TIME SERIES MODELING APPROACH FOR FORECASTING ELECTRICITY DEMAND IN SRI LANKA

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ABSTRACT

In the midst of the current power crisis, forecasting the electricity demand has turned out to be an important component to develop the energy sector. The demand for electricity is one of the utmost essential data compulsories for assessing the quantity of extra capacity essential to make sure an adequate source of energy. Electricity manufacture and consumption are occupying a substantial role in their governmental economy for a country. Therefore, this study suggests a systematic methodology, constructed on the time series forecasting approach to forecast the effective demand of electricity in Sri Lanka. An ARIMA model is chosen to forecast the future demand of Sri Lanka, one of the fast-developing countries. Thus, public planning necessitates good predictions of forthcoming demand. The study engaged secondary data from the Sustainable Energy Authority, Sri Lanka, spanning from 1970 to 2016 and categorized into sectors utilize electricity as commercial, domestic and industrial. In this analysis, the Box-Jenkins and Autoregressive Integrated Moving Average (ARIMA) based outcomes suggested that ARIMA (1, 1, 1), ARIMA (1, 1, 3) and ARIMA (1, 1, 1) are most appropriate to forecast commercial, domestic and industrial electricity demand, correspondingly. The suggested ARIMA models are used to deliver an eight-year forecast of the electricity demands in the country. Also, the domestic and commercial demands were increasing further rapidly than demand in the industrial sector.

Keywords: Electricity, ARIMA, Forecasting, Sri Lanka

1. INTRODUCTION

Electricity is inevitability in the modern world. Satisfactory power supply empowers improved public health and economic growing. Developing countries face exceptional challenges in arranging the power network organization to needed to backing rapidly growing town residents. In this study, 47 years' value of data on growing demand for electricity in Sri Lanka, categorized by sector as commercial, domestic and industrial to forecast energy requirements. This estimate should support city organizers and the administration of Sri Lanka in constructing upcoming prosperity. Conferring to the previous studies, different sorts of elements are straightly affected by the electricity demand of the country. Specific of them are; the increasing populations, wide development, industrial development of economies and progressively larger use of electrical utilizations in everyday lifespan have been contributed openly to upsurge the demand of electricity.

In general, the electricity is generated through out three main sources in Sri Lanka. Those are; thermal power (energy from biomass, coal, and all other fuel-oil sources), hydro-power (comprising small hydro), and other non-conventional renewable energy sources (solar power and wind power) (Sri Lanka Energy Balance Data). Based on the financial reports in 2016, the total electricity generation and total electricity consumption in Sri Lanka is over 14,361.3 GWh (Giga Watts per hour) and 12715 GWh correspondingly, and for the year 1970,

while those for the year 1970 is, 785.7GWh and 619.51 GWh respectively (CEB Statistics, 2014). Also, it is observed that 138.3GWh, 371.46GWh and 90.8GWh utilized by the sectors commercial, domestic and industrial in the year of 1970 and it is increased to 4798.88 GWh, 4141.84 GWh and 3535.51GWh in 2016. (CEB Statistics). Also, the statistics recommended that, the total electricity demand has been increasing rapidly. Because of these conditions, forecasting effective electricity demand in Sri Lanka is occupying a significant part for their prospect development.

Grounded on the available literature, studies connected to the electricity demand are restricted and also have established on the foreign literature. One of the studies carried out by Cooray & Peiris to forecast day and night peak values of electricity demand in Sri Lanka for week-days and weekends using a state space based on structural time (SSST) series model (Cooray & Peiris, 2012) and another study was done by Dissanayake & Perera, fitted an Autoregressive Integrated Moving Average (ARIMA) model to forecast for future domestic electricity demand for Sri Lanka by using quarterly data of Electricity demand from 1997 to 2013 (Dissanayake & Perera, 2013). Also, a sector wise Electricity demand in Sri Lanka was studied throughout a Vector Autoregressive Model by K. A. N. K. Karunarathna and K. Vithyasangaran (2017).

The existing study emphases on analyzing and forecasting the sector wise electricity demand in Sri Lanka over the past 47 years' value of data. The remaining is systematized as follows: Segment II describes about the brief outline of the methods and materials. Segment III examine and compare Sri Lankan electricity demand consequences and Segment IV wind up with the conclusion and upcoming work.

2. METERIALS AND METHODOLOGIES

Most of the developing countries including Sri Lanka face the epileptic problem which is observed when the demand for electricity surpasses its supply (Gam, I and Rajeb, J., 2012). Electricity demand forecasts are usually obligatory for the development, regulate and arranging of power schemes. The predictions benefit in defining the optimal mix of producing capabilities and which strategies to activate in a specified period, in order to reduce cost and guarantee supply even when limited failures might befall in the scheme. The required data was mined from the record of Sri Lanka Sustainable Energy Authority (Sri Lanka Energy Balance); particularly, sector wise total electricity demand (consumption) in Sri Lanka (GWh) from the year 1970 to 2016. The E-Views (version 9) and Minitab (version 16) were used to analyze the data.

