

Forecasting leptospirosis incidence in the Philippines using the Box–Jenkins method

***John Mark Alcaria, Anthony Capili**

Mathematics and Statistics Department, University of Southeastern Philippines, Davao City

*Corresponding author: alcaria_johnmark@yahoo.com

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ABSTRACT

This study aims to investigate and find a suitable model for forecasting the leptospirosis incidence in the Philippines. The Box-Jenkins approach was utilized in the development of an appropriate model. The dataset was retrieved from the Epidemiology Bureau of the Department of Health containing the weekly number of leptospirosis cases in the Philippines from 2016 to 2018. This dataset was analyzed using the R software. The original series is nonstationary with indications of nonconstant variance. Box-Cox transformation and ordinary differencing were performed on the series. The transformed series was analyzed and the results show that ARIMA(0,1,0) or the random walk model is the most appropriate model for forecasting leptospirosis incidence. The residuals and forecast errors of the fitted model behave like a white noise process. The fitted model may be used for forecasting the future number of leptospirosis cases in the Philippines.

Keywords: *forecasting, Box-Jenkins method, leptospirosis, random walk, epidemiology, Philippines.*

The University of Mindanao

INTRODUCTION

Leptospirosis is a bacterial disease that affects humans and animals. It is caused by bacteria of the genus *Leptospira*. *Leptospira* is a spiral-shaped Gram-negative spirochete with internal flagella, which enters the host through mucosa and broken skin. Without treatment, leptospirosis can lead to kidney damage, meningitis (inflammation of the membrane around the brain and spinal cord), liver failure, respiratory distress, and even death (Centers for Disease Control and Prevention, 2017).

Leptospirosis are found throughout the world, but prevalence is higher in tropical regions with high rain fall (Haake & Levett 2015). Leptospirosis is a major public health concern, particularly in developing countries with limited economic resources. However, recent reports indicated its emergence as an important health risk in developed and developing countries including European countries, especially among individuals participating in water sport activities (Dupouey et al., 2014; Haake et al., 2002).

Very little is currently known regarding the true incidence of leptospirosis. It is estimated that 0.1 to 1 per 100,000 people living in temperate climates are affected each year, with the number increasing to 10 or more per 100,000 people living in tropical climates. If there is an epidemic,

the incidence can soar to 100 or more per 100,000 people (World Health Organization, 2018). In the Philippines, leptospirosis incidence tend to be frequent in flood-prone areas of urban setting such as Metro Manila. From 1998 to 2001, about 70% of 1200 suspected leptospirosis patients in Philippines were tested positive for the disease. The average age of patients was 32 years old. Around 87% of the cases were males and 70% were outdoor workers. Case fatality rate was found to be 12 to 14% (Villanueva et al., 2007).

In the Philippines, a total of 2,495 leptospirosis cases were reported nationwide in 2017. This is 49.1% higher compared to 1,673 cases in 2016. Most of the cases were from the National Capital Region (NCR), Region VI, Region I, Region III and Region II (Department of Health, 2017). In response to this problem, the Department of Health coordinated with the College of Public Health (CPH) of the University of the Philippines and employed preventions called Leptospirosis Control (LepCon). They have conducted seminars and lectures in every barangays in Quezon City for preventions and disease planning management. In addition, DOH visits various elementary schools and conducts nationwide advocacy activities, lectures, and awareness programs on leptospirosis.

Over the past years, several studies have been conducted on leptospirosis incidence. The Box-Jenkins method is one of the usual techniques used in forecasting leptospirosis incidence. This method is commonly used because of its applicability on seasonal time series. Seasonal Autoregressive Integrated Moving Average (SARIMA) models have been used in different studies (Chadsuthi et al., 2012; Gnanapragasam, 2017; Phrom, 2012) but there are also instances where the Autoregressive Integrated Moving Average (ARIMA) model was utilized (Ap, 2015).

This study aims to investigate and find a suitable ARIMA model for forecasting Leptospirosis incidence in the Philippines. The model shall be developed using the Box-Jenkins approach.

Box-Jenkins Method

The Box-Jenkins approach is a systematic method of time series model development that involves the stages of model identification, parameter estimation, and diagnostic checking. The models that are presented in the succeeding sections were taken from the books of Adhikari and Agrawal (2009) and Montgomery, Jennings and Kulachi (2008).

Autoregressive models are as their name suggests-regressions on themselves. The future value of a variable is assumed to be a linear combination of p past observations and a random error together with a constant term. An autoregressive model of order p , denoted by $AR(p)$, is given by

$$y_t = c + \sum_{i=1}^p \varphi_i y_{t-i} + \epsilon_t \quad (1)$$

where y_t and ϵ_t are respectively the actual value and random error (or random shock) at time period t , φ_i ($i = 1, 2, \dots, p$) are model parameters and c is a constant. The random shock is assumed to be a white noise process.

