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Sudan Load Forecast for Period 2017 – 2066 Using Seasonal Time Series Model

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Abstract: The importance of this paper is the use of seasonal time series models (some seasonal models of Box & Jenkins) to predict electricity consumption in Sudan National Grid, making it easier to estimate consumption, and provide accurate indicators for planners to develop appropriate future plans in electricity sector. The objective of this paper is to forecast the electric load consumption using different model.

Keywords: *Seasonal Time Series, Electrical Load Forecast***.**

1. INTRODUCTION

This paper deals with using seasonal time series models to study and analyze the monthly consumption data of electricity in Sudan national grid for the period (2007 – 2016), whereas these models are distinct with high accuracy and flexibility in analysis time series.

During the last decade, the annual peak load in Sudan grew steadily at around 13% per year, similar to the growth of energy consumption. In 2011, the annual peak load was 1,517 MW (gross, at generator output), nearly double the peak load in 2006 [1]. The load curve of the national grid varies between seasons as well as between weekday and weekend. The rapid growth in Sudan economy has been accompanied by a remarkable increase in energy consumption including electricity.

2. Assumptions

The study is based on two basic hypotheses:

1. The monthly electricity consumption in the period 2007 – 2016 has been unstable and growing at relatively increasing rates.
2. Forecasting the electricity consumption of the national grid in Sudan is an essential input for the preparation of the estimates of energy consumed, and thus the development of strategic plans and programs.

A. Methodology and tools used

This study is a combination of the analytical approach in the theoretical side and the case study approach in the applied side. Therefore, the study has been divided into two parts: the theoretical part, in which the theoretical bases of the seasonal time series models in terms of the general form, stages of model construction, methods of estimation and prediction. On the Practical side, an empirical study was conducted on realistic data on electricity consumption in the Sudanese National Grid to reach a mathematical model for predicting Electricity Consumption for subsequent periods. The tool used in this study is Minitab.

3. Teoretical part

A. **Seasonal Time Series:** Seasonality is difficult to determine if it is integrated with the general trend and this is a problem that can be avoided by determining the seasonality when the data is stable. In other words, the general trend in the data means that it is unstable and can therefore be converted to stable data using differences. Some statistical criteria that are used to describe the quality and timeliness of the time series are:

a. Autocorrelation (AC)

The coefficient of correlation is defined as a measure of the degree of relationship between the values of the variable itself at different seasonal intervals. The coefficient of self-correlation in the case of seasonal time series at offset (s) is estimated by the following formula [2]:

$$\widehat{\rho_s} = \frac{Cov(Z_t, Z_{t+s})}{\sqrt{\mathrm{Var}(Z_t)\mathrm{Var}(Z_{t+s})}} = \frac{\sum_{t=1}^{n-S}(Z_t - \overline{Z})(Z_{t+s} - \overline{Z})}{\sum_{t=1}^{n}(Z_t - \overline{Z})^2} \quad (1)$$

Where: Z_t: Time series parameter observation

b. Partial Autocorrelation (PAC)

The Partial auto-correlation coefficient is defined as a measure of the degree of relationship between the Z_{t+S} and Z_t observations, with the rest of the other observations $Z_t + 1 \ldots Z_{t+S-1}$.

The Partial auto-correlation Function (PACF) is no less important than the Autocorrelation function (ACF). It is also an important tool in time series analysis. It is also used to diagnose and quantify the model and to examine the suitability of the model by random sampling of the prediction errors [2].

B. Seasonal Time Series Models

Seasonal Autoregressive Model (SAR)

The mathematical formula of the seasonal auto-regression model (p) follows the following [3].

$$Z_t = \Phi_S Z_{t-S} + \Phi_{2S} Z_{t-2S} + \Lambda\ \Lambda + \Phi_{PS} Z_{t-PS} + a_t \quad (2)$$

Whereas:

Z_{t-is}: Values of seasonal time series observations i = 0, 1, 2... P

S: Seasonal period length

Φ_{is}: Parameters of Seasonal Self-Regression, i= 1, 2, 3 ...p

p: The degree of the seasonal model

a_t: Random error, where: $a_t \sim NID\ (0, \sigma_a^2)$

In order to achieve stability, the roots of the equation must be:

$$\Phi_S (B^S) = 1 - \Phi_S \qquad B^S = 0 \quad (3)$$

Out of the unit circle, that is, in order for the model to be stable it must be: $-1< \Phi_S <1$

Where B is the back-shift operator known as:

$$B^S Z_t = Z_{t-s} \qquad \forall\, s = 1, 2, K\ K \quad (4)$$

C. Testing Stability of Time Series

Most applied studies using time series data assume that the series is stable or static, whereas most economic time series are characterized by instability due to instability of surrounding conditions. Through time series propagation, Auto-correlation function (ACF) and Partial Auto-correlation function (PACF) are used to determine the stability or non-stability of the series. The instability is due to one of the following reasons [4]:

- The existence of a general trend.
- The existence of seasonal fluctuations.
- Instability of variance and the arithmetic mean.

a) If variance is inconsistent:

One of the most important conversions used to fix string variation is to obtain the natural logarithm of string data, or to obtain its square root or inverted data.

b) In case of general trend:

One of the methods used to get rid of the general trend is the following:

a. Linear regression method in estimating the general trend and then isolating it and dealing with the residuals as a stable time series and calling this global de-trending.

b. The method of variance: This method requires subtracting the values of the views from each other for certain periods of delay, such as the first degree differences take shape:

$$y_t = \nabla Z_t = Z_t - Z_{t-1} \quad (5)$$

The second-order differences take the following form:

$$y_t = \nabla^2 Z_t = \nabla Z_t - \nabla Z_{t-1}$$
$$= Z_t - 2Z_{t-1} + Z_{t-2} = (1 - B)^2 Z_t \quad (6)$$

D. Elimination of Seasonal Fluctuations (Seasonal Elimination)

To strip the time series of the seasonal element, the seasonal difference is used by subtracting the values from each other according to the deceleration intervals consistent with the data type [4]:

Quarterly differences $y_t = Z_t - Z_{t-4}$

Monthly differences $y_t = Zt - Z_{t-12}$

E. Stages of Building Seasonal Model

a) Identification

After achieving the stability in the seasonal time series, the process of determining the appropriate model for the representation and grade of the series begins with the use of the Auto-correlation Function (ACF) and the Partial Auto-correlation Function (PACF). This method is based on the accuracy of the ACF and PACF graphs. The Auto-correlation coefficients of the seasonal time series are correlated with the theoretical behavior of the Auto-correlations and the Partial Auto-correlation shown in Table 1 [5].

Table1. The Nature of the Model, According to Auto-Correlation Curve.

Model	Auto-correlation Function (ACF)	Partial Auto-correlation Function (PACF)
SAR(PS)	The behavior of the sinusoidal function gradually disappears. (Decays Exponentially)	Displacement after seasonal displacement (Cuts - off)
SMA(QS)	Cut Off After Seasonal Offset Ps (Cuts - off)	The behavior of the sinusoidal function gradually disappears. (Decays Exponentially)
SARMA (PS,QS)	The behavior of the sinusoidal function gradually disappears. (Decays Exponentially)	The behavior of the sinusoidal function gradually disappears. (Decays Exponentially)

Table 2. Monthly Consumption of Electricity in Sudan Electric Network for the Perio4d (2007-2016)

Year/Month	2007 (MWh)	2008 (MWh)	2009 (MWh)	2010 (MWh)	2011 (MWh)
Jan	268497	332738	391701	479654	490309
Feb	301442	317925	390535	463947	520535
Mar	330160	421436	434160	558725	623539
Apr	397480	445001	516328	610642	669266
May	446766	477253	552411	699868	777633
Jun	448096	478047	585991	714008	797548
Jul	424302	483756	577390	678652	820555
Aug	400722	462738	608554	712271	822249
Sep	443469	494436	617997	688252	781245
Oct	480949	495484	615127	734517	820512
Nov	411426	432224	502695	629108	595959
Dec	360030	399819	445027	554417	606691
Year/Month	**2012**	**2013**	**2014**	**2015**	**2016**
Jan	554040	661474	721508	773410	827744
Feb	636172	677683	723839	854338	899749
Mar	718562	836353	948699	1088588	1244781
Apr	804893	863355	1052259	1051643	1283687
May	910595	989966	1114447	1275702	1502717
Jun	885303	993690	1143844	1324738	1508948
Jul	884565	1077013	1137746	1374284	1337975
Aug	838904	877253	1049190	1258756	1322497
Sep	860936	968625	1067424	1213092	1327419
Oct	856344	945520	1043222	1317262	1435543
Nov	741575	822424	908365	1031549	1229523
Dec	668038	740782	883839	845627	1090542

Source: National Control Center - Sudan Electricity Holding Company – Sudan

b) Estimation

After determining the appropriate model, its parameters are estimated using one of the complete or approximate estimation methods which differ according to the model used [6].

