Introduction

Due to travel restrictions, tourism is one of the most affected sectors by the Covid-19 outbreak; this is the worst tourism disaster Malaysia has ever seen. Inbound tourism was suspended as countries closed their borders and restricted travel to prevent the virus from spreading, while the local tourism sector was severely harmed by the Movement Control Orders (MCO). Tourism is Malaysia's third-largest source of revenue, and it plays a significant part in the country's economy. In 2019, tourism accounted for about 15.9% of overall GDP, and it is predicted to lose at least 60% of its tourism business by 2020. (DW, 2020). In addition, the pandemic forced Malaysia to cancel its "Visit Truly Asia Malaysia 2020" campaign, which sought to draw 30 million people and earn RM100 billion in tourism revenue by 2020. As a result, Malaysia's tourism business was crushed by the Covid-19 outbreak. 2021 (Malaysian Investment Development Authority).

This report will first walk you through the process of selecting the best fit ARIMA model to forecast with. The best ARIMA model identified will then be compared to the ETS model identified by R. In time series data forecasting, the ARIMA and ETS models are widely used. The difference between the two models is that ETS models focus on the trend and seasonality of the data, whereas ARIMA models focus on the autocorrelations of the data (Rpubs, 2020).

Our report's goal is to thoroughly investigate the financial impact of the Covid-19 outbreak on tourist arrivals in Malaysia using ETS and ARIMA models. Meanwhile, the ETS and ARIMA models are being compared to see how well they forecasted the loss in tourism arrivals and the difference in both forecast models.

Phase 1: Model identification

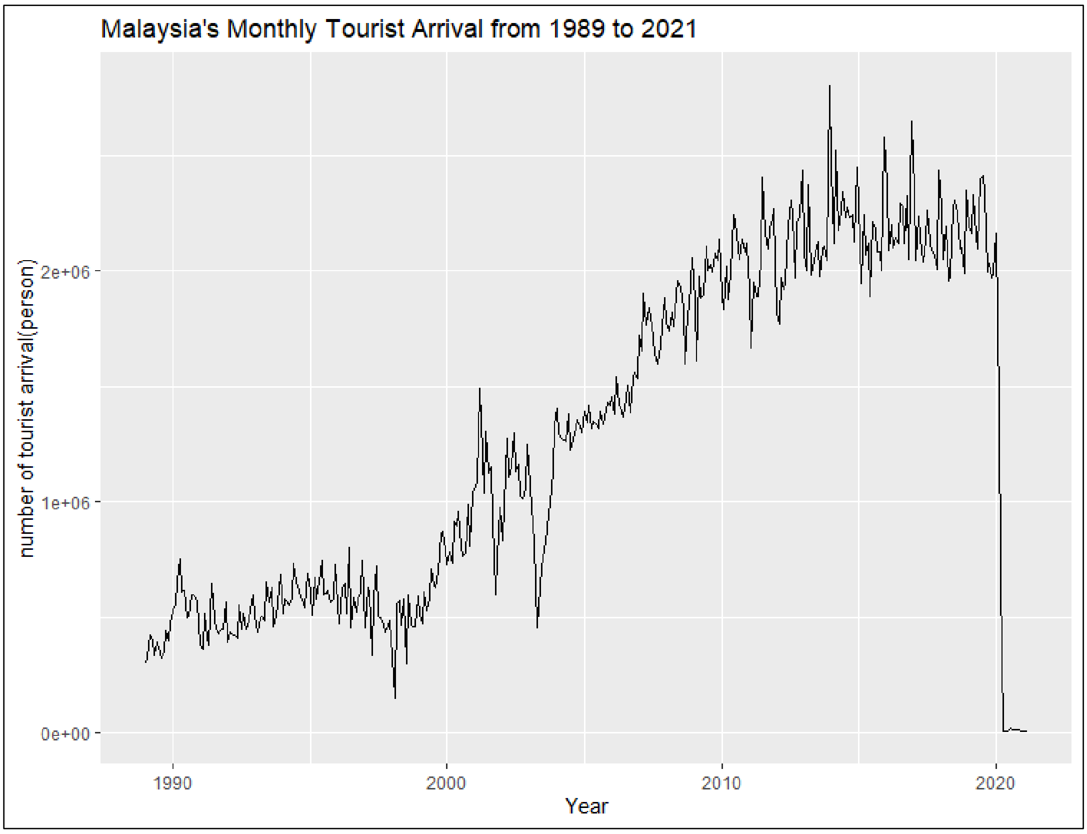

Figure 1: Malaysia's Monthly Tourist Arrival from January 1989 to March 2021.

From Figure 1, we can see a generally increasing upward trend from 1990 to around 2010 where it starts to plateau off. When deciding the length of the forecasting series, the forecasting series should be extended backwards only to times where the environment is believed to be fairly similar to the forecast horizon (Shmueli, 2016). Therefore, we will only take data where it shows a plateauing pattern, from January 2010 onwards to March 2021 to be our full dataset. The full dataset consists of 135 observations.

We then separate the full dataset into "Pre-Covid" and "Covid" where "Pre-Covid" period consists of 121 observations, spanning from January 2010 to January 2020. The "Covid" period consists of 14 observations spanning from February 2020 to March 2021.

The "Pre-Covid" dataset is then partitioned into a training and test set using the 80:20 split ratio. The training set spans from January 2010 to January 2018 and the test set spans from February 2018 to January 2020. The training and test sets have 97 and 24 observations respectively. The training set is plotted out in Figure 2 and shown below.