If the future value of a variable is a linear combination of present and past random shocks, we have what is called a moving average. The moving average model of order q , denoted by MA(q), is given by

$$y_t = \mu + \sum_{j=1}^q \theta_j \epsilon_{t-j} + \epsilon_t \quad (2)$$

where μ is the mean of the series, θ_j ($j = 1, 2, \dots, q$) are the model parameters.

If we assume that the series is partly autoregressive and partly moving average, we obtain a quite general time series model. An autoregressive moving average model of order p and q , denoted by ARMA(p, q) is given by

$$y_t = c + \epsilon_t + \sum_{i=1}^p \varphi_i y_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j} \quad (3)$$

we say that $\{y_t\}$ is a mixed autoregressive moving average process of orders p and q , respectively.

The autoregressive integrated moving average model is capable of representing a non-stationary time series. An autoregressive integrated moving average model of order p , d , and q , denoted by ARIMA(p, d, q) is given by

$$\varphi_p(L)(1-L)^d y_t = \theta_q(L)\epsilon_t \quad (4)$$

where p , d and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively, L is the backward shift operator and the integer d controls the level of differencing. The backshift operator is a notational device that shifts the data back into a specific number of periods. That is, for the backshift notation L then $L^d y_t = y_{t-d}$. In addition, $\varphi_p(L) = 1 - \sum_{i=1}^p \varphi_i y_{t-i}$ and $\theta_q(L) = 1 + \sum_{j=1}^q \theta_j \epsilon_{t-j}$.

When the data is affected by seasonality, a Seasonal ARIMA model SARIMA(p, d, q) \times (P, D, Q) $_S$, where P , D , and Q are the order of the autoregressive, differencing, and moving average for the seasonal component and S is the seasonal length. The mathematical formulation of a SARIMA(p, d, q) \times (P, D, Q) $_S$ model in terms of backshift notation is given by

$$\Phi_P(L^S)\varphi_p(L)(1-L)^d(1-L^S)^D y_t = \Theta_Q(L^S)\theta_q(L)\epsilon_t \quad (5)$$

where $\Phi_P(L^S) = 1 - \sum_{i=1}^P \Phi_i L^{Si}$ and $\Theta_Q(L^S) = 1 + \sum_{j=1}^Q \theta_j L^{Sj}$.

The random walk process, ARIMA (0, 1, 0) is the simplest nonstationary model. The model is given by

$$(1-L)y_t = c + \epsilon_t \quad (6)$$

In a random walk model, the autocorrelation and partial autocorrelation of the first difference of y_t should not be significant. In other words, differencing of the original series eliminates all serial dependence and yields a white noise process.

Table 1 shows the behavior of the autocorrelation and partial autocorrelation (ACF/PACF) functions of an ARMA process (Montgomery, Jennings & Kulahci, 2008).

Table 1. ACF and PACF of ARMA Models

	MA(q)	AR(p)	ARMA (p, q)
ACF	cuts off after lag q	exponential decay and/or damped sinusoid	exponential decay and/or damped sinusoid
PACF	exponential decay and/or damped sinusoid	cuts off after lag p	exponential decay and/or damped sinusoid

The theoretical ACF and PACF of SARIMA Models may be used for identifying seasonal components. The behavior of the ACF and PACF of SARIMA models are shown in Table 2 (Shumway & Stoffer, 2000).

Table 2. ACF and PACF of SARIMA Models

	AR(P) _s	MA(Q) _s	ARMA (P, Q) _s
ACF	Tails off at lag ks , $k=1,2,\dots,$	Cuts off after lag Qs	Tails off at lag ks , $k=1,2,\dots,$
PACF	Cuts off after lag Ps	Tails off at lag ks , $k=1,2,\dots,$	Tails off at lag ks , $k=1,2,\dots,$

METHOD

The data was obtained from the Department of Health (DOH) website, specifically, from the agency's Leptospirosis Surveillance Report. It is composed of weekly number of Leptospirosis cases in the Philippines (1st week of January 2016 – 4th week of December 2018) where 130 data points (1st week of January 2016 – 4th week of June 2018) were used in model building and 26 data points (1st week of July 2018 to 4th week of December 2018) for the forecast evaluation. This dataset contains reported cases only. Considering the possibility of unreported cases, actual leptospirosis incidences may be higher than the reported cases. This study is limited to the analysis of reported cases and unreported cases were not included.