1. Exact Maximum Likelihood Method (EML)
2. Exact Linear Least Square Method (EML)

c) Diagnostic Checking of Model

After estimating the model, the suitability or validity of the model must be chosen to represent the time series data. There are two methods [7]:

1. The coefficients of the model must have a statistical significance, which is significantly different from zero.
2. Residual analysis.

d) Forecasting

After determining the appropriate model through the stages of diagnosis and estimation and checking the suitability of the model is used in the prediction of future values to (L = 1,2,3, ...) the next period by taking the conditional expectation at time (t) to obtain the predictions $Z_t(L) = Z_{t+L}$ with the mean of the least predictive error boxes. Using the Equations Formation formula that contains current and previous values of Zt and current and prior error values (at), predictions of the seasonal mixed model can be calculated as follows [8].

$$Z_{t+L} = \hat{Z}_t(L) = \widehat{\Phi}_s Z_{t+L-S} + \widehat{\Phi}_{2s} Z_{t+L-2S} + \Lambda\Lambda + \widehat{\Phi}_{ps} Z_{t+L-ps} + a_{t+L} - \widehat{\Theta}_s a_{t+L-S} - \widehat{\Theta}_{2s} a_{t+L-2S} - \Lambda\Lambda - \widehat{\Theta}_{Qs} a_{t+L-QS} \quad (7)$$

Whereas:

$a_{t+L} = E(a_{t+L})$; $Z_{t+L} = E(Z_{t+L})$

4. Application side

A. Data description:

The data used in this study consists of a monthly time series of (120) observations representing the actual monthly consumption of electricity of the national grid in Sudan (2007-2016), estimated in megawatts / hour and for all consumption categories (domestic, commercial, governmental, street lighting and exemptions. ...), which was taken from the data of the National Control Center in Sudan as in Table (2), which extends from January 2007 to December 2016 with an average of 767,256 MWh and a minimum value of 268,497 MWh recorded in 2007 and a maximum value (1,508,948 MWh) recorded in 2016. The values of this series differ from their average by a standard deviation of (303,923), which gives us an idea about the degree of heterogeneity of time series data.

The number of observations is sufficient to assume that the chain follows a natural distribution and therefore can be diagnosed in the best way.

B. Time series analysis:

a) Time series plot:

Before starting the time series analysis, the time series data in Table (2) were plotted for the period (2007-2011) as shown in Figure (1) to identify their initial characteristics and compare them with subsequent years (2012-2016) to check model's

Year/Month	2007 (MWh)	2008 (MWh)	2009 (MWh)	2010 (MWh)	2011 (MWh)
Jan	268497	332738	391701	479654	490309
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Year/Month	**2012**	**2013**	**2014**	**2015**	**2016**
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Dec	668038	740782	883839	845627	1090542

validity.

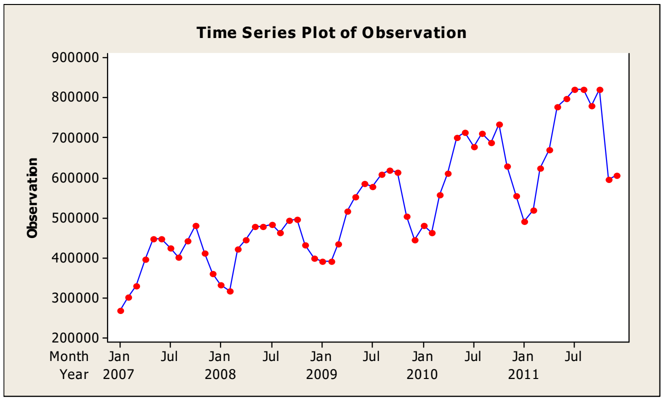

Fig.1. Monthly Consumption Curve of Electric Power for the Period 2007-2011

It is noticeable from figure 1 that there is an increasing general trend with time as well as the presence of oscillations represented in the spines and spikes and these fluctuations are repeated regularly and at the same pace each year with different frequency of increasing from yearly.

b) Time series stability test:

For the purpose of obtaining stability, the series is drawn as in figure (1). It is clear that the chain is unstable.

c) Remove the Chain instability:

1. Elimination of General Trend:

In order to remove the general trend, the differences were taken from the first order and we obtained the modified series where:
$\nabla Z_t = Z_t - Z_{t-1}$

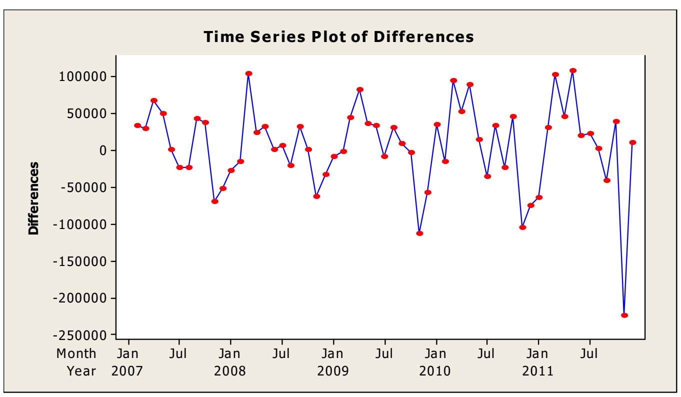

Fig.2. the Observations after Taking the First Differences for the Years 2007-2011

Figure 2 shows the curve of the modified time series after taking the first difference. From the observation of the shape, it is found that the curve is parallel to the axis of the joints, which indicates the absence of the general trend in the chain with the survival of the seasonal movement, that is, the series is unstable and this is confirmed by the statistics of Box and Jenkins.

