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Forecasting the influx of crime cases using seasonal autoregressive integrated moving average model





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ABSTRACT

Crime constitutes a profound challenge to the societal fabric of a nation and often finds its roots in factors such as avarice, destitution, and economic adversity. This study endeavors to proactively address the issue of crime through the employment of a crime forecasting model, aimed at uncovering latent correlations and underlying patterns. Specifically, it employs the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to project the future incidence of criminal cases. The research objectives encompass forecasting crime case numbers through time series analysis, appraising the statistical significance of monthly crime occurrences, and assessing the crime dataset utilizing the MATLAB Econometric Modeler. Leveraging historical crime data spanning from January 2018 to December 2021, sourced from nineteen municipalities in Negros Occidental, Philippines, forms the basis for crime case forecasting. An autoregressive test is applied to ascertain the acceptable confidence interval and goodness of fit for crime occurrences. Furthermore, MATLAB Econometric Modeler employs the Ljung-Box test to differentiate between stationary and non-stationary time series and residual crime cases. Notably, the study reveals a significant cyclic pattern in crime cases occurring every 20 months, underscoring the imperative for targeted crime prevention interventions. This study underscores the necessity for consistent and robust law enforcement measures by local government units across the nineteen municipalities in Negros Occidental, focusing on the five identified categories of criminal cases. It is recommended that these measures be implemented diligently to mitigate crime occurrences in the subsequent twenty-first month. Moreover, the study holds potential for extension to regions grappling with elevated crime rates due to inadequate control strategies in place.

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1. Introduction

In the scholarly work of Saleh and Khan (2019), the concept of crime is delineated as an illicit act perpetrated by an individual, constituting a transgression of the legal statutes within a particular geographic jurisdiction. This phenomenon has garnered considerable attention since the 1960s, given its substantial deleterious ramifications upon the societal fabric and economic framework of

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2313-626X/© 2023 The Authors. Published by IASE. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/) nations. Crime has frequently been associated with underlying factors such as avarice, destitution, and economic adversity. One approach that has demonstrated significant promise in the realm of crime analysis is the utilization of data analytics and forecasting techniques. Notably, the seasonal autoregressive integrated moving average (SARIMA) model has emerged as a valuable tool for the prognostication of time series data, affording the capacity to discern trends and seasonality patterns within crime data (Xu et al., 2017).

Many factors contribute to crime rates (Stickle and Felson, 2020). According to the crime index by continent, the countries with the highest crime rates in Africa are South Africa, Angola, and Namibia. In the Americas, Venezuela, Honduras, and Trinidad and Tobago have the highest crime rates. In Europe, Belarus has the highest crime rate, followed by

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France and Ukraine. In Asia, Afghanistan, Syria, and Bangladesh have the highest crime rates. The Philippines ranks 19th in the world (Park and Baek, 2017) and has a moderately high crime rate, including violence and terrorism. In 2020, the country was among the Asia Pacific Region's least developed five countries in terms of order and security index rankings.

The province of Negros Occidental in the Philippines has sixty-six court branches, and they face many crime cases every month. According to the police provincial office, crime rates decreased by 13 percent in 2021 compared to 2020. However, there was an increase in crime during the second quarter of 2021. The provincial office prosecutor faces challenges analyzing digital information on criminal cases and collaborating with municipalities to develop initiatives to reduce crime. During the COVID-19 pandemic, the prosecutor encountered problems analyzing data from nineteen municipalities in Negros Occidental. Thus, this study helps in analyzing historical data from 2018 to 2021, provided by the Negros Occidental Provincial Prosecutor's Office. to extract helpful information related to crime cases and to detect crime trends. In this study, SARIMA has been used to identify trends and patterns in crime rates and forecast future occurrences.

According to Rosenfeld and Weisburd's (2016), discussions, crime forecasting predicts future events based on past and present data. And using big data and algorithms to predict crime rates becoming more important, especially in countries with many court cases (Brkan, 2019).

The general objective of this study is to forecast the influx of crime cases using the SARIMA model of the top five identified crime cases in the nineteen municipalities of Negros Occidental, Philippines. Specifically, it aims to: Forecast criminal cases using time series analysis; test the significant level of crime cases occurrence based on monthly analysis; and evaluate the criminal cases dataset using MATLAB Econometric Modeler. The study covers only the top five identified criminal cases of all municipalities of Negros Occidental: Illegal gambling, murder, rape, robbery, and violence against women and children. The crime forecasting analysis derived from this study created new knowledge that could help reduce crime and ensure citizens' security through local government crime interventions and programs.

