Mathematical Journal of Modelling and Forecasting
Vol. 1, No. 2, December 2023, pp. 54-64

Electricity Load Forecasting in East Kalimantan on Religious Holidays Using SARIMA

Chindy Alvionita Sari[1], Primadina Hasanah[2,*], Syalam Ali Wira Dinata[3]

[1]Mathematics Study Program, Institut Teknologi Kalimantan, Balikpapan, Indonesia
[2]Actuarial Science Study Program, Institut Teknologi Kalimantan, Balikpapan, Indonesia
[3]Statistics Study Program, Institut Teknologi Kalimantan, Balikpapan, Indonesia
[*]primadina@lecturer.itk.ac.id

Abstract. The availability of electrical energy is one of the main focuses of energy security in East Kalimantan. Power outages often occur in East Kalimantan both on weekdays and holidays. Some previous research was conducted to estimate the electricity demand during specific years. However, some particular events are interesting to be carried out. For example, electricity demands on holidays such as religious holidays, which are essential moments among Indonesians. This research was conducted to find the best model to predict how many electrical loads in East Kalimantan should be prepared by Indonesia's State Electricity Company (PT PLN) to ensure comfortable communities on religious holidays. Two sample religious holidays have been taken: Eid al-Fitr and Christmas Day. Then, the forecasting was carried out using the SARIMA model on historical hourly data from 2015-2018. The result of this research shows that the best SARIMA model on Eid al-Fitr is SARIMA $(0,2,1)(0,1,0)^{24}$ with 16.99% of MAPE, and the best SARIMA model on Christmas Day is SARIMA $(0,2,1)(0,1,0)^{24}$ with 8.68% of MAPE.

Keywords: Electricity load, forecasting, SARIMA

1 Introduction

Religious holidays are among the essential celebrations among people worldwide [1]. Religious holidays are popular with gathering activities between people, family members, or their society. Moreover, Indonesian people usually do their local tradition called "Mudik" (taking off from their daily activities and going back to their hometown to meet their families) because of the critical meaning of this event. This celebration impacts several aspects, such as the increasing volume of traffic jams, the rising price for several commodities, and the electricity loads behind the holidays.

The electricity load has been one of the leading issues in East Kalimantan for several years. The supply of electrical energy and its sustainability have become the primary focus for reaching energy security in East Kalimantan. An interconnected system supplies the electricity system in East Kalimantan through the 150 kV transmission network of the Mahakam System and several supported systems. In 2017, the electrification ratio in East Kalimantan reached 97% over all regions in this province. However, the power outage relatively occurs in some villages. In addition, power outages during holidays will make people uncomfortable in East Kalimantan, especially during religious holidays.

The characteristics of the peak load on religious holidays usually differ from regular days because most industrial sectors are relatively turned off [2]. However, the particular behavior of electricity demand in this event is interesting to investigate and forecast since most of the research only focused on forecasting the electricity demand on global time [3]. Forecasting electricity loads will inform the stakeholders to provide enough capacity to minimize power outages [4]. In particular, the estimation models to forecast the electricity demand on religious holidays will help the stakeholders predict electricity usage in a certain period [5].

Previous research was conducted to evaluate the electricity behavior, for instance, by Cevik et al. [6] titled Short-Term Load Forecasting for Special Days in Anomalous Load Conditions Using Neural Networks and Fuzzy Inference Method. The results obtained from the research show that the Fuzzy Inference Method can provide sufficient accuracy in forecasting holiday electricity loads. Moreover, Azka et al. [7] predicted the short load behavior for the Mahakam System in East Kalimantan using SARIMA, and the model can give the best accuracy. Since the behavior of electricity data in daily periods usually presents seasonal patterns from 12 AM to 12 PM, to forecast the electricity demand, the model that accommodates seasonal patterns is used to make an estimation.

Considering electricity, this study examines the best model for forecasting electric loads on religious holidays for East Kalimantan's electricity data. The popular forecasting method, SARIMA, will be used to estimate the behavior model of electricity on religious holidays since the model can be used for seasonal patterns and accurately predict short-term time series data. Moreover, the religious holidays that will be analyzed in this study are Eid al-Fitr and Christmas Day. By taking the SARIMA approach, the best SARIMA model will be obtained in this study, and the forecasted electricity load will be simulated at the end of this study.

2 Methodology

2.1 SARIMA Model

According to [8], several time series variables show a periodic solid pattern. This is usually referred to as a seasonal time series or a time series with a seasonal nature. Time series with a seasonal nature mainly occur when more specific variables are taken in monthly and weekly intervals. Time series with seasonal behavior are often called Seasonal ARIMA or SARIMA. Therefore, the SARIMA model is an extension of the basic ARIMA model. The following is the ARIMA Seasonal equation with the notation using the following periods.

