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Forecasting Road Traffic Fatalities in Malaysia Using Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

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ABSTRACT

In Malaysia, travel activities become more intense during the festive seasons, whereby traffic volume on the roads on average increases about 30%. Consequently, this inevitably increases road traffic fatalities. An integrated enforcement program called the OPS Bersepadu has been carried out since 2011 to ensure high road safety performance. This study was carried out to develop a statistical model for predicting the seasonality of traffic fatalities. A Seasonal Autoregressive Integrated Moving Average (SARIMA) model was used to fit road fatalities data between 1980 and 2000 and forecast traffic fatalities from 2001 to 2019. The results showed that the SARIMA $(1, 1, 2)(1, 1, 2)_{12}$ model fitted the data fairly well and suggest that the SARIMA model is a possible tool that provides an overview of the seasonal patterns of traffic fatalities in Malaysia. The forecasted traffic fatalities based on the SARIMA model were then compared with the actual traffic fatalities during the festive months to explore the effectiveness of the OPS Bersepadu programme to help enforcement authorities allocate optimal resources that could increase the efficiency of enforcement activities to reduce road traffic fatalities.

Keywords: OPS programme, road traffic fatalities, SARIMA model

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INTRODUCTION

Road traffic fatalities are a serious public health problem worldwide. According to WHO (2018), it is the eighth leading cause of death for all ages and the first leading cause of death for children and young adults aged 5–29 years in the world. Every year, about 1.35 million lives are lost to road traffic crashes, and up to 50 million people sustain life-altering injuries (WHO, 2018). About 93% of the road traffic fatalities occurred in low-and middle-income countries, costing about 3% of the countries' gross domestic product (WHO, 2021). The tremendous burden on the health, social and economic development of the countries is particularly significant as far as the livelihood of children is concerned.

In Malaysia, road traffic fatality is the fourth contributor to death, where an average of 18 people of all ages die on the roads daily (DOSM, 2019). In 2019, 6,167 fatalities were reported, and 50% were motorcyclists. Figure 1 illustrates the traffic fatalities from 1980 to 2019 in Malaysia. Realizing the impacts of road traffic crashes, reducing deaths and injuries on the roads has become one of the country's development goals since the 1970s. As a result, various traffic rules such as the 1973 Motorcycle Rules and the 1987 Road Transport Act were enacted. In 1990, the Cabinet Committee of Road Safety was set up to reduce road traffic fatalities. Then, the National Road Safety Plan was launched in 1996 with several strategies and efforts to improve road safety. The establishment of MIROS is another milestone with a mission to foster the art and science of road safety interventions. Other initiatives include the Automated Awareness Safety System (AwAS) introduced in 2012 to deter the prevalence of excessive speeding and red-light running, the New Car Assessment Program (ASEAN NCAP) for Southeast Asian Countries in promoting the safer vehicle, the new driver education curriculum (KPP) designed to increase driver's competency as well as the implementation of the International Road Assessment Program (iRAP) in identifying high-risk roads. Though there have been encouraging results on the