According to Montgomery, Jennings and Kulahci (2008), the Box-Jenkins approach is composed of three stages, namely, model identification, parameter estimation, and diagnostic checking. An additional step on forecasting evaluation is also recommended and the entire procedure is as follows:

1. *Model Identification.* In this stage, a time series plot shall be constructed. The plot will be used as a tool for the preliminary assessment of stationarity. If non-stationarity is suspected (i.e. there is a trend, seasonality and/or nonconstant variance), differencing and other methods of transformation may be applied. A stationarity test may be performed in order to formally check the stationarity of the series. Once the stationarity can be assumed, the sample autocorrelation and partial autocorrelation functions (ACF/PACF) should be obtained. Tentative models shall be identified based on ACF and PACF plots. The model with the least Akaike's Information Criterion value shall be selected.
2. *Model Estimation.* The parameters of the selected model shall be estimated. By default, *R* uses a combination of conditional sum of squares and maximum likelihood in the estimation process.
3. *Diagnostic Checking.* Residual analysis shall be conducted on the fitted model. The Ljung-Box Test will be used to test if the model is a good fit to the series. In the addition, ACF and PACF plots of the residuals shall be generated. The fitted model is inadequate if there is a lack of fit, spikes on the ACF/PACF plots, and/or patterns in the residual plots. In such cases, the researcher should go back to the model identification stage and identify a new model.
4. *Forecast Evaluation.* The estimated model will be used to generate one-step ahead forecasts of the out-sample dataset. This data refers to the observations that were not used for model identification and estimation. Ideally, the forecast errors should behave like a Gaussian white noise process. The ACF and PACF plots of the forecast errors shall be generated. In addition, Shapiro Wilk test will be performed on these errors. If the forecast errors are Gaussian white noise, there should be no spikes in the ACF and PACF plots. Furthermore, the normality test should not yield a significant result.

This study made use of the following packages: *forecast* for model estimation and forecasting; *tseries* for testing of stationarity; *astsa* for generating ACF and PACF plots; *stats* for the Ljung Box Test; and *lmtest* for checking the parameter significance. All the packages are available in the *R* software.

RESULTS

Figure 1 shows the time series plot of the weekly number of Leptospirosis cases in the Philippines. The time series data is composed of 130 weekly observations from 1st week of January 2016 to 4th week of June 2018. Generally, the plot exhibits changing levels with no apparent seasonality. In addition, the series seems to have a non-constant variance. That is, the variability from the 1st week of January 2016 to 4th week of June 2016 and 1st week of January 2017 to 4th week of June 2017 appears to be smaller than the other weekly periods.

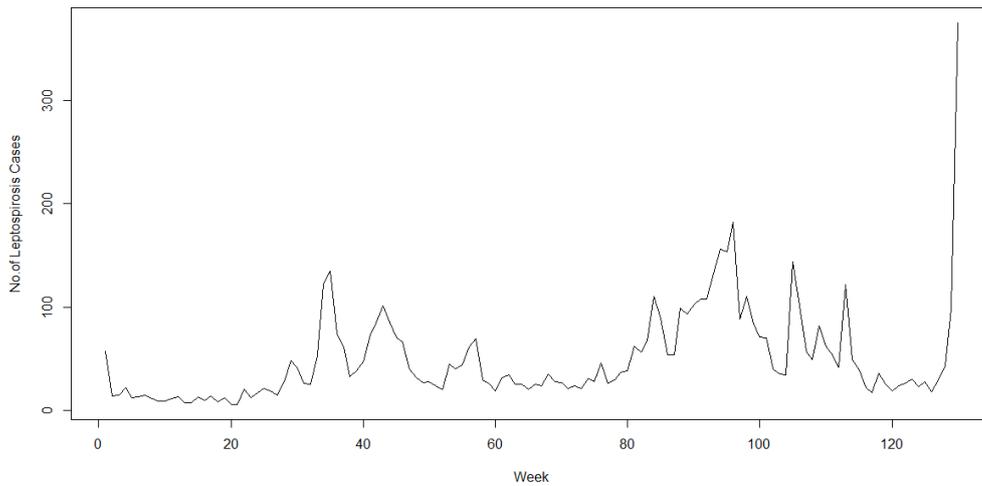


Figure 1. Time Series Plot of Leptospirosis Incidence

In order to correct the problem of variability, the series was subjected to a Box Cox transformation. An optimal lambda of -0.0834 was used in the said transformation. Figure 2 shows the time series plot of the transformed series. The transformed series seems to change levels, an indication of non-stationarity.