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D Z_t = \delta + \Theta_Q(B^s)\theta_q(B)a_t \tag{1}$$

Annotation:

δ = intercept,

Z_t = the value of the response variable at time t,

$(1-B)^d$ = integrated,

$\phi_p(B)$ = Autoregressive parameter of the order-*p*,

$\theta_q(B)$ = Moving Average parameter of the order-*q*,

$(1-B^s)^D$ = seasonal integrated,

$\Phi_P(B^s)$ = $1-\Phi_1 B-\cdots-\Phi_P B^{Ps}$,

$\Theta_Q(B^S)$ = $1-\Theta_1 B-\cdots-\Theta_Q B^{Qs}$,

a_t = error at time *t*,

s = seasonal,

d = regular differencing,

D = seasonal differencing.

Several steps in the forecasting process using Seasonal ARIMA are described below. The goal of this step is to determine the orde of SARIMA.

2.1.1 Differencing Process

Differencing process is carried out to transform non-stationary data into stationary data. Backward shift operators are very appropriate to describe the differencing process. The use of backward shift is as follows:

$$BY_t = Y_{t-1} \tag{2}$$

Annotation:
Y_t : The value of the Y variable at time *t*,
Y_{t-1}: The value of the Y variable at time t-1,

B : Backward shift.

The B notation will shift the data back to a previous time. For example, if a time series data is non-stationary, then the data can be made closer to stationary by doing first-order differencing, namely:

$$Y_t' = Y_t - Y_{t-1} \tag{3}$$

Y_t' is the value of the variable Y at time t after differencing using backward shift, equation (2.3) can be written as follows [9]:

$$Y_t' = (1 - B)Y_t \tag{4}$$

2.1.2 Identifying SARIMA Orde

If the data is stationary, the orde of SARIMA can be identified by looking at which orde of AR and MA made the model stationary. The orde of the model was identified by ACF and PACF plots. There are two types of patterns in ACF and PACF: the cut-off pattern (a pattern that forms a drastic decreasing lag) and a dying down pattern (a pattern that directs the lags slowly toward zero or the pattern forms a sinusoidal). According to [10], the seasonal order of AR or MA will be seen in the PACF and ACF seasonal lags. For example, ARIMA (0.0,0) $(0,0,1)^{12}$, the model will show a spike in lag 12 from the ACF but a non-significant spike in the other lags. Then, the exponential decay will occur in the PACF plot, while the seasonal pattern can be seen in the seasonal period of 12.

2.1.3 Diagnostic Checking

Diagnostic testing is performed to prove the model is adequate. Two critical assumptions exist the white noise and the normally distributed residual. First, the white noise test is used to examine the absence of autocorrelation in the residual series, which means that the residuals have no specific pattern. To examine the white noise process in the model, the L-jung Box test.

Hypothesis:

H_0 : the data does not fill the assumption of white noise,

H_1 : the data fill the white noise assumption.

Testing Criteria :

The significance value (p-value) at L-Jung Box> $\alpha = 0.05$, then reject H_0.

Secondly, to analyze the normality condition in residual series, the Kolmogorov-Smirnov Test was carried out to the model.

H_0 : data does not follow the normal line distribution,

H_1 : the data follows a normal line distribution.

Statistics Test:

$$D = \sup x \,|S(x) - F_0(x)| \tag{5}$$

where:

$F_0(x)$: functions that are thought to be normally distributed,

$S(x)$: cumulative distribution function of the original data.

Testing Criteria:

If $D_{count} > D_{table}$ or if the p-value> $\alpha = 0.05$, then the decision to reject H_0 [11].

2.1.4 Determining the Best Model

The best model is examined by evaluating the AIC (Akaike's Information Criterion) value—the best model selected based on the smallest AIC value [12].

$$AIC = n \ln \hat{\sigma}_{\varepsilon}^{2} + 2\,(p + q + 1) \tag{6}$$

$\hat{\sigma}_{\varepsilon}^{2}$: $\frac{SSE}{n}$,

n : the number of observations,

p : order AR,

q : order MA.

2.2 Model Accuracy

In this study, the accuracy of the model is analyzed using their Mean Absolute Percentage Error (MAPE). MAPE is a calculation between the actual data and the predicted data, which is then summarized and calculated as a percentage. A model is said to have a high level of accuracy if the percentage is below 10% or between 10% -20% [11].

$$MAPE = \frac{\sum_{t=1}^{n} |PE_t|}{n} \tag{7}$$

where,

$$PE_t = \frac{actual_t - predict_t}{actual_t} \times 100\% \tag{8}$$

Where,

PE_t : Percentage Error,

n : count of data.