2. Methodology

2.1. Study approach and design

The study uses correlational and descriptive research methodologies. The design architecture of how data were prepared, processed, and analyzed is described in Fig. 1.

The crime dataset used in this study is comprised of historical data on criminal cases provided by the Provincial Prosecutor's Office of Negros Occidental, Philippines. These crime case datasets cover the nineteen municipalities of Negros Occidental from the year 2018 to 2021 and are considered as the basis to forecast crimes using the SARIMA model. The data were categorized according to the five crime cases: Drugs, murder, rape, robbery, and violence against women and children in a month and the corresponding year of occurrence. These five crime cases were preprocessed to create visualizations of the frequency of crimes in a month and a year using the time series SARIMA model to come up with the result of forecasting the crime cases.



Fig. 1: Design architecture of data treatment and analysis

Table 1 is the cleaned data from the historical data of crime cases. The periods were labeled as Month and Year as identified in the time data or monthly tread crimes.

Autoregressive was used to determine stationary and non-stationary time series before forecasting, which was essential for discovering cyclical trends in the dataset. The Ljung-box test was used in Eq. 1 to check its suitability for the Autoregressive (AR), Integrated (I), and Moving Average (MA) parts of the model remain as that of ARIMA. In Eq. 1, Q is the test statistic, where n is the sample size, Σ is the summation, and h is the degree of freedom in sample autocorrelation at lag k. *Q* follows a chi-square distribution.

$$Q = \frac{n(n+2)\Sigma\rho_k^2}{(n-k)} \tag{1}$$

The addition of seasonality adds robustness to the SARIMA model, which is presented in Eq. 2. In this study, the time series SARIMA model is used to forecast the crimes with two main components: Trend and seasonality. These components are presented in Eq. 2. ARIMA (p, d, q) is expressed in MATLAB® code, with p which means the number of periods used in the model or the preceding ("lagged") Y values that were considered in a regression model of Y, to make better predictions which captures the" autoregressive" nature of ARIMA; d which represents the number of times that the data had to be differentiated to produce a stationary signal which means the "integrated" nature of ARIMA if d equals zero (0) the data was already stationary; if d equals one (1), then it means that the data was going up or down linearly; and if d equals two (2) means that the data was going up or down exponentially; and q which represents the number of preceding/lagged values for the error term which captures the moving average part of ARIMA.

$$(1-L)y_t = (1+\theta_1 L)(1+\theta_{12}L^{12})$$
(2)

SARIMA is similar to ARIMA but for seasonal dataset (P, D, Q, M) seasonal order, which refers to the order of seasonal components of the time series. D indicates the integration order of the seasonal process (the number of transformations needed to

make stationary the time series) P indicates the Auto Regressive order for the seasonal component, Q indicates the Moving Average (MA) order for the seasonal component M indicates the periodicity, i.e., the number of periods in season, such as 12 for monthly data. In this study, SARIMA is utilized for long-term predictions, the model with the (P, D, Q, M) order is more realistic since it reflects the increasing trend. The Model Equation in Eq. 2 was generated in MATLAB® where seasonality was twelve (12). The property P equals 13, corresponding to the sum of the non-seasonal and seasonal differencing degrees (1+12). The property Q was also equal to 13, corresponding to the sum of the degrees of the non-seasonal and seasonal MA polynomials (1+12). Eq. 2 was the result of Gaussian Distribution based on the Box-Jenkins approach using a multiplicative seasonal model to plot the time series of the crime cases from 2018 to 2021, as shown in Fig. 2.



Fig. 2: Time series model building using ARIMA

3. Results and discussions

Results of the forecast of the influx of crime cases using the SARIMA model of the top five identified crime cases in the nineteen municipalities of Negros Occidental, Philippines are as follows.

Table 2 shows the results of the forecast of crime cases using time series analysis. An autoregressive

test or the SARIMA model was used in determining the impact of stationary and nonstationary time series. The Ljung-box test was applied to test the autocorrelation of time series in 5, 10, and 20 months to the residuals of SARIMA. The test indicates that the first autocorrelations of the residuals of SARIMA using the dataset were nonstationary, which means the data varied over time.