2. Elimination of Seasonal Trend:

Considering the values of the Auto-correlations of the modified time series after taking the first difference shown in Figure 2 indicating that the time series is seasonal, i.e., it repeats itself every 12 months. Therefore, for the purpose of elimination of seasonality, differences were taken from class 12. We obtained the modified series where:

$\nabla\nabla_{12} Z_t = Z_{t-1} - Z_{t-12}$

From the observation of these forms, it is found that the stability has been achieved somewhat, and in Figure (2) it is found that there is a general trend in the data and to confirm that and in order to know the nature of the series were extracted the intrinsic and partial correlation coefficients, as in Figure (3),(4).

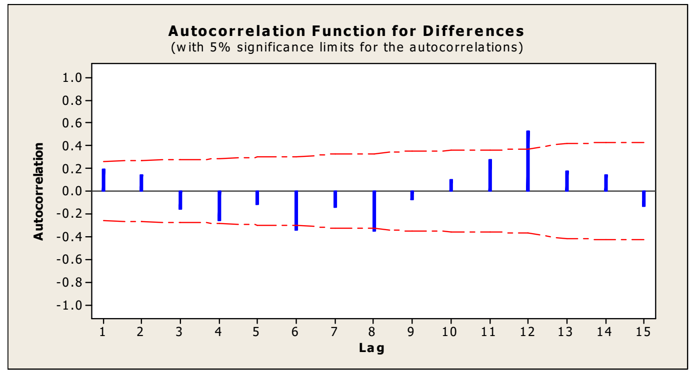

Fig.3. Auto-Correlation after taking the first Differences (2007-2011)

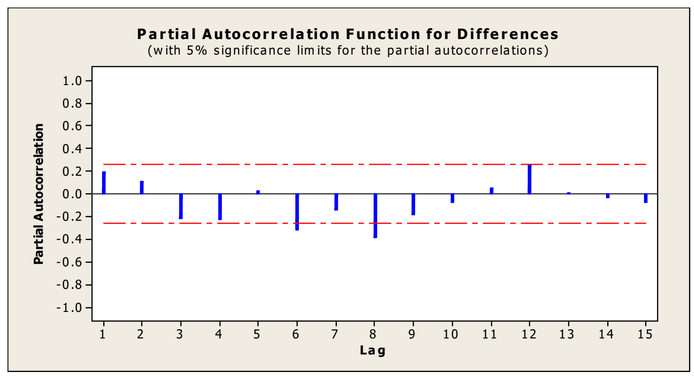

Fig.4. Partial Auto-Correlation after Taking the First Differences (2007-2011)

Which shows that the coefficients of the Auto-correlation function differs significantly from zero.

A. Identification:

The identification of the model by the rank of models AR and MA, depending on the form of the (conelogramme), and when matching the values of the coefficients of Auto-correlation and the Partial Auto-correlation of the time series after taking the first and seasonal differences as in Figures (3) (4) with the theoretical behavior shown in Table (1), it is clear that the Auto-correlation (ACF) and PACF of the sample decreases gradually with the increase of the displacement periods (k) and the result that the model is the double seasonal model of class:

SARIMA $(1 , 1 , 1)x(1 , 1 , 1)_{12}$
or

$$(1 - ø_1 B)(1 - B)(1 - B^{12})Z_t = (1 - \theta_1 B)(1 - \Theta_1 B^{12})a_t \qquad (8)$$

B. Forecasting:

Using ARIMA forecasting model, the monthly consumption quantities of the electric power for the years 2012-2016 were predicted. The results are presented in Table 3 and the time series of these predictions are drawn. It is clear that the series for the forecasted period follows the same behavior as the original series.