2.3 Dataset

The electricity data was collected from PT PLN East Kalimantan from 2015 to 2018. The religious holidays used in this study are Eid al-Fitr and Christmas. The electricity consumption for that day will be predicted for the next period, namely the following year. The data in this study is divided into in-sample and out-sample data. In-sample data is used to predict the model, while out-sample data is used to measure the accuracy. The description of each time series data can be seen in Figures 1 and 2, while the descriptive statistics for each load are given in Table 1.

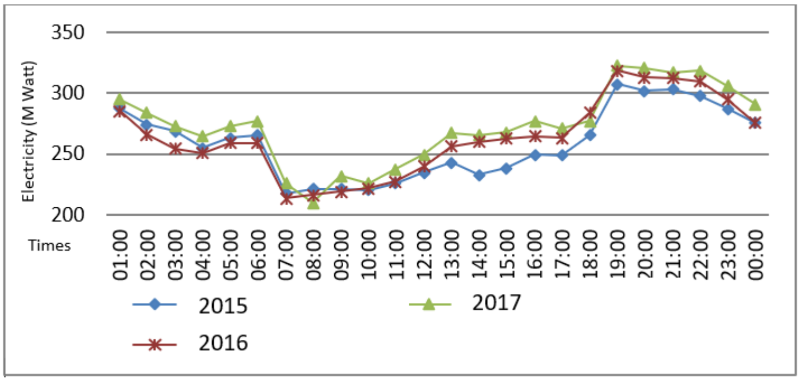

Figure 1. Electricity Loads on Eid Al-Fitr 2015-2017

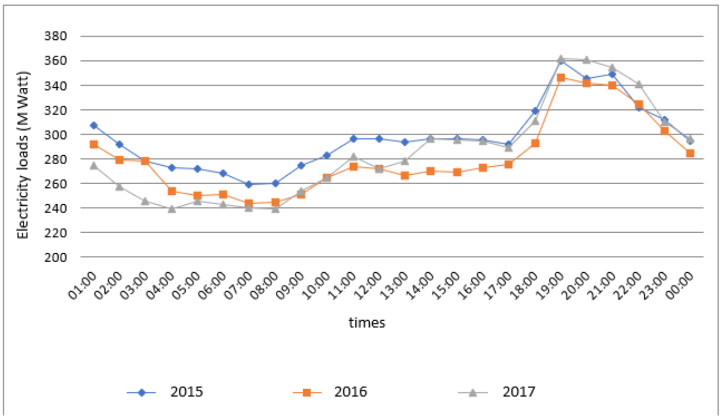

Figure 2. Electricity Loads on Christmas Day 2015-2017

Table 1. Descriptive Statistics of Load data

	Eid al-Fitr	Christmas
Mean	265.087	287.822
Std. Deviation	30.835	32.725
Minimum	209.785	239.310
Maximum	322.778	361.810

From Table 1, it can be inferred that the electricity load on Christmas vacation is slightly higher than on Eid al-Fitr. It can be triggered by the tradition of "mudik" of the residents of East Kalimantan during Eid al-Fitr. Therefore, at this time, many people spend their time outside of East Kalimantan.

3 Results and Discussion

3.1 Model Identification

The first stage is the plotting of data for Eid al-Fitr and Christmas so that it can be identified that the data has seasonal, trend, and cyclic patterns.

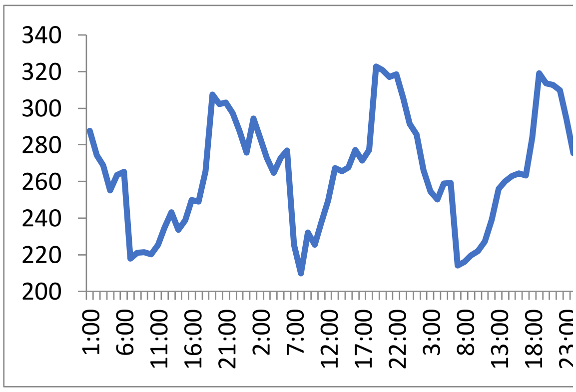

Figure 3. Time Series Plot for Eid al-Fitr

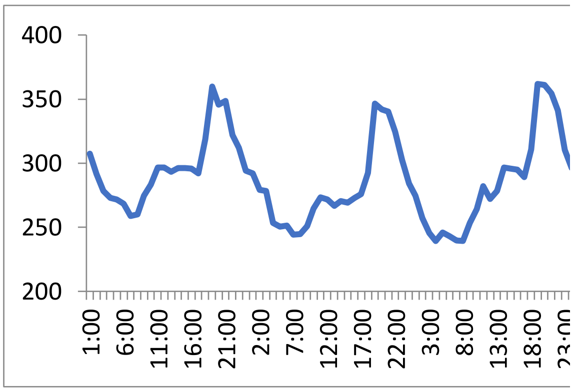

Figure 4. Time Series Plot for Christmas

This figure shows that the data forms a seasonal pattern, where there are repeated up and down trends at a certain point. The data that will be used contain seasonality, so it is necessary to differencing the seasonality. There are 24 seasonal periods in this study because the data used is hourly for each event. The following figure is a time series plot that has been differenced once against its seasonal components along with the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) to determine the seasonal order.

