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Anomalous Electricity Load Events: An Evaluation Based on Mahakam Data

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Abstract: This paper investigates a case study on the short-term forecasting of data from Mahakam with emphasis on special days, such as public holidays. Anomalous load conditions occur on different days, such as public holidays. These conditions are difficult to model because of their infrequent occurrence and significant deviation from standard load. A time series of load demand electricity recorded at hourly intervals contains more than one seasonal pattern. There is a great attraction to using a modeling time series method that is able to capture triple seasonalities. The triple seasonal ARIMA model has been adapted for this purpose and is competitive for modeling load. Herein, we demonstrate the triple seasonal ARIMA is an alternative strategy for providing accurate forecasts of electricity load from Kalimantan for planning, operational maintenance, and market-related activities.

Keywords: electricity, anomalous load, triple seasonal ARIMA, AIC, SBC.

电力负荷异常事件：基于 Mahakam 数据的评估

摘要：本文研究了对 Mahakam 的数据进行短期预测的案例研究，重点是特殊日，例如公共假期。 异常负载情况发生在不同的日期，例如公共假期。 这些条件很难建模，因为它们很少出现并且与标准负载有明显的偏差。 以小时为间隔记录的负载需求电的时间序列包含多个季节性模式。 使用能够捕获三个季节性的建模时间序列方法非常吸引人。 为此，已经修改了三重季节性有马模型，并且在建模负载方面具有竞争力。 在此，我们演示了三重季节性有马是为计划，运营维护和市场相关活动提供准确预测加里曼丹电力负荷的一种替代策略。

关键词：电力，异常负荷，三季度有马，AIC，单板电脑。

1. Introduction

Load forecasting is an important technique for obtaining high-accuracy power estimates. Short-term load forecasting has been a fundamental to the major interests of the electricity industry. In this decade, short-term load forecasting has frequently been applied by researchers. Traditionally, hourly forecasts with a lead time of between one hour and seven days are required for scheduling and controlling power systems [12]. From the perspective of the systems operators and regulatory agencies, they provide a primary source for the safe and reliable operation of the system. For producers, they are a basic tool for determining optimal utilization of generators and power stations, as some facilities are more efficient than others. Accurate short-term forecasts of electricity demand (load) are crucial for making informed decisions regarding unit commitment, energy transfer scheduling, and load frequency control of power systems. An electric utility needs to make these operational decisions daily, often in real-time, to operate in a safe and efficient manner, optimize operational costs, and improve the reliability of distribution networks [11]. Moreover, inaccurate forecasts can have substantial financial implications on energy markets. Electricity demand is often modelled

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in terms of a weather variable. However, univariate methods are frequently considered sufficient for short lead times because weather variables tend to change in a smooth fashion over short time frames and, thus, will be captured in the demand series itself. A variety of univariate methods have been used for short-term load forecasting.

Many different methods and models have been proposed by researchers using a triple seasonal ARIMA time series (Kim et al. [1]; Arora & Taylor [2]; Fidalgo & Lopes [3]) or neural network (Lamedica et al. [4]; Atiya et al. [10]) for load forecasting including anomalous load conditions, such as holidays (Song et al. [5]). Further, they use fuzzy linear regression methods for load forecasting using a variety of approaches, including fuzzy neural computation (Srinivasan et al. [7]; Norizan et al. [8]), state space model (Dordonnat, et al. [6]), and triple seasonal methods for non-anomalous (normal) load forecasting.

In this paper, we extend the triple seasonal methods to include yearly seasonal cycle by a case study using data from Mahakam. However, with an eye on economy and to find a true AR or MA model for higher order selection models, we also consider the polynomial of order triple ARIMA, including all lags, by looking at the sample autocorrelation, partial autocorrelations, and autocorrelation check for white noise. Herein, we present a detailed case study using data from Mahakam-East Kalimantan, which focuses on the short-term forecasting of anomalous loads using a range of different modeling approaches. We treat each special day as having a specific profile in our adaptation of Taylor's system, introduce an additional dummy variable into the model to allow greater flexibility in accommodating special day effects, and model triple seasonality. In addition, a variety of different benchmarks are proposed for testing load forecasts on special days. We test probability density forecasts through regular and special days, in addition to generating point forecasts. To the best of our knowledge, there is no current research on anomalous load density forecasting.

We start with a presentation of the triple seasonal ARIMA model. Then, we discuss the results of this triple seasonal ARIMA model in detail. Finally, we provide our conclusions based on the forecasting evaluation method presented in this study.

2. Methodology

This methodology, developed by G. E. P. Box and G. M. Jenkins [9], approaches a trend and seasonal effects in time series data that is unique from the approach taken by regression or exponential smoothing. The Box–Jenkins methodology begins by determining if the time series under consideration is *stationary*.

This is a distinguishing feature from general seasonal ARIMA models. More broadly, we can write the general ARIMA model as follows:

$$\phi_p(B)\Phi_{P_1}(B^{S_1})\Omega_{P_2}(B^{S_2})\Gamma_{P_3}(B^{S_3})\,\nabla^d\nabla_{S_1}^{D_1}\nabla_{S_2}^{D_2}\nabla_{S_3}^{D_3}\,(Z_t-c) = \theta_q(B)\Theta_{Q_1}(B^{S_1})\Psi_{Q_2}(B^{S_2})\Lambda_{Q_3}(B^{S_3})a_t \tag{1}$$

If d and D are nonnegative integers, then $\{Z_t\}$ is a seasonal

$$\text{ARIMA}(p,d,q)\times(P_1,D_1,Q_1)_{S_1}\times(P_2,D_2,Q_2)_{S_2}\times(P_3,D_3,Q_3)_{S_3}$$

process with period S if the differenced series $\mathrm{Y}_t=\nabla^d\nabla_{S_1}^{D_1}\nabla_{S_2}^{D_2}\nabla_{S_3}^{D_3}\left(Z_t-c\right)$ is a causal ARMA process defined by

$$\phi_p(B)\Phi_{P_1}(B^{S_1})\Omega_{P_2}(B^{S_2})\Gamma_{P_3}(B^{S_3})\mathrm{Y}_t=\theta_q(B)\Theta_{Q_1}(B^{S_1})\Psi_{Q_2}(B^{S_2})\Lambda_{Q_3}(B^{S_3})a_t, \qquad \{a_t\}\sim \mathrm{WN}\left(0,\sigma^2\right)$$

For the current study, due to the presence of a triple seasonal pattern in the short-term Mahakam-East Kalimantan load demand data, which have daily, weekly, and yearly seasonal cycles, we developed a triple seasonal multiplicative ARIMA model. In this section we extend these factors to the general triple seasonal ARIMA for modeling anomalous load data from Mahakam-East Kalimantan. The formulation for this method is presented in the following expressions:

$$\phi_p(B)\Phi_{P_1}(B^{S_1})\Omega_{P_2}(B^{S_2})\Gamma_{P_3}(B^{S_3})\nabla^d\nabla_{S_1}^{D_1}\nabla_{S_2}^{D_2}\nabla_{S_3}^{D_3}$$
$$(\mathrm{I}_{N_t}\xi(B^{S_3})+(1-\mathrm{I}_{N_t})\zeta(B^{S_3}))(Z_t-c)=\theta_q(B)\Theta_{Q_1}(B^{S_1})\Psi_{Q_2}(B^{S_2})\Lambda_{Q_3}(B^{S_3}) \tag{2}$$
$$(\mathrm{I}_{N_t}\lambda(B^{S_3})+(1-\mathrm{I}_{N_t})\kappa(B^{S_3}))((\mathrm{I}_{N_t}a_t^{(N)}+(1-\mathrm{I}_{N_t})a_t^{(S)}))$$

where
Z_t = the load observed at period *t*,
c = constant parameter,
B = the backward shift operator or lag operator,
$\phi_p, \Phi_{P_1}, \Omega_{P_2}$, and Γ_{P_3} = AR polynomial functions of order *p*, P_1, P_2 and P_3,
$\theta_q, \Theta_{Q_1}, \Psi_{Q_2}$, and Λ_{Q_3} = MA polynomial functions of order *q*, Q_1, Q_2 and Q_3,
$a_t^{(N)} \sim NID(0,\sigma_N^2)$ = the model errors for normal,
$a_t^{(S)} \sim NID(0,\sigma_S^2)$ = the model errors for special days, and variances σ_N^2 and σ_S^2, while NID equates to a normally- and independently-distributed process.

The function $\xi(B^{S_3})$ and $\lambda(B^{S_3})$ accommodate the yearly seasonal effect for normal days, the function $\zeta(B^{S_3})$ and $\kappa(B^{S_3})$ accommodate the yearly seasonal effect for special days.