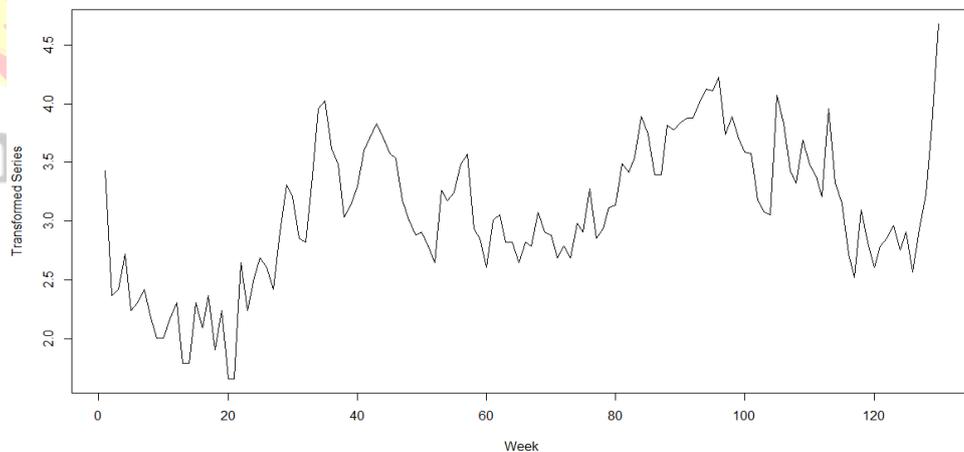


Figure 2. Time Series Plot of the Transformed Series

To formally test the stationarity of the series, the ADF test was used. Table 4 displays the ADF test statistic and its p-value. Since the p-value is larger than the 0.05 level of significance, the null hypothesis of non-stationarity cannot be rejected. The evidence is not enough to conclude that the transformed series is stationary.

Table 3. ADF Test for Stationarity of the Transformed Series

ADF Test Statistic	p-value
-2.4056	0.4079

To make the series stationary, first order differencing was applied to the transformed series and the resulting series is shown in Figure 3. It can be observed that the data points are generally oscillating randomly around a constant mean. This behavior is consistent with the behavior of a stationary series.

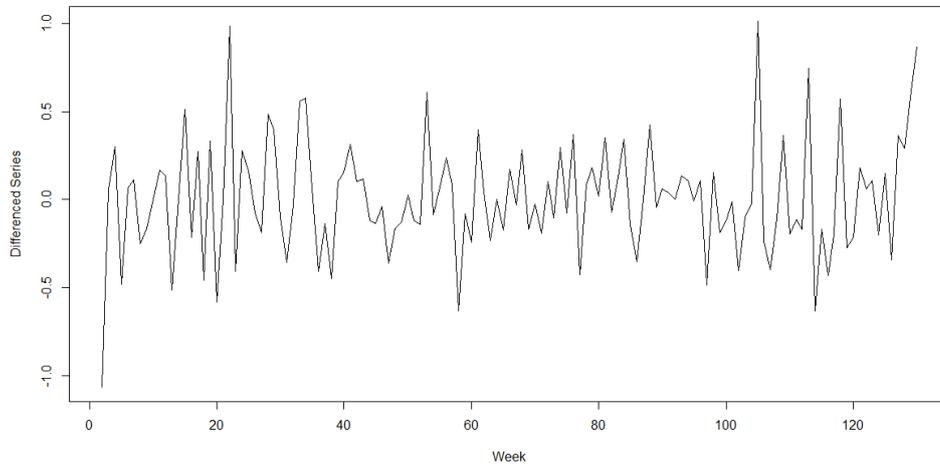


Figure 3. Time Series Plot of the First Difference

To formally test the stationarity of the differenced series, the ADF test was performed. Table 4 displays the ADF test statistic and its p-value. Since the p-value is lower than 0.01, the null hypothesis can be rejected. Hence, the first difference is stationary.

Table 4. ADF Test for Stationarity of the First Difference

ADF Test Statistic	p-value
-4.6964	<0.01

The ACF and PACF plots of the first difference have no significant spikes. This is the behavior of a white noise process. Since the resulting series is possibly white noise after first differencing, the transformed series may be modelled using a random walk process. Thus, ARIMA (0, 1, 0) or the random walk model is chosen for the transformed series.