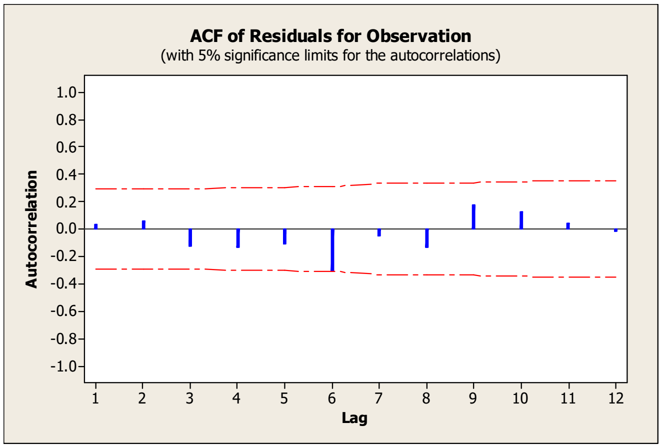

Fig.5. Auto-Correlations of the Forecasted Values 2012-2016

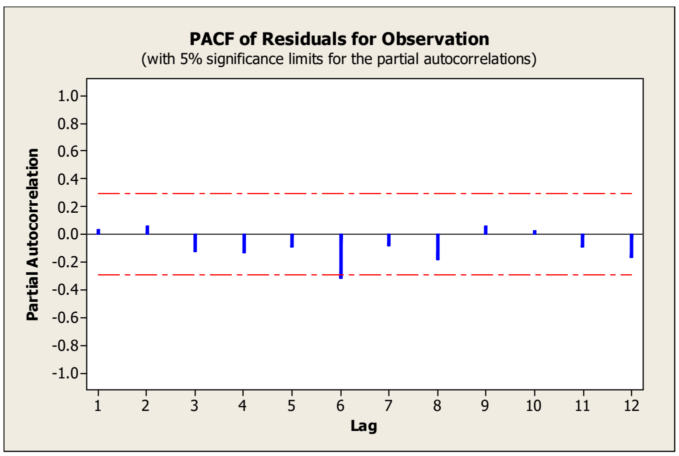

Fig.6. Partial Correlations of Forecasted Values for Years 2012-2016

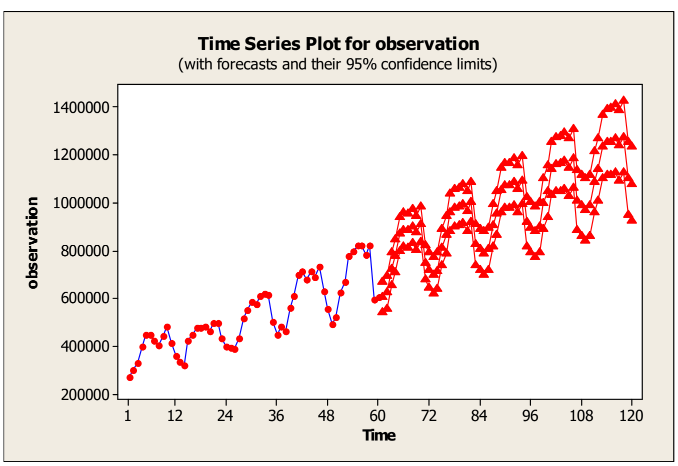

Fig.7. Forecasted Values for Years 2012-2016

5. Electricity Load Forecast of Sudan National Grid for period 2017 to 2066

A. Plot time series:

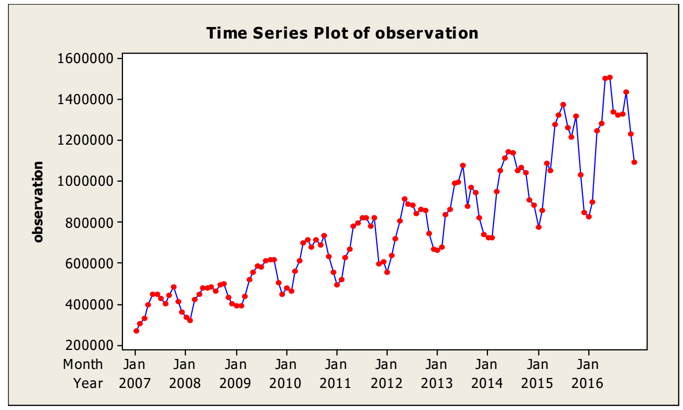

Fig.8. Monthly Consumption Curve of Electric Power for the Period from 2007 to 2016

B. Time series stability test:

In order to obtain stability in variance, the data were treated by taking the differences.

- **Elimination of Chain Instability:**

a) Elimination of the general trend:

In order to remove the general trend, the differences were taken from the first order and we obtained the modified series where:

$\nabla Z_t = Z_t - Z_{t-1}$

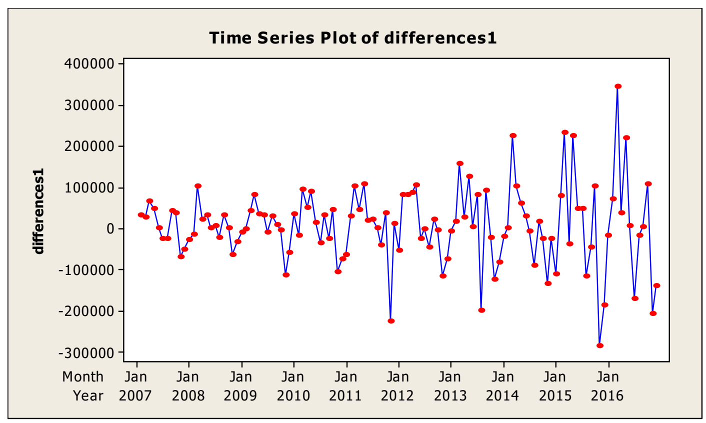

Fig.9. Observations after Taking the First Differences for the Years 2007 – 2016

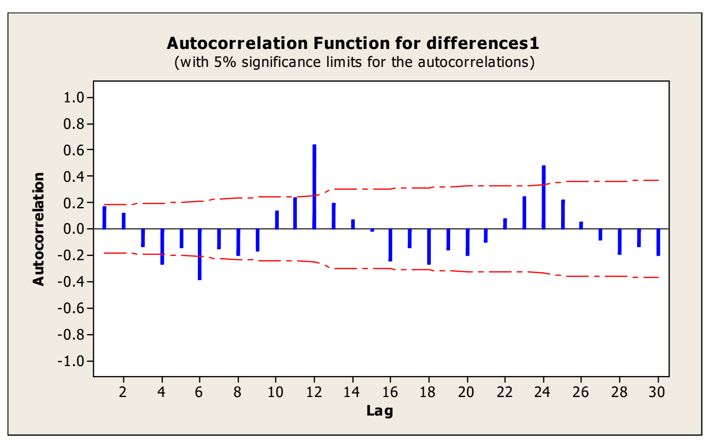

Fig.10. Auto-Correlation after Taking the First Differences (2007 - 2016)

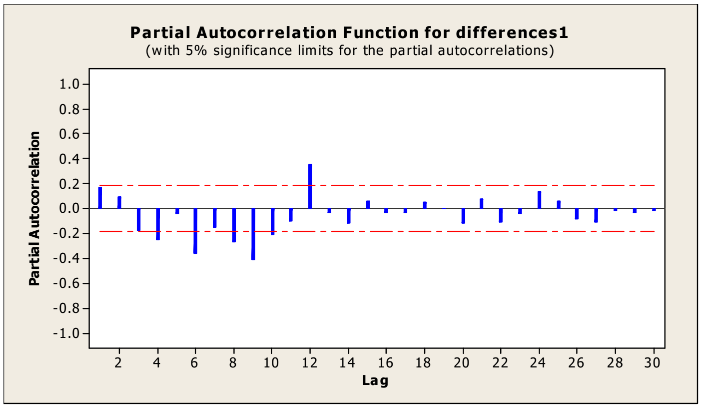

Fig.11. Partial Correlation after taking the first Differences (2007 - 2016)

b) Elimination of Seasonal Component:

Note the values of the Auto-correlations of the modified time series after taking the first difference shown in Figure 9 indicating that the time series is seasonal, i.e., it repeats itself every 12 months. Therefore, for the purpose of elimination of seasonality, differences were taken from class 12. We obtained the modified series where:

$\nabla\nabla_{12} Z_t = Z_{t-1} - Z_{t-12}$

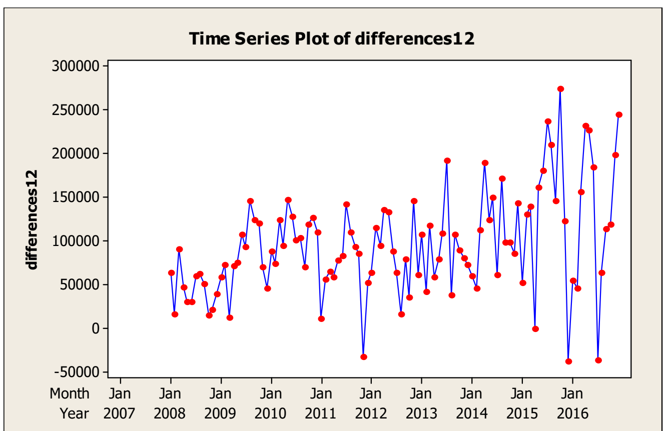

Fig.12. Observations after taking the 12th Difference for the years 2007 - 2016

From the observation of these figures, it is found that the stability has been achieved somewhat. Figure 12 shows that there is a general trend in the data.

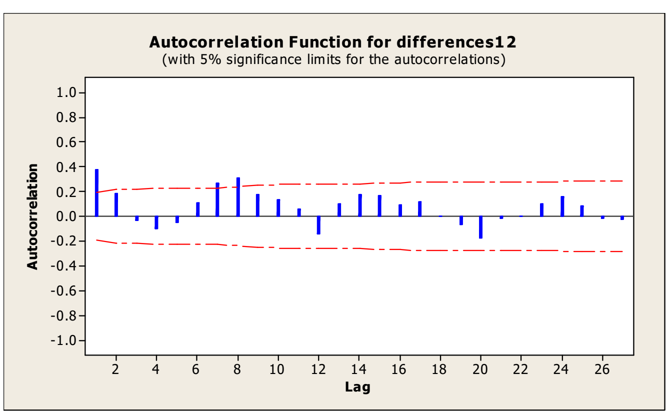

Fig.13. Auto-Correlation after Taking the 12th Difference (2007 - 2016)