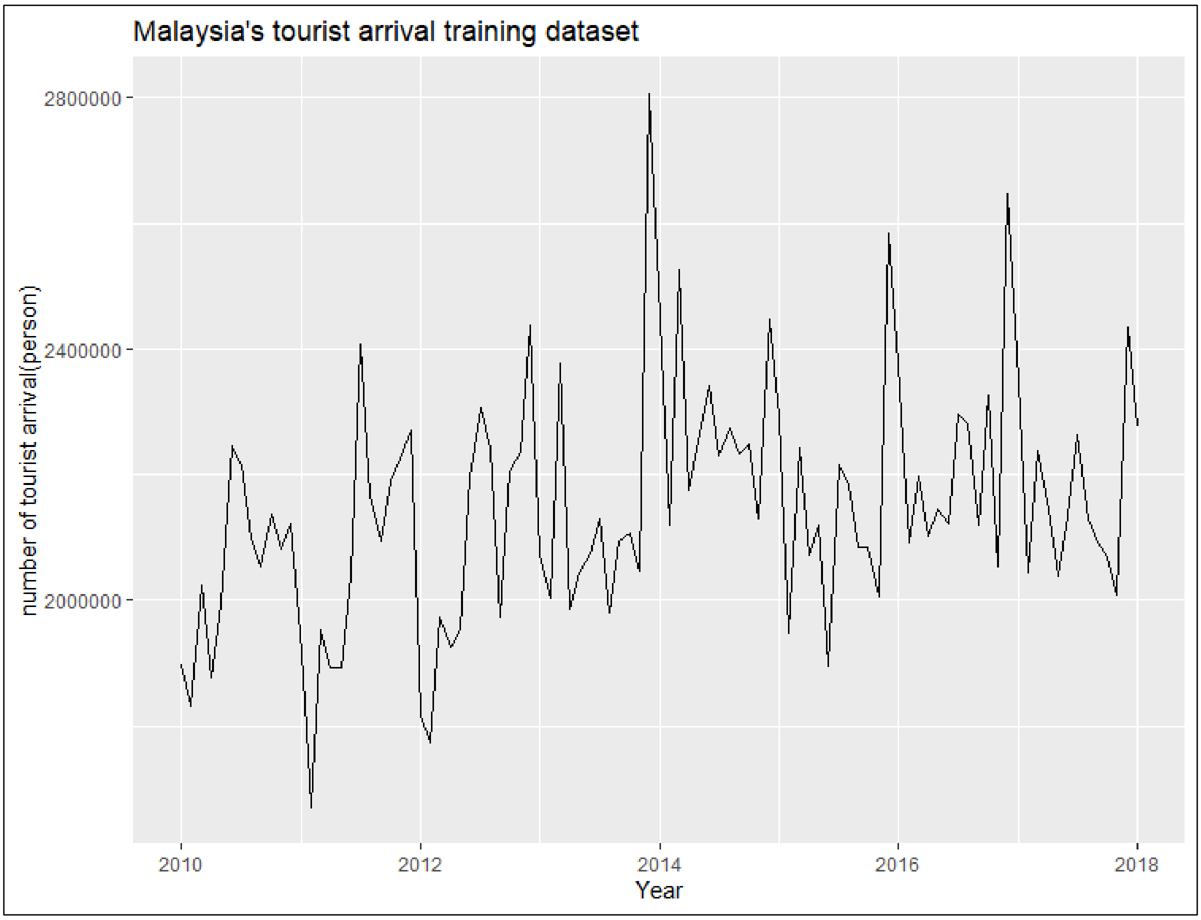

Figure 2: Malaysia's tourist arrival training dataset.

ARIMA models require a stationary series therefore we will be looking at the plot to see if the mean and variance is constant over time. Looking at Figure 2, the training dataset is seen to be non-stationary with slight seasonality present. The variance is seen to be arguably constant therefore a BoxCox transformation is deemed not needed. As for the mean, it is not constant and does not show a mean reverting behaviour and, we can see a mild upward trend from 2010 to around 2014. Hence, differencing would be required to stabilise the mean. Firstly, a seasonal difference will be taken with lag = 12 as it is a monthly dataset. Besides relying on data visualisation, the nsdiffs() function in R is used to help us to determine the number of seasonal differences required for this series to be made stationary. The nsdiffs() function returns a '1' suggesting a need to perform a seasonal difference. The seasonally differenced Malaysia tourist arrival training dataset is plotted and showed below.