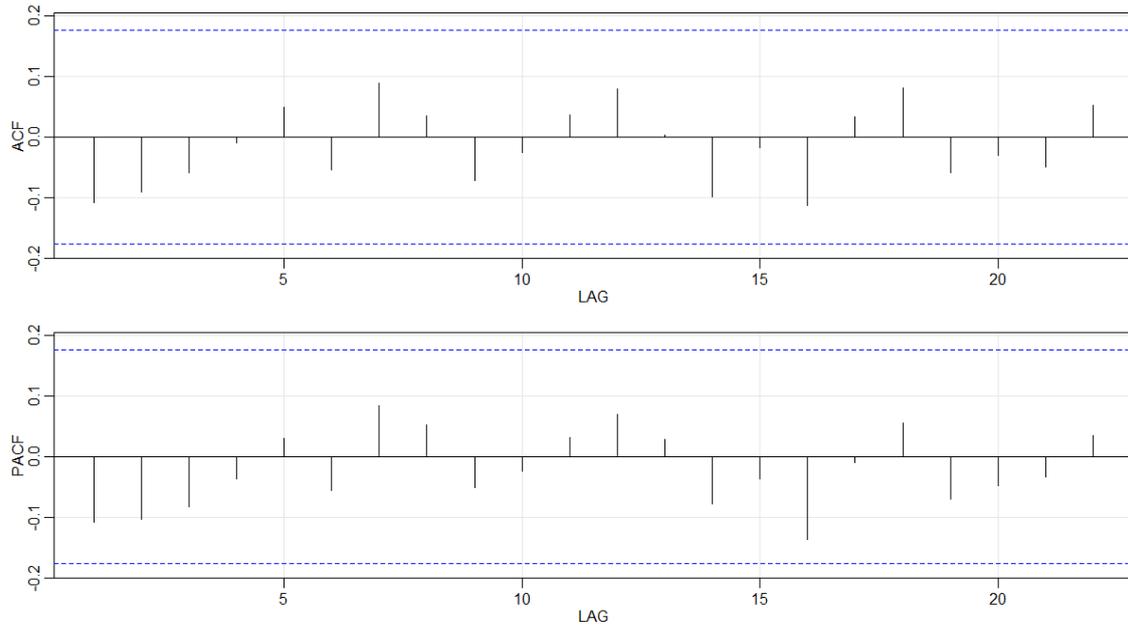


Figure 4. ACF and PACF of the First Difference

The random walk model or ARIMA (0, 1, 0) has no estimated autoregressive and moving average parameters.

To check if there is another model with an AIC value lower than the chosen model, the process of overfitting was performed. Table 5 shows the overfitted models and their corresponding AIC values. There are two models with AIC values that are lower than the chosen model. These models are ARIMA (0, 1, 1) and ARIMA (0, 1, 2).

Table 5. Overfitted Models

Model	AIC
ARIMA (0, 1, 0)	79.38
ARIMA (1, 1, 0)	79.68
ARIMA (2, 1, 0)	79.88
ARIMA (0, 1, 1)	79.07
ARIMA (0, 1, 2)	78.75

Table 6 shows the parameter estimates of ARIMA (0, 1, 2). The estimated MA(1) parameter has a p-value of 0.0607 which is significant at a 0.10 level of significance. However, the estimated MA(2) parameter has a large p-value of 0.1220, therefore this parameter is not significant.

Table 6. Parameter Estimates of ARIMA (0, 1, 2) Model

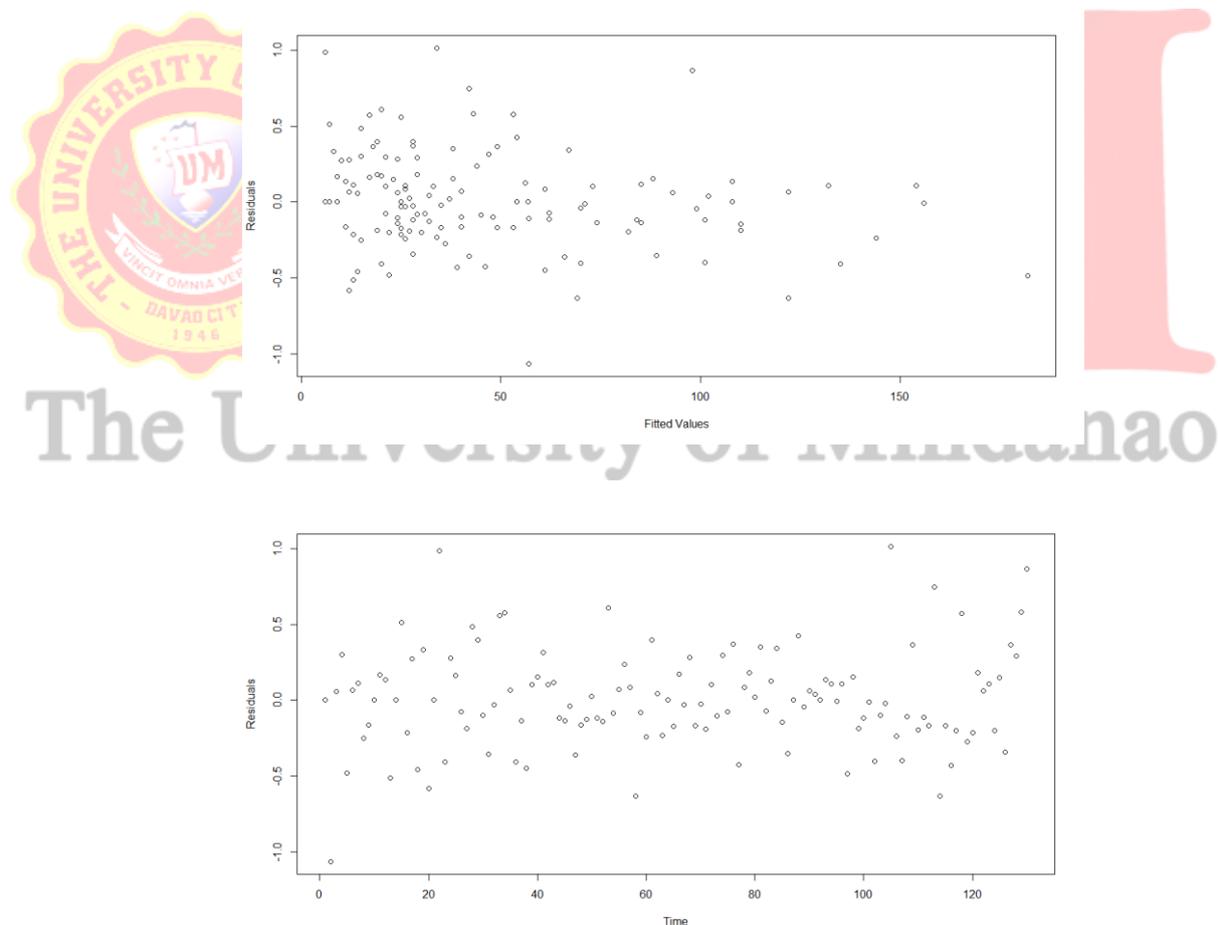
Parameter	Estimate	S.E.	z value	p-value
MA(1)	-0.1794	0.0956	-1.8760	0.0607
MA(2)	-0.1508	0.0975	-1.5464	0.1220