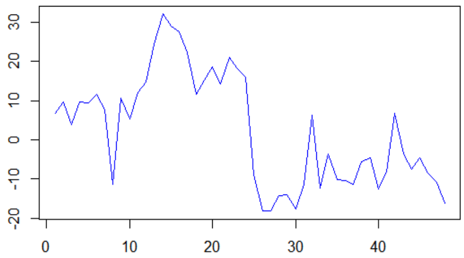

Figure 5. Plot of Time Series Differencing of Eid Al-Fitr against Seasonal Components

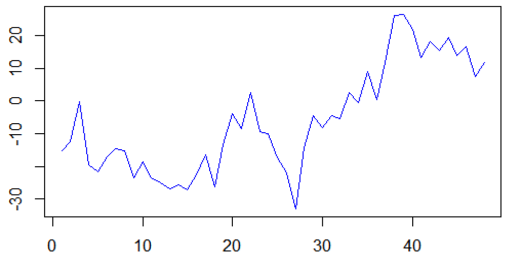

Figure 6. Plot of Time Series Differencing of One-Time Christmas Holidays to Seasonal Components

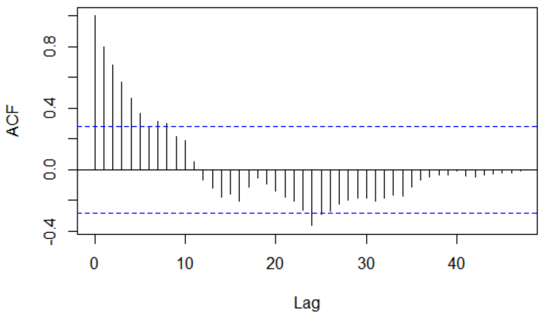

Figure 7. ACF Pattern for Eid Al-Fitr against Seasonal Components

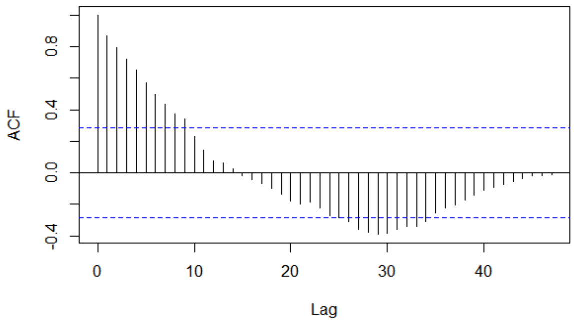

Figure 8. Christmas Day ACF Pattern Against Seasonal Components

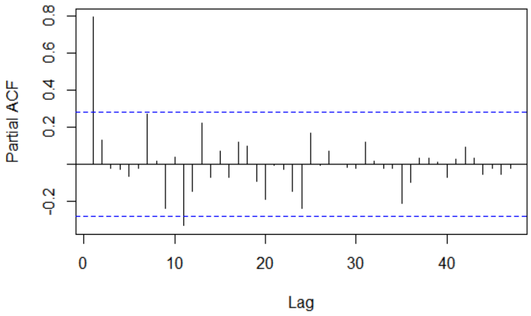

Figure 9. PACF Pattern for Eid Al-Fitr against Seasonal Components

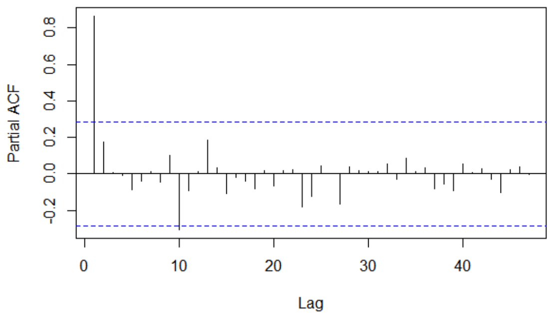

Figure 10. PACF Pattern for Christmas Day Against Seasonal Components

Figures 5 and 6 show the time series plots that are still not stationary because they still form random up-and-down trend patterns. Then, in Figure 7, the ACF pattern shows that lag-24 is insignificant or does not cross the Upper Confidence Limit (UPL) and Lower Confidence Limit (LCL) lines, thus indicating that the SMA model (0). Figure 9 PACF pattern shows that lag-24 is insignificant, indicating the SAR model (0), so the seasonal order on Eid al-Fitr is (0.1,0) 24. The seasonal order on Christmas Day is also seen in the ACF and PACF patterns. In Figure 8, the lag-24 is insignificant; in Figure 10, the lag-24 is also insignificant. Thus, it can be concluded that the seasonal order for Christmas is (0,1,0) 24. After determining the seasonal order, the next step is to determine the regular order, because the data is still not stationary, it is necessary to do two differencing of the non-seasonal components. The next step is to re-evaluate the new series' stationary by plot and its ADF test. The figure of the new differencing stages is given in Figures 11 and 12, while based on the ADF test, the p-value of its test is 0.01; hence, the series is assumed to have already fulfilled a stationary condition.

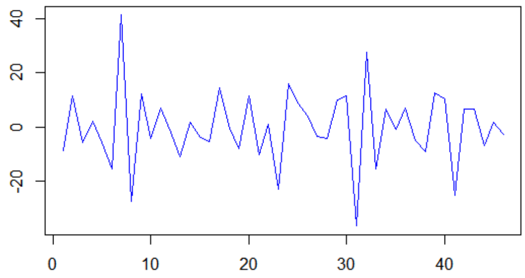

Figure 11. Plot of Time Series Differencing Twice Against Non-Seasonal Components of Eid Al-Fitr

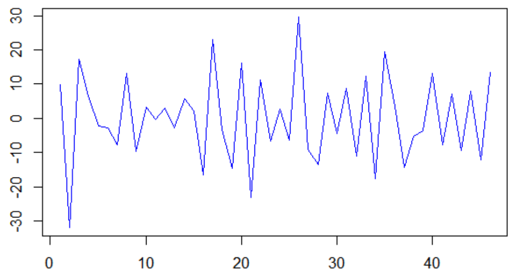

Figure 12. Plot Twice Time Series Differencing of Non-Seasonal Components of Christmas

The next step is to determine the orde of AR and MA through its ACF and PACF plot. The result is given in Figure 13-16.