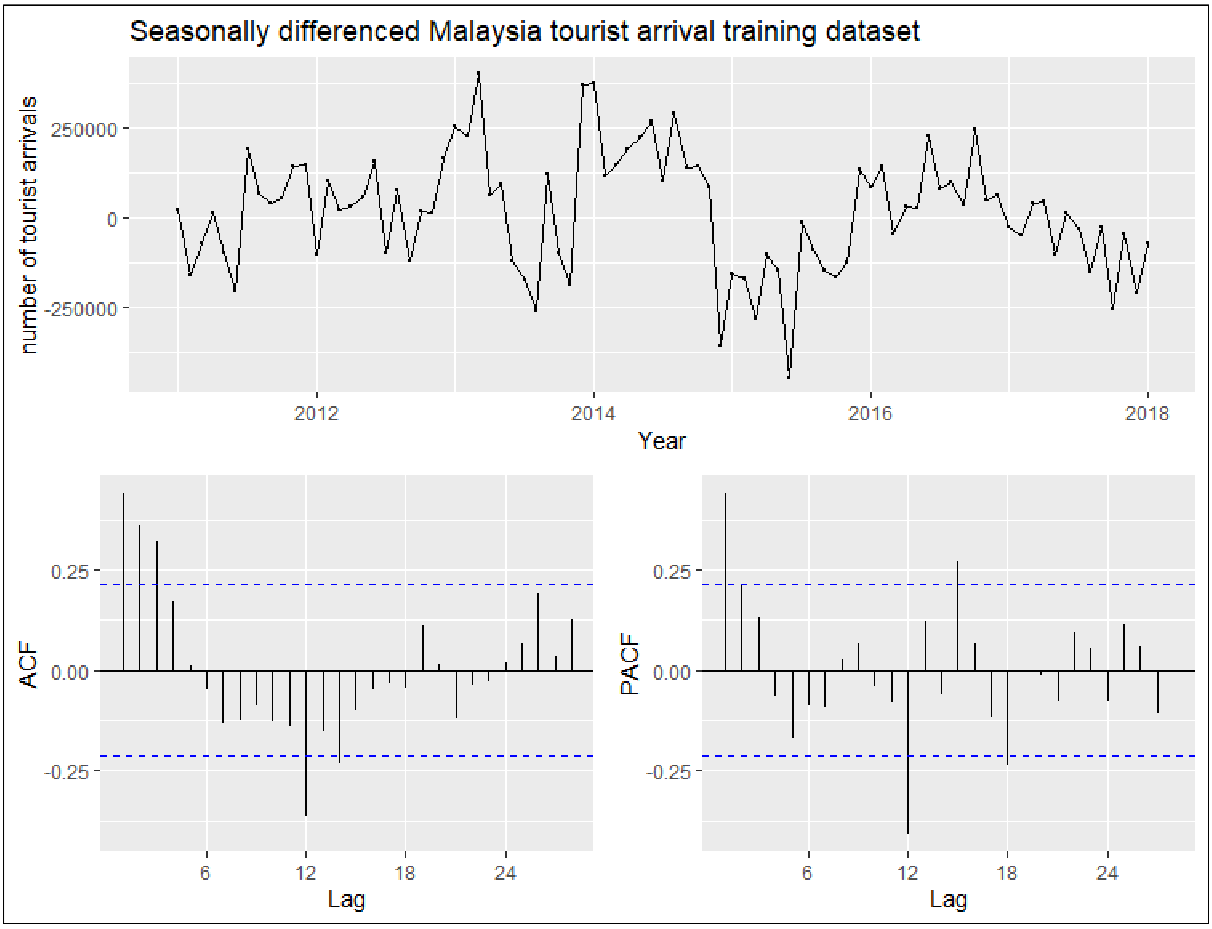

Figure 3: Seasonally differenced Malaysia tourist arrival training data plot, ACF and PACF.

From Figure 3 shown above, the seasonally differenced dataset shows a mean reverting behaviour around 0 with a somewhat constant variance now. To check if the seasonally differenced series is stationary or a further difference is needed, the ndiffs() function is utilised in R. The ndiffs() function returned a '0' which concludes that the seasonally differenced data is stationary and no further first differencing is required.

As the series is now stationary, we will move on to identifying possible $ARIMA(p,d,q)(P,D,Q)_m$ models. (p,d,q) represents the non-seasonal part of the model whereas (P,D,Q) represents the seasonal part of the model. m represents the number of observations per year. In our case, m would be 12 as we are dealing with monthly data. As d and D represents the order of integration for non-seasonal and seasonal differencing order. D = 1 because seasonal difference was performed once and no further first difference was performed hence, d =0.

By looking at the ACF plot for pure MA components and PACF plot for pure AR components. The significant spike at lag 1 to 3 in the ACF plot suggests a non-seasonal MA(3) component, and the significant spike at lag 12 in the ACF suggests a seasonal MA(1) component. From this, we can identify an $ARIMA(0,0,3)(0,1,1)_{12}$ model. As lag 4 in the ACF plot is quite close to being significant, we can identify an $ARIMA(0,0,4)(0,1,1)_{12}$ model as well. Bringing our attention now to the PACF plot, the significant spike at lag 1 and almost significant spike at lag (2) suggests a non-seasonal AR(1) and AR(2) component, and the significant spike at lag 12 in the PACF suggest a seasonal AR(1) component. Therefore, suggesting an $ARIMA(1,0,0)(1,1,0)_{12}$ and $ARIMA(2,0,0)(1,1,0)_{12}$ model.

Furthermore, looking at the training dataset in Figure 1 showing no clear upward or downward trend, all identified ARIMA models will not include a constant as we expect the long-term forecasts to go a non-zero constant determined by the last few observations and not show a upward/downward trending behaviour. Accordingly, a total of 4 ARIMA models are identified which are the $ARIMA(1,0,0)(1,1,0)_{12}$, $ARIMA(2,0,0)(1,1,0)_{12}$, $ARIMA(0,0,3)(0,1,1)_{12}$ *and* $ARIMA(0,0,4)(0,1,1)_{12}$ models.

Phase 2: Estimation and testing

Besides the 4 ARIMA models identified earlier, auto.arima() function in R is used to identify another ARIMA model. However, the ARIMA model suggested by auto.arima() function coincides with the $ARIMA(0,0,4)(0,1,1)_{12}$ model identified earlier. Therefore, we will proceed with only 4 ARIMA models. After estimating all 4 ARIMA models, the estimated parameters and information criterions are displayed in Table 1 and Table 2 below.

ARIMA models	Parameters
ARIMA(1,0,0)(1,1,0)12	$\widehat{\phi_1} = 0.4706, \widehat{\Phi_1} = -0.3934$
ARIMA(2,0,0)(1,1,0)12	$\widehat{\phi_1} = 0.3912,\ \widehat{\phi_2} = 0.1647, \widehat{\Phi_1} = -0.3695$
ARIMA(0,0,3)(0,1,1)12	$\widehat{\theta_1} = 0.3016, \widehat{\theta_2} = 0.1935, \widehat{\theta_3} = 0.3009, \widehat{\Theta_1} = -0.4777$
ARIMA(0,0,4)(0,1,1)12	$\widehat{\theta_1} = 0.3057, \widehat{\theta_2} = 0.2098, \widehat{\theta_3} = 0.4141, \widehat{\theta_4} = 0.3538, \widehat{\Theta_1} = -0.4673$

Table 1: Estimated parameters values for all 4 ARIMA models.

	AIC	AICc	BIC	Rank based on AICc
ARIMA(1,0,0)(1,1,0)12	2255.88	2256.17	2263.21	4
ARIMA(2,0,0)(1,1,0)12	2255.61	2256.11	2265.38	3
ARIMA(0,0,3)(0,1,1)12	2253.58	2254.34	2265.79	2
ARIMA(0,0,4)(0,1,1)12	2246.74	2247.81	2261.39	1

Table 2: Information criterion values of all 4 ARIMA models.