Table 2: Test parameters											
No.	Lags	Lags Degree of freedom Significance let									
1	20	20	0.05								
2	10	10	0.05								
3	5	5	0.05								

As to test the significance level of crime cases occurrence based on a monthly analysis, the results of lags in 5, 10, and 20 months show no significance where the significance level of tested lags was all equal to 0.05. This means that the 5, 10, and 20 lags were all near zero, and the series of residuals exhibited no autocorrelation. It indicates that the crime possibly repeats every 20 months if unmitigated.

As shown in Fig. 3, the seasonal ARIMA was able to forecast monthly, i.e. black, crime cases in Negros Occidental. Two scenarios were generated by a model with a significance level=0.05 which was shown in, i.e. red, and when the cases went up there were chances that it would increase above the significance level. On the contrary, if the significance level was below 0.05, the crime cases decreased. In real situations, those cases were applicable if provided with interventions. The result was consistent with the previous study by Marzan et al. (2017) that the standardized residuals for forecasts were within 95% acceptable confidence interval or goodness-of-fit. The local government units now could be able to foresee that the five cases contribute to these possible issues in the future. Mitigation and contingency were applicable to these scenarios. The study of Marzan et al. (2017) reinforced a proposal for stringent implementation of laws to reduce forecasted values based on the extracted values from Appendix A.



Fig. 3: Forecast of crime cases using the SARIMA model

Tables 3 and 4 offer a comprehensive exposition delineating the monthly incidence of criminal cases across nineteen municipalities within Negros Occidental, Philippines, spanning the temporal spectrum from January 2018 through December 2021. Table 3 delineates the incidence of criminal cases occurring during months 1 to 10, whereas Table 4 expounds upon the incidence of criminal cases during months 11 to 20.

	Table 3: Forecast, increasing, and decreasing trends in 10 months													
Months	1	2	3	4	5	6	7	8	9	10	Mean			
Increasing	45.83	81.25	280.00	50.00	115.38	106.67	106.25	100.00	94.44	89.47	106.93			
Forecast	24	16	5	24	13	15	16	17	18	19	16.70			
Decreasing	-0.63	-0.75	-2.80	-0.88	-0.69	-0.67	-0.75	-0.76	-0.83	-0.84	-0.96			
Mean	23.07	32.17	94.07	24.38	42.56	40.33	40.50	38.75	37.20	35.88	40.89			

Table 4: Forecast, increasing, and decreasing trends in 20 months													
Months	11	12	13	14	15	16	17	18	19	20	Mean		
Increasing	88.89	93.75	107.69	127.27	64.71	48.15	93.33	94.12	114.29	133.33	96.55		
Forecast	18	16	13	11	17	27	15	17	14	12	16.00		
Decreasing	-1.06	-1.19	-1.46	-1.36	-0.53	-1.07	-0.93	-1.00	-1.07	-1.25	-1.09		
Mean	35.28	36.19	39.74	45.64	27.06	24.69	35.80	36.71	42.40	48.03	37.15		

Table's 3 and 4 columns were labeled with the corresponding month number, and the rows were

labeled with three categories: "Increasing," "Forecast," "Decreasing," and "Mean." The "Increasing" row shows the percentage increase of crime cases in each month compared to the previous month. The "Forecast" row shows the projected number of crime cases for each month based on the SARIMA model. The "Decreasing" row shows the percentage decrease of crime cases in each month compared to the previous month. Finally, the "Mean" row shows the average crime cases for each month.

Tables 3 and 4 are important tools for understanding the trends and patterns of crime in the region. It shows that crime cases varied significantly over the course of four years, with some months experiencing sharp increases while others experienced significant declines. For instance, in month 3, there was a significant increase in crime cases, which reached 280.00%. This is a cause for concern and requires immediate attention from law enforcement agencies and policymakers. Similarly, in months 13 and 14, there was a significant increase in crime cases, which reached 107.69% and 127.27%, respectively. These increases suggest that there are underlying factors driving crime rates in the region that need to be addressed.

The "Forecast" row was based on the SARIMA model, which was a statistical model used to forecast time series data. The model takes into account the historical crime case data and uses it to predict future trends. While the forecasts were not perfect and were subject to change, they provide a useful tool for policymakers and law enforcement agencies to anticipate future crime rates and take proactive measures to prevent them. The "Mean" row shows the average crime cases for each month, which provides a more comprehensive view of the overall trends in crime rates. The mean crime cases for the period from January 2018 to December 2021 were 40.89, which was slightly higher than the forecasted mean crime cases of 16.7. This suggests that there was still significant room for improvement in reducing crime rates in the region.