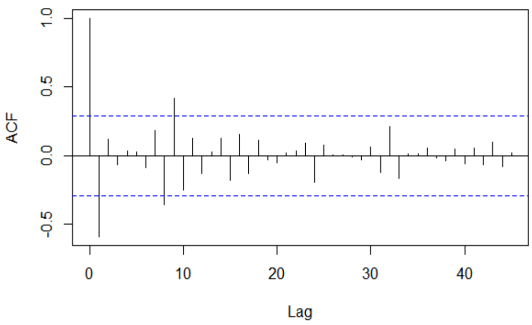

Figure 13. ACF Pattern Against Non-Seasonal Components of Eid Al-Fitr

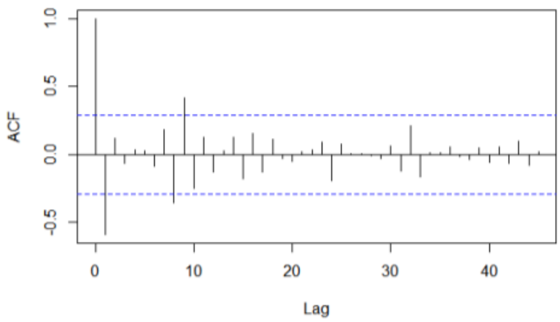

Figure 14. ACF Pattern Against Non-Seasonal Components of Christmas

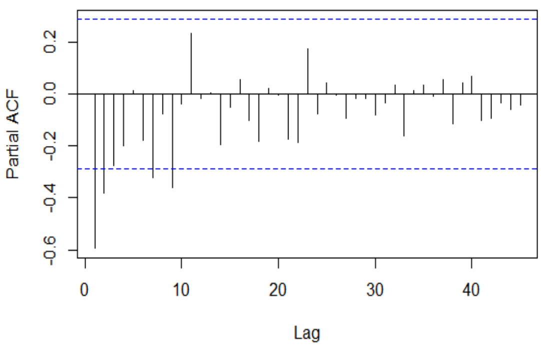

Figure 15. PACF Patterns Against Non-Seasonal Components of Eid Al-Fitr

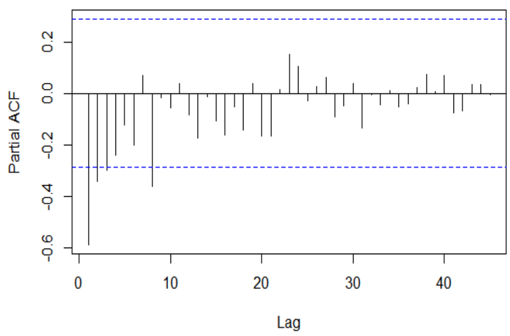

Figure 16. PACF Pattern for Non-Seasonal Components of Christmas

Based on Figures 13 and 14, the ACF pattern has a spike in lag 0 and 1, which means the MA (0) and MA (1) can be used as the alternative model. Furthermore, from Figure 15, the PACF plot spikes in lag-1 and 2, then forms a dying down, and the possible AR model is AR (0), AR (1), and AR (2). A similar pattern is also given in Figure 18, so for the Christmas loads, the possible AR models are AR (0), AR (1), and AR (2). On the seasonal lag, in lag 24, the figure is not significant in both ACF and PACF of those series, therefore, the seasonal component is designed as $(0,1,0)^{24}$.

3.2 Significance Test

Several alternative models to forecast the load data is given in Table 2.

Table 2. Results of the Parameters Significance Test of Eid al-Fitr

Model	Order	*p-value*	*Sig.*
(0,2,1) $(0,1,0)^{24}$	MA(1)	0	Yes
(1,2,0) $(0,1,0)^{24}$	AR(1)	0	Yes
(2,2,0) $(0,1,0)^{24}$	AR(1)	0.000	Yes
	AR(2)	0.008	
(0,2,2) $(0,1,0)^{24}$	MA(1)	0.0000	No
	MA(2)	0.1657	
(1,2,1) $(0,1,0)^{24}$	AR(1)	0.1627	
	MA(1)	0.0000	No
(1,2,2) $(0,1,0)^{24}$	AR(1)	0.8708	
	MA(1)	0.1681	No
	MA(2)	0.9142	No
(2,2,1) $(0,1,0)^{24}$	AR(1)	0.1681	
	AR(2)	0.9235	No
	MA(1)	0.0000	

Table 3. The Results of the Parameters Significance Test for Christmas

Model	Order	*p-value*	*Sig.*
(0,2,1) $(0,1,0)^{24}$	MA(1)	0	Yes
(2,2,0) $(0,1,0)^{24}$	AR(1)	0.0000	Yes