Table 7 shows the parameter estimate of ARIMA (0, 1, 1), its z value and p-value. The estimated parameter is not significant with a large p-value of 0.1331. Both overfitted models have nonsignificant parameters. Thus, the final model is ARIMA (0, 1, 0). The adequacy of the chosen model was examined through a residual analysis.

Table 7. Parameter Estimates of ARIMA (0, 1, 1) Model

Parameter	Estimate	Standard Error	z value	p-value
MA(1)	-0.1707	0.1137	-1.5021	0.1331

Figure 5 shows the residual plots of the chosen model. The plot of the residuals versus fitted values exhibit random behavior. Thus, the residuals seem to have a constant variance. The same random behavior can be observed when the residuals are plotted against time. This is an indication of uncorrelated residuals. Lastly, the normal probability plot of residuals shows severe deviations from normality. That is, some points are far from theoretical line.



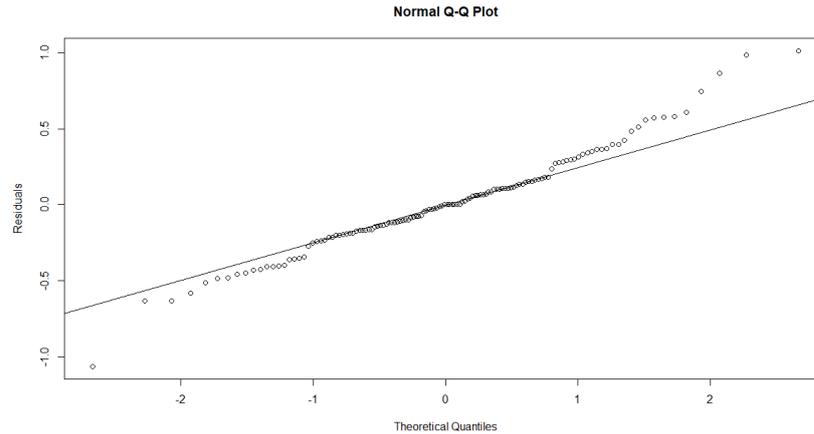


Figure 5. Residual Plots

Figure 6 shows the ACF and PACF plots of the residuals. The autocorrelations and partial autocorrelations are within the maximum and minimum limits as represented by the blue fragmented lines in the plots. Thus, individually, there are no significant autocorrelations and partial autocorrelations among the residuals.