For example, the multiplicative Triple SARIMA model is expressed as $p_1=1, P_1=1, P_2=1, P_3=1$ and differencing is a technique that can also remove seasonal components and trends $d=1, D_1=1, D_2=1, D_3=1, S_1=24, S_2=168, S_3=8760$ $q_1=0, Q_1=0, Q_2=0, Q_3=0$. Hence, the model can be expressed as Model Triple ARIMA (1,1,0) $(1,1,0)^{24}(1,1,0)^{168}(1,1,0)^{8760}$.

$$(1-\phi_1B)(1-\Phi_1B^{24})(1-\Omega_1B^{168})(1-\Gamma_1B^{8760})\,(1-B)(1-B^{24})(1-B^{168})(1-B^{8760})$$
$$(\mathrm{I}_{N_t}\xi(B^{S_3})+(1-\mathrm{I}_{N_t})\zeta(B^{S_3}))(Z_t-c)=(\mathrm{I}_{N_t}\lambda(B^{S_3})+(1-\mathrm{I}_{N_t})\kappa(B^{S_3}))((\mathrm{I}_{N_t}a_t^{(N)}+(1-\mathrm{I}_{N_t})a_t^{(S)})) \tag{3}$$

where

$$\xi(B^{S_3(t)})=1+\tau_1B^{8760}+\tau_2B^{8760+S_3(t-8760)}+\tau_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}$$
$$\zeta(B^{S_3(t)})=1+\omega_1B^{8760}+\omega_2B^{8760+S_3(t-8760)}+\omega_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}$$
$$\lambda(B^{S_3(t)})=1+\mu_1B^{8760}+\mu_2B^{8760+S_3(t-8760)}+\mu_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}$$
$$\kappa(B^{S_3(t)})=1+\upsilon_1B^{8760}+\upsilon_2B^{8760+S_3(t-8760)}+\upsilon_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}$$

For example, the multiplicative Triple SARIMA model is expressed as $p_1=1, P_1=1, P_2=1, P_3=1$ and differencing is a technique that can also remove seasonal components and trends $d=1, D_1=1, D_2=1, D_3=1, S_1=24, S_2=168, S_3=8760$ $q_1=1, Q_1=1, Q_2=1, Q_3=1$. Hence, the model can be expressed as Model Triple ARIMA (1,1,1) $(1,1,1)^{24}(1,1,1)^{168}(1,1,1)^{8760}$. Consider $\phi_1=0.82, \Phi_1=-0.004, \Omega_2=0.87, \Gamma_3=0.33$ and $\theta_1=0.19, \Theta_1=0.80, \Psi_2=0.86, \Lambda_3=0.32$ with variance estimate 219.6865, *AIC* 285319.1, and *SBC* 285378.3, the model can be written as follows:

$$(1-\phi_1B)(1-\Phi_1B^{24})(1-\Omega_1B^{168})(1-\Gamma_1B^{8760})\,(1-B)(1-B^{24})(1-B^{168})(1-B^{8760})$$
$$(\mathrm{I}_{N_t}\xi(B^{S_3})+(1-\mathrm{I}_{N_t})\zeta(B^{S_3}))(Z_t-c)=(1-\theta_1B)(1-\Theta_1B^{24})(1-\Psi_1B^{168})(1-\Lambda_1B^{8760}) \tag{4}$$
$$(\mathrm{I}_{N_t}\lambda(B^{S_3})+(1-\mathrm{I}_{N_t})\kappa(B^{S_3}))((\mathrm{I}_{N_t}a_t^{(N)}+(1-\mathrm{I}_{N_t})a_t^{(S)}))$$

where

$$\xi(B^{S_3(t)})=1+\tau_1B^{8760}+\tau_2B^{8760+S_3(t-8760)}+\tau_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}$$

$$\zeta(B^{S_3(t)}) = 1 + \omega_1 B^{8760} + \omega_2 B^{8760+S_3(t-8760)} + \omega_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}$$
$$\lambda(B^{S_3(t)}) = 1 + \mu_1 B^{8760} + \mu_2 B^{8760+S_3(t-8760)} + \mu_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}$$
$$\kappa(B^{S_3(t)}) = 1 + \upsilon_1 B^{8760} + \upsilon_2 B^{8760+S_3(t-8760)} + \upsilon_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}$$

For special days the rule-based value $S_3(t) = 8760$ allows load findings from three previous unique days to be included, which would be acceptable for improving the model's forecast for a specific special day.

$$\begin{aligned}&(1-0.81B)(1-0.82B^{24})(1-0.87B^{168})(1-0.33B^{8760})\,(1-B)(1-B^{24})(1-B^{168})(1-B^{8760})\\&(\mathrm{I}_{N_t}\xi(B^{S_3}) + (1-\mathrm{I}_{N_t})\zeta(B^{S_3}))(Z_t - c) = (1-0.19B)(1-0.80B^{24})(1-0.86B^{168})(1-0.32B^{8760})\\&(\mathrm{I}_{N_t}\lambda(B^{S_3}) + (1-\mathrm{I}_{N_t})\kappa(B^{S_3}))((\mathrm{I}_{N_t}a_t^{(N)} + (1-\mathrm{I}_{N_t})a_t^{(S)}))\end{aligned} \tag{5}$$

3. Data Set

The data used is the year-hourly load measured in Megawatt (MW) from January 01, 2015 to December 31, 2018. They are gathered from PLN AP2B SISTEM KALTIM-Balikpapan, KM. 15 Karang Joang Nort Balikpapan, Mahakam East Kalimantan electricity utility company, Balikpapan Indonesia. PLN (The State-owned electricity company) is one of the most well-managed power companies in Indonesia. This utility company has powered for decades through the transmission, generation, and distribution of electricity. The data were divided into sets: Initialization set and test set. Fig. 1 plots the initialization set data. It is clear from Figs. 1 and 2 that Mahakam-East Kalimantan load demand data is non-stationary.

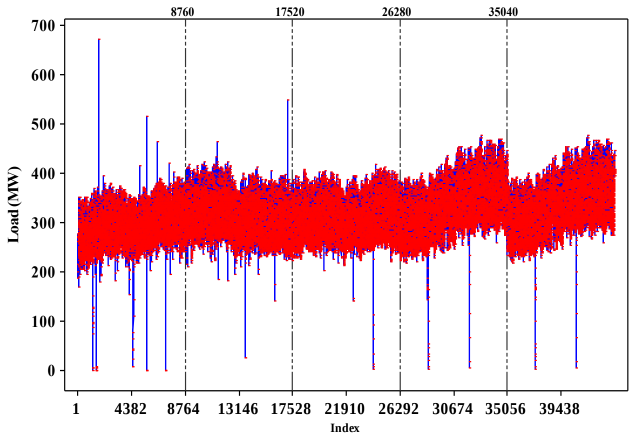


Fig. 1 Hourly load for Mahakam from 1 January 2015 to 31 December 2018

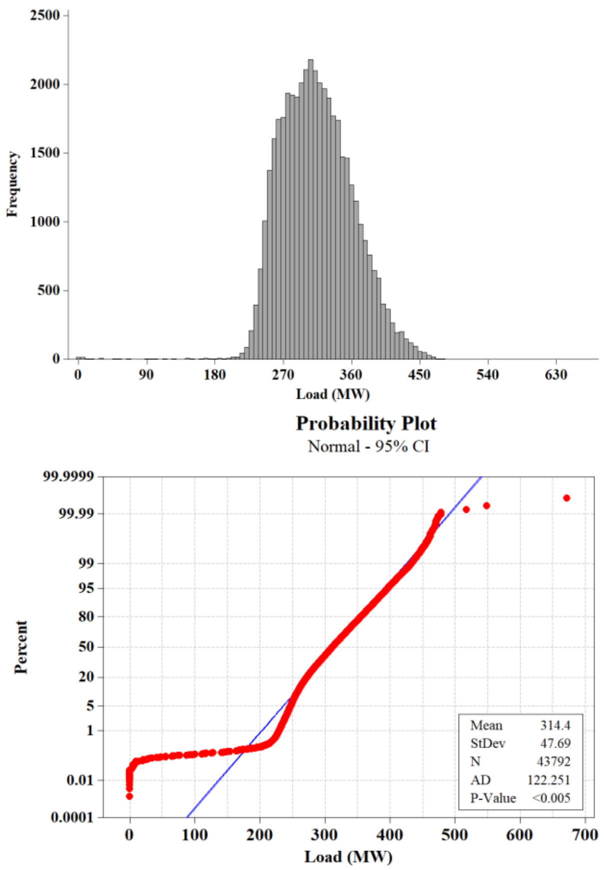


Fig. 2 Plot histogram of load electricity and probability plot

4. Results

Plotting the ACF and PACF of Mahakam-East Kalimantan load data in Fig. 3 shows the seasonal pattern, which is daily seasonality with length 24. Therefore pre-processing data is applied using regular and seasonal differencing to convert non-stationary load series to stationary load series. Plotting the ACF and PACF after non-seasonal differencing and daily seasonal differencing in Fig. 4 indicates another seasonal pattern: weekly seasonality with length and (7 x 24).

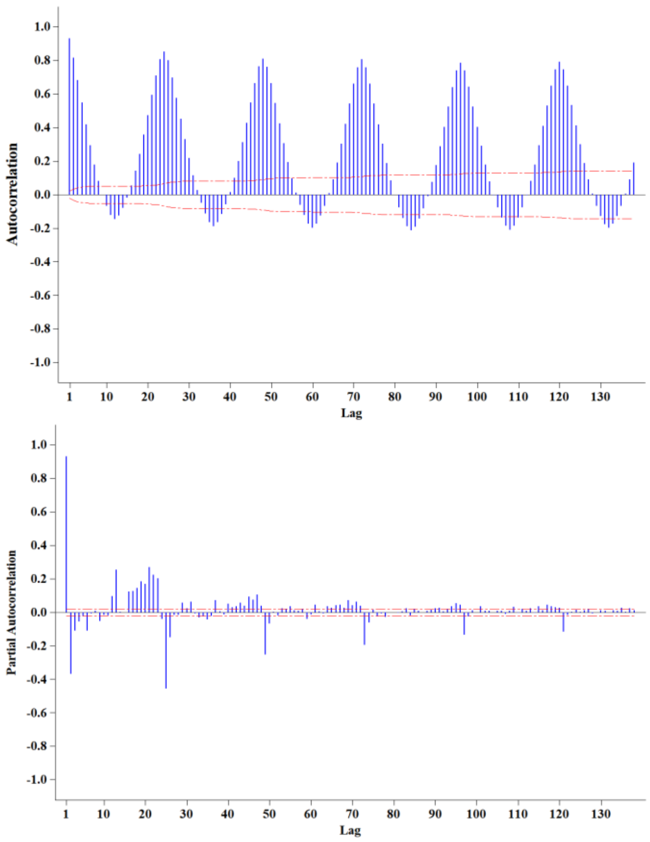
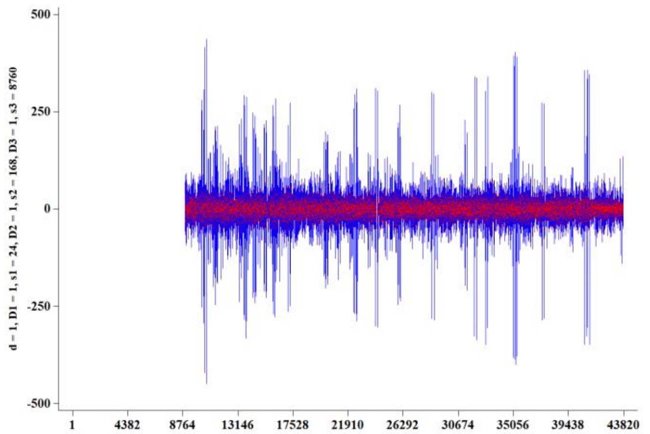


Fig. 3 Plot ACF and PACF load electricity before $Y_t = \nabla^d \nabla_{S_1}^{D_1} \nabla_{S_2}^{D_2} \nabla_{S_3}^{D_3} (Z_t - c)$ and PACF load electricity

Fig. 4 Plotting the load demand series after three times differencing, which are non-seasonal differencing, daily seasonal differencing, weekly, yearly seasonal differencing in Fig. 4 indicates that the load series is stationary. In order words, this identification step shows that the load data have two seasonal periods, which are daily, weekly, and yearly seasonality with length (24), (7 x 24), and (52 x 24), respectively.