	AR(2)	0.0165	
(1,2,0) $(0,1,0)^{24}$	AR(1)	0	Yes
(1,2,1) $(0,1,0)^{24}$	AR(1)	0.1383	No
	MA(1)	0.0000	
(0,2,2) $(0,1,0)^{24}$	MA(1)	0.0000	No
	MA(2)	0.1222	
(1,2,2) $(0,1,0)^{24}$	AR(1)	0.7727	No
	MA(1)	0.0684	
	MA(2)	0.5490	
(2,2,1) $(0,1,0)^{24}$	AR(1)	0.1269	No
	AR(2)	0.7230	
	MA(1)	0.0000	
(2,2,2) $(0,1,0)^{24}$	AR(1)	0.0000	No
	AR(2)	0.0673	
	MA(1)	0.6527	
	MA(2)	0.0000	

The alternative models are tested for significance analysis, whereas if it is significant, the model can be carried out to the next step. Tables 2 and 3 show the results that there are only three significant models, namely, SARIMA (0,2,1) $(0,1,0)^{24}$, SARIMA (1,2,0) $(0,1,0)^{24}$ and SARIMA (2,2,0) $(0,1,0)^{24}$.

3.3 Diagnostic Checking

Three provisional models will be carried to a diagnostic test to analyze whether the model meets the residual white noise test requirements and the Kolmogorov-Smirnov normality test.

Table 4. White Noise Test for Residual (Eid al-Fitr)

Results of Residual *White Noise*			
Model	Df	*p-value*	*White Noise*
(0,2,1) $(0,1,0)^{24}$	1	0.05521	Yes
(2,2,0) $(0,1,0)^{24}$	1	0.3106	Yes
(1,2,0) $(0,1,0)^{24}$	1	0.04542	No

Tabel 5. White Noise Test for Residual (Christmas)

Results of Residual *White Noise*			
Model	Df	*p-value*	*White Noise*
(0,2,1) $(0,1,0)^{24}$	1	0.05811	Yes
(2,2,0) $(0,1,0)^{24}$	1	0.3762	Yes
(1,2,0) $(0,1,0)^{24}$	1	0.08693	Yes

Table 4 shows that there is one model that is not white noise because the p-value is less than 0.05, namely the SARIMA model (2,2,0) $(0,1,0)^{24}$. This model is not included in the Kolmogorov-Smirnov normality test because it does not meet the residual white noise test requirements. In Table 5, all models have met the residual white noise test requirements, where all p-values> 0.05.