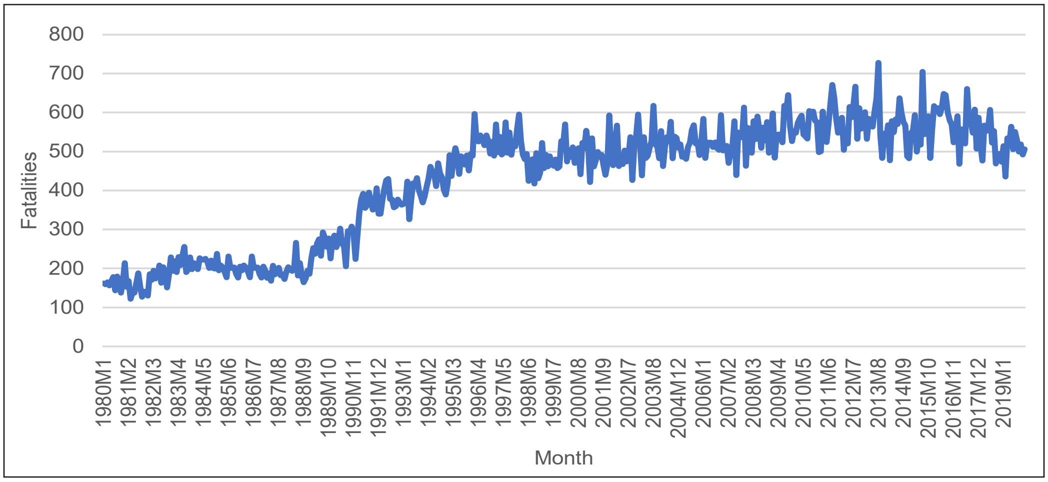


Figure 1. Road traffic fatalities in Malaysia between 1980 and 2019

progressive decline in road traffic fatalities, it is still far from the target to achieve at least a 50% reduction from the forecasted 10,716 fatalities in 2020 (Sarani et al., 2012).

During long holidays in Malaysia such as the Chinese New Year, Hari Raya Eid, Deepavali festival, and school holidays, people from all walks of life would take the opportunity to travel. For instance, during the Hari Raya Eid holiday, the traffic volume on the roads would increase about 28% compared to normal days (Low et al., 2017). The high traffic volumes have inevitably increased the risk of crashes, prompting the Royal Malaysia Police (RMP), Road Transport Department (RTD), Ministry of Transport and Ministry of Works to jointly carry out an integrated enforcement operation named the OPS Bersepadu since 2001. This two-week program aims to reduce the number of road traffic crashes by intensifying enforcement activities, especially at the black spots on expressways, federal roads, state roads, and local roads. Various strategies include banning heavy vehicles on the expressways, reducing speed limits on the federal and state road networks, and increasing advocacy campaigns on road safety. The government concluded that these strategies are effective to a certain extent despite seeing mixed results over the years. Since its inception, 41 OPS Bersepadu programmes have been carried out.

Nevertheless, the festive celebrations in Malaysia give rise to a certain extent seasonal trend on the traffic conditions. It has been a norm to see high traffic demand long-distance trips, either traveling back to hometown or vacation points during these long holidays, usually in January, February, July, August, November, and December. It is essential to understand the seasonal trends in traffic conditions which can provide important insight to decision-makers in planning for road safety interventions. The accurate prediction of traffic fatalities enables all relevant agencies to effectively optimize their resources in terms of staff, budget, and equipment to implement road safety measures to reduce the likelihood of road traffic fatalities.

SARIMA (Seasonal Autoregressive Integrated Moving Average) is one of the statistical tools used to model the seasonality factors for time series data and has evidently worked very well in forecasting traffic crashes. Zolala et al. (2016) studied traffic crash fatalities in Iran from January 2013 to December 2015 using the SARIMA model. The results indicated that SARIMA models outperformed the ARIMA model. Zhang et al. (2015) developed a SARIMA model for the monthly road traffic fatalities in China from 2000 to 2011. The findings concluded that the SARIMA model best-fitted China mortality rates with minimum forecasted errors. The results were also in line with the study by Akhtar and Ziyab (2013), where the SARIMA model was also found to be the best fitting prediction model for monthly road traffic injuries in Kuwait from 2003 to 2009. Likewise, Bahadorimonfared et al. (2013) proved that the SARIMA model is appropriate in presenting the seasonal trend of the monthly number of road traffic fatalities in Iran from 2004 to 2011. Paz et al. (2015), in their study, showed that SARIMA was the appropriate model to predict the fatalities and serious injuries in Nevada over a five-year horizon. Wang et al. (2017)

adopted SARIMA models in forecasting short-term vehicle volumes in Yunnan, China, and the results were very encouraging compared to the Holt-Winters model. By fitting the data for road traffic crashes between January 1999 to December 2013 in the SARIMA model, Sunny et al. (2018) had shown that the number of road traffic crashes in Kerala could be well predicted using the SARIMA model. Findings by Zhang et al. (2019), who attempted to predict vulnerable road user crashes based on the seasonal pattern, were consistent with other studies, which indicated the SARIMA model is able to analyze seasonal data.