From Table 2 above, we will rank the ARIMA models according to their AICc values and select the top 2 models. Based on the AICc, $ARIMA(0,0,3)(0,1,1)_{12}$ *and* $ARIMA(0,0,4)(0,1,1)_{12}$ models have the lowest AICc values of 2254.34 and 2247.81, respectively. We will proceed with diagnostic checks on the residuals for these 2 models to see if both models are adequate for forecasting.

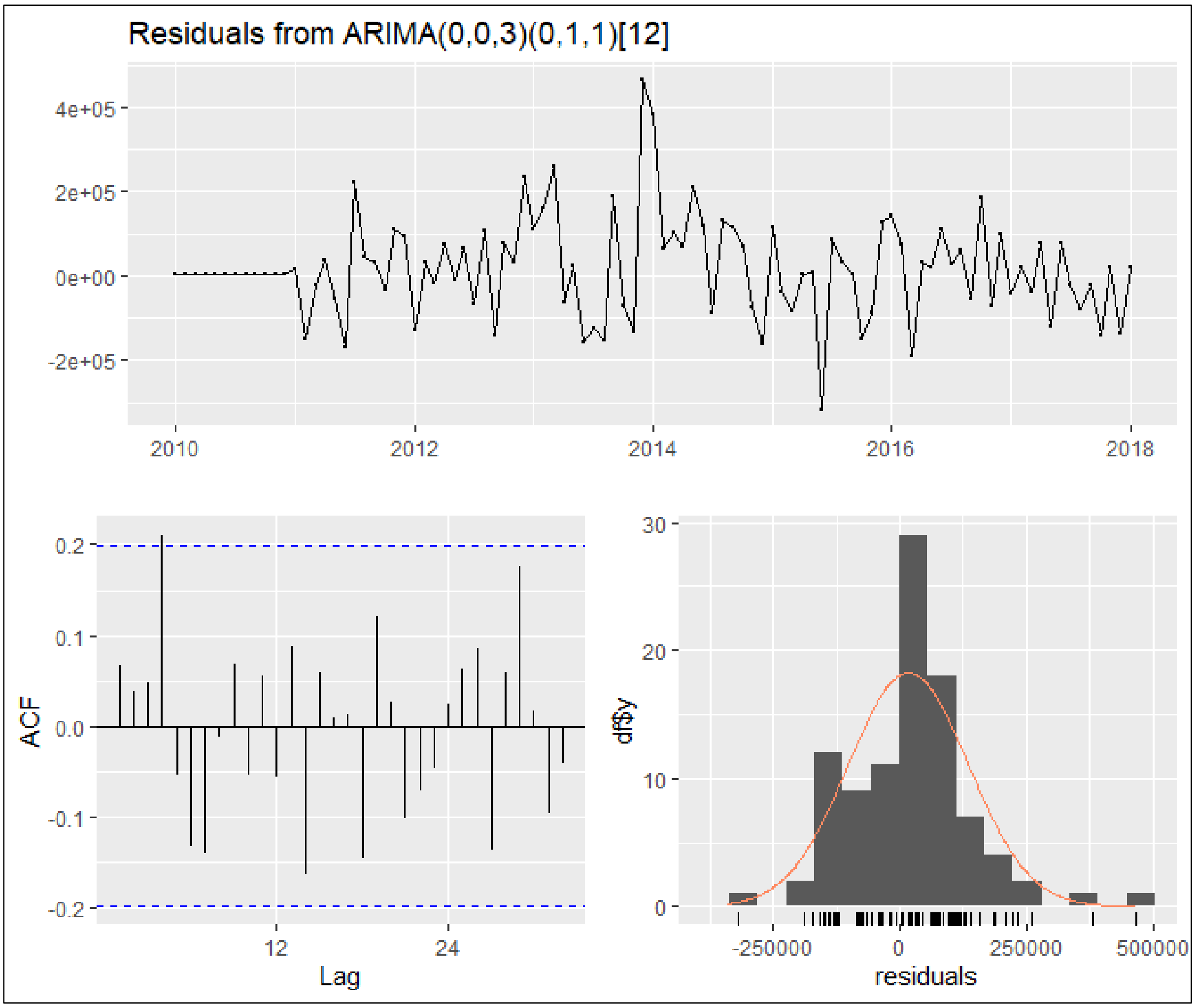

Figure 4: Residual plot for ARIMA(0,0,3)(0,1,1)[12] model.

Looking at the residual plot for the $ARIMA(0,0,3)(0,1,1)_{12}$ model, the plot shows a mean reverting behaviour with an arguably constant variance. The residuals seem to be normally distributed by looking at the normal distribution plot. The ACF plot shows only one significant autocorrelation at lag 4. However, the autocorrelation value around 0.2 is relatively small. All the other autocorrelations fall within the 95% confidence limits. From Figure 3, the residuals appear to be white noise and normally distributed. Nonetheless, a formal Ljung Box test is conducted below to check if the residuals are white noise or not.

$H_0: \rho_1 = \rho_2 = \rho_3 = \cdots = \rho_{19}$

$H_1: at\ least\ one\ \rho_i \neq 0\ for\ i = 1,2,3, \ldots ,19$

Decision rule: Reject $H_0\ if\ p - value < \alpha(= 0.05)$

Decision: $Since\ p - value\ (= 0.1719) > \alpha(= 0.05), we\ will\ not\ reject\ H_O$ and conclude that the residuals are white noise.

