Energy Saving Potential Prediction and Anomaly Detection in College Buildings

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Abstract: Prediction of building electricity consumption has been studied in recent years. Several approaches have been applied to get accurate and robust prediction of electricity usage. In this report, we highlight methods to make buildings and college campus more efficient in using electricity through statistical modeling. We focus on four main buildings in Syarif Hidayatullah State Islamic University Jakarta and collect each building's kWh energy consumption on a monthly basis. Two methods are utilized to the time series data, SARIMA model and Artificial Neural Network (ANN) model. The ANN was found to have better model performance than SARIMA with the smallest error prediction.

1 INTRODUCTION

Electricity consumption throughout the world is witnessing an increasing trend from year to year as world population continues to grow. Electricity consumption in Indonesia was reported to have increased by an average 7% per year over period 2004 – 2014. This growth is led by increment of household incomes as well as electrification ratio (the percentage of households in Indonesia that are connected to the nation's electricity grid) and therefore usage of electricity devices such as air conditioners, refrigerators, etc. continue to rise.

Table 1: Electricity consumption from 2004 to 2014 (source: PLN statistics).

Year	Electricity (GWh)
2004	100.097
2005	107.032
2006	112.610
2007	121.247
2008	129.019
2009	134.582
2010	147.297
2011	157.993
2012	173.990
2013	208.935
2014	221.296

Another major area of concern is the production of electricity and the environmental pollution that is caused in the process of generating the electricity. As we know, most of electricity that we use every day for many purposes is generated using fossil fuels. The basic power plants are thermal based and depend on coal, diesel or other petroleum products for converting water into high pressure stream which is used to produce electricity through turbine-generator mechanism. These fossil fuels are predicted to become extinct in another 40-50 years. Moreover, the amount of electricity use also responsible for a significant proportion of total carbon dioxide emissions. For these reasons, management of energy consumption is a very important issue to resolve the losses due to consumption increment patterns and to lessen more damage to environment. With regards to energy management, our government have implemented a number of policies including energy audit. Energy audit is the process of evaluating energy utilization and identifying chances for energy savings and also recommending for improvement in energy efficiency (PERMEN ESDM No. 14 2012).

Energy usage prediction in buildings has received much consideration among researchers, as a method to reduce consumption of energy, with intention for energy savings and also to diminish environmental impacts. These motivate us to study

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as well as to predict energy usage buildings particularly at the UIN Syarif Hidayatullah buildings. Activities inside buildings of UIN Jakarta contribute a great proportion in using electricity, especially to support teaching and learning activities. In classrooms and administration buildings, ventilation, lighting, and particularly cooling give the biggest contribution for electricity consumption. Therefore, these areas are the best targets for energy savings. Another consideration is that many universities, including UIN Syarif Hidayatullah, have tight facility budgets, so finding lower cost ways is a very important task to reduce energy bills. We can also help campus to save energy expenses by engaging faculty and students to involve in energy efficiency. Therefore, through this research study, we wish to model total electricity consumption at the UIN Syarif Hidayatullah in order to understand electricity consumption behaviour over time and to accurately predict total consumption in the future. Finally, we can use it as a decision making to save energy and participate for the world energy efficiency and particularly to support our government policy for energy efficiency. This report discusses the basics of electricity, its measurement, worldwide trends with an emphasis on methods that can be implemented to save electricity especially in relation to the building and college campuses.

2 PREDICTION MODEL

This section is devoted to describe the two approaches used for energy prediction, i.e. SARIMA and ANN. In the last part of this section, the method for anomaly detection is discussed in details.

2.1 SARIMA Models

The Autoregressive Moving Average Models or also known as ARMA model is a stationary process that plays a key role in the modeling of time series data. To motivate the model, for a series y_t, the level of its current observations can be modeled through the level of its lagged distribution. This kind of model is known as an autoregressive (AR) model. The AR(p) model has order p and is expressed as follow:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + e_t.$$

In addition, we can also model the data at time t where they are influenced by random innovation at time t and the random innovation before time t. This kind of model is known as a moving average (MA). The MA(q) model has order q and is expressed as follows:

$$y_t = e_t - \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q}.$$

If the two models are combined, we get a general ARMA(p,q) with p AR terms and q MA terms:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q}.$$

Using ARMA processes, we can approximate many real data sets in a more parsimonious way by a mixed ARMA model that contains both AR and MA process.