The review of literature has noted that the SARIMA model is better than other predicting tools such as the moving average, exponential smoothing, neural network, and fuzzy logic models due to its predicting capability and the information carried within the model (Zhang et al., 2015; Linthicum et al., 1999; Feng et al., 2014). Though the SARIMA model has the advantage of capturing the seasonal characteristics of road traffic injuries (Wen et al., 2005; Pang et al., 2013), it is not without limitations. The SARIMA model only works well if the data contains repeating seasonality fluctuations in a year and has difficulty optimizing the best parameters (Farsi et al., 2021). In the Malaysia context, several traffic fatalities prediction models have been developed, such as the Generalized Estimating Equation (GEE) by Danlami et al. (2017), ARIMA model by Aida et al. (2018), Poisson GLM, and Negative Binomial by Ho et al. (2019) and Support Vector Machine (SVM) by Radzuan et al. (2020). Though these models work well in forecasting the traffic fatalities, thus far, no study was performed on monthly road traffic fatalities in Malaysia using the SARIMA model. This study would add value to the existing traffic prediction models in Malaysia, whereby the models were developed based on yearly data. Therefore, this study was set to develop a SARIMA model for Malaysian monthly road fatalities with respect to the OPS Bersepadu implementation periods. The out-sample forecasted values were compared with the actual road traffic fatalities to see how far the forecasted values differ from the actual values during the festive months. The findings can shed some light on the relevant authorities in optimizing the resources, thereby reducing the burden of various parties in supporting policy changes and prioritizing budget allocation.

The rest of this paper is organized as follows. Section 2 describes the methodological approach, and the results are presented in Section 3. Discussion on the comparison of a forecasted model on the traffic fatalities during festive seasons and the outcome of the OPS Bersepadu program is highlighted in Section 4. Lastly, Section 5 provides the conclusions drawn from this study.

METHODOLOGY

Road traffic fatalities data used in this study was obtained from the Royal Malaysian Police (RMP) database from 1980 to 2019. This road traffic fatalities prediction model was developed based on the Box-Jenkins methodology for Seasonal Autoregressive Integrated Moving Average (SARIMA) model. In evaluating the effect of the OPS Bersepadu programme implemented over the years, the data set was divided into 1980 to 2000 and 2001 to 2019. In order to ease the discussion, the first phase is known as pre-OPS, and the second phase is known as post-OPS. On the other hand, the fatalities data between 1980 and 2006 were used as an in-sample estimation, and the remaining data from 2007 to 2019 were used as an out-sample forecast.

A general SARIMA model can be denoted with parameters as (p, d, q) (P, D, Q) where the p is the autoregressive order, d is the number of differencing operations, q is the moving average order, and P, D, Q refers to the respective seasonal orders. The development of SARIMA models involved several steps. The first step is to examine the stationarity of the time series using the Augmented Dickey-Fuller test. Then, the non-stationary time series data can be transformed into stationary time series at the first differencing. Then, followed by the estimation of model parameters, p, d, q, P, D, and Q for the SARIMA model. The initial parameters can be identified from the AutoCorrelation Function (ACF) and Partial AutoCorrelation (PCF) plots. Then, a set of models with various combinations of parameters can be developed whereby the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to compare the models in which the best-fit model is the model with the lowest AIC and BIC values (Claeskens & Hjort, 2008). The last step is about the validation of the model by performing the goodness-of-fit test to the model. The flow of the model development stages is presented in Figure 2, and the Eviews software was used for developing the models.

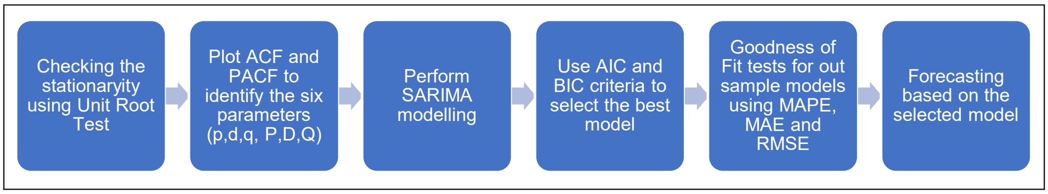


Figure 2. Steps involved in SARIMA model development

The equation for SARIMA (p, d, q) (P, D, Q) is denoted as Equations 1 and 2:

$$\emptyset(B)\Phi(B^S)(h_t - \mu) = \theta(B)\Theta(B)\Theta(B^s)e_t \qquad (1)$$

$$h_t = (1-B)^d(1-B^s)^D Y_t = \Delta^d \Delta_S^D(Y_t) \qquad (2)$$

where:

$B^s =$ seasonal lag operator $B^S(Y_t) = Y_{t-s}$

$\Delta^d =$ $(1-B)$

$\Delta_S^D =$ $(1-B^S)$ seasonal difference operator

$h_t =$ stationary series

$Y_t =$ observed series
B= lag operator
$\phi(B) =$ autoregressive order p (ordinary part of the series)
$\theta(B) =$ moving average order q (ordinary part of the series)
$\Phi B^S =$ autoregressive order P (seasonal part of the series)
$\Theta(B^S) =$ moving average order Q (seasonal part of the series)
$\mu =$ average of stationary series
$e_t =$ model error
D, d = seasonal difference and normal difference for the original series

The robustness of the prediction model was evaluated by using the mean average error (MAE), mean absolute percentage error (MAPE), and Root Mean Square Error (RMSE). Equations 3-5 are as follows:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|(y_t - \hat{y}_t)| \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}|(y_t - \hat{y}_t)/y_t| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}((y_t - \hat{y}_t)^2}{n}} \tag{5}$$

RESULTS

A total of 204,989 road traffic fatalities were recorded in Malaysia between 1980 and 2019. The descriptive results for the two periods, 1980–2000 and 2001–2019, are presented in Table 1. The first period consisted of 252 months, and an average of 323 fatalities per month were reported. However, the second period had higher monthly fatalities where the highest number of fatalities was recorded at 728, which can be translated into 24 deaths in a day. This value is huge and takes a tremendous toll on society and national economic growth.

Figures 3 and 4 illustrate the number of road traffic fatalities for the two periods. Figures 3 and 4 showed almost similar trends where the month of August had the highest number of fatalities. On the other hand, September had the lowest rate of fatalities in the pre-OPS period, while in the post-OPS periods, February recorded the lowest number of fatalities. The high number of road fatalities in August was attributed to the Hari Raya Eid festive celebration, school holidays, and Malaysia National Day, where many inter-urban travels were recorded. During these festivals, the number of vehicles on major expressways increases tremendously. For instance, during Chinese New Year 2019, the number of vehicles on the PLUS expressway increased from 1.45 million vehicles on a normal day to 1.9 million vehicles (PLUS, 2019).

Table 1
Descriptive statistics for the road traffic fatalities in Malaysia between 1980–2019

Variable	Pre-OPS 1980–2000 (no. of months = 252)	Post-OPS 2001–2019 (no. of months = 228)	Total 1980–2019
Mean	323	542	427
Median	285	539	487
Maximum	597	728	728
Minimum	122	421	122
Standard Deviation	136.9	51.851	151.926
Skewness	0.2735	0.391	-0.600
Kurtosis	1.547	3.323	1.952
Jarque - Bera	25.317	6.789	50.788
p-value	0.000	0.034	0.000

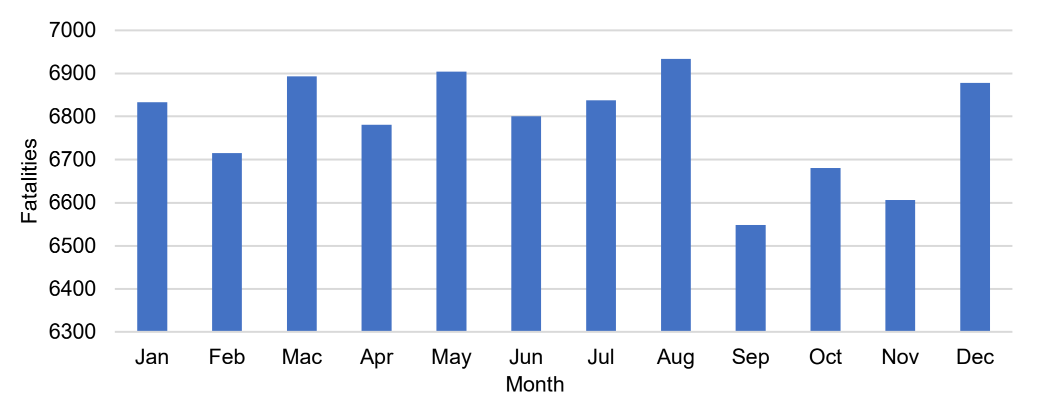


Figure 3. Average monthly road traffic fatalities between 1980–2000 (pre-OPS)