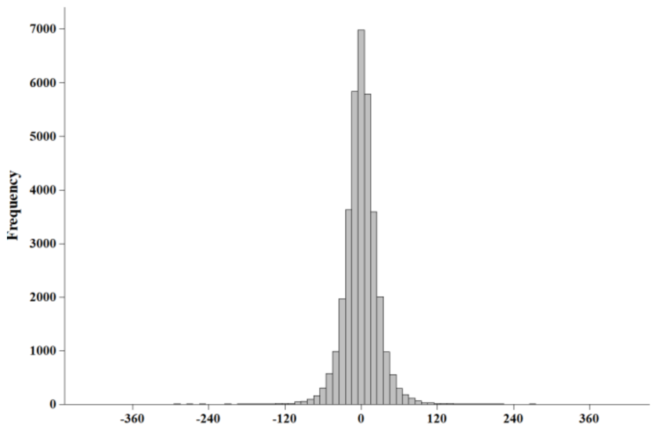


Fig. 4 Plot load electricity with $Y_t = \nabla^d \nabla_{S_1}^{D_1} \nabla_{S_2}^{D_2} \nabla_{S_3}^{D_3} (Z_t - c)$ and histogram load electricity

Fig. 1 shows the Mahakam-East Kalimantan load demand series for the fortnight in the middle of the 52 weeks, a within-day seasonal cycle of duration $s_1 = 24$ periods, and a within-week seasonal cycle of duration s_2 = (14 x 24) periods. The weekdays show similar patterns of demand, whereas Saturday and Sunday have different levels and profiles. A visual inspection reveals that the mean and variance remain stable. Simultaneously, there are some short runs where successive observations tend to follow each other for very brief durations, suggesting that there is indeed some negative autocorrelation as confirmed by the sample ACF plot.

Before the first seasonal data, the ACF plot shows that ACF at lag 1 and lag 12 are significantly different from zero or are greater than the confidence interval of ACF. There are several non-seasonal lags (lag 1, lag 2,..., lag 48), and the ACF tends to be cut off after lag 1, whereas PACF diminishes dies down. On the other hand, ACF and PACF at seasonal lags (lag 12, lag 24, ...) tend to cut off after lag 12, lag 24, lag 168, and lag 8760. Once parameters have been estimated, we check on the model's adequacy for the load data series. The estimate values of these regular, seasonal, and non-seasonal parameters of Model 1 until Model 6 are greater than 2%, with highly significant at alpha less than 0.0001 significance level. The theoretical ACF and PACF of Eq. 2 are presented in Fig. 2.

This model also found that all the parameters are significant at alpha 0.05 significance level with white noise residuals based on Ljung-Box * Q statistic until lags 48. This model also gives 10 extreme residual values. In terms of the residuals' magnitude, these are at 11633th, 11632th, 6305th, 7265th, 3041th, 7456th, 11651th, 2415th, 11681th, and 12659th observations. Similar to the first model, the model residual does not satisfy the Normal Distribution. The AIC and the SBC of this model are 194259.2 and 194435.3, respectively.

The transformed series still possesses seasonality, but the transformation has substantially reduced the skewness in the data. An assumption of Gaussian errors would seem to be considerably more appropriate for the transformed series. For model 1, these parameters' estimate values are less than ±10% except (AR1,1) and (AR1,2). The estimate values of these parameters are less than ±10% except MA(1,2).

4.1. Model 1

The multiplicative Triple SARIMA model is expressed as $p_1 = 1, P_1 = (1,12), P_2 = 2, P_3 = 1$ and differencing is a technique that can also be used to remove seasonal components and trends with $d = 1, D_1 = 1, D_2 = 1, D_3 = 1, S_1 = 24, S_2 = 168, S_3 = 8760$ and $q_1 = 1, Q_1 = (1,168,672), Q_2 = 1, Q_3 = 1$ hence the model can be expressed as Model Triple ARIMA (1,1,1) $([1,12],1,1)^{24}(2,1,1)^{168}(1,1,1)^{8760}$. Consider $\phi_1 = 0.82, \Phi_1 = -0.004, \Omega_2 = 0.87, \Gamma_3 = 0.33$ and $\theta_1 = 0.19, \Theta_1 = 0.80, \Psi_2 = 0.86, \Lambda_3 = 0.32$ with variance estimate 219.6772, *AIC* 285320.7, and *SBC* 285405.2, the model can be written as follows:

$$\begin{aligned}&(1-0.78634B)(1+0.17525B+0.01017B^{12})(1-B)(1-B^{24})(1-B^{168})(1-B^{8760})\\&(\mathrm{I}_{N_t}\xi(B^{S_3})+(1-\mathrm{I}_{N_t})\zeta(B^{S_3}))(Z_t-c)=(1-0.95B)(1+0.005B-0.85B^{168}+0.001B^{672})(1-0.80B^{24})\\&(1-0.02456B^{168})(1-0.32173B^{8760})(\mathrm{I}_{N_t}\lambda(B^{S_3})+(1-\mathrm{I}_{N_t})\kappa(B^{S_3}))((\mathrm{I}_{N_t}a_t^{(N)}+(1-\mathrm{I}_{N_t})a_t^{(S)}))\end{aligned} \tag{6}$$

where

$$\begin{aligned}\xi(B^{S_3(t)})&=1+\tau_1B^{8760}+\tau_2B^{8760+S_3(t-8760)}+\tau_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\\zeta(B^{S_3(t)})&=1+\omega_1B^{8760}+\omega_2B^{8760+S_3(t-8760)}+\omega_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\\lambda(B^{S_3(t)})&=1+\mu_1B^{8760}+\mu_2B^{8760+S_3(t-8760)}+\mu_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\\kappa(B^{S_3(t)})&=1+\upsilon_1B^{8760}+\upsilon_2B^{8760+S_3(t-8760)}+\upsilon_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\end{aligned}$$

4.2. Model 2

The multiplicative Triple SARIMA model is expressed as $p_1 = 1, P_1 = 2, P_2 = 2, P_3 = 1$ and differencing is a technique that can also remove seasonal components and trends $d = 1, D_1 = 1, D_2 = 1, D_3 = 1, S_1 = 24, S_2 = 168, S_3 = 8760$ $q_1 = 1, Q_1 = 1, Q_2 = 1, Q_3 = 1$. Hence, the model can be expressed as Model Triple ARIMA (1,1,1) $(1,1,2)^{24}(1,1,2)^{168}(1,1,1)^{8760}$. Consider $\phi_1 = 0.82, \Phi_1 = -0.004, \Omega_2 = 0.87, \Gamma_3 = 0.33$ and $\theta_1 = 0.19, \Theta_1 = 0.80, \Psi_2 = 0.86, \Lambda_3 = 0.32$ with variance estimate 223.1565, *AIC* 285860.4, and *SBC* 285902.7, the model can be written as follows:

$$\begin{aligned}&(1-0.64863B)\,(1-B)(1-B^{24})(1-B^{168})(1-B^{8760})(\mathrm{I}_{N_t}\xi(B^{S_3})+(1-\mathrm{I}_{N_t})\zeta(B^{S_3}))\\&(Z_t-c)=(1-0.91169B)(1-0.81108B^{24})(1-0.86272B^{168})(1-0.32178B^{8760})\\&(\mathrm{I}_{N_t}\lambda(B^{S_3})+(1-\mathrm{I}_{N_t})\kappa(B^{S_3}))((\mathrm{I}_{N_t}a_t^{(N)}+(1-\mathrm{I}_{N_t})a_t^{(S)}))\end{aligned} \tag{7}$$

where

$$\begin{aligned}\xi(B^{S_3(t)})&=1+\tau_1B^{8760}+\tau_2B^{8760+S_3(t-8760)}+\tau_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\\zeta(B^{S_3(t)})&=1+\omega_1B^{8760}+\omega_2B^{8760+S_3(t-8760)}+\omega_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\\lambda(B^{S_3(t)})&=1+\mu_1B^{8760}+\mu_2B^{8760+S_3(t-8760)}+\mu_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\\kappa(B^{S_3(t)})&=1+\upsilon_1B^{8760}+\upsilon_2B^{8760+S_3(t-8760)}+\upsilon_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\end{aligned}$$

