Application of Time Series Analysis in Projecting Philippines' Electric Consumption

Allemar Jhone P. Delima

Abstract—**This paper employed the famous ARIMA(p,d,q) model in forecasting Philippines' electric consumption for the years 2018 to 2022 using the univariate historical data of the country's power statistics in megawatt-hour from 2003-2017. The ACF and PACF plots were considered as well as stationarity of the data in assigning appropriate (p,d,q) values. By selecting the model with the lowest Akaike Information Criterion (AIC) value, an optimal model is then identified. The simulation result showed that ARIMA(1,2,1) model appeared to be the statistically appropriate model to forecast the Philippines' electrical consumption allocated for residential, commercial, and industrial use. A forecasted value of 28,281,111Mwh, 29,786,410Mwh, 31,291,820Mwh, 32,797,232 Mwh, and 34,302,644 Mwh for the residential use in the years 2018, 2019, 2020, 2021, and 2022 respectively are expected. While the forecast for commercial use has the value of 23,866,067Mwh, 24,950,677Mwh, 26,037,098Mwh, 27,123,275Mwh, and 28,209,485Mwh for the same sequence of years. Further, years 2018, 2019, 2020, 2021, and 2022 has forecasted electrical consumption value of 26,963,287Mwh, 28,373,297Mwh, 29,777,292Mwh, 31,183,097Mwh, and 32,588,357Mwh respectively for industrial use.**

Index Terms—**ARIMA, electricity, electric consumption, forecasting, time series.**

I. Introduction

In 2017, the Philippines was identified as one of the top three economic growth performers in East Asia after Vietnam and China. The Philippines economic growth performance stretched to 6.7 percent in 2017 [1]. Along with the Philippines' economic growth is the increase of supply and demand for goods and services [2] especially the drive for demand in electricity across sectors [3].

The Department of Energy is the agency that distributes electricity into the many sectors of the economy but primarily distributes energy for residential, commercial, and industrial use [4]. As important as it is, electric load projection is essential in designing power and grid distribution systems [5].

The use of data mining techniques [6]-[9] and other prediction models [10]-[12] are vital for the operation of energy functions as they are important variables where policies in power grid management decisions are based [5].

The purpose of this paper is to forecast the electric consumption of the Philippines in terms of residential, commercial, and industrial use. This paper implemented the famous ARIMA methodology, a type of time series analysis model, in predicting electric consumption for years 2018-2022. Different ARIMA models were observed, and the best model was selected from it.

II. Related Literature

Prediction [13] is one of the renowned data mining approach that is commonly used in educational data mining (EDM) [14], crime mining [15], business and finance [16], health [17], and more.

The literature in forecasting and prediction is extensive. Various models were developed and utilized in response to the problems the researchers sought to answer. According to [13], there are two general categories for forecasting and prediction namely the classical and modern methods. Classical methods include econometrics-based approaches, statistical inferences, and traditional mathematical programming while the modern method employs soft computing algorithms and artificial intelligence.

For example, a forecasting approach that combines the strengths of the neural network and multivariate time series models was proposed. In the proposed approach, forecasting the exchange rate of UK, USA, and Japan was done first by time series, and then GRNN was used to correct the forecasting errors [18]. On the other hand, the performance of state space models and ARIMA model was compared for predicting sales by applying both to a case study of women footwear retail sales [19]. Further, an enhanced seasonal ARIMA model was developed for daily food sales forecasting. The result revealed that the enhanced method provides better prediction and deep insights for the effect of demand influencing factors [20].

Furthermore, the forecasting accuracy of the exchange rate in Brazil using different approaches was examined. They employed intelligent systems like multilayer perceptron and radial basis function neural networks and the Takagi–Sugeno fuzzy system versus the traditional methods of forecasting such as autoregressive moving average (ARMA) and ARMA-generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) linear models. It was found out that the intelligent-based methods provided more accurate results than the traditional ones [21].

