-Cox shows that the variance is not stable as the interval between the lower control limit and upper control limit does not consists of the value of 1, which means that transformation of data is needed to achieve a stability in variance. Data transformation using Box-Cox transformation with optimal λ was applied.

The main characteristic of ARIMA is data stationarity. If the data are not stationary, differentiation of 1 would be necessary in order to convert the initial time series data into stationary data. The stationarity of the data can be determined using the Augmented Dickey-Fuller (ADF) test. The output of the ADF test of the transformed data is shown as:

```
        Augmented Dickey-Fuller Test

data:  diff
Dickey-Fuller = -6.9721, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

Figure 2: ADF test for differenced data

ADF test resulted in a *p*-value of 0.01, which is less than the 0.05 critical value. Because the *p*-value is less than the critical value, there is enough data to rule out the null hypothesis. Which indicates, the data are stationary at level of significance = 0.05.

The orders of the ARIMA model must then be determined. The significant lags in the ACF and PACF plot can be used to calculate the number of orders in ARIMA. These plots are shown in Figure 3 and Figure 4

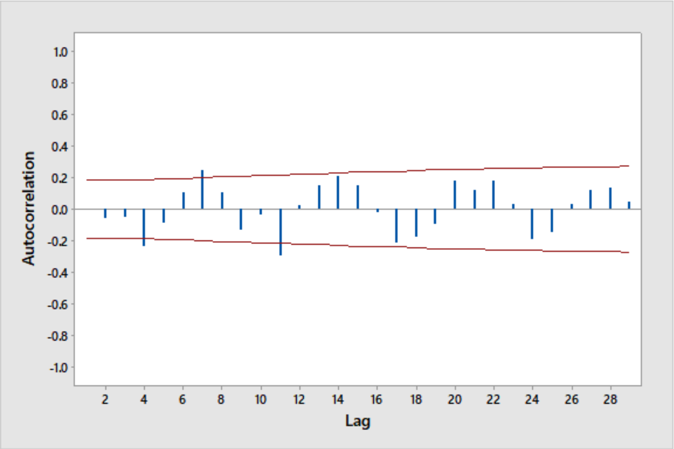

Figure 3: ACF plot for ARIMA identification

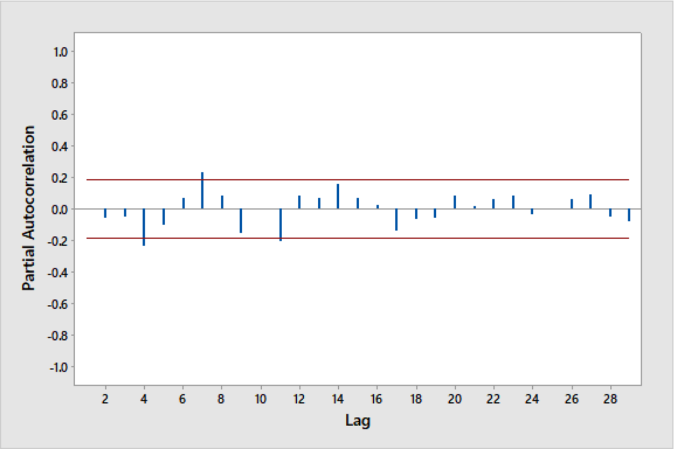

Figure 4: PACF plot for ARIMA identification

From the figure, a few tentative model such as ARIMA (4,1,2), ARIMA (2,1,4), ARIMA (3,1,2), ARIMA (4,1,3), ARIMA (2,1,3), and ARIMA (3,1,4) was obtained.

The next step is checking the model adequacy. The final ARIMA estimates must have a *p*-value ≤ 0.05, indicating that the parameter is significant. Additionally, the Ljung-Box Statistics *p*-value ≥ 0.05 in order for the model to be considered uncorrelated. Upon research, only model ARIMA (2,1,4) is adequate for forecasting.

Table 1: ARIMA models estimates parameters and Ljung-Box Statistics

ARIMA Model	Parameters Coefficients	Parameters *p*-value	Ljung-Box Statistics *p*-value
(2,1,4)	AR 1: 1.1820	0.000	Lag 12: 0.066
	AR 2: -0.9509	0.000	Lag 24: 0.584

	MA 1: 1.2687	0.000	Lag 36: 0.801
	MA 2: -1.0900	0.000	Lag 48: 0.920
	MA 3: 0.1236	0.016	
	MA 4: 0.1279	0.037	

Figure 5 illustrated the forecast value of new COVID-19 cases from 26/07/2022 to 30/07/2022 by using ARIMA (2,1,4).