4.3. Model 3

The multiplicative Triple SARIMA model is expressed as $p_1 = 1, P_1 = [1,12], P_2 = 1, P_3 = 1$ and differencing is a technique that can also be used to remove seasonal components and trends with $d = 1, D_1 = 1, D_2 = 1, D_3 = 1, S_1 = 24, S_2 = 168, S_3 = 8760$ and $q_1 = 2, Q_1 = [1,168,672], Q_2 = 1, Q_3 = 1$ hence the model can be expressed as Model Triple ARIMA (1,1,2) $([1,12],1,[1,168,672])^{24}(1,1,1)^{168}(1,1,1)^{8760}$. Consider the number of observations 34863, with $\phi_1 = 0.7863, \Phi_1 = -0.175, \Phi_2 = -0.01017$ and

$$\theta_1 = 0.95, \Theta_1 = -0.0051, \Theta_2 = 0.856, \Theta_3 = -0.0016, \Psi_1 = 0.8075, \Psi_2 = 0.02456, \Lambda_1 = 0.32173$$

with variance estimate 219.6772, the number of residuals 34667, *AIC* 285320.7 and *SBC* 285405.2 the model can be written as follows:

$$\begin{aligned}&(1-0.78634B)(1+0.1752B+0.010B^{12})(1-B)(1-B^{24})(1-B^{168})(1-B^{8760})(\mathrm{I}_{N_t}\xi(B^{S_3})+(1-\mathrm{I}_{N_t})\zeta(B^{S_3}))(Z_t-c)\\&=(1-0.951B)(1+0.0051B-0.856B^{168}+0.0016B^{672})(1-0.81B^{24})(1-0.02456B^{168})(1-0.32173B^{8760})\\&(\mathrm{I}_{N_t}\lambda(B^{S_3})+(1-\mathrm{I}_{N_t})\kappa(B^{S_3}))((\mathrm{I}_{N_t}a_t^{(N)}+(1-\mathrm{I}_{N_t})a_t^{(S)}))\end{aligned} \quad (8)$$

where

$$\begin{aligned}\xi(B^{S_3(t)}) &= 1+\tau_1 B^{8760}+\tau_2 B^{8760+S_3(t-8760)}+\tau_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\ \zeta(B^{S_3(t)}) &= 1+\omega_1 B^{8760}+\omega_2 B^{8760+S_3(t-8760)}+\omega_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\ \lambda(B^{S_3(t)}) &= 1+\mu_1 B^{8760}+\mu_2 B^{8760+S_3(t-8760)}+\mu_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\ \kappa(B^{S_3(t)}) &= 1+\upsilon_1 B^{8760}+\upsilon_2 B^{8760+S_3(t-8760)}+\upsilon_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\end{aligned}$$

4.4. Model 4

The multiplicative Triple SARIMA model is expressed as $p_1 = 3, P_1 = 2, P_2 = 2, P_3 = 1$ and differencing is a technique that can also remove seasonal components and trends $d = 1, D_1 = 1, D_2 = 1, D_3 = 1, S_1 = 24, S_2 = 168, S_3 = 8760$ $q_1 = 3, Q_1 = 2, Q_2 = 1, Q_3 = 1$. Hence, the model can be expressed as Model Triple ARIMA (3,1,3)(1,1,2)^{24}(1,1,2)^{168}(1,1,1)^{8760}. Consider $\phi_1 = 0.82, \Phi_1 = -0.004, \Omega_2 = 0.87, \Gamma_3 = 0.33$ and $\theta_1 = 0.19, \Theta_1 = 0.80, \Psi_2 = 0.86, \Lambda_3 = 0.32$ with variance estimate 2262587, *AIC* 286341, and *SBC* 286400, the model can be written as follows:

$$\begin{aligned}&(1-0.607B)(1+0.32173B^{24})\,(1-B)(1-B^{24})(1-B^{168})(1-B^{8760})(\mathrm{I}_{N_t}\xi(B^{S_3})+(1-\mathrm{I}_{N_t})\zeta(B^{S_3}))(Z_t-c)=\\&(1-0.6886B^3)(1-0.19621B^2)(1-0.86474B^{168})(1-0.31917B^{8760})\\&(\mathrm{I}_{N_t}\lambda(B^{S_3})+(1-\mathrm{I}_{N_t})\kappa(B^{S_3}))((\mathrm{I}_{N_t}a_t^{(N)}+(1-\mathrm{I}_{N_t})a_t^{(S)}))\end{aligned} \quad (9)$$

where

$$\begin{aligned}\xi(B^{S_3(t)}) &= 1+\tau_1 B^{8760}+\tau_2 B^{8760+S_3(t-8760)}+\tau_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\ \zeta(B^{S_3(t)}) &= 1+\omega_1 B^{8760}+\omega_2 B^{8760+S_3(t-8760)}+\omega_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\ \lambda(B^{S_3(t)}) &= 1+\mu_1 B^{8760}+\mu_2 B^{8760+S_3(t-8760)}+\mu_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\ \kappa(B^{S_3(t)}) &= 1+\upsilon_1 B^{8760}+\upsilon_2 B^{8760+S_3(t-8760)}+\upsilon_3 B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\end{aligned}$$

4.5. Model 5

The multiplicative Triple SARIMA model is expressed as $p_1 = 3, P_1 = 2, P_2 = 2, P_3 = 1$ and differencing is a technique that can also remove seasonal components and trends $d = 1, D_1 = 1, D_2 = 1, D_3 = 1, S_1 = 24, S_2 = 168, S_3 = 8760$ $q_1 = 2, Q_1 = 2, Q_2 = 1, Q_3 = 1$. Hence, the model can be expressed as Model Triple ARIMA ([1,2,3,4,5,6],1,[1,2,3,4,5,6])(1,1,1)^{24}(1,1,1)^{168}(1,1,1)^{8760}. Consider $\phi_1 = 1.01, \phi_2 = -0.79, \phi_3 = 0.92, \phi_4 = -1.004, \phi_5 = 0.41, \phi_6 = -0.1,$ and

$$\theta_1 = 0.35, \theta_2 = 0.29, \theta_3 = 0.14, \theta_4 = -0.08, \theta_5 = -0.54, \theta_6 = 0.71, \Theta_1 = 0.80, \Psi_2 = 0.86, \Lambda_3 = 0.32$$

with variance estimate 219.6865, *AIC* 285235.7, and *SBC* 285379.4, the model can be written as follows:

$$
\begin{aligned}
&(1-1.015B+0.797B^2-0.924B^3+1.0048B^4-0.419B^5-0.1011B^6)(1+0.988B)\\
&(1-B)(1-B^{24})(1-B^{168})(1-B^{8760})(\mathrm{I}_{N_t}\xi(B^{S_3})+(1-\mathrm{I}_{N_t})\zeta(B^{S_3}))(Z_t-c)\\
&=(1-0.35B-0.29B^2-0.14B^3+0.08B^4+0.546B^5-0.71B^6)\\
&(1-0.803B^{24})(1-0.86B^{168})(1-0.32067B^{8760})(\mathrm{I}_{N_t}\lambda(B^{S_3})+(1-\mathrm{I}_{N_t})\kappa(B^{S_3}))\\
&((\mathrm{I}_{N_t}a_t^{(N)}+(1-\mathrm{I}_{N_t})a_t^{(S)}))
\end{aligned}
\tag{10}
$$

where

$$
\begin{aligned}
\xi(B^{S_3(t)})&=1+\tau_1B^{8760}+\tau_2B^{8760+S_3(t-8760)}+\tau_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\
\zeta(B^{S_3(t)})&=1+\omega_1B^{8760}+\omega_2B^{8760+S_3(t-8760)}+\omega_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\
\lambda(B^{S_3(t)})&=1+\mu_1B^{8760}+\mu_2B^{8760+S_3(t-8760)}+\mu_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}\\
\kappa(B^{S_3(t)})&=1+\upsilon_1B^{8760}+\upsilon_2B^{8760+S_3(t-8760)}+\upsilon_3B^{8760+S_3(t-8760)+S_3(t-S_3(t-8760))}
\end{aligned}
$$

Forecasting Using Model Triple ARIMA $(1,1,1)^{24}(1,1,1)^{168}(1,1,1)^{8760}$ ([1,2,3,4,5,6],1,[1,2,3,4,5,6]) The fifth model can be expressed as follows:

Model for variable x
Period(s) of Differencing 1,24,168,8760
No mean term in this model.

ARIMA Estimation Optimization Summary

Estimation Method	Conditional Least Squares
Parameters Estimated	17
Termination Criteria	Maximum Relative Change in Estimates
Iteration Stopping Value	0.001
Criteria Value	6.86E-14
Maximum Absolute Value of Gradient	38902.21
R-Square Change from Last Iteration	0.001243
Objective Function	Sum of Squared Residuals
Objective Function Value	7591639
Marquardt's Lambda Coefficient	1E12
Numerical Derivative Perturbation Delta	0.001
Iterations	33
Warning Message	Estimates may not have converged.

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.35065	0.09228	3.80	0.0001	1
MA1,2	0.29056	0.07215	4.03	<.0001	2
MA1,3	0.14270	0.06524	2.19	0.0287	3
MA1,4	-0.08485	0.07688	-1.10	0.2697	4
MA1,5	-0.54600	0.06849	-7.97	<.0001	5
MA1,6	0.71776	0.07237	9.92	<.0001	6
MA2,1	0.01285	0.07024	0.18	0.8549	1
MA3,1	0.80309	0.0034967	229.67	<.0001	24
MA4,1	0.86170	0.0028267	304.85	<.0001	168
MA5,1	0.32067	0.0053343	60.12	<.0001	8760
AR1,1	1.01522	0.10285	9.87	<.0001	1
AR1,2	-0.79760	0.12169	-6.55	<.0001	2
AR1,3	0.92411	0.06676	13.84	<.0001	3
AR1,4	-1.00483	0.11075	-9.07	<.0001	4
AR1,5	0.41921	0.10533	3.98	<.0001	5
AR1,6	0.10115	0.03135	3.23	0.0013	6
AR2,1	-0.98842	0.0012556	-787.23	<.0001	1

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The ARIMA Procedure

Variance Estimate	219.0949
Std Error Estimate	14.80186
AIC	285235.7
SBC	285379.4
Number of Residuals	34667

* AIC and SBC do not include log determinant.

