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(Research Article)

Forecasting Road Traffic Accidents in Metro Manila Using ARIMA Modeling

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Abstract

In this paper, we have determined and analyzed the behavior of road traffic accidents (RTAs) in Metro Manila, Philippines over the period of 2012-2021, and created a forecast for the next 5 years using ARIMA modeling. This study used 10-year historical monthly data collated through the Metro Manila Accident Recording and Analysis System program for the years 2012 through 2021. Our result suggests that the total RTAs in Metro Manila gradually increased until the first quarter of 2020, then it plummeted and reached its lowest point in April 2020 due to COVID-19 lockdown. As lockdown eases, it bounced back but only halfway. Similarly, RTAs resulting in damage to property also bounced back to only halfway as lockdown eases, while RTAs resulting in injuries (fatal and nonfatal) bounced back to their normal range as before the lockdown. Despite the decrease in total RTAs, the ratio of RTAs resulting in injuries drastically increased during the lockdown due to reckless driving behaviors. Using Box-Jenkins methodology of ARIMA modeling, this study identified ARIMA (1, 1, 12) as the best model. With this model, the forecast shows that the total RTAs will stay halfway in 2022 and gradually decrease for the next 4 years.

Keywords: ARIMA; Road accidents; Forecasting; RTA; Box-Jenkins methodology

1. Introduction

Road traffic accidents (RTAs), which is simply defined by Collins Dictionaries (n.d.) as "an accident involving vehicles", kill at least 1,670 Filipino children every year (PSA). It cost the Philippines approximately 12,690 Filipino lives in 2016 and 2.6% of its GDP (WHO, 2018). It is also responsible for the 25% of deaths out of all deaths due to external causes (for example suicide, transport accidents, falls, poisoning, etc.) in 2017 (PSA). RTAs resulting to injuries affect mainly males and young adults, resulting to the loss of family breadwinners. A study conducted by Lu et al. (2022) found out that most victims were drivers, males, and from the younger age group (0-30 years old). This may result in long term psychological problems and costs the individuals and their families financial losses due to medical costs and lost productivity of those killed or disabled.

In Metro Manila, the capital region of the Philippines, most of the RTAs occurred on Fridays in Quezon City and cars are the type of vehicles that are mostly involved (Gayo et al., 2014). Factors such as gender, junction-type, weather, location, time, and vehicle-type were identified to be statistically significant in the accident fatality of road accidents in the region (Urrutia et al., 2018).

This research aimed to study the trend or behavior and to forecast the number of RTAs in Metro Manila that may happen for the next 5 years. Because of the simplicity and wide acceptability of ARIMA modeling (as discussed in the succeeding section of this paper), in addition to the nonstationary of the data used in this study, the researchers employed ARIMA modeling in forecasting.

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Objective of the Study

The objectives of this study are the following:

- To analyze the behavior of the road traffic accidents (RTAs) in Metro Manila for the years 2012 through 2021
- To create a forecast of the RTAs in Metro Manila for the next 5 years (2022 to 2026) using ARIMA modeling

1.1. Conceptual Framework

This research uses an Input-Process-Output (IPO) model as a guide in forecasting the number of RTAs in Metro Manila. This involves Box-Jenkins Methodology of ARIMA modeling as the process which is composed of 4 stages: identification, estimation, model checking and forecasting. The IPO model is depicted as follows.