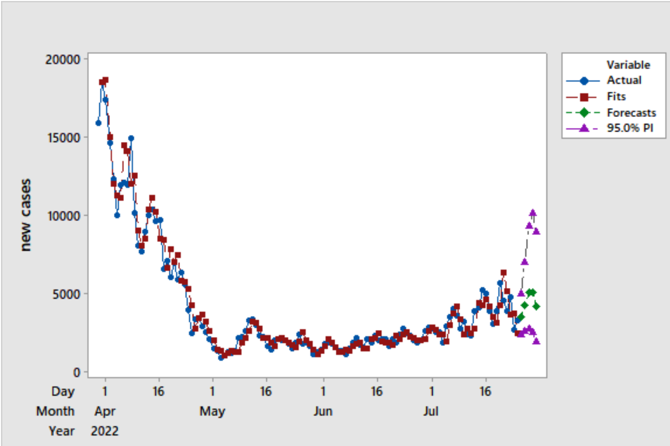

Figure 5: Time series plot and forecast value for ARIMA (2,1,4)

3.2 Holt's Linear Trend Method

Trial and error experimentation can be used to determine the smoothing parameters to get the optimum results. Software Minitab can help in producing the smoothing parameters to get optimal results. According to the Minitab output, the smoothing parameters α(level) and γ(trend) for in-sample data are respectively, 0.938051 and 0.025669. The time series plot of data, forecast value, and fitted value are shown in Figure 6

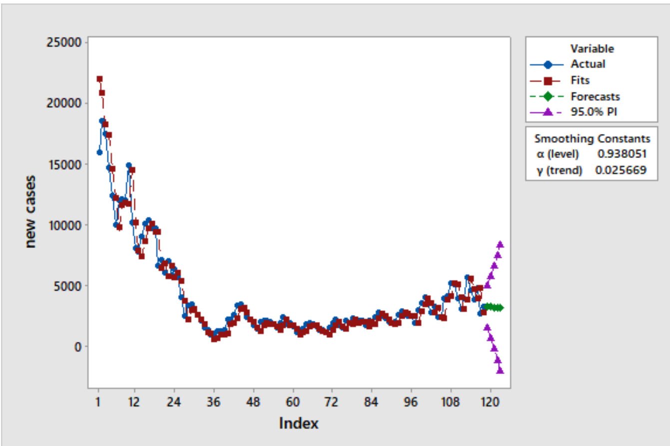

Figure 6: Time series plot, forecast value and fitted value using Holt's Linear Trend method

3.3 Naïve Method

This method uses the actual value of the last period as the next periods forecast. Table 4.4 display the forecast value of new COVID-19 cases in Malaysia by using Naïve method which is shown to be constant at 3300 cases. The time series plot of the data, fitted value and forecast value are displayed in Figure 7.

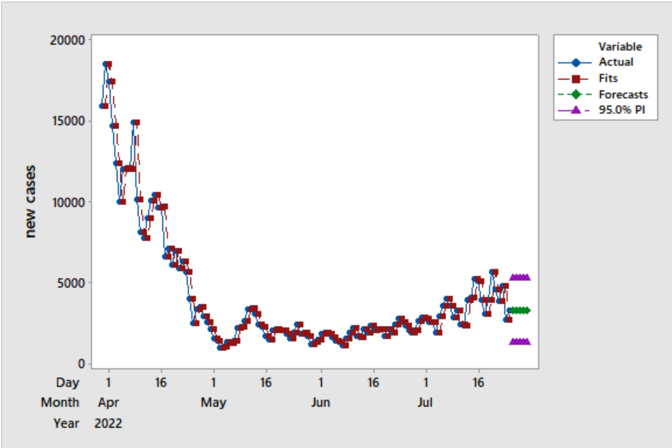

Figure 7: Time series plot, forecast value and fitted value using Naïve method

3.4 Comparison of forecasting methods

Table 3 shows the comparison between the actual data of new COVID-19 cases and the forecast numbers from ARIMA Method, Holt's Linear Trend Method and Naïve Method. A time series plot is used to compare the forecast from each model to the actual data in order to help us visualise the forecast more clearly as shown in Figure 8

Table 2: Comparison of forecasting values for each method

Date	Actual Value	Forecast Value		
		ARIMA (2,1,4)	Holt's Linear Trend	Naïve
26/7/2022	4579	3516	3246	3300
27/7/2022	4503	4281	3223	3300
28/7/2022	3926	5129	3200	3300
29/7/2022	4860	5085	3176	3300
30/7/2022	4271	4237	3153	3300

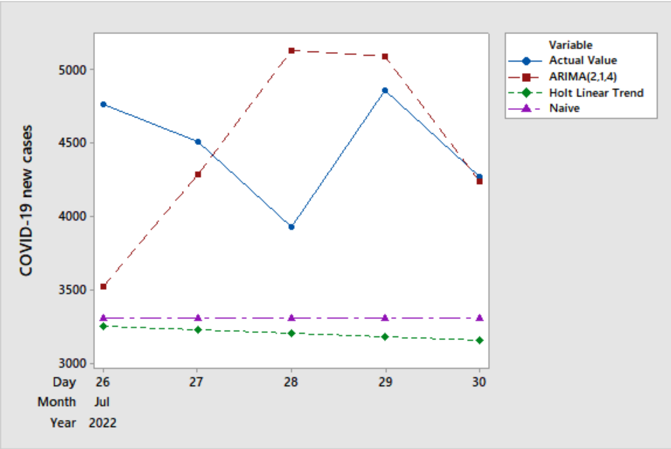

Figure 8: Comparison of forecast values

3.5 Performance Evaluation

To determine which model is most capable of accurately forecasting the data, the three models' performances will be compared. The performance of each methods were evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RSME) is displayed on Table 3.