Meanwhile, the adaptation of hybrid methodology combining ARIMA and Deep Neural Network (DNN), which is an ANN model with multiple hidden layers, was considered as the optimal model for predicting roll motion compared to the non-hybrid models. It was found out that DNN-ARIMA hybrid model showed improved forecast accuracy and was identified to be very effective [22].

Recently, a model for predicting OTOP's products was developed using K-Nearest Neighbor (KNN) in a 5, 10, 15,

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Allemar Jhone P. Delima is with the College of Engineering and Information Technology, SSCT, Surigao City, 8400, Philippines (e-mail: allemarjpd@ssct.edu.ph).

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20, and 25 k-fold cross-validations and K-NN with k value assigned with 3, 5, and 7. The model with 5 folds cross-validation and K-NN with k=3 yields the best prediction with 87.73% accuracy. Moreover, the authors suggested to compare the reliability of the results using Naïve Bayes, C4.5 and Rule base algorithms in order to search for the optimal model for prediction [23].

Meanwhile, a lot of studies related to electric consumption prediction using various methods are found in the literature [24]. For example, the use of univariate dataset was observed to feed in ARIMA(p,d,q) model in predicting electric energy usage in Eastern Saudi Arabia. Findings showed that the ARIMA(1,1,0) model is the optimum model to be used in forecasting their electric usage in monthly data [25].

Further, the statistic linear parametric model was used to measure the growth of electrical demand in Chile, particularly for residential use [26]. Meanwhile, a short-term electricity demand forecasting in Queensland, Australia was done using Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR) and Multivariate Adaptive Regression Spline (MARS), model. The accuracy of the forecast was evaluated using statistical metrics such as RMSE and MAE [27].

On the other hand, the estimation of the electricity demand in Turkey was done using ARIMA. The result revealed that their current official projection of electric consumption is way too high than the forecasted result generated using ARIMA. The overestimation in the forecast of electric consumption affects energy policy and the electricity market [28]. Meanwhile, forecasting Turkey's electric consumption was done using the artificial neural network (ANN) and regression models. The variables used were the GDP, population rate, historical data of electricity consumed, and other demographic variables and datasets in Turkey. The result revealed that prediction made using ANN was effective than those of the multiple linear regression and power regression models [29].

Moreover, the ARIMA algorithm was employed to forecast electric consumption in a healthcare institution. The datasets used was obtained from Apollo Hospital in India for the year 2005 to 2016. Various forecasting validation tools and statistical metrics such as AIC, SBC, root mean squared error (RSME) and mean percentage error(MPE) were considered in selecting the appropriate model for forecasting electric consumption in monthly, bimonthly, and quarterly period. The result showed that ARIMA(2,1,3) was the most appropriate model to be used in forecasting monthly series while the ARIMA(2,1,1) model is used for both bi-monthly and quarterly series. The data was analyzed using the three series, and it was found out that the best method to be used in forecasting the electric consumption of the said healthcare institution is the monthly forecasting method. The ARIMA(2,1,3) has the lowest RMSE and MPE value among the three models [30].

Additionally, forecasting and visualization of Philippine electricity consumption using ANN, PSO, and ARIMA were done using the historical data of electric consumption only from years 2008 to 2016. A future prediction was conducted for the years 2017 to 2021. The result revealed that the use of PSO-ANN and ARIMA models yielded the highest accuracy rate than of BP-ANN and ARIMA being tested [31].

III. METHODOLOGY

A. Datasets

The datasets used in this paper are the historical data of the Philippines' electric consumption in Megawatt Hour (Mwh) categorized as residential, commercial, and industrial use for the years 2003 to 2017. The datasets were obtained from the Philippines' Department of Energy.