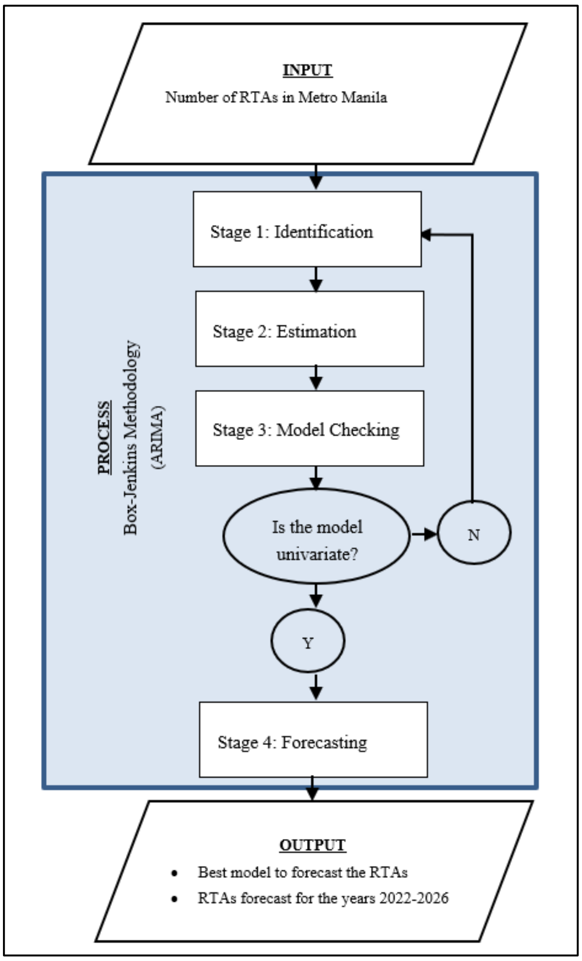


Figure 1 Research Paradigm

1.2. Scope and Limitation

This study used monthly road traffic accidents in National Capital Region composed of City of Manila and the cities of Caloocan, Las Piñas, Makati, Malabon, Mandaluyong, Marikina, Muntinlupa, Navotas, Parañaque, Pasay, Pasig, Quezon City, San Juan, Taguig, Valenzuela, and Municipality of Pateros. Road accidents for the years 2012 through 2021 are based on the data collated by the Metro Manila Development Authority (MMDA) through its Metro Manila Accident Recording and Analysis System (MMARAS) program.

1.3. Review of Related Literature

This section of the paper will provide an overview of the current knowledge and related research to determine the nature of this study. This will also help the researchers explain the possible cause for the behavior of the data.

A research conducted by Avuglah et al. (2014) applied the Autoregressive Integrated Moving Average (ARIMA) time series model to study the trends and patterns of road traffic accident cases in Ghana and makes a five- year forecast using annual accident data from 1991 to 2011. The results showed that road traffic accident cases are increasing in Ghana. Models were subsequently developed for accident cases and ARIMA (0,2,1) was identified as the best model. A 5- year forecast was made using the best model and it showed that road traffic accident cases would continue to increase.

A study conducted by Hassouna et al. (2020) suggested that based on the developed model using ARIMA, a generally increasing trend of road accidents was observed in Palestine in 2017 and was expected to continue in the future.

A study conducted by Ghédira et al. (2018), showed that the time series of accidents in Tunisia are mainly characterized by two different periods in terms of trend. A low decrease in the number of accidents before the revolution (2011) (between 2007 and the end of 2010) and the irregular evolution in the rest of the series. Then, models were developed in accident cases and ARIMA (0, 1, 2) was identified as the best model. A three-year forecast was made using the best model and it showed that the number of road accidents would decrease due to several factors.

A comparative analysis conducted by Jadaan et al. (2018), about traffic safety in developed and developing countries, found out that the fatality rates per population for the developing countries were found to be substantially higher than those in developed countries. The results suggested that road safety is more appreciated in developed countries than the developing countries.

In the Philippines, there are several researches conducted to study the road accidents in Metro Manila. Gayo et al. (2014) found out that most of the accidents occurred on Fridays in Quezon City and cars are the most prone to this. Urrutia et al. (2018) also found out that factors such as gender, junction-type, weather, location, time, and vehicle-type are statistically significant in the accident fatality of road accidents in Metro Manila.

Considering the pandemic, a lot of research was also conducted interlinking the lockdown and the RTAs. A study conducted by Rapoport et al. (2021) found out that the physical distancing measures that aimed to reduce the spread of COVID-19 resulted in a marked reduction in injuries and fatalities in drivers aged 80 years old and over. The absolute number of fatal road accidents also declined in Greece, Australia and New York City (Catchpole, 2020) (Masri, 2020) (Katrakazas et al., 2020). Yasin et al. (2021) found out the COVID-19 pandemic has generally reduced the overall absolute numbers of road traffic collisions, and their deaths and injuries, however the ratio of severe injuries and deaths significantly increased. The identified factors that affected the RTAs are decreased mobility with empty lines, reduced crowding, and increased speeding. In addition, the relative percentage of fatal accidents to all RTAs dramatically increased due to excessive speed in Madrid (Spain), Chicago, New York, and Boston, by 470%, 292%, 167% and 65%, respectively (Masri, 2020).