Table 3: Comparison of forecasting values for each method

Performance Evaluation	ARIMA (2,1,4)	Holt's Linear Trend	Naïve
MAE	585.4	1264.2	1163.8
MAPE	786.6	1306.9	1211.9
RMSE	13.42 %	27.91 %	25.63 %

From the table above, it is shown that the Naïve produce the smallest value of MAE, MAPE and RMSE compared to Holt's Linear Trend and ARIMA method. This is expected as the Naïve method produce the smallest forecast value compared to the other two methods.

3.6 Uncertainty of methods

The uncertainty is measure by the percentage of the difference between the point forecast and the 95% upper prediction interval in the furthest horizon, divided by the point forecast. The uncertainty comparison is shown in Table 4.

Table 4: Uncertainty of all methods

Date	ARIMA (2,1,4)		Holt's Linear Trend		Naïve	
	Forecast Value	Uncertainty	Forecast Value	Uncertainty	Forecast Value	Uncertainty
26/7/2022	3516	156.28 %	3246	156.88 %	3498	59.67 %

27/7/2022	4281	110.48 %	3223	158.71 %	3948	59.67 %
28/7/2022	5129	75.68 %	3200	160.57 %	3948	59.67 %
29/7/2022	5085	77.20 %	3176	162.54 %	3948	59.67 %
30/7/2022	4237	112.67 %	3153	164.46 %	3948	59.67 %

From Table 4, the Naïve methods produce the smallest uncertainty compared to ARIMA and Holt's Linear Trend method. However, this is due to the forecast produce are the smallest and constant from the five days.

4. Conclusion

To forecast the COVID-19 cases in Malaysia, this study applied the univariate time series forecasting techniques ARIMA Model, Naïve method, and Holt's Linear Trend method. Cases prediction that are accurate can be used as information as it could help the government, healthcare management and citizens prepare for the wave of new cases and help for similar pandemic issues in future. Having accurate forecasts can help healthcare services to prepare enough space, or energy to handle the upcoming number of cases.

The methods used in this study are suitable for short-term forecasting however, are not always appropriate for use in long-term forecasting. This study only uses daily data on new COVID-19 cases in Malaysia, without considering the factors that may influence the cases. Furthermore, it is hard to search for suitable methods to adapt to the data. Compared to advanced forecasting techniques such as Artificial Neural Networks (ANN) and Machine Learning (LM), the methods used in this research are traditional methods that are not capable to learn from the data and create a suitable model to accommodate the data.

Forecasts of the number of COVID-19 cases in Malaysia can be inaccurate due to several predictable and unpredictable factors. For instance, the creation and distribution of COVID-19 vaccines and boosters can help reduce the number of COVID-19. Moreover, the implementation of the Movement Control Order which included the lock-down helps to stop the spread of the COVID-19 virus. The obligation of wearing a face mask also helps to stop the transmission of the virus from one person to another.

However, some factors contribute to the increasing number of COVID-19 cases. For example, the mutation of the COVID-19 virus leads to the existences of a variety of variants such as the Omicron, Alpha and Delta variants that are far stronger than the original SARS-COV-2 virus. Not only that, there are a lot of people who refuse to take the COVID-19 vaccines or to wear masks daily. Combine with the factors of misinformation and lies especially regarding the topics of vaccines which lead to mass fear of the public getting the vaccines. These reasons and more were the main contributing reasons why the number of COVID-19 cases increased in Malaysia.

Acknowledgement

First, I would like to express my deepest gratitude and gratefulness to my supervisor for her continuous support on this study. She has help me during the course of this study with her guidance, expertise and patients. My sincerest gratitude to my friends who have help me and been with me in completing this study. Their wonderful insights and kindness are well appreciated.

Next, I would love to thank my family members who helped give my moral support at any time. Their encouragement has really help me to stay focus during this research. Lastly, I want to thank myself for being me. I would like to thank myself for not giving up, not giving myself a break and believing that I can survive this research.

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