Table 6. Eid Al-Fitr Normality Test

Results of Normality *Kolmogorov-smirnov*			
Model	**D**	***p-value***	***Normality***
(0,2,1) $(0,1,0)^{24}$	0.287	9.8×10^{-6}	Yes
(2,2,0) $(0,1,0)^{24}$	0.264	6.3×10^{-5}	Yes

Table 7. Christmas Normality Test

Results of Normality *Kolmogorov-smirnov*			
Model	**D**	***p-value***	***Normality***
(0,2,1) $(0,1,0)^{24}$	0.272	3.5×10^{-5}	Yes
(2,2,0) $(0,1,0)^{24}$	0.276	2.3×10^{-5}	Yes
(1,2,0) $(0,1,0)^{24}$	0.253	1.5×10^{-4}	Yes

Tables 6 and 7 can be interpreted to mean that all models have met the requirements of the Kolmogorov-Smirnov normality test because $D_{count} > D_{table}$, and D_{table} in this study is worth 0.1603.

3.4 Determining the Best Model

Models that have met the requirements of the parameter significance test and diagnostic tests will be compared with the AIC value; the best model is the one with the smallest AIC value.

Table 8. The Best Model for Eid al-Fitr

Model	**Sig.**	***White Noise***	**Normality**	***AIC***
(0,2,1)$(0,1,0)^{24}$	Yes	Yes	Yes	341.80
(2,2,0)$(0,1,0)^{24}$	Yes	Yes	Yes	354.26

Table 9. The Best Model for Christmas

Model	**Sig.**	***White Noise***	**Normality**	***AIC***
(0,2,1)$(0,1,0)^{24}$	Yes	Yes	Yes	333.01
(2,2,0)$(0,1,0)^{24}$	Yes	Yes	Yes	347.12
(1,2,0)$(0,1,0)^{24}$	Yes	Yes	Yes	350.71

In Table 8, two models meet the requirements for determining the best model. The SARIMA (0,2,1) (0,1,0) 24 model is the best model for Eid al-Fitr because it has the smallest AIC value. In Table 9, three models have met the requirements. The SARIMA model (0,2,1) (0,1,0) 24 is the best model for Christmas because it has the smallest AIC value.

3.5 Forecasting Results

After finding the best model, the next step is to form a forecasting model according to equation (1). Here is the SARIMA (0,2,1) $(0,1,0)^{24}$ for predicting the Eid al-Fitr holidays:

$$Z_t = 2Z_{t-1} - Z_{t-2} + Z_{t-24} - 2Z_{t-25} + Z_{t-26} + 0{,}9980a_{t-1} \quad (9)$$

Furthermore, forecasting is carried out for the following 24 periods or predicting Eid al-Fitr 2018. After forecasting in the following 24 periods, it is necessary to compare the out-sample forecast data with the actual out-sample data to find out how big the error is in the forecast data compared to the actual data. The following is a plot of forecasting the SARIMA (0,2,1) $(0,1,0)^{24}$ model within-sample and out-sample data.

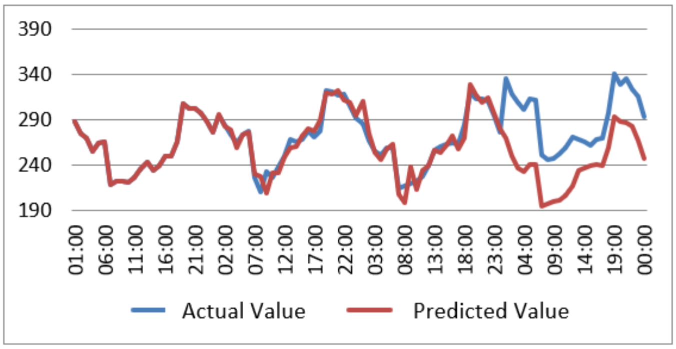

Figure 17. Plot for Comparison of Actual Data and Eid Al-Fitr Forecasts

From Figure 17, it can be seen that the actual out-sample data with the forecast is not too far away, and in the forecast, the out-sample around 17:00 to 21:00 experiences a peak load. The predicted value seems to be lower than the actual value of the out-sample data. However, the forecasting figure can catch up with the pattern of the actual data. Moreover, MAPE calculated this process's accuracy to be 16.99%. The accuracy is higher than 10%. However, based on [9], it is adequate if the model has a range of accuracy between 10-20%.

On the other hand, in the case of Christmas Day prediction, the SARIMA $(0,2,1)(0,1,0)^{24}$ is denoted as

$$.Z_t = 2Z_{t-1} - Z_{t-2} + Z_{t-24} - 2Z_{t-25} + Z_{t-26} + 0{,}9981a_{t-1} \quad (10)$$

Furthermore, forecasting is carried out for the following 24 periods or predicting Christmas 2018. After forecasting for the next 24 periods, it is necessary to compare the out-sample forecast data with the actual out-sample data to find out how big the error is in the forecast data compared to the actual data. The following is a plot of forecasting the SARIMA (0,2,1) $(0,1,0)^{24}$ model within-sample and out-sample data.