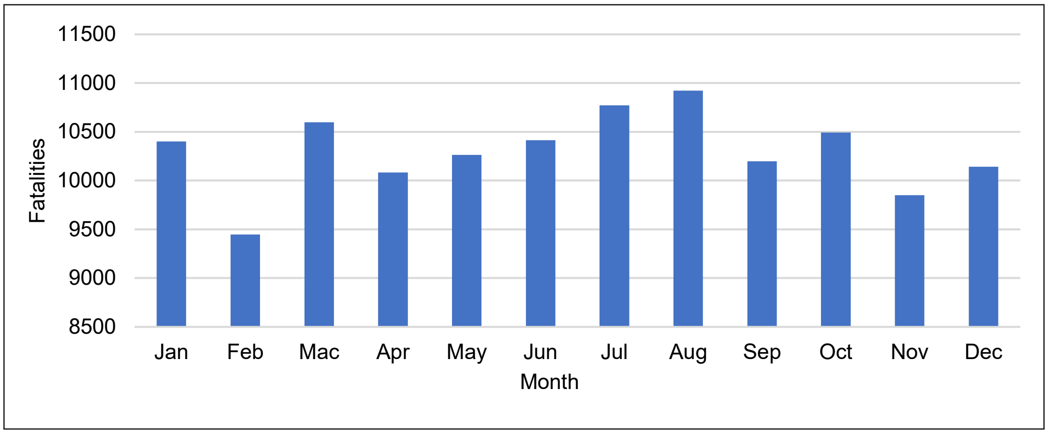


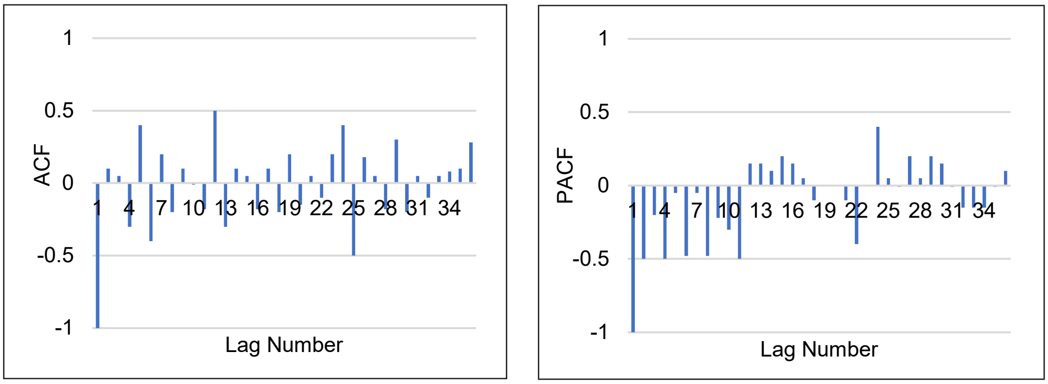
Figure 4. Average monthly road traffic fatalities between 2001–2019 (post-OPS)

Table 2 presents the results of the Augmented Dickey-Fuller (ADF) and Phillip- Perron (PP) unit root tests for the road traffic fatalities at levels and first differences. It is expected that the traffic fatalities were not stationary at their levels but became stationary after the first difference at a 1% significance level.

Table 2
Stationarity using ADF and PP tests

	Augmented Dickey-Fuller (ADF)				Phillip-Perron (PP)			
	Intercept		Trend & Intercept		Intercept		Trend & Intercept	
Level	-1.932	0.317	0.095	0.997	-2.589	0.096	-9.299	0.000
First	-12.846	0.000	-13.081	0.000	-76.852	0.000	-82.519	0.000

Figure 5 presents the ACF and PACF plots for the initial selection of the parameters of SARIMA (p, d, q)(P, D, Q). Both the plots indicate the presence of seasonality effects, thereby suggesting that AR term and MA terms to be included in the model, with reference to ACF and PACF plots, respectively, where the terms varied between 1 to 8. Nonetheless, the best parameters for p and q for the SARIMA model are determined using AIC and BIC information criteria.



(a) (b)

Figure 5. Monthly road fatalities between 1980 - 2019: (a) ACF; and (b) PACF

A total of 30 possible SARIMA models corresponding to various p and q parameters choices were developed and tested. Only seven of the best-fitted models were summarized in Table 3. Based on the goodness-of-fit tests such as the AIC, BIC, and R^2, it was found that Model 4, SARIMA (1, 1, 1) $(2, 1, 2)_{12}$ is the best-fitted model among all. The parameters and p-values for the best-fitted SARIMA models are presented in Table 4.