In real world setting, many time series data shows non-stationary behavior. To model such situation, Box and Jenkins (1976) formulated the concepts of ARIMA. ARIMA is an acronym for Autoregressive Integrated Moving Average Model. This model has order p, d, and q and usually written as ARIMA(p,d,q). We can express the model as follows:

$$w_t = \phi_1 w_{t-1} + \phi_2 w_{t-2} + \cdots + \phi_p w_{t-p} + e_t - \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q},$$

where $w_t = \Delta^d y_t$ and d denotes the number of differencing or integration order. We call this as an ARIMA(p,d,q) model. If order of integration equals to zero, then the original time series data is stationary and ARIMA models come down to ARMA models.

To account for seasonal behavior, Box and Jenkins (1976) proposed SARIMA. In SARIMA model, non-stationary can be eliminated from the model by using the corresponding order of seasonal differencing. The primary concept with seasonal time series of period *s* is that the data with *s* intervals apart are similar. The SARIMA model is generally indicated as $SARIMA(p,d,q) \times (P,D,Q)_s$, where 's' denotes the seasonal period length, P is the seasonal AR order, D is the seasonal integration order, and Q is the seasonal MA order.

2.2 Artifical Neural Networks

Artificial neural networks (ANNs) have received much interest in the past few years. It is a relatively new approach that can handle complex situation and offer flexibility for prediction and classification as compared to traditional statistical approach such as regression (Cheng and Titterington, 1994). ANNs provide alternative solution to model non-linear data and have been used among researchers to solve energy prediction problem (Bishop, 2007).

ANN method comprises three important features. The first feature is neurons or nodes. It is the elementary processing elements in ANN. The basic processing elements, or neurons, are arranged in layers. The layers between the input and the output layers are called hidden layers. The second feature is the network architecture. It explains the connections between neurons. Finally the last feature is the training algorithm. The network parameter values are searched by this training algorithm to work a specific task for classification (Allende et al., 2002). A neural network class can be defined by the following expression:

$$S_\lambda = \{g_\lambda(\underline{x}, \underline{w}), \underline{x} \in R^m, \underline{w} \in W\}, W \subseteq R^\tau,$$

where $g_\lambda(\underline{x}, \underline{w})$ is a non-linear function of $\underline{x}$, λ is the number of hidden neurons $\underline{w}$ is the vector of parameter, and τ is the number of free parameters that is determined by A_λ, i.e. $\tau = \rho(A_\lambda)$.

A trained ANN method needs the performance error to convergence to a unique minimum (local). For any particular topologyA_λ, where a trained network has to convergence, we introduce the requirement and a restricted search is performed in the function space. The general algorithms of ANN are summarized in the following:

1. The parameters $\underline{w}$ in the model is estimated by minimizing the empirical loss $L_n(\underline{w})$ iteratively.
2. The error Hessian $\hat{A}_n$ is computed to carry on convergence test.
3. Matrix $\hat{A}_n$is examined to check if it has negative eigen values. This is used to perform convergence and uniqueness test.
4. The prediction risk $P_\lambda = E[L_n(\underline{w})]$ is estimated which adjust the empirical loss for complexity.
5. The model is selected by using the principle of minimum prediction risk. This expresses the trade-off between the generalization ability of the network and its complexity.

2.3 Statistical Measure

A good learner (model) is the one which has good prediction accuracy. In other words, it has the smallest prediction error. In this study, several statistical measures are used such as MAPE, MAD, and RMSE.

The mean absolute percentage error (MAPE) is a measure of prediction accuracy of a forecasting method and can be expressed as:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|,$$

where N is the number of sample data, y_i is the actual data on time *i*, $\hat{y}_i$ is the predicted data on time *i*.