B. Autoregressive Integrated Moving Average

The ARIMA(p,d,q) model is used to predict values in a time series manner where p,d,q denotes the autoregressive order, differenced t times and the moving average order respectively. The model represented in an equation below:

$$\emptyset(B)(w_t - \mu) = \theta(B)a_t \tag{1}$$

where the time index is represented by t, B as the backshift operator, $\emptyset(B)$ for the autoregressive parameter, $\theta(B)$ for MA, w_t for d value in the ARIMA(p,d,q) model and white noise a_t [32].

C. ACF and PACF

The graphical representation of the autoregressive (p) order is shown in the Partial Autocorrelation Function (PACF) plot while the Autocorrelation Function (ACF) plot denotes the moving average (q) of the model. By inspecting each ACF and PACF plot, the initial basis of the ARIMA(p,d,q) model can now be identified. The equation is stressed as:

$$P_k = \frac{\sum_{t=k+1}^{r}(Y_t-\bar{Y})(Y_{t-k}-\bar{Y})}{\sum_{t=1}^{r}(Y_t-\bar{Y})^2} \tag{2}$$

where P_k denotes the ACF coefficient in lag k, and the observed period is expressed as t, while observation in period t is denoted by Y_t. The mean is denoted by $\bar{Y}$ and lastly, the observation in t-k is expressed as Y_{t-k} [32].

D. Akaike Information Criterion (AIC)

In various papers where ARIMA modeling is observed, the candidate model with the lowest AIC value is selected and considered as the most appropriate model to be used in forecasting. Akaike Information Criterion is expressed as:

$$AIC = 1n\frac{\sum_{i=1}^{t}\hat{\varepsilon}_i^2}{T-n} + \frac{2n}{T} \tag{3}$$

where the squared residual estimate is expressed as $\hat{\varepsilon}_i^2$ and T for observation size within samples while n for estimated parameters [33].

E. Forecast Evaluation

In [34], forecast evaluation was observed employing different forecasting statistical error measures that are equated as:

Mean Absolute Percentage Error (MAPE) (4)

$$M.A.P.E. = 100 \times \sum_{t=T+1}^{T+h} |\frac{\hat{y}_t - y_t}{y_t}|/h$$

where forecast sample is denoted as $j = T+1, T+2, \ldots, T+h$ while the actual and forecasted values are denoted by y_t and $\hat{y}_t$ respectively within the t period. It is being said that the smaller the error value, the better the model.

Mean Absolute Scaled Error (MASE) (5)

$$M.A.S.E. = \frac{1}{k}\frac{|Y_t - \hat{Y}_t|}{\frac{1}{n-m}\sum_{t=m+1}^{n}|Y_t - Y_{t-m}|}$$

where the number of historical observation and time series frequency are denoted by n and m, respectively [35].

IV. Results and Simulation

A. *Graphical and Statistical Method*

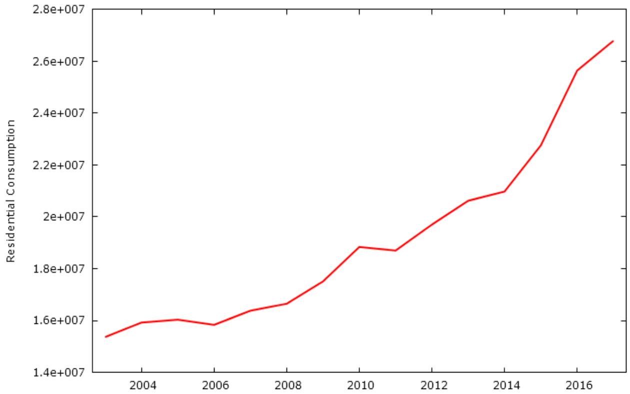

Fig. 1. Time series plot of Philippines' electric consumption allocated for residential use from 2003-2017.