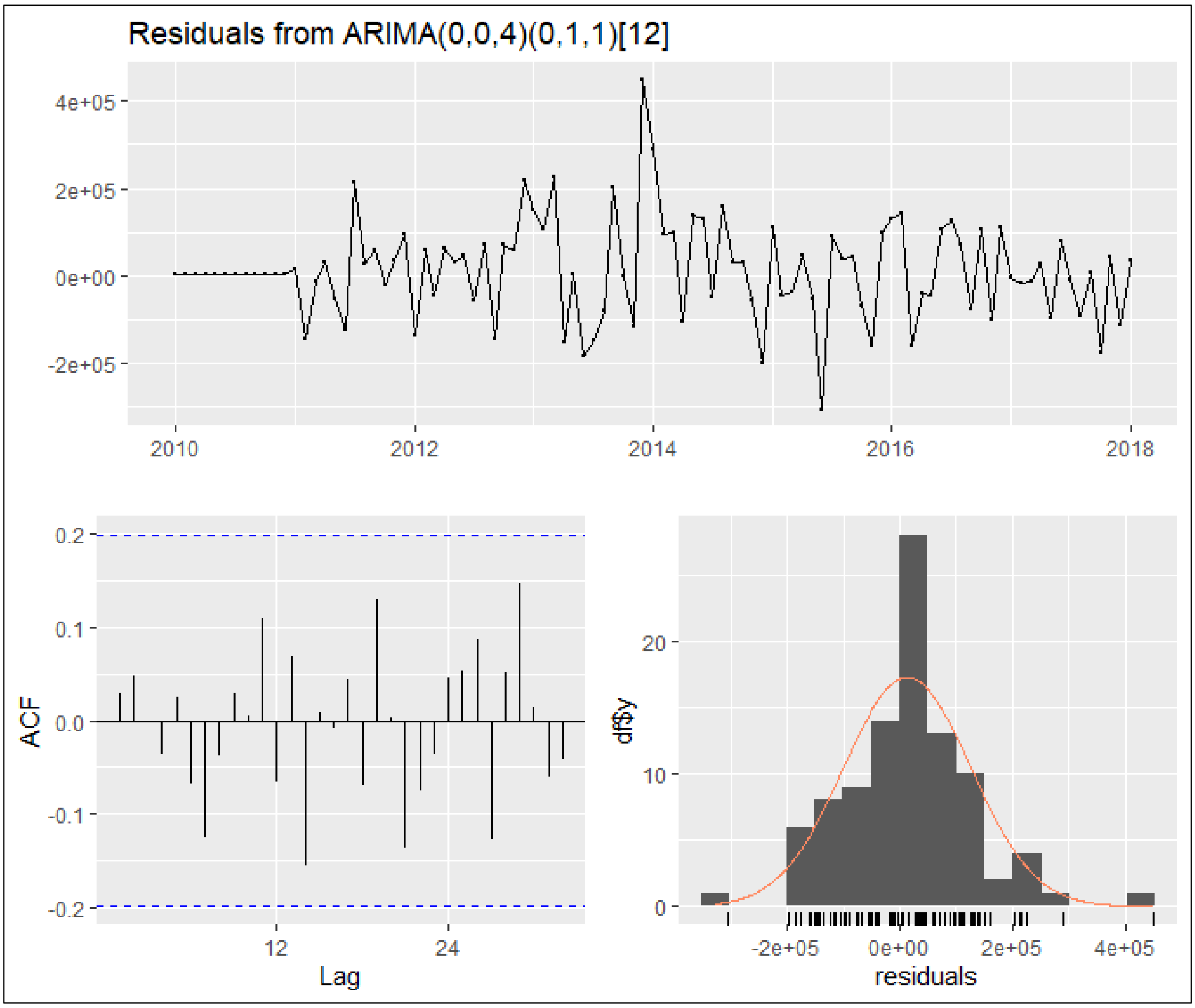

Figure 5: Residual plot, ACF and normal distribution plot for ARIMA(0,0,4)(0,1,1)[12] model.

Looking at the residual plot for the $ARIMA(0,0,4)(0,1,1)_{12}$ model, the plot shows a mean reverting behaviour with an arguably constant variance. The residuals seem to be normally distributed by looking at the normal distribution plot. The ACF plot shows that all autocorrelations fall within the 95% confidence limits. From Figure 4, the residuals appear to be white noise and normally distributed. Nonetheless, a formal Ljung Box test is conducted below to check if the residuals are white noise or not.

$H_0: \rho_1 = \rho_2 = \rho_3 = \cdots = \rho_{19}$

$H_1: at\ least\ one\ \rho_i \neq 0\ for\ i = 1,2,3, \ldots ,19$

Decision rule: Reject $H_0\ if\ p - value < \alpha(= 0.05)$

$Since\ p - value\ (= 0.6824) > \alpha(= 0.05), we\ will\ not\ reject\ H_0$ and conclude that the residuals are white noise.

Both models can be used for forecasting as both series are concluded to be white noise. Using the same training and test set mentioned in Phase 1, we fitted both ARIMA models using data from January 2010 to January 2018 to forecast the test set ranging from February 2018 to

January 2020. The forecast of the test set using both models are computed and plotted below in Figure 6.