The mean absolute deviation (MAD) is defined as an error statistic that average the distance between each pair of actual and fitted data points. The formula for calculating MAD is given as:

$$MAD = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|.$$

The root mean squared error (RMSE) is an absolute error measures the squares the deviations to keep the positive and negative deviations from cancelling one another out. This measure also tends to exaggerate large errors, which can help when comparing methods. The formula to calculate RMSE is given as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}.$$

2.4 Anomaly Detection

The selected model with the highest prediction accuracy according to MAPE criteria will be used to detect anomaly. The basic idea is to use the model to predict the electricity consumption on time t. If the difference between the observed and the predicted value is greater than a certain threshold we classify it as an anomaly (Halldor et al, 2014). The error is defined as follows:

$$E = |y_i - \hat{y}_i|.$$

A sample will be classified an anomaly if the error is above a certain threshold. This threshold value can be determined through an experiment. Intuitively, a value is considered an outlier if its error is higher than the other errors. Three-sigma-rule will be considered in this research as the threshold. If the error of a sample data is greater than three times the standard deviation then it will be classified as an anomaly.

3 EXPERIMENT AND RESULTS

3.1 Exploratory Data Analysis

Data for electricity consumption at the UIN Syarif Hidayatullah buildings were collected from the 4 main buildings:

1. Rectorate building.
2. Campus 1 (main campus that consists of Tarbiya and Teaching Sciences Faculty, Shari'a and Law Faculty, Dirasat Islamiyah Faculty, Da'wa and Communications Faculty, Adab and Humanities Faculty, Usul al-Din and Philosophy Faculty, Economics and Business Faculty, and Science and Technology Faculty)
3. Campus 2 (located on Kertamukti Street that consists of Faculty of Psychology and Faculty of Social and Political Science)
4. Campus 3 (located on Kertamukti street that consists of Faculty of Medical and Health Science)

The data were measured in kWh (kilowatt hours) and were collected in 56 months from January 2013 to August 2017. Figure 1 displays the energy consumption profiles of electricity consumption in the four buildings over the months. It shows that Campus 2 and Campus 3 behave relatively similar from month to month. The plots also indicate fluctuations as well as seasonal pattern in the monthly energy consumption. One can see that there is greater energy consumed during teaching periods due to increased use of the lighting and air conditioning in classes. The least energy consumed happened during semester break when normal classes are not conducted. It can also be observed that energy consumptions were slightly increased over the years for Campus 1, 2, and 3 but showed a decreasing trend for Rectorate building starting from middle of year 2015.

Table 2: General characteristics of data sets.

Building	n	Mean	Std. Deviation	Min.	Max.
Rectorate	56	26,284	3,977	17,644	34,541
Campus 1	56	302,492	80,271	157,488	433,536
Campus 2	56	79,129	15,401	47,937	108,474
Campus 3	56	81,499	14,919	50,600	110,403

Table 2 summarizes their respective descriptive statistics. As can be expected, Campus 1 used the largest energy by 302,494 kWh on average since Campus 1 is the main building that consists of many faculties. The second and the third largest were Campus 3 (81,499 kWh) and Campus 2 (79,129 kWh), respectively. Rectorate building consumed the least by 26,284 kWh.

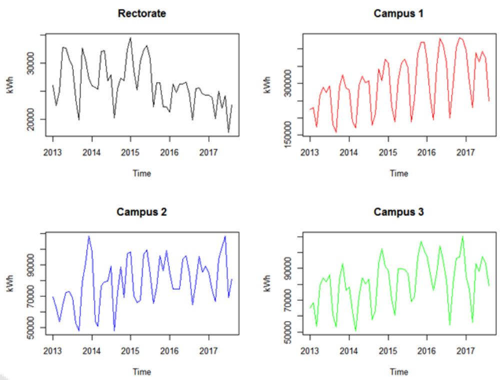

Figure 1: Electricity consumption profile over the months.

3.2 SARIMA Models

Visual examination of Figure 1 shows that the process is non-stationary with both trend and seasonality components. This is also confirmed from the ACF plots (Figure 2) that clearly show the existence of strong seasonal dependency with high coefficients in 12, 24, 36, and so on which fade slowly with the lag.