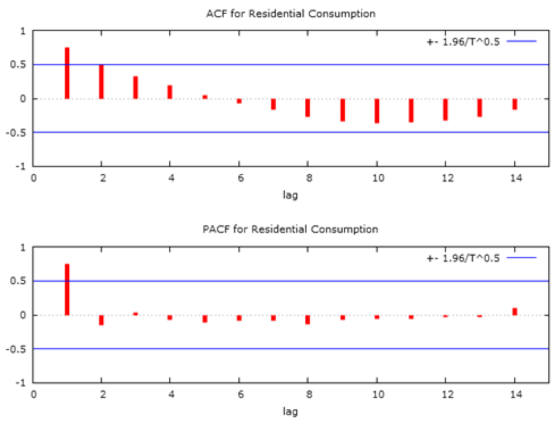

Fig. 2. Correlogram plot for residential electric consumption.

Fig. 1 displayed the time series plot for the Philippines' electric consumption that is allocated for residential use from 2013 to 2017. An upward trend is evident in the graph which denotes the increasing consumption of electricity for residential use through the years.

Fig. 2 showed the correlogram plot of both moving average (MA)(q) and autoregressive (AR)(p) models denoted by ACF and PACF, respectively, for lags 1 to 14.

Both ACF and PACF showed a pattern. The ACF is decaying, and the PACF is also decaying but in an abrupt manner. This denotes an autoregressive (p) and moving average (q) process. Meanwhile, a trend is evident in Fig. 1 making the data non-stationary. So we put value in d in the ARIMA(p,d,q) model.

The search for the optimal model to be used is shown in Tables V and VI and will be determined according to the model with the lowest Akaike Information Criterion (AIC) value.

TABLE I: ARIMA(1,1,*) Order Selection Using AIC

ARIMA Model	AIC	MAPE	MASE
1,1,1	428.41	3.145586	0.7306038
**** 1,1,2 ****	**428.33**	**2.920446**	**0.6770730**
1,1,3	429.19	2.601566	0.6074049
1,1,4	430.03	2.325064	0.5360936
1,1,5	431.95	2.307884	0.5313290
1,1,6	431.2	1.864805	0.4257474

TABLE II: ARIMA(1,2,*) Order Selection Using AIC

ARIMA Model	AIC	MAPE	MASE
**** 1,2,1 ****	**396.53**	**2.792342**	**0.6595627**
1,2,2	397.29	2.646507	0.6224351
1,2,3	397.38	2.23525	0.5200635
1,2,4	399.77	2.231395	0.5244364
1,2,5	400.39	1.896248	0.4405353
1,2,6	400.18	1.709528	0.3919931

Assigning 1 to d denotes adoptive process level while assigning 2 to d denotes adoptive trend in addition to the level of the process. As showed in Table I, the ARIMA (1,1,2) appeared to have the lowest AIC value considering d=1 while ARIMA (1,2,1) has the lowest AIC value considering d=2, as evident in Table II.

TABLE III: Summary of ARIMA(p,d,q) Model

ARIMA Model	AIC	MAPE	MASE
1,1,2	428.33	2.920446	0.677073
**** 1,2,1 ****	**396.53**	**2.792342**	**0.6595627**

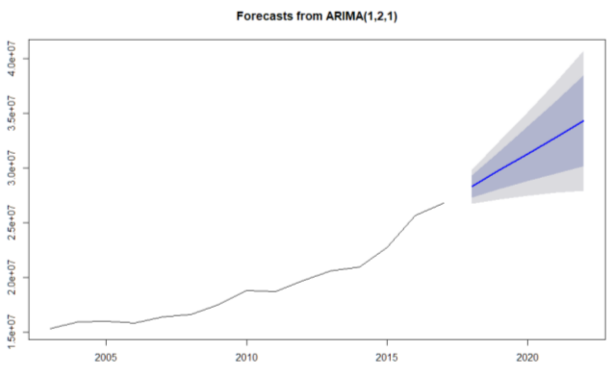

Fig. 3. Forecasted electric consumption allocated for residential use for 2018-2022 using ARIMA(1,2,1).

Table III showed that ARIMA (1,2,1) model appeared to be the statistically appropriate model to forecast the Philippines' electrical consumption for residential use. The model established the lowest AIC value as supported by the forecast error statistical tools.