Correlations of Parameter Estimates

Parameter	MA1,1	MA1,2	MA1,3	MA1,4	MA1,5	MA1,6
MA1,1	1.000	0.463	-0.571	-0.920	-0.726	0.567
MA1,2	0.463	1.000	0.335	-0.479	-0.821	-0.383
MA1,3	-0.571	0.335	1.000	0.547	-0.146	-0.871
MA1,4	-0.920	-0.479	0.547	1.000	0.654	-0.625
MA1,5	-0.726	-0.821	-0.146	0.654	1.000	0.029
MA1,6	0.567	-0.383	-0.871	-0.625	0.029	1.000
MA2,1	-0.221	-0.650	-0.277	0.224	0.496	0.354
MA3,1	0.177	0.183	-0.004	-0.153	-0.217	-0.007
MA4,1	-0.013	-0.018	0.019	0.019	-0.001	-0.007
MA5,1	-0.004	-0.004	-0.001	0.006	0.006	-0.003
AR1,1	0.746	-0.030	-0.702	-0.672	-0.313	0.751
AR1,2	-0.099	0.736	0.645	0.048	-0.408	-0.716
AR1,3	0.119	-0.394	-0.193	-0.033	0.006	0.410
AR1,4	-0.590	0.236	0.682	0.596	0.152	-0.850
AR1,5	0.041	-0.697	-0.600	-0.064	0.444	0.695
AR1,6	0.277	0.477	0.059	-0.323	-0.383	-0.097
AR2,1	0.037	0.090	0.059	-0.042	-0.064	-0.059

Correlations of Parameter Estimates

Parameter	MA2,1	MA3,1	MA4,1	MA5,1	AR1,1	AR1,2
MA1,1	-0.221	0.177	-0.013	-0.004	0.746	-0.099
MA1,2	-0.650	0.183	-0.018	-0.004	-0.030	0.736
MA1,3	-0.277	-0.004	0.019	-0.001	-0.702	0.645
MA1,4	0.224	-0.153	0.019	0.006	-0.672	0.048
MA1,5	0.496	-0.217	-0.001	0.006	-0.313	-0.408
MA1,6	0.354	-0.007	-0.007	-0.003	0.751	-0.716
MA2,1	1.000	-0.098	-0.001	-0.006	0.482	-0.867
MA3,1	-0.098	1.000	-0.231	-0.024	0.094	0.073
MA4,1	-0.001	-0.231	1.000	-0.041	-0.013	-0.002
MA5,1	-0.006	-0.024	-0.041	1.000	-0.007	0.003
AR1,1	0.482	0.094	-0.013	-0.007	1.000	-0.683
AR1,2	-0.867	0.073	-0.002	0.003	-0.683	1.000
AR1,3	0.834	-0.003	0.011	-0.008	0.678	-0.795
AR1,4	-0.606	-0.045	0.007	0.008	-0.945	0.799
AR1,5	0.912	-0.086	-0.005	-0.005	0.662	-0.976

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The ARIMA Procedure

Correlations of Parameter Estimates

Parameter	MA2,1	MA3,1	MA4,1	MA5,1	AR1,1	AR1,2
AR1,6	-0.938	0.058	0.004	0.007	-0.395	0.712
AR2,1	-0.145	-0.100	0.092	0.005	-0.079	0.140

Correlations of Parameter Estimates

Parameter	AR1,3	AR1,4	AR1,5	AR1,6	AR2,1
MA1,1	0.119	-0.590	0.041	0.277	0.037

MA1,2	-0.394	0.236	-0.697	0.477	0.090
MA1,3	-0.193	0.682	-0.600	0.059	0.059
MA1,4	-0.033	0.596	-0.064	-0.323	-0.042
MA1,5	0.006	0.152	0.444	-0.383	-0.064
MA1,6	0.410	-0.850	0.695	-0.097	-0.059
MA2,1	0.834	-0.606	0.912	-0.938	-0.145
MA3,1	-0.003	-0.045	-0.086	0.058	-0.100
MA4,1	0.011	0.007	-0.005	0.004	0.092
MA5,1	-0.008	0.008	-0.005	0.007	0.005
AR1,1	0.678	-0.945	0.662	-0.395	-0.079
AR1,2	-0.795	0.799	-0.976	0.712	0.140
AR1,3	1.000	-0.764	0.787	-0.824	-0.133
AR1,4	-0.764	1.000	-0.802	0.466	0.098
AR1,5	0.787	-0.802	1.000	-0.758	-0.144
AR1,6	-0.824	0.466	-0.758	1.000	0.163
AR2,1	-0.133	0.098	-0.144	0.163	1.000

Autoregressive Factors

Factor 1: 1 - 1.01522 B**(1) + 0.7976 B**(2) - 0.92411 B**(3)
+ 1.00483 B**(4) - 0.41921 B**(5) - 0.10115 B**(6)
Factor 2: 1 + 0.98842 B**(1)
Moving Average Factors

Factor 1: 1 - 0.35065 B**(1) - 0.29056 B**(2) - 0.1427 B**(3)
+ 0.08485 B**(4) + 0.546 B**(5) - 0.71776 B**(6)
Factor 2: 1 - 0.01285 B**(1)
Factor 3: 1 - 0.80309 B**(24)
Factor 4: 1 - 0.8617 B**(168)
Factor 5: 1 - 0.32067 B**(8760)

Fig. 5 An output SAS Model 5 for Model Triple ARIMA ([1,2,3,4,5,6],1,[1,2,3,4,5,6]) $(1,1,1)^{24}(1,1,1)^{168}(1,1,1)^{8760}$

We have seen that a simple and widely applicable stochastic model for non-stationary time series' analysis, containing seasonal component is triple seasonal multiplicative Model 5.

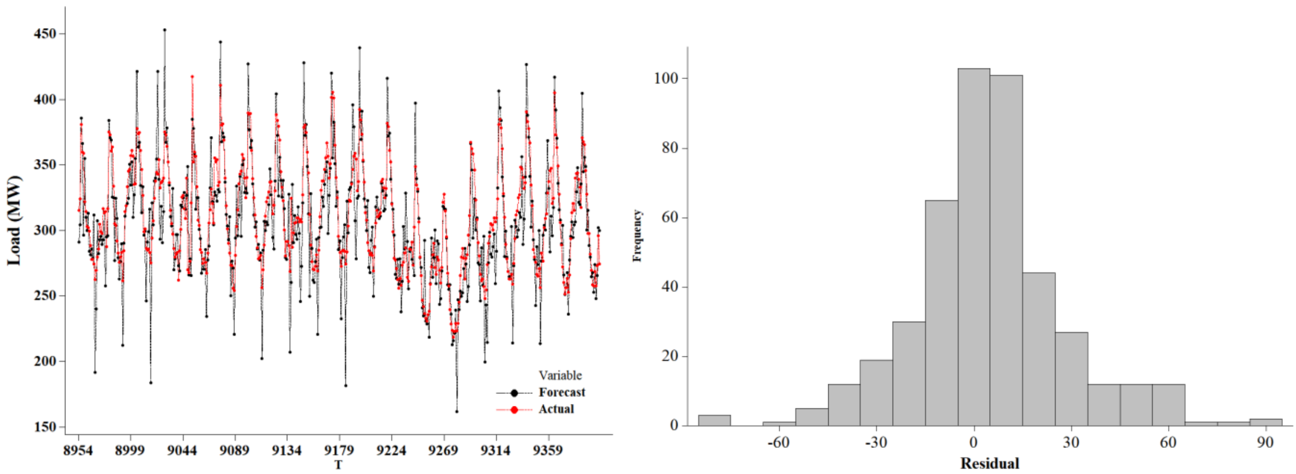

Fig. 6 Model 5 for ARIMA ([1,2,3,4,5,6],1,[1,2,3,4,5,6]) $(1,1,1)^{24}(1,1,1)^{168}(1,1,1)^{8760}$ and histogram of residuals appear to be white noise

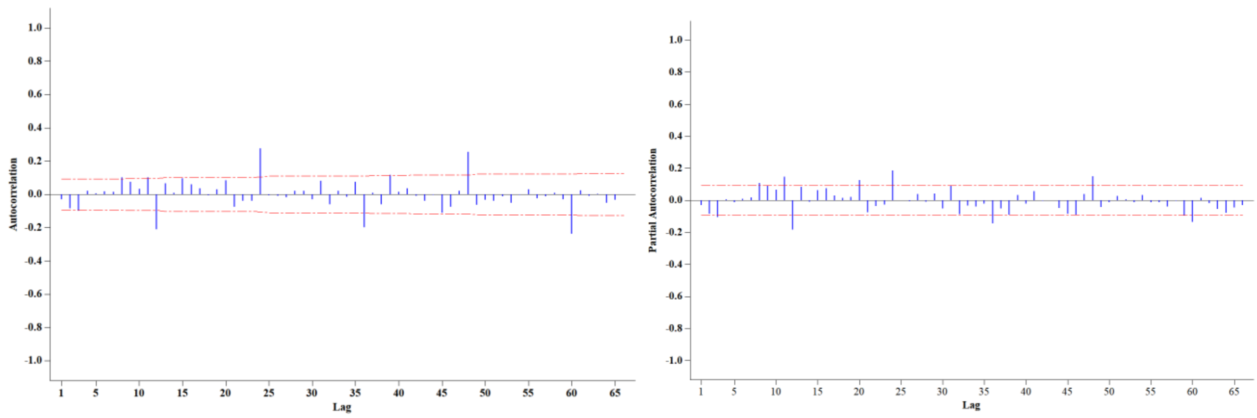

Fig. 7 Residual ACF and PACF Model 5 for ARIMA ([1,2,3,4,5,6],1,[1,2,3,4,5,6]) $(1,1,1)^{24}(1,1,1)^{168}(1,1,1)^{8760}$

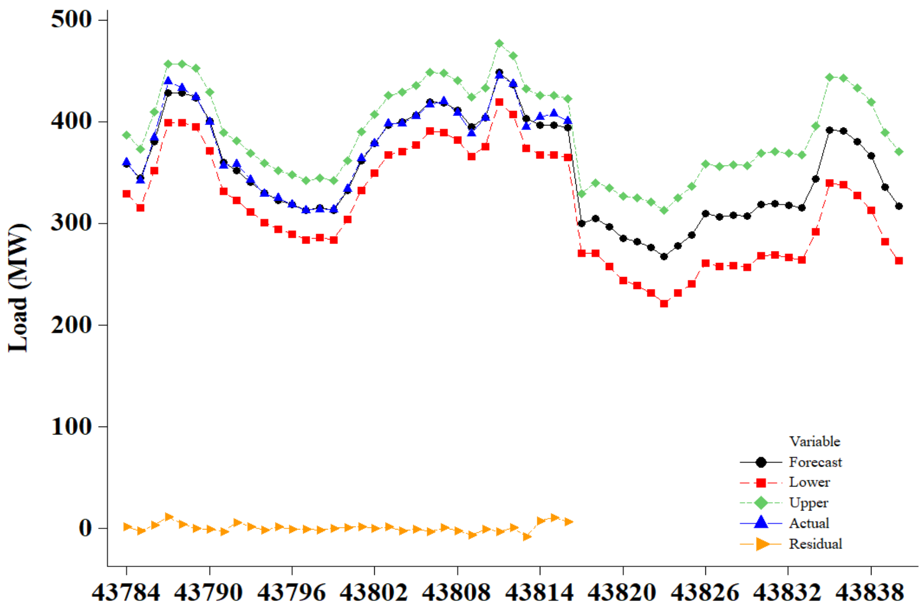

Fig. 8 Model 5 for ARIMA ([1,2,3,4,5,6],1,[1,2,3,4,5,6]) $(1,1,1)^{24}(1,1,1)^{168}(1,1,1)^{8760}$