Overall, Tables 3 and 4 provide valuable insight into the monthly crime cases in Negros Occidental and can aid in developing effective crime prevention and intervention strategies in the future. Tables 3 and 4 could be used as a reference for various stakeholders, including law enforcement agencies, policymakers, and researchers.

Policymakers might use the data to identify trends and patterns in crime cases and develop policies and programs that target the specific types of crimes that are prevalent in the region. Law enforcement agencies could use the data to allocate resources and manpower more effectively and to identify the areas that require more attention and intervention. Researchers could use the data to conduct further analysis and identify the underlying causes of crime in the region.

It was worth noting that the SARIMA model used to generate the forecasted data was just one of the many statistical models available for time series analysis. While it was widely used and has been found to be effective in many cases, it was not a perfect model and had its limitations. Therefore, it was necessary to interpret the forecasted data with caution and to consider other factors that might affect the crime rates in the region.

Using the dataset of the crime cases (cs), the data were plotted using MATLAB® from the SARIMA model shown in Fig. 4 based on Appendix A. This finding was consistent with the work of Ying et al. (2017) where monthly data was used, and lag lengths in calculating SARIMA in complex crime data based on Table 3 and Table 4.



Fig. 4: Time series plot of dataset (cs)

Using the SARIMA model on the criminal cases dataset, the residual errors seem fine with near zero mean and uniform variance as shown in Fig. 5. Zhong et al. (2013) supported that the mean value of the residual was near 0 and is considered an acceptable value of SARIMA_cs where sequences for residual

were independent of time based on Appendix A. Correlation was used to analyze the relationship between the data gathered and the forecasted data. The scatter plot shows the relationship between the mean and forecast.



Fig. 5: Plot of the residuals of criminal cases using the seasonal ARIMA model

Fig. 6 shows a scatter plot of the correlation between the forecast and mean crime cases for the period from January 2018 to December 2021 in nineteen municipalities in Negros Occidental, Philippines based on Table 3. The plot shows that there is a strong positive correlation between the forecast and mean crime cases, indicating that the SARIMA model used to generate the forecasted data was reasonably accurate. However, there were a few outliers that deviated significantly from the trend line, suggesting that there may be other factors that influence crime rates in these municipalities. Overall, the plot provides a useful tool for evaluating the accuracy of the SARIMA model and could aid in developing effective crime prevention and intervention strategies in the future.



Fig. 6: Scatterplot of the mean and forecast for 10 months

Fig. 7 scatter plot visually represents the relationship between the mean and forecasted crime cases in Negros Occidental, Philippines, from January 2018 to December 2021 based on Table 4. The data

points on the plot show a strong, positive correlation between the mean and forecasted crime cases. This indicates that the SARIMA model predicted crime cases fairly accurately. However, there were a few outliers that showed a significant deviation from the trend line. These outliers may suggest the presence of other factors that could impact crime rates in these areas, and it may be necessary to consider these factors when developing crime prevention and intervention strategies. Overall, the scatter plot provides valuable insights into the accuracy of the SARIMA model and could aid policymakers, law enforcement agencies, and researchers in mitigating the occurrence of crime in the region.



Fig. 7: Scatterplot of the mean and forecast for 20 months

4. Conclusion

The study analyzes data related to five types of crimes: Illegal gambling, murder, rape, robbery, and violence against women and children. The SARIMA model was applied to four years of time series data, with a 95% confidence interval. The best fits were found using lags of 5, 10, and 20, as no lag was outside the 95% confidence interval of the SARIMA model. The increase or decrease in crime cases occurs every 20 months. The gathered and forecasted data were highly correlated, indicating that the data was reliable and accurate. A few outliers were discovered during the forecasting process using the SARIMA model. Therefore, this study recommends that the local government units of the nineteen municipalities of Negros Occidental consistently and intensively implement laws regarding the five identified types of crimes, to ensure a reduction of crime occurrences during the next twenty-first month. The use of this study could be extended to areas where high crime rates occur due to poor control strategies of various municipalities.

In conclusion, the study provides a valuable resource for understanding monthly crime cases in Negros Occidental and could be used for various purposes. It was a significant contribution to the field of criminology and could aid in the development of evidence-based policies and programs aimed at reducing crime rates in the region.

Appendix A. Top five crime cases

Table A1 reveals the top five crime cases from 2018 to 2021 based on the consolidated data presented in Table A2.