The ARIMA model is useful in providing accurate forecasts across a wide range of disciplines. Several researchers used this model to forecast oil consumption (Dritsaki et al., 2021), wheat production (Biswas et al., 2014), rice and corn production (Urrutia et al., 2017), stock prices (Gayo et al., 2015), tax revenue (Urrutia et al., 2015), and even life expectancy (Torri & Vaupel, 2012) and road accidents, as discussed above. Because of its simplicity and wide acceptability, in addition to the nonstationary of the RTA monthly data, this study uses ARIMA model to forecast the RTAs in Metro Manila.

2. Material and methods

2.1. Data Source

In forecasting future time series, this study uses 10-years historical monthly data of RTAs in Metro Manila, Philippines. This is based on the data collated by the MMDA through its Metro Manila Accident Recording and Analysis System program for the years 2012 through 2021.

2.2. Statistical Tool

In analyzing the behavior of the data and forecasting the time series, the researchers used Econometrics Views 12 (Eviews12), a software that offers statistical, forecasting and modeling tools.

2.3. Model Description

Autoregressive Integrated Moving Average (ARIMA) Modeling is a method for forecasting future time series using historical data (Investopedia, 2022). The data used in this study was determined to be nonstationary in the identification stage of Box-Jenkins Methodology, thus the researchers used ARIMA modeling. ARIMA modeling uses differencing to convert a non-stationary time series into a stationary one, and then predict future values from historical data (Box et al., 2015). It has the following components:

- Autoregression - AR(p): indicates that the data is regressed on its past values
- Integrated I(d) - indicates that data is stationary
- Moving average - MA(q) - indicates that the forecast depends linearly on the past values

Generally, ARIMA can be written as the following formula

$$\phi(B)(\nabla z_t - \mu) = \theta(B)a_t,$$

where $\phi(B)$ is a stationary autoregressive operator and $\theta(B)$ is an invertible **moving average** operator,

∇ is the backward difference operator, z_t is a nonstationary series,

μ is the intercept or mean term,

a_t is a random residual series,

Box-Jenkins Methodology. It refers to a systematic method of identifying, fitting, checking, and using ARIMA time series models for forecasting (Meyer & Penman, 2016). It was introduced by George Box and Gwilym Jenkins in 1970 to select appropriate models for estimating and forecasting univariate models. It involves 4 stages, namely, (1) identification, (2) estimation, (3) model checking, and (4) forecasting (JD Economics, 2020).

- **Identification.** This involves analyzing the variable of interest and determining whether it is stationary or not. The researchers analyzed the graph and correlogram of the data and conducted unit root test using Augmented Dickey Fuller Test (ADF). As a result, it was found out that the data is nonstationary, thus ARIMA modeling was used. ARIMA modeling involves differencing to convert a non-stationary time series into a stationary one. The correlogram of the stationary data was used by the researchers in identifying the possible models.
- **Estimation.** This involves estimating all possible models. The researchers analyzed the significance of the ARMA components and compared the Akaike Information, Schwarz, and Hannan-Quinn model Criterion of the possible models to come up with stationary and parsimonious model that fits the data well.
- **Model Checking.** This involves checking whether the chosen model is a univariate model. The researchers examined whether the residuals of the model are white noise using Ljung-Box Q Statistics, and checked whether the ARMA process is (covariance) stationary and invertible using the ARMA structure.
- **Forecasting.** Using the chosen model, the researchers created a 5-year forecast in the form of a graph.