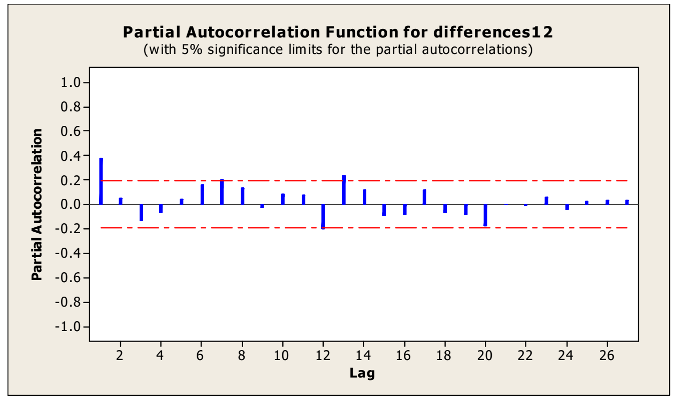

Fig.14. Partial Correlation after Taking the Difference 12 (2007 - 2016)

C. Forecasting:

Using the ARIMA forecasting model, the monthly consumption quantities of the electric power of the year (2017-2066) were forecasted. The results are presented in Table 3. It is obvious that the series for the forecasted period follows the same behavior as the original series.

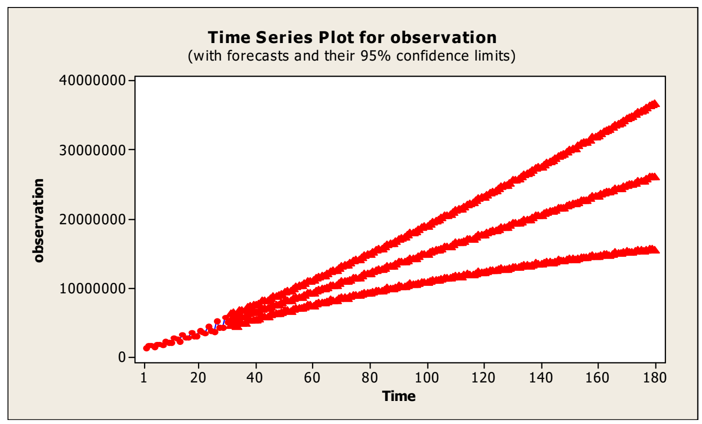

Fig.15. Forecasted Values for the Years 2017-2066

Table 3: Forecasted load Values for Period 2017 to 2066

	Forecast (MWh)	Lower (MWh)	Upper (MWh)
2017	15,934,992	13,296,378	18,573,605
2018	17,304,589	14,524,404	20,084,775
2019	18,856,775	15,882,355	21,831,196
2020	19,866,898	16,590,230	23,143,567
2021	21,041,685	17,494,417	24,588,953
2022	22,421,784	18,575,791	26,267,777
2023	23,788,588	19,617,471	27,959,705
2024	24,934,924	20,430,433	29,439,416
2025	26,094,149	21,187,615	31,000,682
2026	27,473,479	22,184,098	32,762,860
2027	28,853,003	23,155,918	34,550,088
2028	29,989,994	23,874,147	36,105,841
2029	31,150,286	24,560,749	37,739,823
2030	32,529,669	25,484,818	39,574,521

2031	33,908,320	26,387,554	41,429,086
2032	35,045,953	27,041,743	43,050,163
2033	36,206,172	27,668,905	44,743,438
2034	37,585,551	28,533,765	46,637,337
2035	38,964,262	29,379,959	48,548,564
2036	40,101,851	29,979,191	50,224,510
2037	41,262,074	30,555,745	51,968,404
2038	42,641,454	31,369,348	53,913,560
2039	44,020,161	32,166,087	55,874,235
2040	45,157,753	32,716,916	57,598,589
2041	46,317,976	33,248,397	59,387,555
2042	47,697,356	34,016,122	61,378,590
2043	49,076,063	34,768,304	63,383,821
2044	50,213,654	35,275,261	65,152,048
2045	51,373,878	35,765,556	66,982,200
2046	52,753,258	36,491,283	69,015,232
2047	54,131,965	37,202,491	71,061,438
2048	55,269,556	37,668,948	72,870,165
2049	56,429,779	38,120,969	74,738,590
2050	57,809,159	38,807,663	76,810,656
2051	59,187,866	39,480,660	78,895,073
2052	60,325,458	39,909,252	80,741,664
2053	61,485,681	40,325,294	82,646,068
2054	62,865,061	40,975,315	84,754,807
2055	64,243,768	41,612,321	86,875,215
2056	65,381,359	42,005,189	88,757,530
2057	66,541,583	42,387,128	90,696,037
2058	67,920,963	43,002,421	92,839,505
2059	69,299,670	43,605,277	94,994,063
2060	70,437,261	43,964,206	96,910,317
2061	71,597,485	44,313,621	98,881,348
2062	72,976,864	44,895,826	101,057,903
2063	74,355,572	45,466,094	103,245,049
2064	75,493,163	45,792,606	105,193,720
2065	76,653,386	46,110,855	107,195,917
2066	78,032,766	46,661,384	109,404,148