 Table A1: Data gathered in the local government units

 based on the rank of crime

Rank	2018-2021	Porcontago
Nalik	Top five crime cases	Tercentage
1	Illegal gambling	13.33%
2	Murder	3.98%
3	Rape	2.44%
4	Robbery	2.44%
5	Violence against women and children	2.93%

Table A2:	Top 5	crime	cases

	Α	В	С	D	Е	F	G	Н	Ι	J	К	L	М	Ν	0	Р	Q	R	S	Mean
1	1	3			2	5	1	1	2	1	1	2	2		2	1	1			25
2	6	5	1	2	3	2	4	6	3	1		1			1	1			1	37
3	5	5		4		1	6	3	2	1	3	1	2		2	1		5	2	43
4	3	1	3	6	2	2	4	1	1	1				4				1	2	31
5	8	5	1	4	3	4	1	3	1				2	2	1			1	2	38
6	5	7	4	3	2	2	2	4	2	2	7	2	2	2	1	2		1	1	51
7	2	3	2	3	1	4	4	3	1	2	3	3		2	2					35
8	2	2		1		3	1	1					1	4	1	2		1		19
9				1					1	2								2		6
10	8	5	2	2	5	6	2	3	2			2		3	2	2			1	45
11	6	3	3	6	4	2	3	1	4	3	3	2				1	1		1	43
12	6	2	3	7	5	3	2	5	4	1		2	1	2	1			1		45
13	3	1	1	2	1	7	1	2	1	6	4	1		1	2	2		1	4	40
14	5	3	4	3	6	2		3	1	1	2	2	1	2	4	2	2		1	45

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15	8	4	3	2	4	6	2	3	2	1	5	1		1	1	1	1		1	46
16	5	5	1	3	4	8	1	1	1	2	2	2			5	3		1		44
17	4	2	2	3	2	2	7	1	2	2	5	3		1	3	4		2		45
18	9	6		7	3	1	1	2	5	3	5	3	3	4	2	2	2	1	1	60
19	10	11	8	4	8	8	7	9	4	6	7	11	3	5		5	1	2	2	111
20	5	5		2	3	4	5	2	2		5	3		1	1	1		1	1	41
21	4	1	5	8	3	4	2		2	2		1	1		1		1			35
22	3	6	2	3			3	2		1	1	1			2	1		1	2	28
23		7	10	7	3	8	1	7	2	6	1	2			1		3			58
24	12	8	4	8	4	1		3	2	4	5	3		4		2			1	61
25	1	2	2	3			1	1		1		1	1	1	2	7		1		24
26	4		8		6		2		2	4	3			3		1		4		37
27	5	4	4	13	8	7	6	3		4	7	6	13	6	1	3	1		1	92
28	14	7	2	6	2	3	2	3	1	9	3	5	29	3		4	1	2		96
29	12	6	8	5	1	11	2		4	7	1	2	10	4	1	1	1	1	1	78
30	3	1	5	1	3	4	2		4	2	2	6	5	4	8	2	1	2		55
31	3	2	3	4	9		5	2	1	4	1	5	2	1	2	1	4	1	2	52
32	2	4	10	4	5	8	6	2	5	5	2	7	1	5	5	3	4	4	1	83
33	4	8	9	4	3		1	10	8	6	1	2	2	2	2	3	4	1	3	73
34	7	1	6	3	4	3	3	5	7	2	1	4	3	5	6	2	2			64
35	7	9	7	5	7	6	3	4	4	6	3	4	4	5		3	1	1		79
36	5	6	9	2	3	6	8	3	5	4	5	3	4	3	4	4	5	1	3	83
37	10	4	3	3	8	3	5	4	2	5	4	2	6	3	6	_	3	1	2	74
38	6	7	7	4	8	5	4	3	2	4	5	3	1	-	5	5	3	1	_	73
39	7	4	13	8	6	6	19	2	4	7	9		4	2	5	3	1	1	3	104
40	7	8	6	6	6	11	6	4	8	4	2	4	_	3	2	3	1	2	1	84
41	12	8	3	1	5	8	6	3	2	2	4	2	2		3	2	1		1	65
42	4	3	11	5	6	3	8	3	8		4	5	1	3		3	4	1	1	73
43	7	3	7	6	7	3	7	2	7		3	3	3	3	4		1	3		69
44	5	3	5	3	11	4	2	10	3	1	2	1	2	4	5		2	1	1	65
45	10	7	4	7	Я	5	3	7	Я	1	3	3		2	3		2		1	76

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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