Correlogram. A correlogram (also called Auto Correlation Function ACF Plot or Autocorrelation plot) is a visual way to show serial correlation in time series data. The autocorrelation coefficient can be written as the following formula:

$$\rho_k = \frac{\sum_{t=k+1}^{r}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{r}(Y_t - \bar{Y})^2}$$

where ρ_k is the ACF coefficient in lag k, t is the amount of observed periods, Y_t is the observation in t period, $\bar{Y}$ is the mean, and Y_{t-k} is the observation in t-k period.
Partial Auto Correlation Function - At lag k, this is the correlation between series values that are k intervals apart, accounting for the values of the intervals between. It is examined to identify the AR orders.[15]

The Augmented Dickey Fuller Test is used to test the time series samples for the presence of unit root. It is commonly used to analyze the stationary of a series. The ADF test employs the following formula:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{k} \infty_i \, \Delta Y_{t-i} + \varepsilon_t$$

where:
Δ is the first difference operator
Y_{t-1} is lagged values of the dependent variable
ε_t is a white noise error term
β_1 is a constant
β_2 is a slope coefficient on time trend t
δ is a coefficient of lagged Y_{t-1}
Y_t is the logarithm of the stock price or market price index

3. Results and discussion

This part of the paper is organized as follows. The first section discussed the behavior and related analysis of the RTAs in Metro Manila from 2012 to 2021. Considering the results of the previous studies of Yasin et al., (2021), the researchers also broke down and analyzed the 3 RTA variables (RTAs resulting in damage to property, fatal injury, and nonfatal injury). This will help provide a detailed analysis of the RTA behavior. The next section discussed the steps and results of forecasting using the ARIMA modeling.

3.1. Behavior of the RTAs

It can be observed that in the figure below (Figure 2), total RTAs have an increasing trend up until the first quarter of 2020. Afterwards, it plummeted and reached its lowest point in April 2020 due to lockdown. It bounced back again as lockdown eases but only halfway. Additional figures below (Figure 3, 4, and 5) show the behavior of the components or variables of total RTAs.

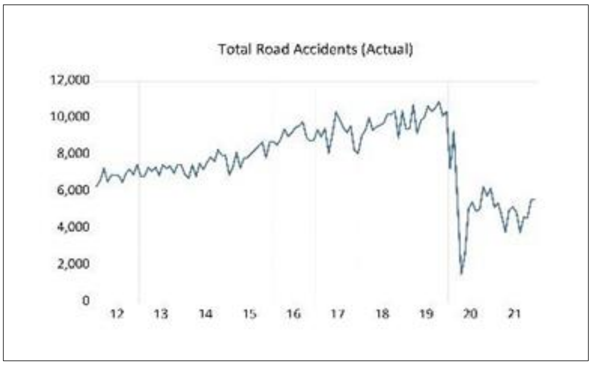


Figure 2 Overall RTAs in Metro Manila (2012-2021)