2.1. Test for Unit Root

As the preliminary stage, stationary and non-stationary conditions of the series were estimated built on two different unit root statistics, Augmented Dickey-Fuller (ADF)

and Phillips-Perron (PP) test statistics. If series not stationary then systematic differencing will be implied.

2.2. Time series methods of forecasting

In the year of 1976, Box and Jenkins suggested a collection of models, called Auto Regressive Integrated Moving Average (ARIMA) models which can be applied to a huge variety of conditions of non-stationary series (Ariffin, S., Kann, A. and Alwi, A. S., 2013). ARIMA models are exactly suitable for short term predictions. This significance on the recent past proposes that the short-term predictions from ARIMA models are more consistent than long-term predictions, (Pankratz, 2012). ARIMA model is a simplification of an Autoregressive moving average model. Mostly, it involves three portions; the auto regressive parameter (p), the number of differencing permits (d) and moving average parameter (q). The ARIMA (p,d,q) can be written as follows.

$$dy_{t} = \alpha_{0} + \alpha_{1}dy_{t-1} + \dots + \alpha_{p}dy_{t-p} + \beta_{1}e_{t-1} + \dots + \beta_{q}e_{t-q} + e_{t}$$
 (1) Where;

 dy_t – differenced series

 e_t – Sequence of independent random variables

 α_i , β_i are fixed constant (i=0,1,...,p and j=1,2,....,q)

The study is carried out in three phases; those are, data analysis, identification of best model and validation model and forecasting. Specially, Box Jenkins methodology was applied for fitting the suitable ARIMA model. Moreover, the best model was nominated by using the least values of Akaike Information Criterion (AIC) value, Schwarz's Bayesian Information Criterion (BIC) value and Hannan-Quinn Criterian (HQIC) value. The coefficients of the best models were checked using the wald test.

2.3. Diagnostic Tests for Model Adequacy

As the following step, the diagnostic tests were made on the residuals to realize their randomness and pattern of normal distribution. Also to signify the normality of outcomes, the Jarque-Bera test and ARCH test for Heteroskedasticity were utilized (Khan, M. A. and Qayyum, A., 2009). The correlations of the residual series of three sectors were observed through their corresponding ACF and PACF plots. If the residuals series of designated model accepted diagnostic checking, then the model could be used in forecasting future values.

3. RESULTS AND DISCUSSIONS

3.1. Results of Unit Root Test

The time series plot below designates that the demand monitors an increasing trend and most of the points are not placed around zero. This suggests that the demand series is not stationary and hence essential to execute a unit root test for additional inquiries.

Figure 1: Time series plots of sector wise Electricity Demand of Sri Lanka (1970-2016)

The estimated results of unit root test are presented in Table 1 as follows and illustrates that all three variables are stationary at order one by rejecting the null hypothesis; the series are non-stationary at 5% significance level.

Table 1: Test Results of Unit	Root Test
Augmented Dickey–Fuller	Phillip

variables	Augmented Dickey–Fuller	Phillip-Perron				
ln(COM)	0.8555	0.8139				
$\Delta ln(COM)$	0.0000***	0.0000***				
ln(DOMS)	0.3736	0.3736				
$\Delta ln(DOMS)$	0.0000***	0.0000***				
ln(IND)	0.6938	0.5084				
$\Delta ln(IND)$	0.0000***	0.0000***				

Note: **** Denotes Significance at 5% Level

Figure 2: Time series plots of first differenced series of sector wise Electricity Demand of Sri Lanka (1970-2016)

Figure 2 reveals that the first differenced series of three sectors, commercial, domestic and industrial shows a stationary pattern (Yasmeen F, Sharif M., 2015).

3.2. ARIMA Procedure

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Figure 3 provides a spike at lag 1 indicating an Autoregressive component of order one, AR(1) in the PACF correlogram whiles the ACF correlogram indicates a spike at lag 1,2 and 3 representing a moving average process of order 1,2 and 3; MA(1), MA(2) and MA(3) for commercial electricity demand.

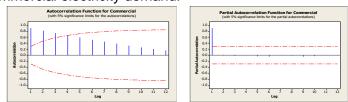


Figure 3: ACF and PACF plot of Commercial Electricity Demand

For domestic electricity demand, AR(1) and a moving average process of order 1,2, 3 and 4; MA(1), MA(2), MA(3) and MA(4) were obtained. Similarly, for industrial electricity demand AR(1) and a moving average process of order 1,2, and 3; MA(1), MA(2) and MA(3) were obtained throughout their corresponding PACF and ACF plots (Ruwanthi KDR, Wickremasinghe WN, 1999).