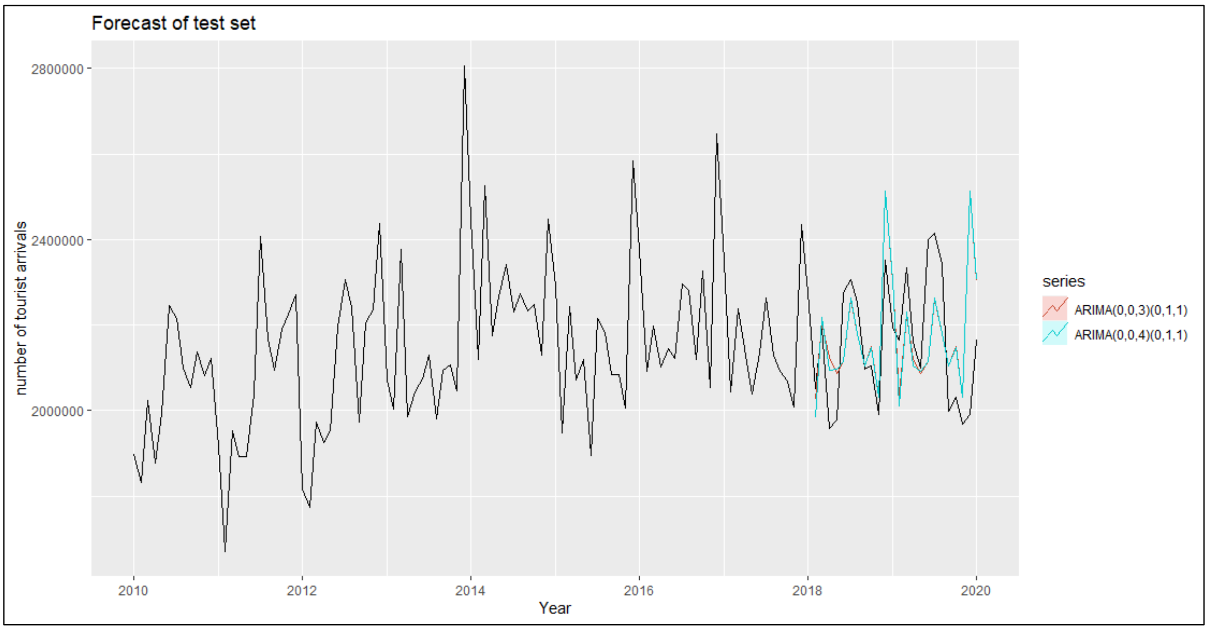

Figure 6: Forecast of test set using both ARIMA models.

From the plot above, both $ARIMA(0,0,3)(0,1,1)_{12}$ *and* $ARIMA(0,0,4)(0,1,1)_{12}$ models' forecast of the test set are quite similar as the forecasts are constantly overlapping each other. Both ARIMA models are able to forecast the seasonality and trend present in the test set.

We will proceed with evaluating which model out of the two is the better forecasting model using the traditional approach. The training data set is used to estimate the parameters of the forecasting method/model whereas the test set is used to evaluate its accuracy. Since the test set was not used when determining the forecasts, it will give a good indicator of how capable the model is able to predict on new data (Hyndman & Athanasopoulos, 2018). Using the accuracy() function in R, the RMSE, MAE, MAPE and MASE values of the training and test set for the $ARIMA(0,0,3)(0,1,1)_{12}$ *and* $ARIMA(0,0,4)(0,1,1)_{12}$ models are obtained and shown in Table 2 below.

ARIMA models		RMSE	MAE	MAPE	MASE
ARIMA(0,0,3)(0,1,1)12	Training	119629.8	86831.85	3.9540	0.6601
	Test	158518.1	117046.82	5.4280	0.8898
ARIMA(0,0,4)(0,1,1)12	Training	113077.3	83205.9	3.8110	0.6325
	Test	158819.8	119364.5	5.5352	0.9074

Table 3: Training and test set error values for each ARIMA model.

As shown in Table 3, $ARIMA(0,0,3)(0,1,1)_{12}$ model has the lower RMSE, MAE, MAPE and MASE test set error values as compared to the $ARIMA(0,0,4)(0,1,1)_{12}$ model. Therefore, the final model chosen to be the best forecasting model would be the $ARIMA(0,0,3)(0,1,1)_{12}$ model.

Backshift notation for $ARIMA(0,0,3)(0,1,1)_{12}$ model

$$(1 - B^{12})y_t = (1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3)(1 + \Theta_1 B^{12})\ \varepsilon_t$$

Phase 3: Application

$ARIMA(0,0,3)(0,1,1)_{12}$ model is re-estimated using the "Pre-Covid" data and the backshift notation is shown below.

Estimated $ARIMA(0,0,3)(0,1,1)_{12}$ model using backshift notation

$$(1 - B^{12})y_t = (1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3)(1 + \Theta_1 B^{12})\ \varepsilon_t$$

$$(1 - B^{12})y_t = (1 + 0.2963B + 0.1852B^2 + 0.3187B^3)(1 - 0.3935B^{12})\varepsilon_t$$

Forecasts for the "Covid" time period using the final $ARIMA(0,0,3)(0,1,1)_{12}$ model and produced and plotted below in Figure 7.