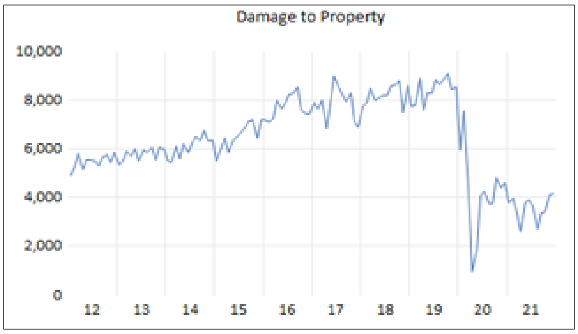


Figure 3 RTAs resulting in damage to properties

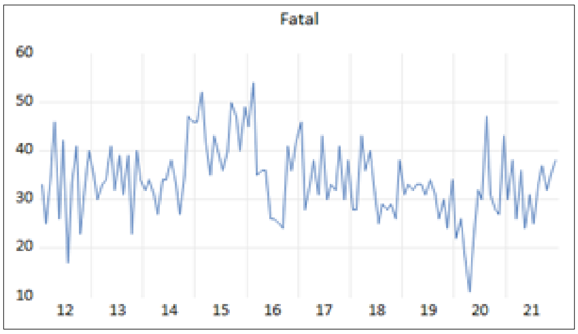


Figure 4 RTAs resulting in fatal injuries

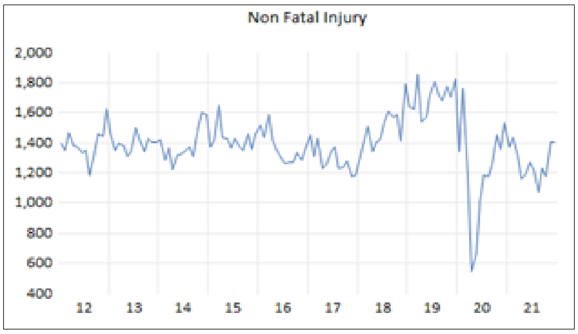


Figure 5 RTAs resulting in non-fatal injuries

The graph of RTAs resulting in damage to properties (Figure 3) shows an irregular rise and fall movement but an upward trend throughout the series up until the first quarter of 2020. It reached its peak at 9,098 cases in October 2019. The upward trend can be attributed to the rapid increase of motorization rate, rapid development, and population growth, but with a slow implementation of effective national road safety strategies (Jadaan et al., 2018). This behavior is similar to other developing countries. As a result of the COVID-19 lockdown, the graph shows a drastic decline in April 2020 at 979 cases. The factors that may have affected this decline are decreased mobility with empty lines and reduced crowding (Yasin et al., 2021). It bounced back as the lockdown eases but only halfway.

It can be seen from the graph of RTAs resulting to fatal injuries (Figure 4) that the number of fatal road accidents shows an irregular rise and fall movement throughout the series. It also shows no particular upward or downward trend in a long-term series. It reached its peak in February 2016 at 54 cases, followed by a sharp decline to 24 in September 2016. Similar to damage to property, it also reached its lowest point during the lockdown in April 2020 with 11 cases. However, fatal accidents started to bounce back rapidly starting May 2020 until it reached the same normal range as before the pandemic, and comfortably stayed on that range throughout 2020 and 2021. This is despite a significant decrease in total RTAs (figure 2). This results in a significant increase in the percentage of fatal road accidents relative to total RTAs. The relative percentage of fatal accidents rose significantly from 0.34% in March 2020 to 0.72% in April 2020 and maintained its high percentage throughout the remaining years. This can be attributed to the increased speed, empty lanes, and reduced law enforcement (Yasin et al., 2021).

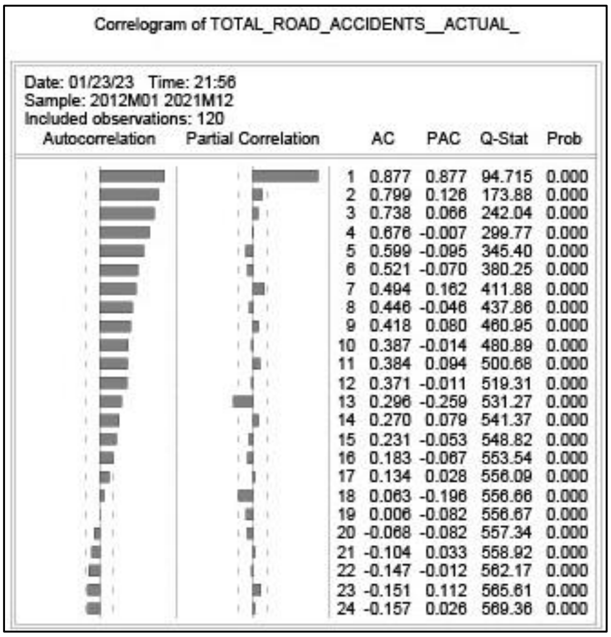
Similar to the graph for fatal injury, the graph for RTAs resulting in nonfatal road accidents (Figure 5) shows an irregular rise and fall movement throughout the series with no particular upward or downward trend. It reached its peak in March 2019 at 1,851 cases and made a sharp decline in April 2020 with 545 cases. However, this decline is not proportional to total RTAs, resulting in April 2020 having the highest relative percentage through the series at 0.36%. This may be because the decline in traffic may increase risky driving behaviors such as over-speeding (Yasin et al., 2021).