3.3. Model Selection and Parameter Estimation

Table 2: Selection of ARIMA model for sector wise electricity demand

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Model	AIC	BIC	HQIC					
Commercial								
ARIMA(1,1,1)	11.30563*	11.46464*	11.36520*					
ARIMA(1,1,2)	11.34282	11.54159	11.41728					
ARIMA(1,1,3)	11.64461	11.88313	11.73396					
	Domestic							
ARIMA(1,1,1)	12.05046	12.20947	12.11003					
ARIMA(1,1,2)	11.91810	12.12687	11.99256					
ARIMA(1,1,3)	11.88777*	12.11628*	11.97712*					
	Industry							
ARIMA(1,1,1) 12.38049* 12.53950* 12.44006*								
ARIMA(1,1,2)	12.44223	12.64100	12.51669					
ARIMA(1,1,3)	12.43980	12.67831	12.52915					

Note: * denote the least information criterion values

ARIMA (1, 1, 1), ARIMA (1, 1, 3) and ARIMA (1, 1, 1) as indicated above were selected as the best models since they have minimum AIC, BIC and HQIC (Abde-Aal, R.E. and Al-Garni, A. Z., 1997).

Table 3: Estimates of Parameters for best models - WaldsTest

		Table 6. Estimated 617 diameters for bost models. Trainer out						
	Sectors	Model	Estimates	Std.error	p-value	95% CI		
			of Coeffi. Coeffi.		P 13	Lcl	Ucl	
	Commercial	ARIMA(1,1,1)	106.9835 0.979566 -0.684402	104.9990 0.064422 0.144205	0.3141 0.0000 0.0000	-104.9130 0.849557 -0.975420	318.8799 1.109575 -0.393384	
	Domestic	ARIMA(1,1,3)	88.43553 0.958906 -1.046987 -0.315415 0.678282	119.5264 0.083347 0.152120 0.178637 0.119619	0.4637 0.0000 0.0000 0.0851 0.0000	-153.1364 0.790455 -1.354434 -0.676455 0.436522	330.0075 1.127358 -0.739540 0.045625 0.920042	
=	Industry	ARIMA(1,1,1)	84.58459 0.940597 -0.875618	46.51304 0.215900 0.286106	0.0761 0.0001 0.0038	-9.282532 0.504894 -1.453003	178.4517 1.376299 -0.298233	

Hence the proposed ARIMA models for forecasting commercial, domestic and industrial electricity demand for three sectors (commercial, domestic and industrial respectively) in Sri Lanka are given by:

$$\Delta y_t = 106.9835 + 0.979566 \, \Delta y_{t-1} - 0.684402 \, \varepsilon_{t-1} + \, \varepsilon_t$$

$$\Delta y_t = 88.43553 + 0.958906 \Delta y_{t-1} - 1.046987 \varepsilon_{t-1} - 0.315415 \, \varepsilon_{t-2} + 0.678282 \varepsilon_{t-2} + \, \varepsilon_t$$

$$\Delta y_t = 84.58459 + 0.940597 \, \Delta y_{t-1} - 0.875618 \, \varepsilon_{t-1} + \, \varepsilon_t$$

3.4. Model Diagnostic

P-value ARCH-LM Test for Normality of Model Hetroschedasticty Residuals 0.442535* 0.9195* Commercial ARIMA(1,1,1) 0.0937* 0.984270* **Domestic** ARIMA(1,1,3) 0.1701* 0.108442* Industry ARIMA(1,1,1)

Table 4: Test for Hetroschedasticty and Normality of Residuals of Jarque-Bera Test

Note: * fail to reject null hypothesis of no ARCH effect and existence of normality of residuals at 5% level

The null hypothesis of "no ARCH effect" is tested using the ARCH–LM test and Table 4 exhibits that there is no heteroschedasticity exist in the final models as the relevant p-values are greater than 0.05 alpha level. Also, the normality test signifies the probabilities greater than 0.05 alpha level suggests that the residuals follow a normal distribution.

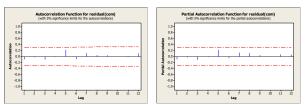


Figure 4: ACF and PACF plot of Commercial Electricity Demand

From Figure 4, the residuals are within the 95% confidence interval indicating that the residuals are insignificant that they reveal an uncorrelated pattern of mean approximately zero and a constant variance for commercial sector. The same ACF and PACF plots were obtained for the other two sectors as well.

3.5. Forecasting with ARIMA model

From the above diagnosis test, the suggested ARIMA models for Commercial, Domestic, and Industrial electricity demand can be supposed to be the best in terms of forecasting for electricity demand in Sri Lanka (Erdogdu, 2007). ARIMA models are principally established to estimate the consistent dependent variable. There are two types of predictions: sample period predictions and post sample period predictions. The sample period prediction is used to develop confidence interval in the model and the post sample forecast is used to generate genuine forecasts for planning and other purposes.