Fig. 3 showed the plot of forecasted Philippines' electrical consumption allocated for residential use using the ARIMA(1,2,1) model. An increasing trend is observed from the year 2018-2022. A forecasted consumption of 28,281,111Mwh is expected by 2018 and 29,786,410Mwh for the year 2019 is depicted. Meanwhile, the specific values for the predicted electric consumption for residential use in the next five years, having a 95% confidence interval are shown in Table IV.

TABLE IV: FORECASTED VALUE OF ELECTRIC CONSUMPTION ALLOCATED FOR RESIDENTIAL USE WITH 95% INTERVAL

Year	Forecast	Lo 95	Hi 95
2018	28,281,111	26,728,399	29,833,824
2019	29,786,410	27,132,203	32,440,617
2020	31,291,820	27,480,239	35,103,401
2021	32,797,232	27,743,669	37,850,795
2022	34,302,644	27,918,704	40,686,584

An increasing trend in the Philippines' electric consumption assigned for commercial use in megawatt-hour for years 2013 to 2017 is shown in Fig. 4.

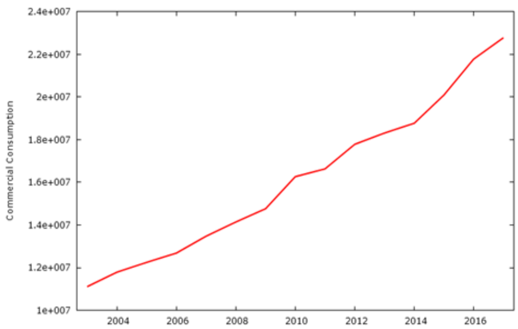

Fig. 4. Time series plot of Philippines' electric consumption allocated for commercial use from 2003-2017.

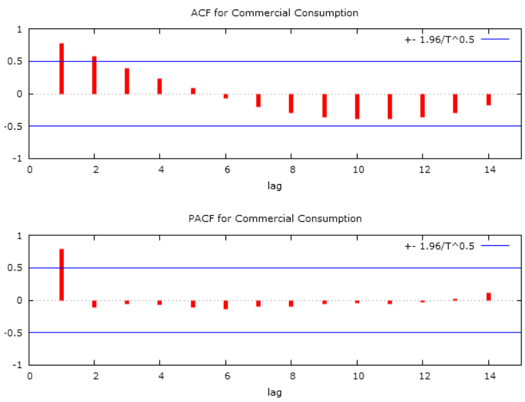

Fig. 5. Correlogram plot for commercial electric consumption.

The ACF and PACF plot with 14 lags are showed in Fig. 5. Similar characteristics like in Fig. 2 is depicted in this type of data. Hence, the p and q denote a process. We also put a value on d since the data is non-stationary as evident in Fig. 4.

The initial possible model to be used is shown in the tables below but will depend as to which model has the lowest Akaike Information Criterion (AIC) value.

TABLE V: ARIMA(1,1,*) ORDER SELECTION USING AIC

ARIMA Model	AIC	MAPE	MASE
**** 1,1,1 ****	**412.23**	**1.876225**	**0.3831316**
1,1,2	414.11	1.867566	0.3826523
1,1,3	415.45	1.591924	0.3289213
1,1,4	418.04	1.880954	0.3860897
1,1,5	417.69	1.423858	0.2911742
1,1,6	419.44	1.261452	0.2560356

TABLE VI: ARIMA(1,2,*) ORDER SELECTION USING AIC

ARIMA Model	AIC	MAPE	MASE
**** 1,2,1 ****	**381.94**	**1.712975**	**0.3582291**
1,2,2	382.59	1.515642	0.3165797
1,2,3	384.51	1.514133	0.316075
1,2,4	386.48	1.498313	0.3125714
1,2,5	387.3	1.230399	0.2566131
1,2,6	388.99	1.181283	0.2449928