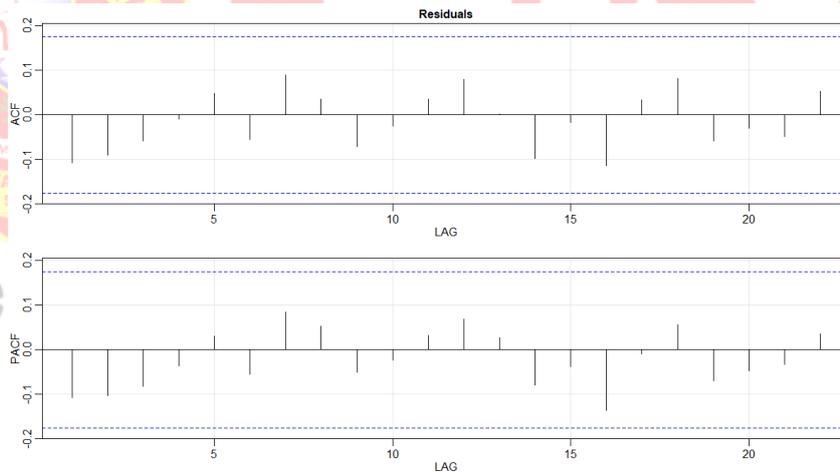


Figure 6. ACF and PACF of the Residuals

To formally test the presence of a serial autocorrelation over several lags, the Ljung-Box Test was performed. Table 8 shows the Ljung-Box test statistic with its degrees of freedom and p-value. Since the p-value of 0.9032 is greater than 0.05, the null hypothesis of no serial autocorrelation cannot be rejected. The statistical evidence does not support the existence of autocorrelated residuals. Given the previous results, it is reasonable to conclude that the residuals were generated by a white noise process.

Table 8. Ljung-Box Test for Residuals

Test Statistic	Degrees of Freedom	p-value
12.3590	20	0.9032

Table 9 contains the actual data from the 1st week of July 2018 to 4th week of December 2018, one-step ahead forecast values, and forecast errors. The model's performance was evaluated using these forecast errors.

Table 9. One-Step Ahead Forecast and Forecast Errors

Week	Date	Actual	Forecast	Forecast Error
Week 27	July 01 - July 07, 2018	180	375	-195
Week 28	July 08 - July 14, 2018	151	180	-29
Week 29	July 15 - July 21, 2018	160	151	9
Week 30	July 22 - July 28, 2018	193	160	33
Week 31	July 29 - Aug. 04, 2018	385	193	192
Week 32	Aug. 05 - Aug. 11, 2018	310	385	-75
Week 33	Aug. 12 - Aug. 18, 2018	180	310	-130
Week 34	Aug. 19 - Aug. 25, 2018	295	180	115
Week 35	Aug. 26 - Sept 01, 2018	326	295	31
Week 36	Sept. 02 - Sept. 08, 2018	178	326	-148
Week 37	Sept. 09 - Sept. 15, 2018	120	178	-58
Week 38	Sept.16 - Sept. 22, 2018	139	120	19
Week 39	Sept. 23 - Sept. 29, 2018	178	139	39
Week 40	Sept. 30 - Oct. 06, 2018	174	178	-4
Week 41	Oct. 07 - Oct. 13, 2018	102	174	-72
Week 42	Oct. 14 - Oct. 20, 2018	127	102	25
Week 43	Oct. 21 - Oct. 27, 2018	67	127	-60
Week 44	Oct. 28 - Nov. 03, 2018	58	67	-9
Week 45	Nov. 04 - Nov. 10, 2018	59	58	1
Week 46	Nov. 11 - Nov. 17, 2018	45	59	-14
Week 47	Nov. 18 - Nov. 24, 2018	42	45	-3
Week 48	Nov. 25 - Dec. 01, 2018	38	42	-4
Week 49	Dec. 02 - Dec. 08, 2018	42	38	4
Week 50	Dec. 09 - Dec. 15, 2018	31	42	-11
Week 51	Dec. 16 - Dec. 22, 2018	23	31	-8
Week 52	Dec. 23 - Dec. 31, 2018	16	23	-7

Figure 7 displays the ACF and PACF plots of the forecast errors. Most of the autocorrelations and partial autocorrelations are not significant. However, in both plots there is a small spike at lag 2. This is still an indication of uncorrelated residuals.