3.2. Forecasting using ARIMA Modeling

This section uses Box-Jenkins Methodology of ARIMA modeling as a process of forecasting the RTAs in Metro Manila for the next 5 years (2022-2026). This is divided into 4 stages– identification, estimation, model checking and forecasting.

3.2.1. Identification

Based on the previous graph of total road traffic accidents (Figure 2), the time series exhibits a nonstationary. Also, by examining its correlogram (Figure 6), the data does not have seasonal pattern. Finally, the result of the formal test (Figure 7) revealed that the data has a unit root.



	AC	PAC	Q-Stat	Prob
1	0.877	0.877	94.715	0.000
2	0.799	0.126	173.88	0.000
3	0.738	0.066	242.04	0.000
4	0.676	-0.007	299.77	0.000
5	0.599	-0.095	345.40	0.000
6	0.521	-0.070	380.25	0.000
7	0.494	0.162	411.88	0.000
8	0.446	-0.046	437.86	0.000
9	0.418	0.080	460.95	0.000
10	0.387	-0.014	480.89	0.000
11	0.384	0.094	500.68	0.000
12	0.371	-0.011	519.31	0.000
13	0.296	-0.259	531.27	0.000
14	0.270	0.079	541.37	0.000
15	0.231	-0.053	548.82	0.000
16	0.183	-0.067	553.54	0.000
17	0.134	0.028	556.09	0.000
18	0.063	-0.196	556.66	0.000
19	0.006	-0.082	556.67	0.000
20	-0.068	-0.082	557.34	0.000
21	-0.104	0.033	558.92	0.000
22	-0.147	-0.012	562.17	0.000
23	-0.151	0.112	565.61	0.000
24	-0.157	0.026	569.36	0.000

Figure 6 Correlogram of Overall RTAs at level

Augmented Dickey-Fuller Unit Root Test on TOTAL_ROAD_ACCIDENTS__ACTUAL_

Null Hypothesis: TOTAL_ROAD_ACCIDENTS__ACTUAL_ has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.666182	0.2526
Test critical values:	1% level	-4.036983	
	5% level	-3.448021	
	10% level	-3.149135	

Figure 7 Formal Test of Overall RTAs

With these, the researchers determined that the data is an ARIMA model. Then, the researchers converted the nonstationary time series into stationary one through differencing. Stationary was obtained at first differencing and proved by Augmented Dickey Fuller Test (See Figure 8).

Augmented Dickey-Fuller Unit Root Test on D(TOTAL_ROAD_ACCIDENTS__ACTUAL_)

Null Hypothesis: D(TOTAL_ROAD_ACCIDENTS__ACTUAL_) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.03854	0.0000
Test critical values:	1% level	-4.037668	
	5% level	-3.448348	
	10% level	-3.149326	

Figure 8 Augmented Dickey Fuller Test

The correlogram of the stationary data was used by the researchers in identifying the possible models. Considering the idea of parsimony, the researchers presented only the 3 possible models out of 15 identified models (Table 1).

3.2.2. Estimation

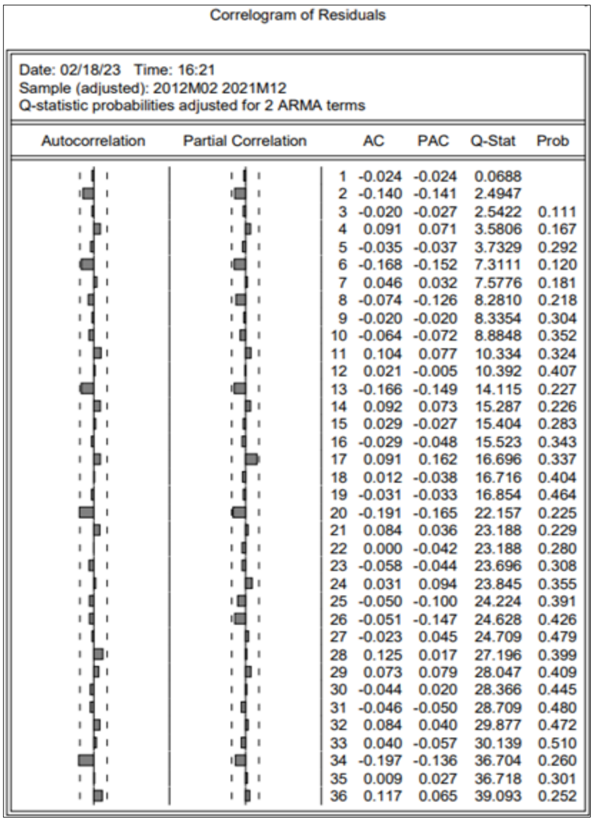
By looking at the significance of the ARMA components and comparing the Akaike Information, Schwarz and Hannan-Quinn model Criterion (see Table 1), ARIMA (1,1,12) was selected to be the potential candidate.