TABLE VII: SUMMARY OF ARIMA(P,D,Q) MODEL

ARIMA Model	AIC	MAPE	MASE
** 1,1,1 **	412.23	1.876225	0.3831316
**** 1,2,1 ****	**381.94**	**1.712975**	**0.3582291**

Both Tables V and VI with differenced d times value of 1 and 2 respectively showed which ARIMA model is the best fitted for forecasting. Table VII showed that ARIMA(1,2,1) model appeared to be the statistically appropriate model to forecast the Philippines' electric consumption that is assigned for commercial use in the years 2018 to 2022. The model has the lowest AIC value and is supported by the forecast error evaluation statistical tools such as MAPE and MASE.

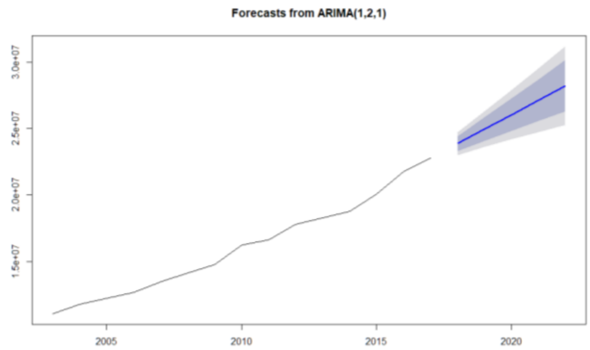

Fig. 6. Forecasted electric consumption distributed for commercial use for 2018-2022 using ARIMA(1,2,1).

TABLE VIII: FORECASTED VALUE OF ELECTRIC CONSUMPTION ALLOCATED FOR COMMERCIAL USE WITH 95% INTERVAL

Year	Forecast	Lo 95	Hi 95
2018	23,866,067	22,992,332	24,739,801
2019	24,950,677	23,604,305	26,297,048
2020	26,037,098	24,184,776	27,889,419
2021	27,123,275	24,735,429	29,511,121
2022	28,209,485	25,252,936	31,166,034

Fig. 6 showed the plot of the forecasted data of Philippines' electrical consumption allotted for commercial use with its 95% confidence interval using the ARIMA(1,2,1) model. The same increasing trend is projected from the year 2003-2022. An expected electric consumption of 23,866,067Mwh is expected by the last quarter of 2018 and 24,950,677Mwh for the year 2019 is depicted. The specific forecasted value of electric consumption for commercial use in the Philippines for years 2018-2022 is showed in Table VIII.

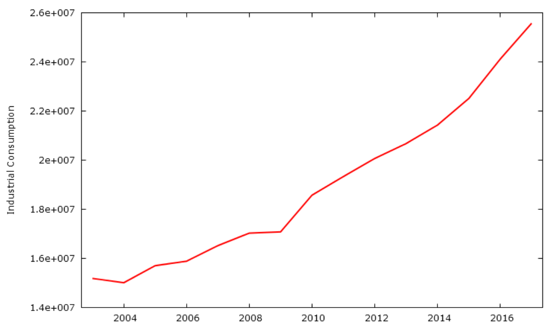

Fig. 7. Time series plot of Philippines' electric consumption for industrial use from 2003-2017.

Fig. 7 showed the plot of Philippines' electric consumption for the years 2003-2017 that is distributed for industrial use. There is a depicted increase in trend over the years.

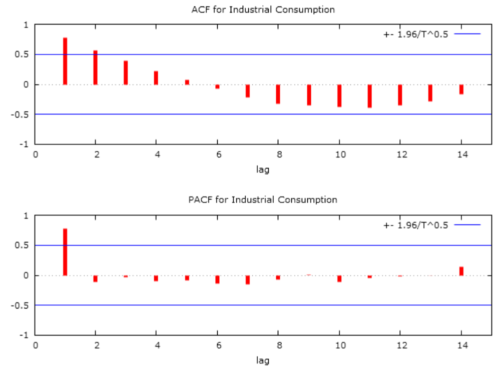

Fig. 8. Correlogram plot for industrial electric consumption.