The goodness-of-fit statistics do not guarantee good performance in terms of in-sample forecasting. Similarly, the good performance in terms of in-sample diagnostics might not guarantee the good performance of out-sample forecasting. A good forecasting method

Table 3
SARIMA models for road traffic fatalities in Malaysia

Model No	SARIMA Models	AIC	BIC	R-squared
1	(0,1,0) (1,1,1)	-1.674	-1.632	0.294
2	(1,1,0) (1,1,1)	-1.665	-1.608	0.295
3	(1,1,1) (1,1,1)	-1.657	-1.586	0.295
4	(1,1,1) (2,1,2)	**-1.685**	**-1.614**	**0.317**
5	(1,1,1) (1,1,2)	-1.682	-1.612	0.313
6	(1,1,2) (1,1,2)	-1.674	-1.604	0.309
7	(2,1,1) (1,1,1)	-1.653	-1.582	0.295

Table 4
Parameter estimates and their testing results of the SARIMA (1, 1, 1) (2,1, 2)$_{12}$ model

Parameter	Coefficients	Standard Error	P-value
C	0.0056	0.0009	00.000
Stationary lags			
AR1	-0.0385	0.1084	0.7229
MA1	-0.6597	0.0865	0.0000
Seasonal lags			
SAR2	0.9172	0.0285	0.0000
SMA2	-0.9841	0.0104	0.0000

should be the one that can withstand the robustness of the post-sample test. Tables 5 and 6 summarized the performance of in-sample and out-sample results, respectively. A model with smaller MAE, RMSE, and MAPE values is the better-fitted model. For the in-sample prediction results, Model 6, SARIMA (1, 1, 2) (1, 1, 2)$_{12}$ was the best performing model across the two error measures, RMSE and MAPE but ranked the second-lowest under MAE evaluation criterion.

Table 5
Summary of MAE, RMSE and MAPE for in-sample estimation

Model No	SARIMA Models	MAE	RMSE	MAPE
1	(0,1,0) (1,1,1)	25.892	33.517	0.0772
2	(1,1,0) (1,1,1)	25.955	33.560	0.0773
3	(1,1,1) (1,1,1)	25.837	33.419	0.0771
4	(1,1,1) (2,1,2)	26.210	34.375	0.0798
5	(1,1,1) (1,1,2)	25.840	33.314	0.0770
6	(1,1,2) (1,1,2)	**25.720**	**33.281**	**0.0766**
7	(2,1,1) (1,1,1)	24.423	34.671	0.0803

It is interesting to note that in the post sample performance, model 6 (SARIMA (1, 1, 2) (1, 1, 2)$_{12}$) also appeared to surpass all other models in terms of MAE, RMSE, and

MAPE evaluation criteria. The forecasted traffic fatalities estimated from the SARIMA model (1, 1, 2) $(1, 1, 2)_{12}$ were illustrated in Figure 6 and compared with observed monthly road traffic fatalities. As shown in Figure 6, the plots indicated that the observed values and forecasted values matched reasonably well.

Table 6
Summary of MAE, RMSE and MAPE for out-sample forecasts

Model No	SARIMA Models	MAE	RMSE	MAPE
1	(0,1,0) $(1,1,1)_{12}$	38.781	49.452	0.0711
2	(1,1,0) $(1,1,1)_{12}$	38.634	49.332	0.0709
3	(1,1,1) $(1,1,1)_{12}$	38.706	49.371	0.0708
4	(1,1,1) $(2,1,2)_{12}$	37.965	48.658	0.0696
5	(1,1,1) $(1,1,2)_{12}$	39.230	49.745	0.0717
6	(1,1,2) $(1,1,2)_{12}$	**37.769**	**48.496**	**0.0692**
7	(2,1,1) $(1,1,1)_{12}$	38.647	49.335	0.0709