Table 1 Estimation of potential candidate

Criteria	ARIMA (1,1,1) (Model A)	ARIMA (1,1,6) (Model B)	ARIMA (1,1,12) (Model C)	Best Model
AR p-value	0.0137	0.0001	0.0079	B
MA p-value	0.0001	0.3485	0.0649	A
Akaike Information Criterion (AIC)	16.42151	16.41336	16.36961	C
Schwarz Criterion	16.51492	16.50677	16.46303	C
Hannan-Quinn Criterion	16.45944	16.45129	16.40755	C

3.2.3. Model Checking

The researcher tested the potential model for the requirements of a stable univariate process. Using Ljung-Box Q Statistics, the potential model ARIMA (1,1,12) exhibits a p-value greater than 0.05 which indicates that the residuals of the model are white noise (Figure 9). Also, the ARMA structure of the model below (Figure 10) shows the estimated ARMA process is (covariance) stationary and invertible.



Correlogram of Residuals

Date: 02/18/23 Time: 16:21
Sample (adjusted): 2012M02 2021M12
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.024	-0.024	0.0688	
		2	-0.140	-0.141	2.4947	
		3	-0.020	-0.027	2.5422	0.111
		4	0.091	0.071	3.5806	0.167
		5	-0.035	-0.037	3.7329	0.292
		6	-0.168	-0.152	7.3111	0.120
		7	0.046	0.032	7.5776	0.181
		8	-0.074	-0.126	8.2810	0.218
		9	-0.020	-0.020	8.3354	0.304
		10	-0.064	-0.072	8.8848	0.352
		11	0.104	0.077	10.334	0.324
		12	0.021	-0.005	10.392	0.407
		13	-0.166	-0.149	14.115	0.227
		14	0.092	0.073	15.287	0.226
		15	0.029	-0.027	15.404	0.283
		16	-0.029	-0.048	15.523	0.343
		17	0.091	0.162	16.696	0.337
		18	0.012	-0.038	16.716	0.404
		19	-0.031	-0.033	16.854	0.464
		20	-0.191	-0.165	22.157	0.225
		21	0.084	0.036	23.188	0.229
		22	0.000	-0.042	23.188	0.280
		23	-0.058	-0.044	23.696	0.308
		24	0.031	0.094	23.845	0.355
		25	-0.050	-0.100	24.224	0.391
		26	-0.051	-0.147	24.628	0.426
		27	-0.023	0.045	24.709	0.479
		28	0.125	0.017	27.196	0.399
		29	0.073	0.079	28.047	0.409
		30	-0.044	0.020	28.366	0.445
		31	-0.046	-0.050	28.709	0.480
		32	0.084	0.040	29.877	0.472
		33	0.040	-0.057	30.139	0.510
		34	-0.197	-0.136	36.704	0.260
		35	0.009	0.027	36.718	0.301
		36	0.117	0.065	39.093	0.252

Figure 9 Correlogram of Residuals – ARIMA (1,1,12)