Table 4: Sector wise Electricity Demand Forecasted for the Periods of 2017 and 2024 at 95% Confidence Interval

	CO/V COMMONICO MICO VAI								
	ARIMA(1,1,1)			ARIMA(1,1,3)			ARIMA(1,1,1)		
Year	Forecast 95% CI		Forecast	95% CI		Forecast	95% CI		
	(Comm)	LCL	UCL	(Dome)	LCL	UCL	(Indu)	LCL	UCL
2017	3765.032	3622	3908	4829.52	4660	4999	4255.972	4011	4501
2018	3992.05	3745	4236	4895.384	4657	5134	4368.349	3987	4750
2019	4216.615	3859	4574	5079.045	4816	5342	4479.075	3971	4987
2020	4438.777	3962	4915	5258.792	4948	5570	4588.248	3956	5221
2021	4658.586	4052	5265	5434.786	5053	5816	4695.961	3938	5454
2022	4876.09	4128	5624	5607.183	5137	6077	4802.299	3917	5687

2023	5091.335	4191	5992	5776.129	5203	6350	4907.346	3893	5922
2024	5304.368	4240	6369	5941.767	5253	6631	5011.176	3864	6158

The table above displays the values of the forecast of sector wise electricity demand from 2017 to 2024. The given upper and lower limits designate the choice with which the forecast values can spread or decrease to correspondingly.

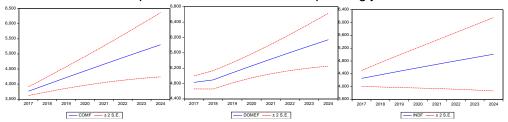


Figure 4: ACF and PACF plot of Electricity Demand sector wise

The forecast values were produced by the help of the selected three ARIMA models. By comparing the scales of the forecast values, it can be detected that there is a significant upsurge from 2017 down to 2024, representing a comparative growth in the demand of electricity with time for the all three sectors.

4. CONCLUSION

This study utilizes an ARIMA model to forecast annual electricity demand in Sri Lanka, sector wise. Data gained from Sri Lanka Sustainable Energy Authority clustered customers into commercial, domestic and industrial sectors. This finished it essential to produce diverse models to forecast demand from every sector. Using ordinary procedures for choosing the order of a time series, we found that an ARIMA (1, 1, 1) model as long as the best fit for commercial customer demand. Correspondingly, the domestic demand was best labeled by an ARIMA (1, 1, 3) model and industrial demand was best illustrated by an ARIMA (1,1,1) model. Model diagnostics exhibited that all of the residuals seemed to be random and normally distributed, as one needs. This authorizes that the designated models are suitable. The suggested models were then used to forecast eight years forecast of the various sectors' electricity demand, ranging from 2017 to 2024.

The forecast plot of the various electricity demand presented that the commercial and domestic electricity demand increases with time though the industrial demand rises more slowly. Based on the results of the study, we can conclude that ARIMA (1, 1, 1), ARIMA (1, 1, 3) and ARIMA (1, 1, 1) can be suitable to forecast commercial, domestic and industrial electricity demand in Sri Lanka. The estimates advise that significant development in commercial and domestic electricity demand can be predictable in Sri Lanka for the years 2017 to 2024. The forecast development in commercial and domestic electricity demand is reliable with the growth in population and the growing economic movements in the country. The country turns out to be the location of many corporations in South Asia and this has facilitated to determine its significant development.

REFERENCES

- Abde-Aal, R.E. and Al-Garni, A. Z. (1997). Forecasting monthly electric energy consumption in eastern Saudi Arabia using univariate time-series analysis. Energy 1997, 22, 1059-1069.
- Adom PK, Bekoe W, Akoena SKK. (2012). Modelling aggregate domestic electricity demand in Ghana: An autoregressive distributed lag bounds cointegration approach. 42, 530-537.
- Ariffin, S., Kann, A. and Alwi, A. S. (2013). Electricity Load Forecasting in UTP using Moving Average and Exponential Smoothing Techniques.
- Erdogdu, E. (2007). Electricity demand analysis using cointegration and ARIMA modelling: A case study of Turkey. 35(2), 1129-1146.
- Gam, I and Rajeb, J. (2012). Electricity demand in Tunisia. Energy Policy, 714-720.
- Khan, M. A. and Qayyum, A. (2009). The Demand for Electricity in Pakistan. OPEC Energy Review.
- Ruwanthi KDR, Wickremasinghe WN. (1999). Modelling sector-wise demand for electricity in Sri Lanka using a multivariate regression approach. 27(1), 55-64.
- Yasmeen F, Sharif M. (2015). Functional Time Series Forecasting of Electricity Consumption in Pakistan. International Journal of Computer Application, 15-19.