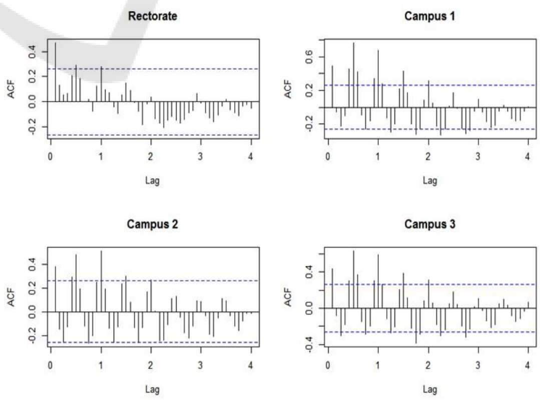

Figure 2: Plot of ACF of the time series data.

Table 3 also confirms that the data is non-stationary by using three different methods (ADF, KPSS and PP tests). The ADF test is not significant, meaning the null hypothesis of unit root cannot be rejected. The results of KPSS tests are significant meaning the null hypothesis of stationary process is rejected. Therefore, we need to take first difference to the time series data. The general upward trend has disappeared after we take first difference to the data but the strong seasonality is still present.

Table 3: ADF, KPSS, and PP tests for the time series data.

	ADF test		KPSS test		PP test	
	test statistic	p	test statistic	p	test statistic	p
Rectorate	-2.111	0.530	0.872	0.010	-27.440	0.010
Campus 1	-1.672	0.707	1.024	0.010	-16.400	0.129
Campus 2	-2.943	0.194	0.649	0.018	-21.381	0.036
Campus 3	-1.658	0.713	0.698	0.014	-20.291	0.046

Observing both ACF and PACF plots of the series after taking first and seasonal difference (see Appendix), we come up with several potential models for each building as summarized in Table 4.

For electricity consumption pattern in Rectorate building, the PACF shows a clear spike at lag 2 or 4. A non-seasonal AR(2) or AR(4) may be useful part of the model. In the ACF, there appears no significant lag. Thus, the proposed model for the series of electricity consumption in Rectorate building is $ARIMA(2,1,0) \times (0,1,0)_{12}$ or $ARIMA(4,1,0) \times (0,1,0)_{12}$.

For electricity consumption pattern in Campus 1 building, the PACF also shows a clear spike at lag 2 or 4. A non-seasonal AR(2) or AR(4) may be useful part of the model. Thus, the proposed model for the series of electricity consumption in Campus 1 building is $ARIMA(2,1,0) \times (0,1,0)_{12}$ or $ARIMA(4,1,0) \times (0,1,0)_{12}$.

For electricity consumption pattern in Campus 2 building, the ACF shows a clear spike at lag 1. A non-seasonal MA(1) may be useful part of the model. In the PACF, there's a cluster of (negative) spikes around lag 12 and then not much else. This might indicate the need for a seasonal MA(1) component. Thus, the proposed model for the series of electricity consumption in Campus 2 building is $ARIMA(0,1,1) \times (0,1,1)_{12}$.

For electricity consumption pattern in Campus 3 building, the ACF shows a clear spike at lag 1. A non-seasonal MA(1) may be useful part of the model. In the PACF, there's a cluster of (negative) spikes around lag 12 and then not much else. This might indicate the need for a seasonal MA(1) component. Thus, the proposed model for the series of electricity consumption in Campus 2 building is $ARIMA(0,1,1) \times (0,1,1)_{12}$.

Automatic procedure to select the order of seasonal and non-seasonal component was also performed with R by using auto.arima function. The comparisons of the proposed models are shown in Table 4.4. Based on AIC and BIC values, the best fitted model for electricity consumption pattern in Rectorate building is $ARIMA(2,1,0) \times (0,1,0)_{12}$. The best fitted model for electricity consumption pattern in Campus 1 building is $ARIMA(4,1,0) \times (0,1,0)_{12}$ with drift. The best fitted model for electricity consumption pattern in Campus 2 building is $ARIMA(0,1,1) \times (0,1,1)_{12}$. The best fitted model for electricity consumption pattern in Campus 3 building is $ARIMA(0,1,1) \times (0,1,1)_{12}$.