This model's parameters are significant at alpha 5% significance level with white noise residuals based on Ljung-Box statistic Q^* until lags 24. Fig. 5 shows three of our diagnostic tools in one display a sequence plot of the standardized residuals, the sample ACF of the residuals, and *p*-values for the Ljung-Box test statistic for a whole range of values of k from 6 to 48. The horizontal dashed line at 5% helps judge the size of the *p*-values. It is seen that the series has significant autocorrelation at lags 1 and 24. The estimated $\Theta_{1,1} = 1.07611$ with lag 1, $\Theta_{1,9} = 0.01178$ with lag 24, $\Theta_{3,1} = 0.81804$ with lag 168, models seem to be caught on the dependence structure of the color property time series quite well. The standard error on the lag 1 = 0.02099, lag 24 = 0.01746, lag 168 = 0.0065190, models seem to be caught on the color property time series' dependence structure quite well. The horizontal dashed line at 5% helps judge the size of the *p*-values. It is seen that the series has significant autocorrelation at lags 1 and 24. The estimated MA(1,1), MA(2,1), MA(3,1) models seem to be caught on the dependence structure of the color property time series quite well. Specifically, the models are first-order moving average, or MA(1,2), MA(1,3), MA(1,4) models with parameters 0.29056, 0.142, and -0.084, respectively. Moving average models are always weakly stationary because they are finite linear combinations of a white noise sequence for which the first two moments are time-invariant.

These two criteria penalize the sum of squared residuals for including additional parameters in the model. Models that have small values of the AIC or SBC are considered good models. Good models are obtained by minimizing either the AIC or BIC. Our preference is to use SBC. It generally results in a smaller and hence simpler model. Its use is consistent with the time-honored model-building principle of parsimony (all other things being equal, simple models are preferred to complex ones. This section presents the AIC and SBC results for hourly lead times up to one day ahead calculated for the one month post sample period of each of the two series of load data. The MAPEs of one-step and *l*-step ahead out-sample forecasts using Model Triple ARIMA ([1,2,3,4,5,6],1,[1,2,3,4,5,6]) $(1,1,1)^{24}(1,1,1)^{168}(1,1,1)^{8760}$.

Fig. 8 shows that the one-step-ahead out-sample forecasts are not as much influenced by lead times as the *l*-step ahead out-sample forecasts. The out-sample forecasts based on *l*-step ahead are highly influenced by lead times, as shown in Table 1. This is because the *l*-step ahead forecasts accumulate the error terms resulting in low accuracy in forecasting performances. We then illustrate the MAPE of *l*-step and one-step ahead out-sample forecasts of the third model in Fig. 10; the out-samples of actual data and *l*-step ahead out-sample forecasts in Fig. 5 and the out-samples of actual data and one-step ahead out-sample forecasts in Fig. 4. When one-step ahead out-sample forecasts are calculated and compared to *l*-step ahead out-sample forecasts, the MAPE are reduced with the reduction percentages of 8,93436%.

Table 1 The SAS output of the model

The ARIMA Procedure Conditional Least Squares Estimation

Parameter	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Count	168	168	168	168	168
N	168	168	168	168	168
N*	0	0	0	0	0
CumN	168	168	168	168	168
Percent	100	100	100	100	100
CumPct	100	100	100	100	100
Mean	0.006593	0.006460	0.006463	0.006460	0.006452

SE Mean	0.00042	0.000423	0.000423	0.000423	0.000426
TrMean	0.006101	0.005959	0.005960	0.005959	0.005964
StDev	0.005453	0.005481	0.005481	0.005481	0.005520
Variance	0.000030	0.000030	0.000030	0.000030	0.000030
CoefVar	82.70	84.84	84.81	84.84	85.56
Sumof Sum	1.107689	1.085225	1.085830	1.085225	1.083909
Sum of squares	0.012269	0.012026	0.012036	0.012026	0.012082
Minimum	0.000047	0.000346	0.000233	0.000346	0.000033
Q1	0.002669	0.002604	0.002624	0.002604	0.002406
Median	0.004729	0.004826	0.004911	0.004826	0.005090

Q3	0.009378	0.009289	0.009061	0.009289	0.008496
Maximum	0.026740	0.02744	0.027640	0.027445	0.028229
Range	0.026693	0.027099	0.027406	0.027099	0.028196
IQR	0.006709	0.006685	0.006438	0.006685	0.006090
Mode	0	0		0	0
Skewness	1.38	1.41	1.43	1.41	1.35
Kurtosis	1.67	1.95	1.99	1.95	1.77
MSSD	0.000025	0.000023	0.000023	0.000023	0.000023