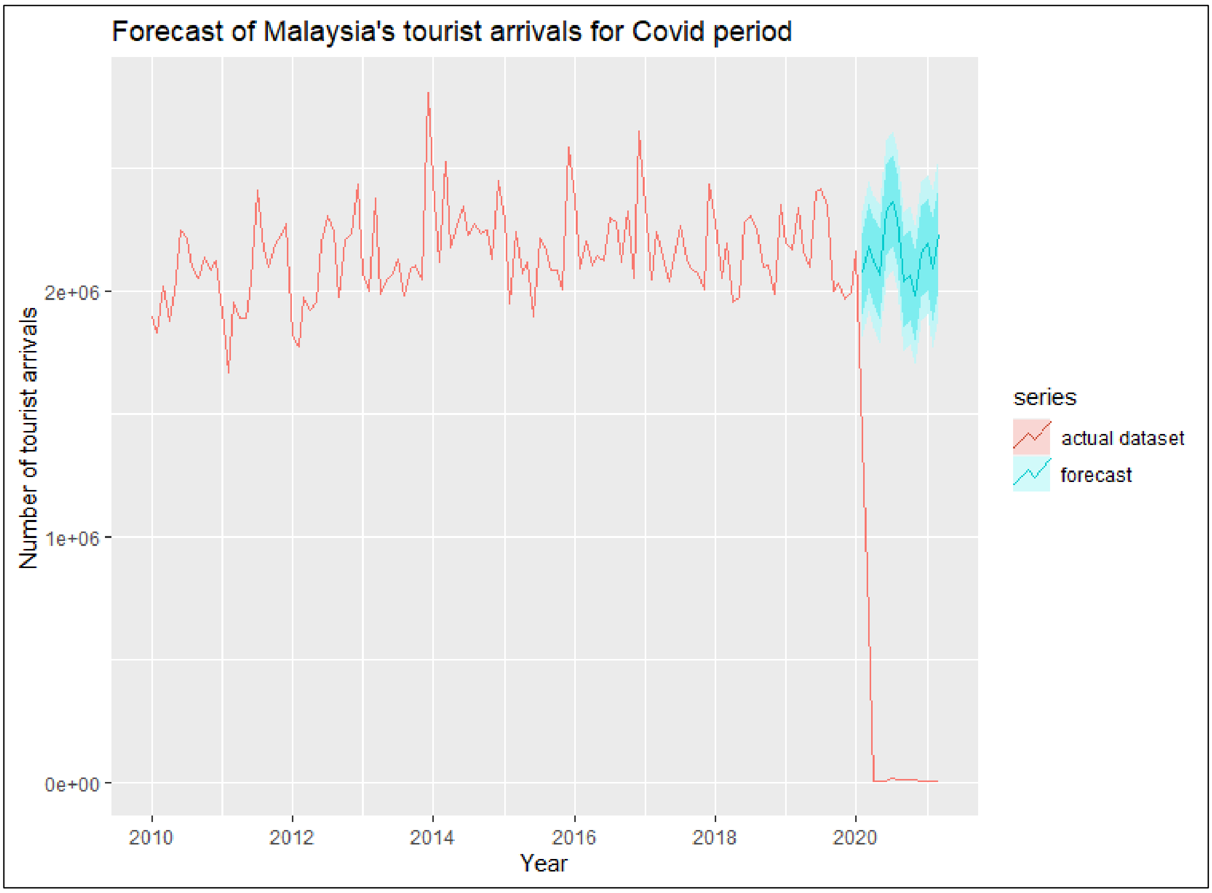

Figure 7: Forecast of Malaysia's tourist arrival for Covid period.

From Figure 7 above, the blue line shown is the point forecasts for the Covid period from February 2021 to March 2021 by the selected $ARIMA(0,0,3)(0,1,1)_{12}$ model and the light blue and darker blue shades represent the 95% and 80% prediction intervals respectively. The model is able to capture the seasonality present in the data well. The point forecasts are shown to be following the plateauing trend as seen from year 2015 onwards. As for the prediction intervals, the 95% and 80% prediction intervals are reasonably narrow and follows the pattern of the point forecasts. The narrow prediction intervals can be explained by the fact that ARIMA based intervals take into account only the variations in the errors when in fact, there are also variations in the parameter estimates and model order (Brockwell & David, 2016). Overall, the forecast by $ARIMA(0,0,3)(0,1,1)_{12}$ model seems fairly reasonable as it is able to forecast the seasonality and follow the trend from the previous data. Comparing the forecasts with the actual tourist arrivals in the "Covid" period, the selected ARIMA model is unable to forecast the structural break caused by the pandemic.

Comparison with an ETS model

Using the "Pre-Covid" dataset, forecasts for the "Covid" period using the ets() and forecast() functions are produced. The ETS model automatically selected by R is an ETS(M,N,A) model which suggests a multiplicative error, no trend and additive seasonality. After generating forecasts using the ETS(M,N,A) model. The full dataset consisting of the "PreCovid" and "Covid" time frame, $ARIMA(0,0,3)(0,1,1)_{12}$ model forecasts and ETS(M,N,A) model forecasts are plotted and shown in Figure 7 below.

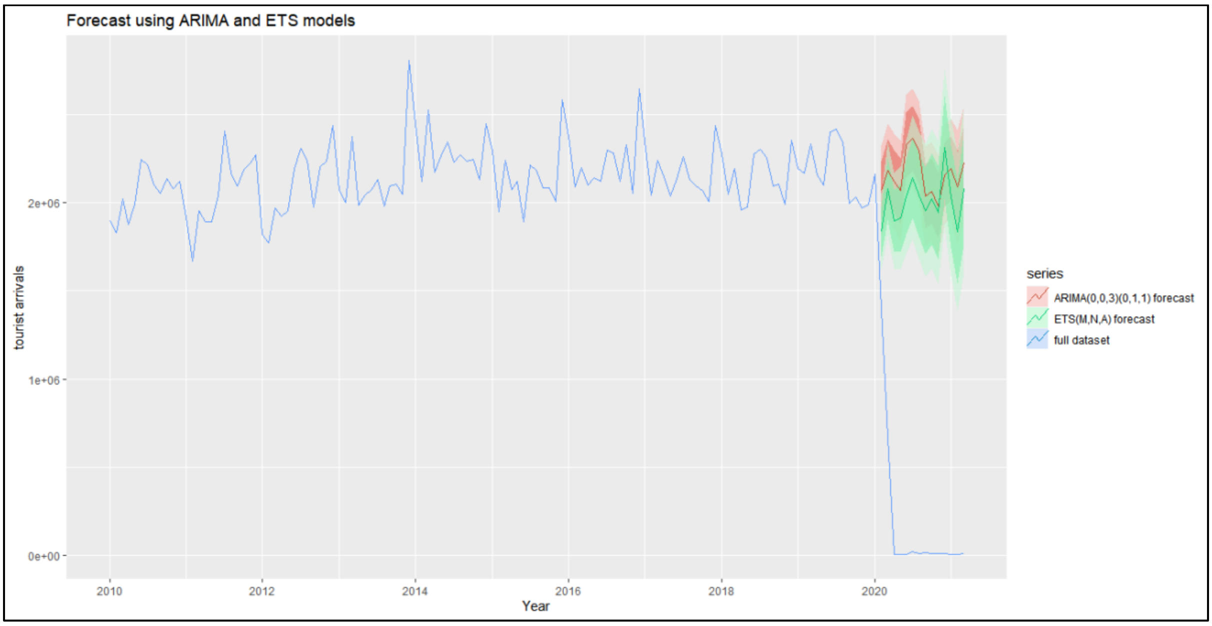

Figure 8: Forecasts of Malaysia's tourist arrivals during Covid period using ARIMA and ETS models.