Table 4: AIC and BIC comparison for the proposed models.

	Model	AIC	AICc	BIC
Rectorate	$ARIMA(1,1,1) \times (1,0,0)_{12}$	1055.9	1056.7	1063.9
	$\boldsymbol{ARIMA(2,1,0) \times (0,1,0)_{12}}$	**845.2**	**845.8**	**850.5**
	$ARIMA(4,1,0) \times (0,1,0)_{12}$	844.6	846.2	853.4
Campus 1	$ARIMA(0,0,0) \times (0,1,1)_{12}$ with drift	1040.4	1041.0	1045.7
	$ARIMA(2,1,0) \times (0,1,0)_{12}$	1032.5	1033.1	1037.7
	$\boldsymbol{ARIMA(4,1,0) \times (0,1,0)_{12}}$	**1021.6**	**1023.2**	**1030.4**
Campus 2	$ARIMA(2,1,1) \times (1,0,0)_{12}$	1194.2	1195.4	1204.2
	$\boldsymbol{ARIMA(0,1,1) \times (0,1,1)_{12}}$	**935.5**	**933.1**	**937.8**
Campus 3	$ARIMA(2,0,2) \times (1,1,0)_{12}$ with drift	922.1	925.2	934.6
	$\boldsymbol{ARIMA(0,1,1) \times (0,1,1)_{12}}$	**907.2**	**907.8**	**912.5**

Based on AIC and BIC values, the best fitted model for electricity consumption pattern in Rectorate building is $ARIMA(2,1,0) \times (0,1,0)_{12}$. The best fitted model for electricity consumption pattern in Campus 1 building is $ARIMA(4,1,0) \times (0,1,0)_{12}$ with drift. The best fitted model for electricity consumption pattern in Campus 2 building is $ARIMA(0,1,1) \times (0,1,1)_{12}$. The best fitted model for electricity consumption pattern in Campus 3 building is $ARIMA(0,1,1) \times (0,1,1)_{12}$.

Using the Maximum Likelihood estimator, the model parameters are estimated. Table 5 summarizes the estimated coefficient and standard error of the best fitted seasonal ARIMA models.

Diagnosis analyses are also performed to the four models to evaluate the model assumption such as no correlation in the residual series. Assumption of no correlation in residuals is investigated by performing Ljung-Box test (Table 6). The result of Ljung-Box for the residual series from the model fitted to the Rectorate data are not significant since the test fails reject the null hypothesis of no autocorrelation in the residual series (p = 0.422). The result of Ljung-Box for the residual series from the model fitted to the Campus 1 data are not significant since the test fails reject the null hypothesis of no autocorrelation in the residual series (p = 0.882). The result of Ljung-Box for the residual series from the model fitted to the Campus 2 data are not significant since the test fails reject the null hypothesis of no autocorrelation in the residual series (p = 0.785). The result of Ljung-Box for the residual series from the model fitted to the Campus 3 data are not significant since the test fails reject the null hypothesis of no autocorrelation in the residual series (p = 0.690). Thus, we can conclude that there is no autocorrelation in the residual series.

Table 5: The estimated parameters of seasonal models.

	Parameter	Estimated Coefficient	Standard Error
Rectorate	AR(1)	-0.213	0.156
$\boldsymbol{ARIMA}(2,1,0)\times(0,1,0)_{12}$	AR(2)	-0.239	0.156
Campus 1	AR(1)	-0.642	0.142
$\boldsymbol{ARIMA}(4,1,0)\times(0,1,0)_{12}$	AR(2)	-0.742	0.152
	AR(3)	-0.604	0.150
	AR(4)	-0.500	0.151
Campus 2	MA(1)	-0.953	0.110
$\boldsymbol{ARIMA}(0,1,1)\times(0,1,1)_{12}$	SMA(1)	-0.402	0.236
Campus 3	MA(1)	-0.737	0.129
$\boldsymbol{ARIMA}(0,1,1)\times(0,1,1)_{12}$	SMA(1)	-0.999	1.198

Table 6: The estimated parameters of seasonal models.