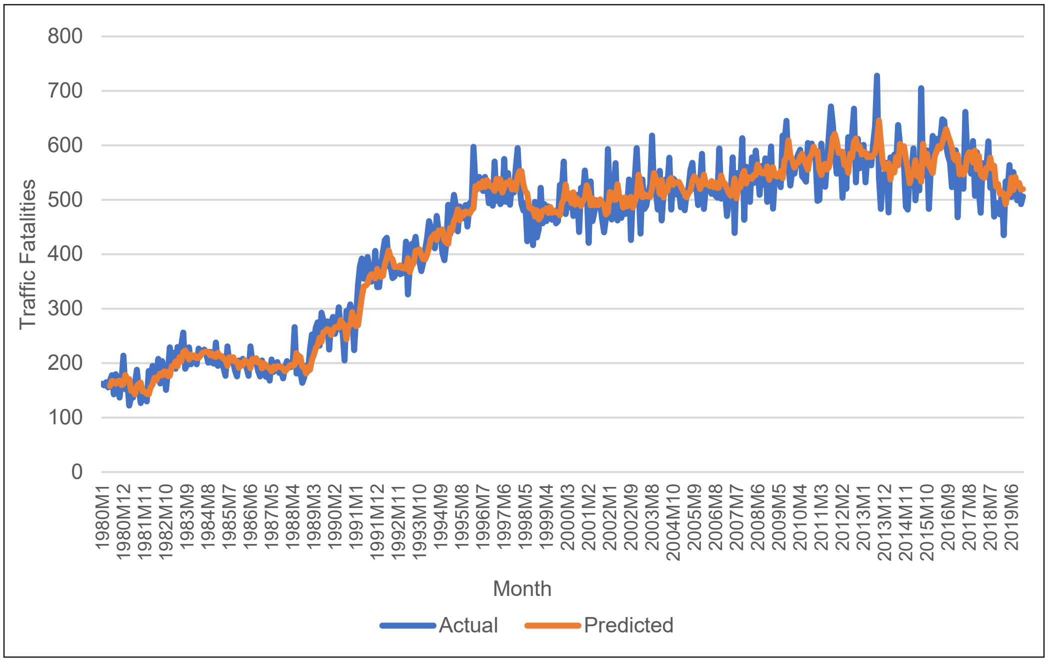


Figure 6. Comparison between actual and fitted road traffic fatalities between 1980 to 2019

Table 7 compares the forecasted road traffic fatalities and the actual traffic fatalities during the particular festive seasons or the OPS Bersepadu operations based on the SARIMA (1, 1, 2) $(1, 1, 2)_{12}$ model. Of the 40 OPS Bersepadu intervention programs since 2001, 22 OPS had higher actual fatalities than the forecasted values differences, ranging from 0.4% to 24.7%.

Table 7
Difference between the forecasted road traffic fatalities and the actual road fatalities

Year	Month	Actual	Forecasted	Difference		Year	Month	Actual	Forecasted	Difference	
				n	%					n	%
2001	Dec	593	473.7	119.3	20.1	2010	Feb	573	569.6	3.4	0.6
2002	Feb	462	533.7	-71.7	-15.5	2010	Sep	598	580.5	17.5	2.9
2002	Nov-Dec	1083	992.5	90.5	8.4	2011	Jan-Feb	998	1141.5	-143.5	-14.4
2003	Jan-Feb	949	1024.6	-75.6	-8.0	2011	Aug-Sep	1309	1217.1	91.9	7.0
2003	Nov-Dec	1115	1069.1	45.9	4.1	2012	Jan	587	580.8	6.2	1.1
2004	Jan	513	548.9	-35.9	-7.0	2012	Aug	667	612.3	54.7	8.2
2004	Nov	535	528.8	6.2	1.2	2013	Feb	532	585.7	-53.7	-10.1
2005	Feb	486	524	-38	-7.8	2013	Aug	728	613.5	114.5	15.7
2005	Oct-Nov	1014	1073.9	-59.9	-5.9	2014	Jan-Feb	1045	1139.3	-94.3	-9.0
2006	Jan-Feb	1067	1079.35	-12.35	-1.2	2015	Feb -Mar	1148	1098.9	49.1	4.3
2006	Oct	594	524	70	11.8	2015	Jul-Aug	1249	1141.7	107.3	8.6
2007	Feb	470	514.8	-44.8	-9.5	2015	Jul	705	530.6	174.4	24.7
2007	Oct	613	557.8	55.2	9.0	2016	Feb	602	581	21	3.5
2007	Nov	463	555.2	-92.2	-19.9	2016	Jun-Jul	1293	1227	66	5.1
2007 - 2008	Dec-Jan	1116	1069.4	46.6	4.2	2017	Jan-Feb	1059	1152.2	-93.2	-8.8
2008	Jan-Feb	1051	1077.4	-26.4	-2.5	2017	Jun-Jul	1242	1141	101	8.1
2008	Sep-Oct	1104	1095.3	8.7	0.8	2018	Feb	476	545.7	-69.7	-14.6
2008	Oct	576	550.6	25.4	4.4	2018	Jun-Jul	1129	1145	-16	-1.4
2009	Jan-Feb	1082	1110.7	-28.7	-2.7	2019	Jan-Feb	949	1025.3	-76.3	-8.0
2009	Oct	564	619.4	-55.4	-9.8	2019	Mei-Jun	1069	1064.6	4.4	0.4