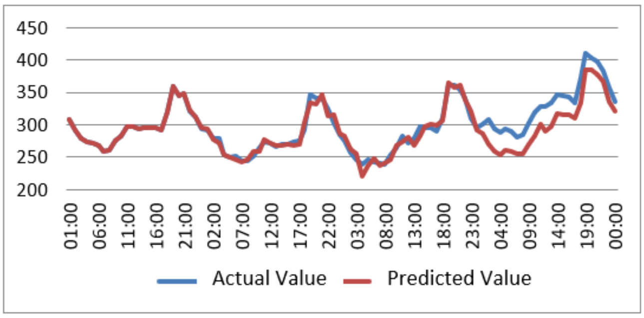

Figure 18. Plot for Comparing the Actual Data and Christmas Forecasts

The accuracy of this SARIMA is calculated by MAPE of 8.68%, which is good enough because the percentage is below 10%. Moreover, the forecasting trend can also follow the actual data pattern, so it can be supposed to be a suitable method for this type of data.

4 Conclusion

The electricity loads during the Religious Holiday in East Kalimantan can be predicted using the SARIMA model. The best model for Eid al-Fitr is SARIMA (0.2.1) $(0.1.0)^{24}$ with MAPE of 16.99%. Meanwhile, the best SARIMA model for Christmas Day is (0.2.1)$(0.1.0)^{24}$ with an accuracy MAPE of 8.68%. By evaluating this result, the model's accuracy is adequate to predict electricity loads in East Kalimantan on Religious Holidays. The prediction data shows that the electricity loads for these holidays can reach 400 megawatts, which will happen at a similar time after 7 PM. By this result, PT PLN East Kalimantan can evaluate the pattern of electricity loads with religious holidays' impacts and provide adequate transmission to supply the electricity demand.

References

[1] Tara P S 2018 Keunikan Perayaan Hari Raya Keagamaan sebagai Aset Budaya Masyrakat Malaysia, *Jurnal Sekolah Tinggi Pariwisata Ambarrukmo Yogyakarta,* p.10.

[2] Bintang M P, Arief W 2018 Aplikasi Metode ARIMA Box-Jenkins untuk meramalkan kasus DBD di Provinsi Jawa Timur, *The Indonesian Journal Public Health,* Vol. 13(2) pp 181-194.

[3] Irmanita A 2016 Peramalan Kebutuhan Energi Listrik Bulanan di Gresik, Jawa Timur Menggunakan Metode Autoregressive Integrated Moving Average Adaptive Neuro Fuzzy, (Surabaya: Repository of Institut Teknologi Sepuluh Nopember)

[4] Syarif, M. B 2014 Peramalan Beban dengan Menggunakan Metode Time Series untuk Kebutuhan Tenaga Listrik di Gardu Induk Sungai Raya, *Jurnal Unviersitas Tanjungpura,* hal 1-3.

[5] Supranto J 1981 *Peramalan Kuantitatif untuk Perencanaan* (Jakarta: Gramedia)

[6] Cevik H H, and Cunkas M 2016 A Fuzzy Logic Based Short Term Load Forecast for The Holoday. Int. Journal of Machine Learning and Computing vol 6 (1) pp. 57-61

[7] Azka M, Wiradinata SA, Faisal M, Suhartono 2020 Double Seasonal ARIMA for Forecasting Electricity Demand of Kuaro Main Gate in East Kalimantan. IOP *Conf* Series vol 846(1 pp.1–6.

[8] Montgomery DC, Jennings CL, Kulahci M, (2008), *Introduction to Time Series Analysis and Forecasting, Wiley Series in Probability and Statistics, A John Wiley & Sons, Inc*., New Jersey.

[9] Supranto, J, (1981), *Peramalan Kuantitatif untuk Perencanaan*, PT. Gramedia Pustaka, Jakarta.

[10] Hynmand, R.J, Athanasopoulos G 2018 *Forecasting: Principles and Practice,* 2nd Edition, OTexts: Melbourne, Australia. OTexts.com/fpp2.Accesed on <28 May 2020>.

[11] Mutmainnah 2019 Perbandingan Metode SARIMA dan Exponential Smoothing Holt-Winters Dalam Meramalkan Curah Hujan di Kota Makassar", *Repository Universitas Islam Negeri Alauddin*

[12] Rosadi D 2010 *Analisis Ekonometrika & Runtun Waktu Terapan dengan R*, LKiS Pelangi Aksara, Yogyakarta.