	Ljung-Box test		
	Chi-Square	**df**	**p**
Rectorate	15.420	15	0.422
Campus 1	8.909	15	0.882
Campus 2	10.528	15	0.785
Campus 3	11.853	15	0.690

3.3 ANN Models

The ANN models are also fitted to the time series data using feed-forward with multilayer perceptrons (MLP). Mean square error (MSE) is used as a criteria for model selection according to the number of hidden nodes. MSE measures how good the fitted model by computing how many errors it makes. The lower the MSE score, the better the model. Table 7 reveals that ANN model 7 hidden nodes is appropriate to model kWh consumption in both Rectorate and Campus 1 buildings. ANN model with 4 hidden nodes is appropriate to model kWh consumption in Campus 2 building. ANN model with 6 hidden nodes is appropriate to model kWh consumption in Campus 3 building.

3.4 Model Comparison

Table 8 summarizes the comparison of forecasting precision between the two methods according to MAPE, MAD, and RMSE criteria. Empirical results on the four data set by utilizing two different approaches clearly show the efficiency of the ANN model since the values of MAPE, MAD, and RMSE are the lowest. Figure 3 displays the comparison between actual data and fitted values based on SARIMA and ANN. The plots also confirm that ANN is the best model since it can approximately predict the true values, the ANN lines are almost overlap with the actual lines.

Table 7: Comparison of MSE scores for the different hidden nodes in ANN model.

Hidden Nodes	Rectorate	Campus 1	Campus 2	Campus 3
1	3035701	276138947	34673173	14043375
2	187006	84373301	1826663	2730417
3	7898	21469240	128846	1020675
4	4202	11114334	**63585**	842439
5	5431	5829708	101430	491480
6	4276	5604356	72053	**367589**
7	**1617**	**3971442**	71327	388695
8	3210	4881048	100646	378852

Table 8: Comparison of MAPE, MAD, and RMSE.

Statistical Measure	Building	SARIMA	ANN
MAPE	Rectorate	0.103	0.001
	Campus 1	0.058	0.003
	Campus 2	0.086	0.001
	Campus 3	0.055	0.004
MAD	Rectorate	2581.600	25.733
	Campus 1	17031.813	1035.153
	Campus 2	6489.175	144.022
	Campus 3	4327.664	330.030
RMSE	Rectorate	3661.917	40.217
	Campus 1	26597.027	1992.848
	Campus 2	9556.023	252.160
	Campus 3	6045.996	606.291

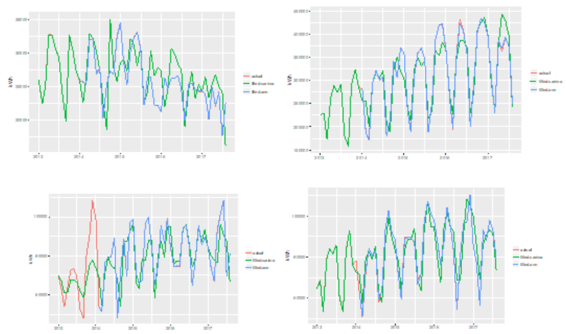

Figure 3: Plot of actual vs. predicted value based on SARIMA and ANN model for Rectorate (top left), Campus 1 (top right), Campus 2 (bottom left), and Campus 3 (bottom right).

3.5 Anomaly Detection

Figure 4 shows the monthly analysis for the anomaly detection set. The threshold (red dashed line) is calculated from the standard deviation of the error, where error is calculated as the absolute value of the difference between the actual and the predicted kWh consumption. If the error is greater than 3σ or less than -3σ, we detect the series as outlier or anomaly data. From the Rectorate dataset, there are 3 anomaly data. From Campus 1 dataset, there are 2 anomaly data. From Campus 2 and 3 dataset, there are 2 anomaly data for each. In total, there are 9 anomalies detected from all buildings. These anomalies are further listed in Table 9 because their calculated errors are greater than three-sigma-rule.