DISCUSSION

The SARIMA model has been widely applied to predict monthly or seasonal trend time-series data (Zhang et al., 2019; Zhang et al., 2015; Akhtar & Ziyab, 2013). It has evidently proved that the SARIMA model has the ability to capture the changes of time-related information and therefore outperforms other forecasting methods such as the moving average, exponential smoothing, ARIMA, and neural network (Zhang et al., 2015; Akhtar and Ziyab 2013).

This study adopted the SARIMA model in forecasting the monthly road traffic fatalities in Malaysia with respect to the OPS Bersepadu implementation periods. It is aimed to understand the forecasted road traffic fatalities based on the historical trends and how much the actual road traffic fatalities during the festive seasons deviated from the forecasted values.

The road traffic crashes in Malaysia have exhibited some seasonal trends. Malaysia is a multi-racial country with various celebrations throughout the year, namely Chinese New Year (January to February), Hari Raya Eid (May, July, August), mid-year school holiday break (July to August), National Day (August), Hari Deepavali (November) and Christmas festival in December. During these periods, the residents in the urban areas would take the opportunity to travel out of town, which increases the traffic volumes by 20% to 30%. Consequently, this led to an increased risk of crashes due to a higher degree of exposure. In response to such circumstances, the enforcement agencies such as the Royal Malaysian Police (RMP), Ministry of Transport, Ministry of Works and the Road Transport Department (RTD) have jointly carried out an integrated program known as the OPS Bersepadu during Chinese New Year and Hari Raya Eid since 2001. The program is a periodic program that includes strategies such as banning heavy vehicles on the expressways, reduction of speed limit on the federal and state road networks, intensifying enforcement activities and safety campaigns. Over the years, MIROS has played an active role in evaluating the effectiveness of each of the OPS Bersepadu programs and concluded that the programs have mixed effects on traffic fatalities.

The festive months of Hari Raya Eid during Aug-Sept 2011 had recorded the highest number of road traffic fatalities (1,309) among all the festive months. On the other hand, the festive seasons in July–August 2015 were another festival that had seen many road traffic fatalities (1,249 fatalities) where it was declared by the Royal Malaysian Police (BH Online, 2015) as the worst OPS 7/2015 program since 1994 for the highest number of crashes. However, the road traffic fatalities during the festive seasons after 2015 were seen to be on the constant rise though the same or even stringent OPS programs were implemented. There are many causal factors to high road traffic fatalities, such as increased registered vehicles, longer vehicle-kilometer traveled, and the most important driver behavior. Based on the findings in this study, the actual road traffic fatalities during the festive seasons were much higher than the forecasted values. Therefore, policymakers should reassess the approach taken in the OPS program to increase its effectiveness.

CONCLUSIONS AND RECOMMENDATIONS

This study has shown significant empirical evidence that the SARIMA model can capture the seasonal characteristics of time series data. Nonetheless, this study is not without flaws. The finding showed that SARIMA (1, 1, 2) $(1, 1, 2)_{12}$ is the best-fitted model for road traffic fatalities. As motorcycle fatalities comprised 60% of the total fatalities, it is important to investigate if the model is also suitable for predicting motorcycle fatalities. Besides, it is recommended to conduct exploratory analysis on the relationship between economic factors, other socioeconomic factors, vehicle data, travel exposure data, and the trends of road traffic fatalities in Malaysia. It is also of interest to test the SARIMA (1, 1, 2) $(1, 1, 2)_{12}$ to predict traffic fatalities by localities, such as at the state level in Malaysia. It would enable the government to prioritize resources in battling road safety issues in each state.

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