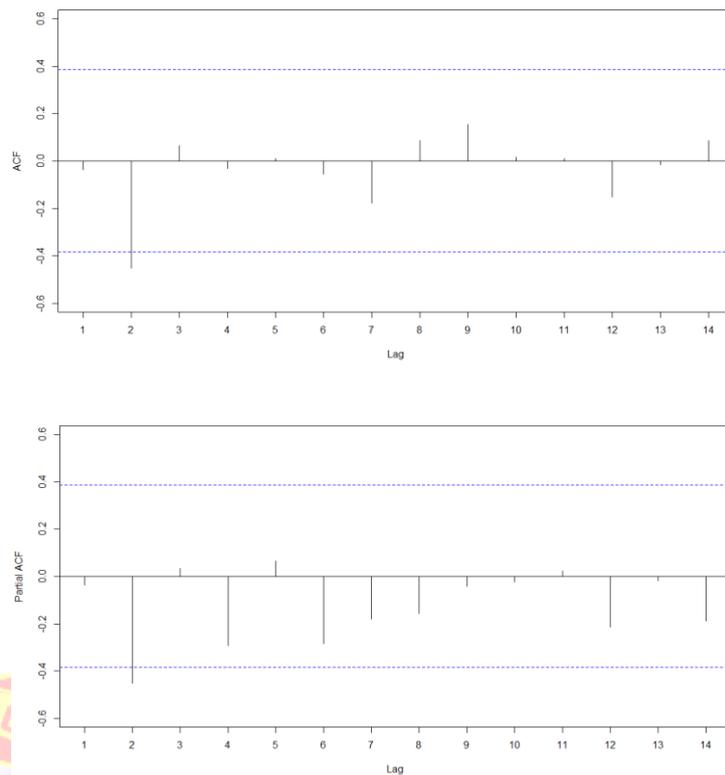


Figure 7. ACF and PACF Plots of the Forecast Errors

Table 10 shows the results of the Shapiro-Wilk test. Since the p-value of 0.0058 is lower than 0.05, the forecast errors are not normally distributed. Finally, given the previous results, the residuals behave like a white noise process.

Table 10. Shapiro-Wilk Test of Normality

Test Statistic	p-value
0.8803	0.0058

Table 11 shows the forecasted values for the 1st week of January 2019 to the 4th week of June 2019. The 95% confidence limits are also shown in the table.

Table 11. Forecasted Values

Week	Date	Forecast	95% Confidence Limit	
			Lower	Upper
Week 1	Jan. 01 - Jan. 05, 2019	16	7.3292	36.8818
Week 2	Jan. 06 - Jan. 12, 2019	16	5.3807	53.0608
Week 3	Jan. 13 - Jan. 19, 2019	16	4.2672	70.6834
Week 4	Jan. 20 - Jan. 26, 2019	16	3.5216	90.5062
Week 5	Jan. 27 - Feb. 02, 2019	16	2.9809	113.0148
Week 6	Feb. 03 - Feb. 09, 2019	16	2.5690	138.6450
Week 7	Feb. 10 - Feb. 16, 2019	16	2.2442	167.8393
Week 8	Feb. 17 - Feb. 23, 2019	16	1.9816	201.0692
Week 9	Feb. 24 - Mar. 02, 2019	16	1.7651	238.8480
Week 10	Mar. 03 - Mar. 09, 2019	16	1.5837	281.7402
Week 11	Mar. 10 - Mar. 16, 2019	16	1.4298	330.3696
Week 12	Mar. 17 - Mar, 23 2019	16	1.2978	385.4275
Week 13	Mar. 24 - Mar. 30, 2019	16	1.1835	447.6807
Week 14	Mar. 31 - Apr. 06, 2019	16	1.0838	517.9810
Week 15	Apr. 07 - Apr. 13, 2019	16	0.9961	597.2746
Week 16	Apr. 14 - Apr. 20, 2019	16	0.9186	686.6128
Week 17	Apr. 21 - Apr. 27, 2019	16	0.8497	787.1640
Week 18	Apr. 28 - May 04, 2019	16	0.7881	900.2267
Week 19	May 05 - May 11, 2019	16	0.7328	1027.2443
Week 20	May 12 - May 18, 2019	16	0.6830	1169.8209
Week 21	May 19 - May 25, 2019	16	0.6379	1329.7394
Week 22	May 26 - Jun. 01, 2019	16	0.5970	1508.9814
Week 23	Jun. 02 - Jun. 08, 2019	16	0.5597	1709.7495
Week 24	Jun. 09 - Jun. 15, 2019	16	0.5257	1934.4918
Week 25	Jun. 16 - Jun. 22, 2019	16	0.4950	2185.9297
Week 26	Jun. 23 - Jun. 29, 2019	16	0.4659	2467.0881

CONCLUSION

The weekly incidence of leptospirosis from the 1st week of January 2016 to the 4th week of June 2018 showed changing levels with no clear seasonality. The series exhibits a non-constant variance. The random walk model or ARIMA (0, 1, 0) is the chosen model for Leptospirosis incidence. The model is given by

$$(1-B)y'_t = \epsilon_t$$

where

y'_t = the series after Box Cox transformation

Overfitting was performed on ARIMA (0, 1, 0). However, the other models with lower AIC values have nonsignificant parameters. Thus, ARIMA (0, 1,0) is the final model.

Based on the ACF and PACF plots, the autocorrelation and partial autocorrelation values of the residuals are within acceptable limits. The plot of residuals versus fitted values and residuals versus time are structureless. In addition, some of the residuals are far from the theoretical line of normality. Finally, the result of the Ljung-Box test does not support the existence of autocorrelated residuals. Thus, the residuals are generated by a white noise process.

The autocorrelation and partial autocorrelation values of the forecast errors are significant at lag 2. Still, most of the ACF and PACF values are not significant. The result of the Shapiro-wilk test is significant. Hence, the forecast errors generally behave like a white noise process.

The forecasted values for the 1st week of January 2019 to the 4th week of June 2019 is 16 cases. This forecast should be updated whenever new data becomes available.

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