From the plot above, both the $ARIMA(0,0,3)(0,1,1)_{12}$ and ETS(M,N,A) models were able to forecast seasonality. The red line represents the point forecasts for the $ARIMA(0,0,3)(0,1,1)_{12}$ model and the green line represent the point forecasts for the ETS(M,N,A) model. The point forecast for $ARIMA(0,0,3)(0,1,1)_{12}$ is generally higher than the point forecasts for the ETS(M,N,A) model. Both model's point forecasts follow the plateauing pattern as shown in the plot. As for the 80% and 95% prediction intervals of the $ARIMA(0,0,3)(0,1,1)_{12}$ model, the prediction intervals seem relatively narrow, it does not portray any pattern of increasing or decreasing trend. As for the ETS(M,N,A) model, the 80% and 95% prediction intervals are relatively wider as compared to the ARIMA model. Also, the wider prediction intervals of the ETS models shows the possibility of an increasing or decreasing trend in tourist arrivals unlike the prediction intervals of the ARIMA model. The reason why there is no such possibility based on the ARIMA model's prediction interval is because the prediction interval calculations for ARIMA implies that historical patterns that were previously modelled will continue into the forecasting period (Brockwell & Davis, 2016). As seen in Figure 8, the historical pattern shows a plateauing trend which is why the point forecasts and prediction intervals for the ARIMA model is relatively following a horizontal trend. Generally, ARIMA model's prediction intervals would increase as the forecast horizon increases. However, in our case, having a stationary ARIMA models with d = 0 produces prediction intervals that converge showing prediction intervals for long horizons to be the same (Brockwell & Davis, 2016).

Sadly enough, both models are unable to forecast the drastic drop in tourist arrivals in Malaysia caused by the pandemic as both model's point forecast follows the plateauing pattern.

Average forecasted loss in tourism revenue

As what we have forecasted using the ARIMA and ETS model in Figure 7 would be a plausible forecast for Malaysia's tourist arrivals if the structural break (Covid) did not occur, we will be able to use this piece of information to calculate the average forecasted loss in tourism revenue for both the $ARIMA(0,0,3)(0,1,1)_{12}$ model and ETS(M,N,A) model. Firstly, the loss in tourist numbers is obtained by deducting each month's actual tourist arrivals during the Covid period (14 months) from the point forecasts of each month. It is then summed up to get the total loss in tourist numbers of the 14 months.

The total loss in tourist numbers is then multiplied by the average spending per tourist of RM2930 obtained from Tourism Malaysia's statistics on Malaysia's tourism for the year of 2020 (Tourism Malaysia, n.d.). The value obtained is divided by 1 billion to obtain the financial loss in billions. In order to obtain the range of forecasted loss, we used the upper and lower 95% prediction interval bound values to replace the point forecast, respectively, and repeated the steps above.

Using the point forecasts of the $ARIMA(0,0,3)(0,1,1)_{12}$ model, we calculated the average forecasted loss in tourism revenue to be RM82 billion. The range of forecasted loss is between RM70.38 billion to RM93.61 billion. As for the ETS (M,N,A) model, the average forecasted loss in tourism revenue is RM75.96 billion. The range of forecasted loss is between RM61 billion to RM90.79 billion.

The average forecasted loss in tourism revenue using the ETS model is lower than the ARIMA model's forecast by RM6.04 billion which makes sense as the point forecasts for the ETS model is generally lower than the ARIMA model as mentioned earlier. The ETS(M,N,A) model having a wider range of forecasted loss as compared to the $ARIMA(0,0,3)(0,1,1)_{12}$ model also makes sense as well as it was presumed to be so by looking at Figure 8 earlier.

Conclusion

The ARIMA framework was used to quantify the forecasted financial loss in Malaysian tourism revenue in RM billion since the Covid-19 pandemic. The Box-Jenkins methodology was applied to find the best ARIMA model to forecast the financial loss in a systematic manner. Unlike ETS models which components are decided based on the trend and seasonality seen in the data plot. ARIMA focuses on the autocorrelations in the data. After deciding the time frame of our full dataset. We separated it to "Pre-Covid" and "Covid" period. The "Pre-Covid" period was then partitioned into training and test set. The training set was plotted to see if the mean and variance of the series was stationary as the key requirement of ARIMA models is that the data is stationary. After performing a seasonal difference, the series became stationary. Moving on to the identification part, as we are dealing with data with seasonality present, we had to identify $ARIMA(p,d,q)(P,D,Q)_m$ models. After looking at the ACF and PACF plots to identify suitable ARIMA models, we identified a total of 4 ARIMA models which are the $ARIMA(1,0,0)(1,1,0)_{12}$, $ARIMA(2,0,0)(1,1,0)_{12}$, $ARIMA(0,0,3)(0,1,1)_{12}$ *and* $ARIMA(0,0,4)(0,1,1)_{12}$ models. A constant was not added to all identified models. Subsequently, we ranked the models based on their AICc values and selected the top 2 models with the lowest AICc values which were the $ARIMA(0,0,3)(0,1,1)_{12}$ *and* $ARIMA(0,0,4)(0,1,1)_{12}$ model. Diagnostic checks were performed on these 2 models and both models were found to be white noise. Using the traditional approach of evaluation, $ARIMA(0,0,3)(0,1,1)_{12}$ model's RMSE, MASE, MAPE, MAE test set error values were all smaller than $ARIMA(0,0,4)(0,1,1)_{12}$ model's indicating $ARIMA(0,0,3)(0,1,1)_{12}$ model to be the better forecasting model.

Moving on to the application part, the chosen $ARIMA(0,0,3)(0,1,1)_{12}$ model was re-estimated using the full dataset. An ETS (M,N,A) model suggested by R was then estimated and the forecasts for both ETS and ARIMA models were plotted alongside the full dataset. Both models were unable to forecast the sharp drop in tourist arrivals during the Covid period.

Lastly, the average forecasted loss in tourism revenue was calculated using the ETS and ARIMA models. As for the $ARIMA(0,0,3)(0,1,1)_{12}$ model, we calculated the average forecasted loss in tourism revenue to be RM82 billion with a range of forecasted loss between RM70.38 billion to RM93.61 billion. As for the ETS(M,N,A) model, the average forecasted loss in tourism revenue is RM75.96 billion with the range of forecasted loss between RM61 billion to RM90.79 billion. The estimated forecasted loss of RM82 billion and RM70.38 billion seems plausible as it was reported that Malaysia has lost over RM100 billion in 2020 due to

Covid (Reuters, 2020). The higher estimated loss could be due to the inclusion of financial loss from the local tourism sector.

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