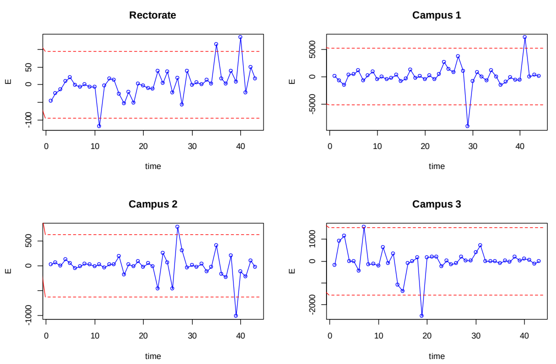

Figure 4: Plot of anomaly detection.

In June 2017, the actual consumption in Campus 1 building was 393,132 kWh and the model predicts 7107.7 kWh lower than what was recorded. These kind of anomalies found in Campus 1 are peak anomalies and were found during semester break where electricity consumption should be generally lower than semester dataset (classes) since there is no activities inside campuses especially for teaching and learning activities. Logical explanation for this peculiar behaviour could be due to waste of energy such as usage of electricity components (like air conditioner, etc.) when there are no activities inside the building. There are however many significant peak anomalies in the data that cannot be explained due to very limit source of information from secondary data and need further investigation.

Table 9: The listed anomalies from the four buildings.

Building	Month	Error	Actual kWh
Rectorate	Dec-14	118.4	32434
	Dec-16	114.6	24275
	May-17	133.5	21987
Campus 1	Jun-16	9133.3	409231
	Jun-17	7107.7	393132
Campus 2	Apr-16	780.3	74540
	Apr-17	1014.5	93747
Campus 3	Aug-14	1563.2	57920
	Aug-15	2503.1	69154

4 CONCLUSIONS

From statistical point of view and by considering electricity consumption data at the UIN Syarif Hidayatullah building, two different approaches were conducted to analyze the behavior of energy usage over time in the four main campuses building. According to the electricity consumption trend found in the data, the behavior of electricity consumption in the four buildings can be categorized into two states, i.e. high demand during class semester and low demand during semester break. This is a very logical explanation because during class semester, activities inside campuses will increase so electricity demand will also increase. Higher consumptions will be for lighting and cooling to support teaching and learning activities. The demand will be low when there is no class during semester break; therefore electricity consumption will be relatively low.

In terms of energy prediction, the results indicate that artificial neural network outperforms the other methods, with the smallest MAPE values. This shows that ANN can best approximately the electricity usage in the future. From the forecast plot, we can see that electricity consumption will increase in the near future. From the anomaly detection section, we could only point several peak anomalies during semester break. This, of course, need further investigation because it could lead to energy efficiency.

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APPENDIX

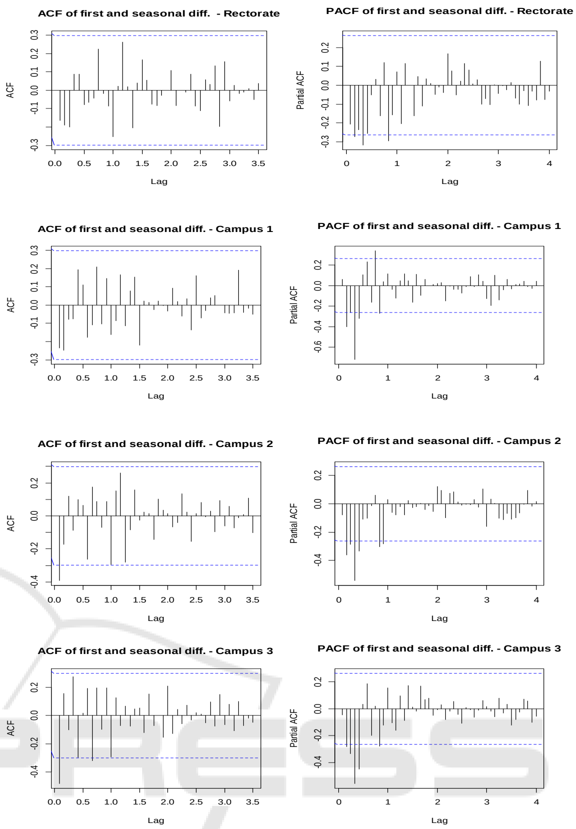

Figure: ACF and PACF of first and seasonal difference of kWh consumption in the four buildings.