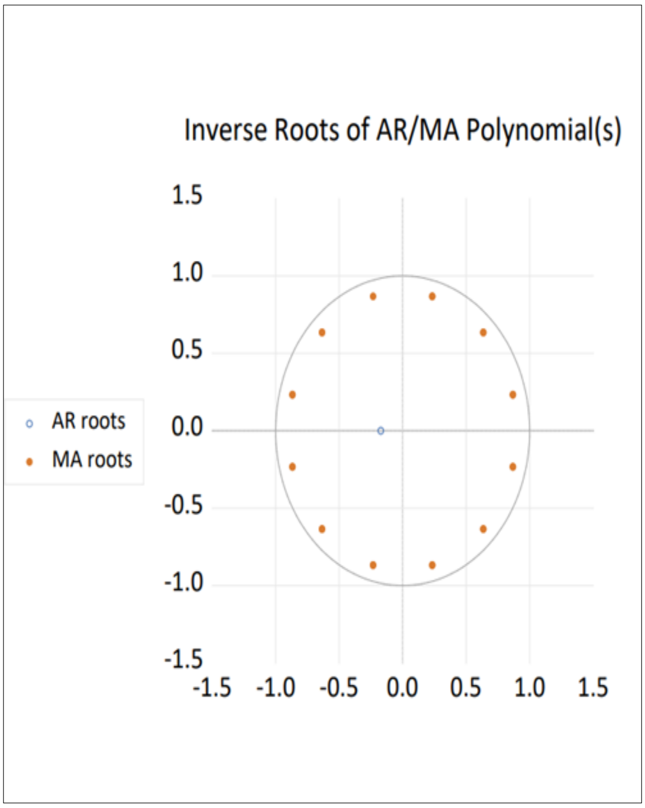


Figure 10 ARMA Structure – ARIMA (1,1,12)

Considering all of these, the potential model ARIMA (1,1,12) satisfies the requirements for a stable univariate process, thus the model can be used to forecast using ARIMA modeling.

3.2.4. Forecasting

Using EVIEWS 12, the researcher created a forecast of RTAs for the next 5 years starting 2022 (Figure 16). The graph shows that the forecast for 2022 stays halfway and gradually decreases for the next 4 years.

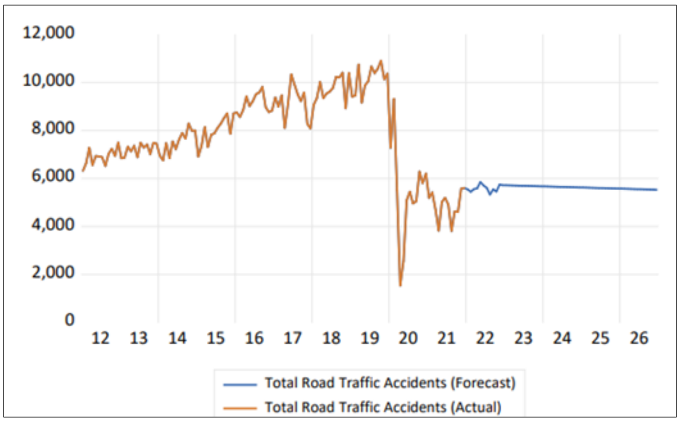


Figure 11 Actual and Forecast of the Overall RTAs in Metro Manila

4. Conclusion

The total RTAs in Metro Manila gradually increased until the first quarter of 2020, then it plummeted and reached its lowest point in April 2020 due to COVID-19 lockdown. As lockdown eases, it bounced back but only halfway. Similarly, RTAs resulting in damage to property also bounced back to only halfway as lockdown eases, while RTAs resulting in fatal and nonfatal injuries bounced back to its normal range as before the lockdown. Despite the decrease in overall RTAs, the relative percentage of fatal and nonfatal drastically increased during the lockdown because of reckless driving behaviors.

Using Box-Jenkins methodology of ARIMA modeling, this study identified ARIMA (1,1,12) as the best model. With this model, the forecast shows that the overall RTAs will stay halfway in 2022 and gradually decrease for the next 4 years.

Compliance with ethical standards

Acknowledgments

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Disclosure of conflict of interest

We, Rofel F. Sabenorio, Marivic Enriquez and Lorenzo Miguel Ramel, the authors, declare that we have no conflict of interest.

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