Fig. 8 showed the ACF and PACF plot of the data with 14 lags. Both ACF and PACF exhibited a decreasing trend whereas the PACF value automatically decays to zero at lag 2 hence value is placed in the p and q as well as in the differenced d times since an upward trend is depicted in Fig. 7. The initial possible model to be used is shown in Table IX having the differenced d times value of 2 to forecast the adoptive trend in addition to the level of the process.

TABLE IX: ARIMA(1,2,*) ORDER SELECTION USING AIC

ARIMA Model	AIC	MAPE	MASE
**** 1,2,1 ****	**383.51**	**1.655751**	**0.4133418**
1,2,2	385.51	1.655938	0.4134326
1,2,3	386.81	1.51903	0.3787369

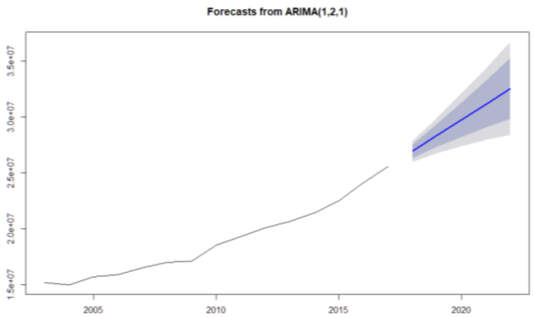

Fig. 9. Forecasted Philippines' electric consumption allotted for industrial use for 2018-2022 using ARIMA(1,2,1).

TABLE X: FORECASTED VALUE OF ELECTRIC CONSUMPTION ALLOCATED FOR INDUSTRIAL USE WITH 95% INTERVAL

Year	Forecast	Lo 95	Hi 95
2018	26,963,287	26,021,257	27,905,316
2019	28,373,297	26,809,833	29,936,762
2020	29,777,292	27,434,302	32,120,282
2021	31,183,097	27,979,602	34,386,591
2022	32,588,357	28,436,177	36,740,537

The same with the model from the previous data, ARIMA(1,2,1) model appeared be the statistically appropriate model to forecast the Philippines' electric consumption allocated for industrial use in the years 2018 to 2022.

Fig. 9 showed the plot of the forecasted data of Philippines' electrical consumption allotted for industrial use having the 95% confidence interval using the ARIMA(1,2,1) model. An increasing trend is evident in the graph from the historical years of 2003-2017 up to the predicted years of 2018-2022. The Philippines' electric consumption allocated for industrial use is expected to reach at 26,963,287 megawatt-hours by the end of this quarter and 28,373,297 megawatt-hours for the year 2019. The specific forecasted value of electric consumption for industrial use in the Philippines for years 2018-2022 is showed in Table X.

V. CONCLUSION

In this paper, the optimal ARIMA(p,d,q) model to forecast the Philippines' electric consumption distributed in three different sectors such that of residential, commercial, and industrial use for the year 2018-2022 was revealed. The assignment of ACF and PACF process as well as the differenced d value was considered. To come up with the best model, the selection based on the lowest AIC criterion was observed. Simulation results showed that ARIMA(1,2,1) model was determined to be the best fit for the Philippines' electric consumption prediction. The forecast showed an increasing trend in consumption in both residential, commercial, and industrial use having 28,281,111Mwh, 23,866,067Mwh, and 26,963,287Mwh respectively by the end of the quarter.

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Allemar Jhone P. Delima was born in Surigao City, province of Surigao del Norte, Philippines. He is a faculty under the College of Engineering and Information Technology at Surigao State College of Technology. He received his B.S. degree from Surigao State College of Technology, Surigao City, in 2014 and his master's degree from the same institution in 2016, both in information technology. He is currently pursuing his doctor in information technology degree in the Technological Institute of the Philippines, Quezon City. His research interest is in data mining, data analytics, and machine learning.