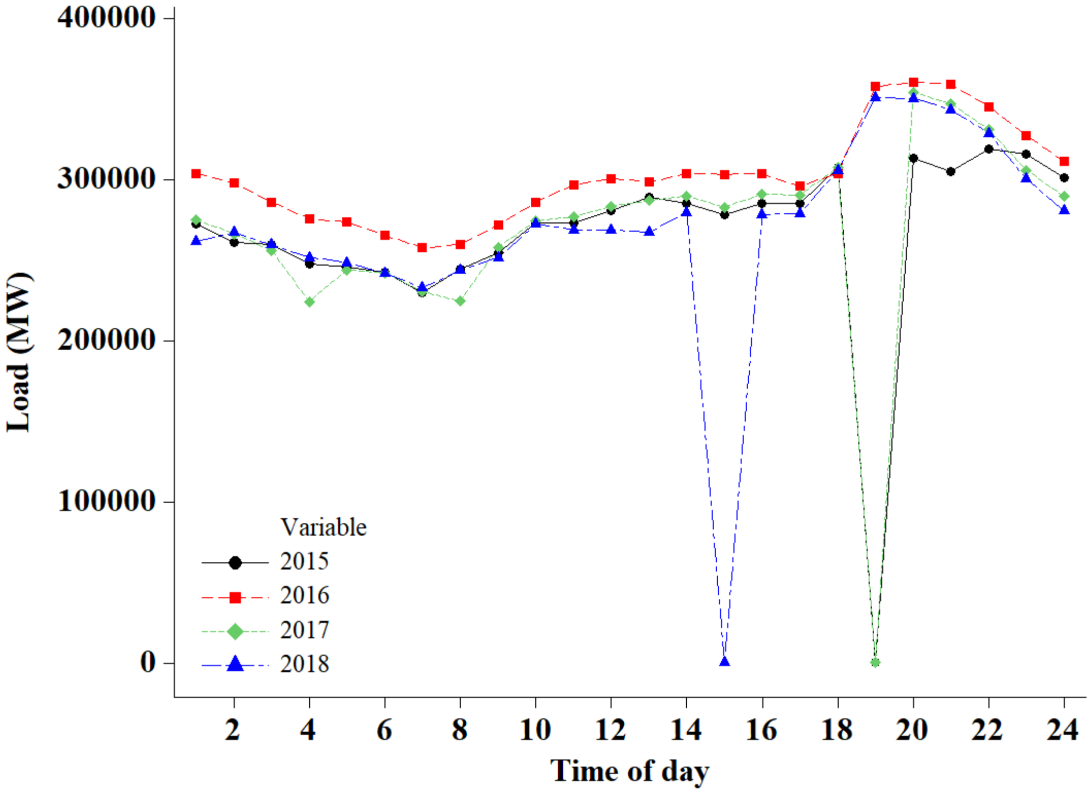

Fig. 9 Load profile for New Year's Day

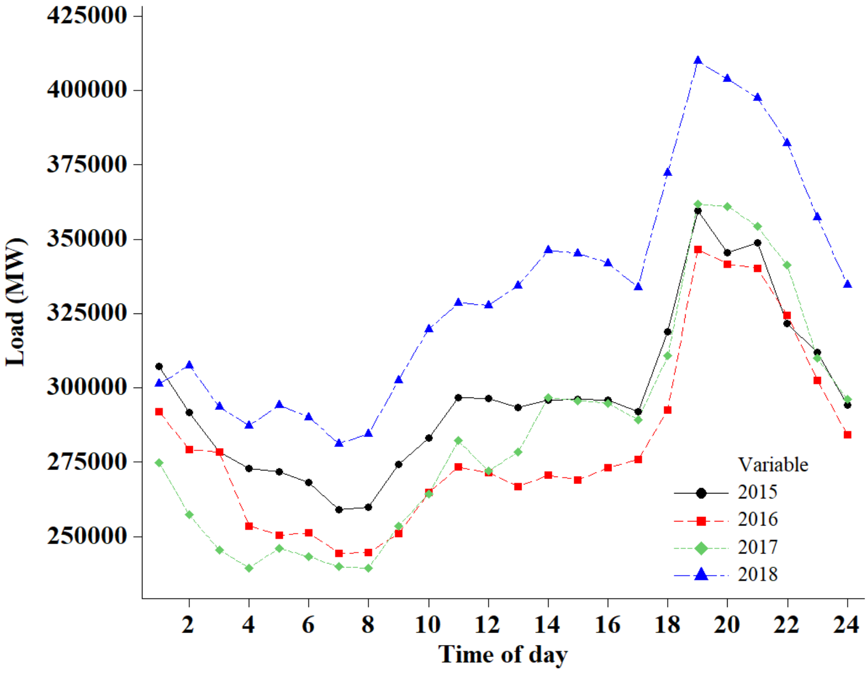

Fig. 10 Load profile for Christmas Day

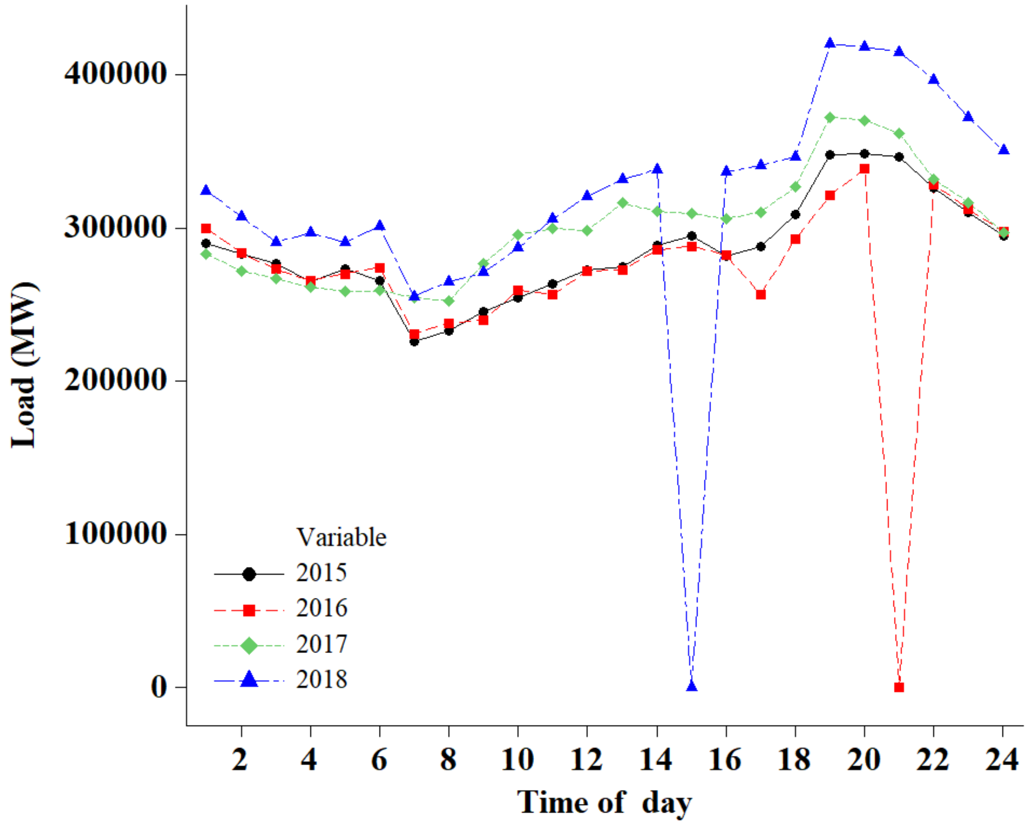

Fig. 11 Load profile for Eid Adha Day

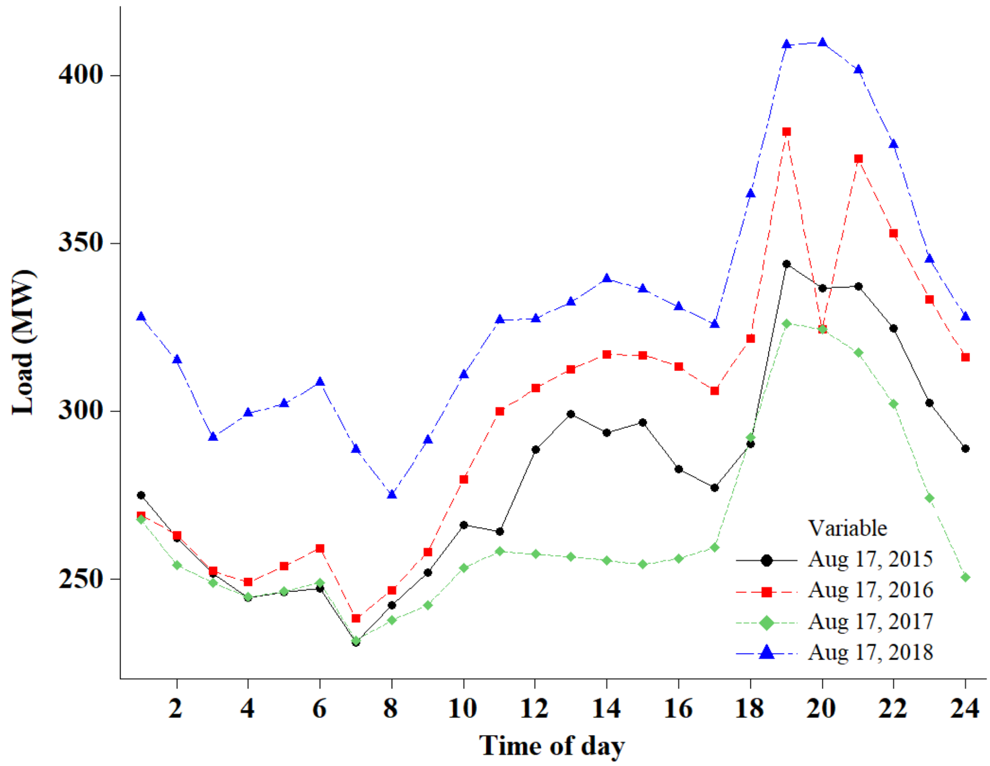

Fig. 12 Load profile for Day

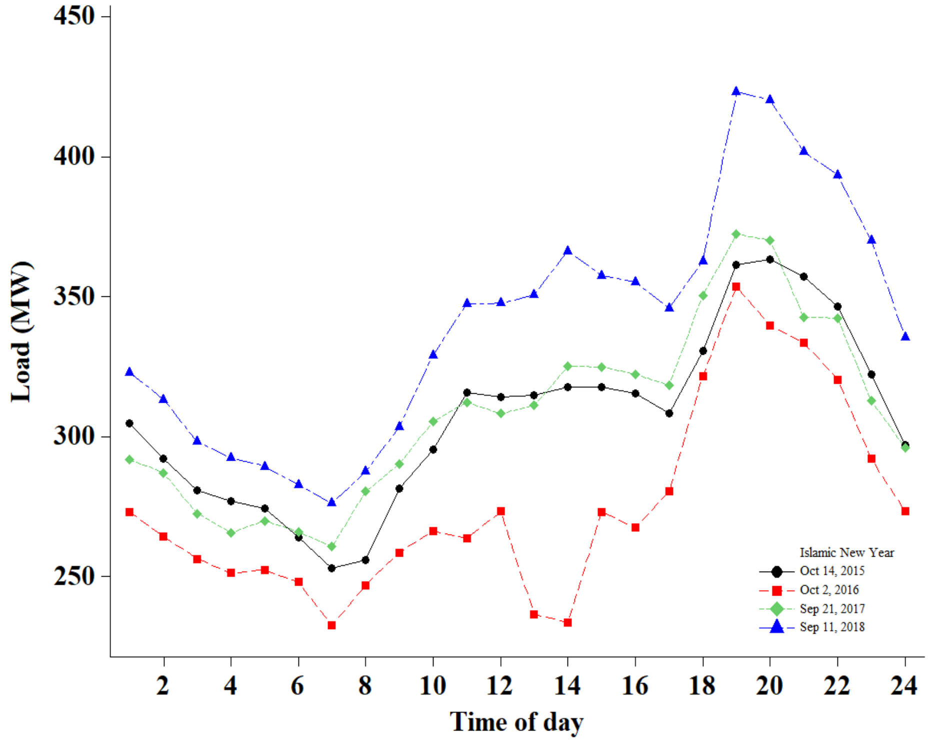

Fig. 13 Load profile for Islamic New Year holiday

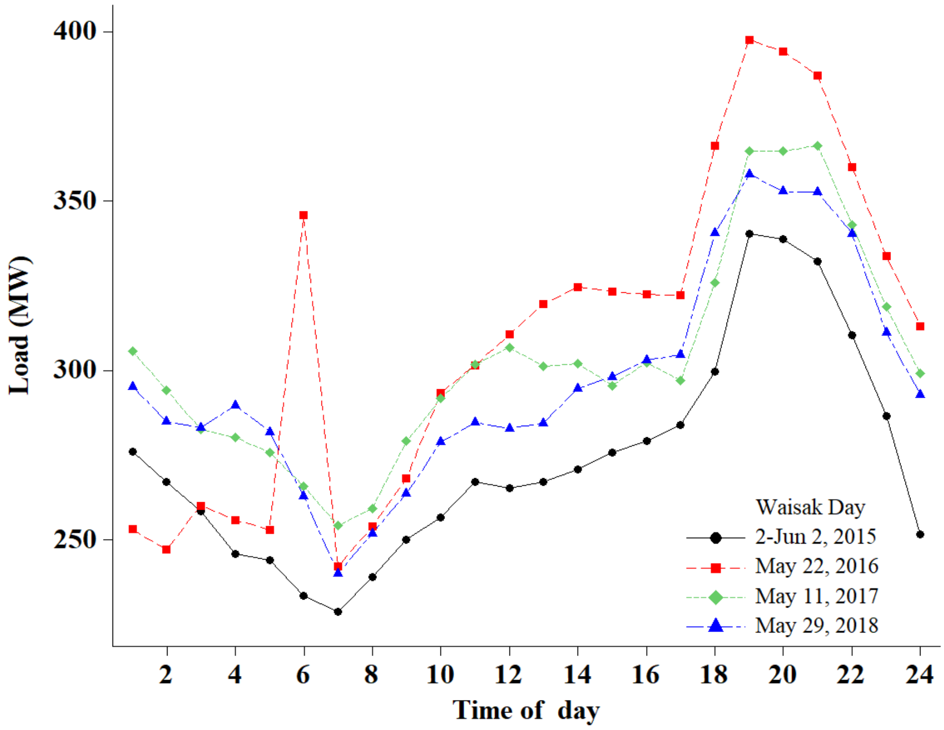

Fig. 14 Load profile for Waisak holiday

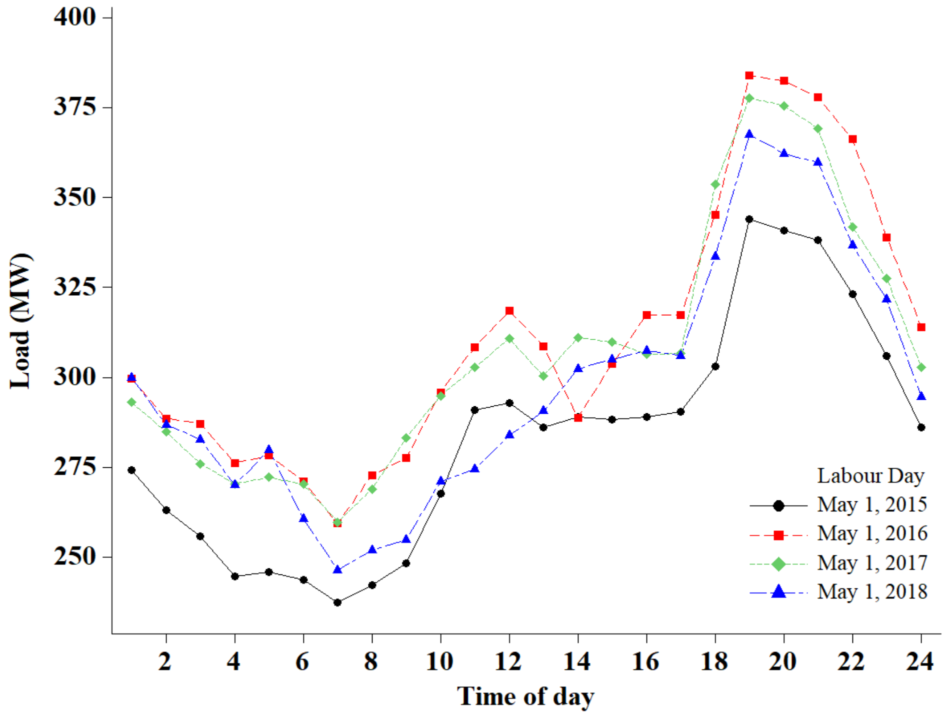

Fig. 15 Load profile for Labour Day

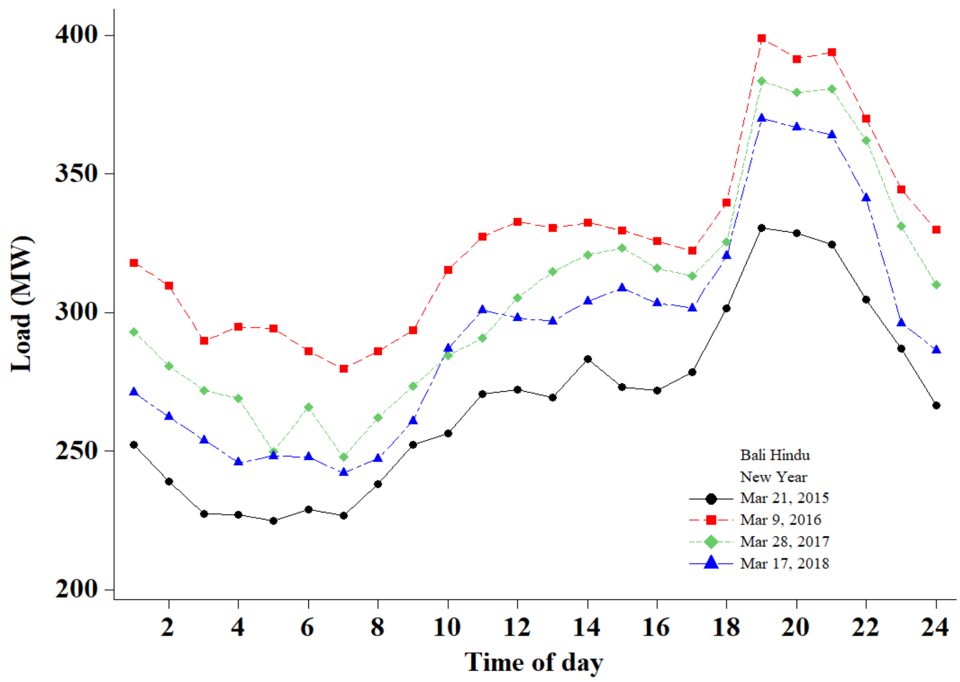

Fig. 16 Load profile for Bali Hindu holiday

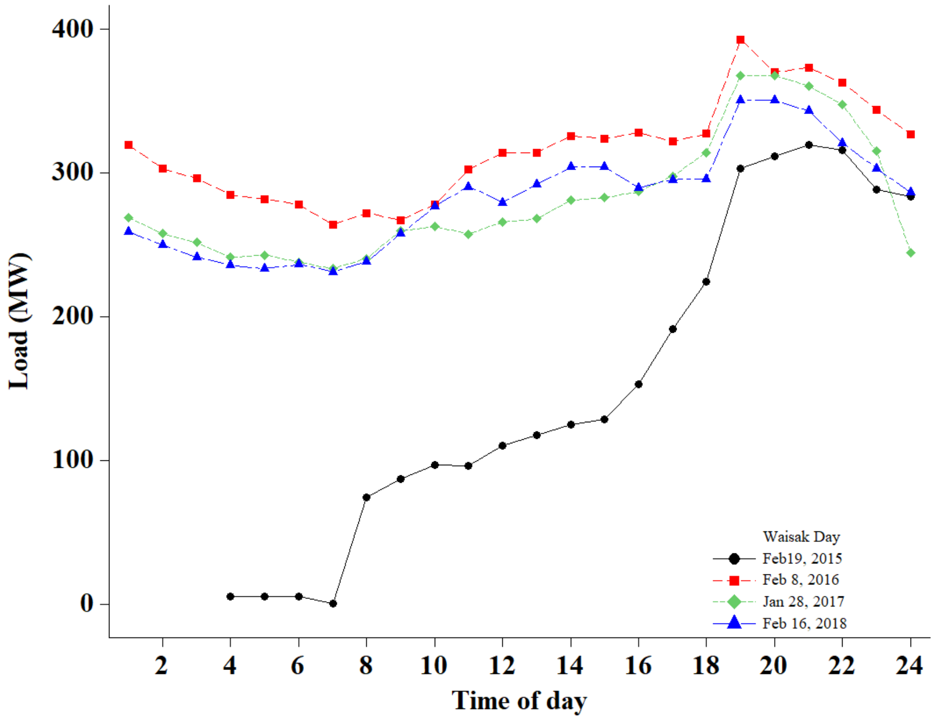

Fig. 17 Load profile for Waisak Day

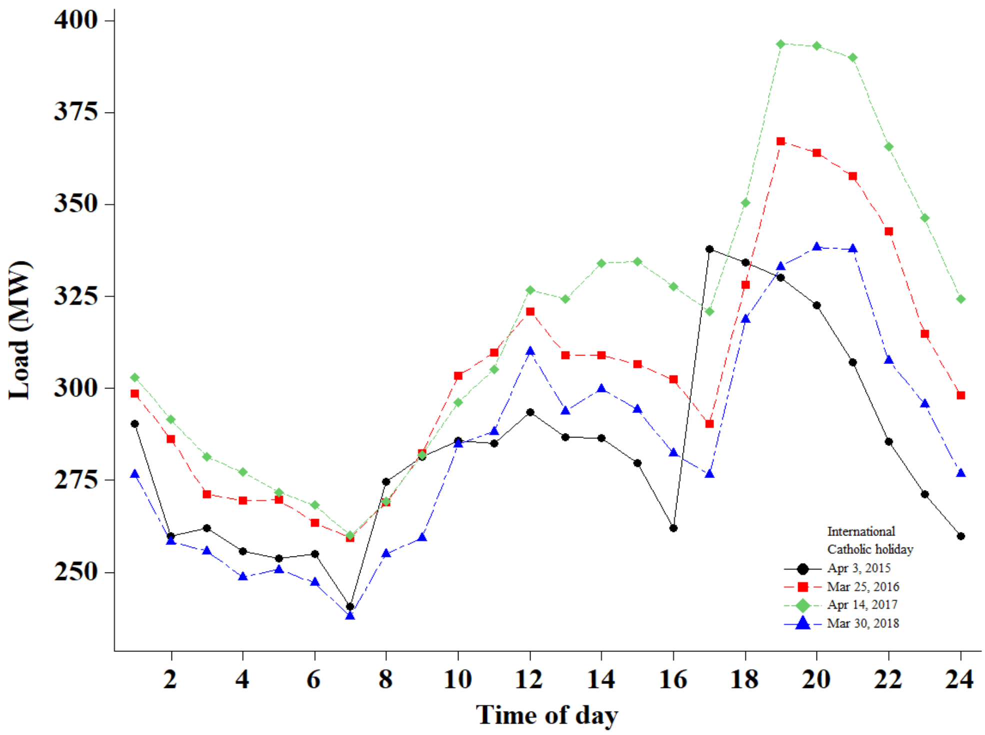

Fig. 18 Load profile for International Catholic holiday

5. Conclusion

This paper presented a case study on load forecasting for East Kalimantan, emphasizing forecasting load on special days using a rule-based triple Seasonal ARIMA method for Mahakam load data. In comparison with that study, modeling anomalous load for East Kalimantan is more challenging due to the relatively large number of different types of special days in Mahakam. This extra complexity in the data necessitated our development of a new rule. Each special day is treated as having a unique profile that allows for greater flexibility during the modeling. Further methodological development in this paper is our adaptation of a Seasonal ARMA method recently proposed in this journal for an anomalous load. Overall, we found that the rule-based triple Seasonal ARIMA method generated the most accurate forecasts for special days. For these days, the

MAPE obtained using rule-based Seasonal ARIMA was about one-third of the MAPE for the simple benchmark methods, and about a half of the MAPE of the original Seasonal ARIMA method, not rule-based and making no attempt to model special days. One of the most encouraging findings in our study was that, compared with the original Seasonal ARIMA model, treating special days with no difference from normal days, the use of rule-based Seasonal ARIMA led to a noticeable improvement in accuracy when evaluated over special days.

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