Table 4. Annual Loads (normal) Forecast for Period 2017 to 2066

Year	Energy Demand Forecast (MWh)	Growth %
2017	15,934,992	6.20
2018	17,304,589	8.60
2019	18,856,775	8.70
2020	19,866,898	5.30
2021	21,041,685	5.90
2022	22,421,784	6.60
2023	23,788,588	6.10
2024	24,934,924	4.80
2025	26,094,149	4.60
2026	27,473,479	5.30
2027	28,853,003	5.00
2028	29,989,994	3.90
2029	31,150,286	3.90
2030	32,529,669	4.40
2031	33,908,320	4.20
2032	35,045,953	3.40
2033	36,206,172	3.30
2034	37,585,551	3.80
2035	38,964,262	3.70
2036	40,101,851	2.90
2037	41,262,074	2.90
2038	42,641,454	3.30
2039	44,020,161	3.20
2040	45,157,753	2.60
2041	46,317,976	2.60
2042	47,697,356	3.00
2043	49,076,063	2.90
2044	50,213,654	2.30
2045	51,373,878	2.30
2046	52,753,258	2.70
2047	54,131,965	2.60
2048	55,269,556	2.10
2049	56,429,779	2.10
2050	57,809,159	2.40
2051	59,187,866	2.40
2052	60,325,458	1.90
2053	61,485,681	1.90
2054	62,865,061	2.20
2055	64,243,768	2.20
2056	65,381,359	1.80
2057	66,541,583	1.80
2058	67,920,963	2.10
2059	69,299,670	2.00
2060	70,437,261	1.60
2061	71,597,485	1.60
2062	72,976,864	1.90
2063	74,355,572	1.90
2064	75,493,163	1.50
2065	76,653,386	1.50
2066	78,032,766	1.80

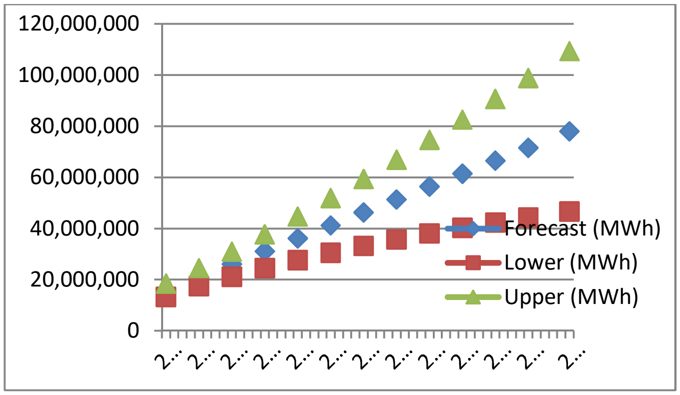

Fig.16. Forecasted values for the years 2017-2066

6. Load Forecast Comparison between Lahmeyer study and Actual Load Consumption for Period 2012 – 2016

In 2011, the Ministry of Electricity and Dams (MED) has contracted Lahmeyer International (LI) for the consultancy services for the development of:

1. A long term power system planning study to cover the period 2012-2031; and
2. A medium term plan for the period 2012 – 2016.

The following results were obtained for load forecast for the period 2012 – 2031.

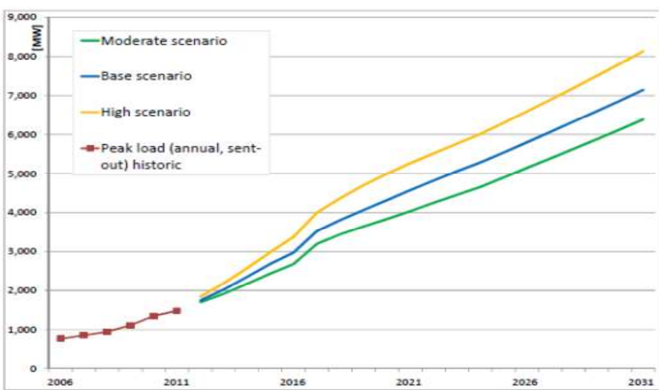

Fig.17. Peak load – Moderate, base and high Scenario (2006 - 2031)

For the base scenario, demand for energy and peak load are forecasted to grow by an average annual rate of 12.5% for the period until 2021, 4.5% for the period 2021 to 2031 and 8.4% for the whole study period.

Table 5. A comparison between Lahmeyer Load Forecast and Actual Load Consumption for Period 2012- 2016

Year	Lahmeyer Forecast (GWh)	Growth %	Actual consumption (GWh)	Growth %
2012	9,742	20	9,360	12.0
2013	11,241	15	10,454	11.7
2014	12,819	14	11,794	12.8
2015	14,662	14	13,409	13.7
2016	16,262	11	15,011	11.9

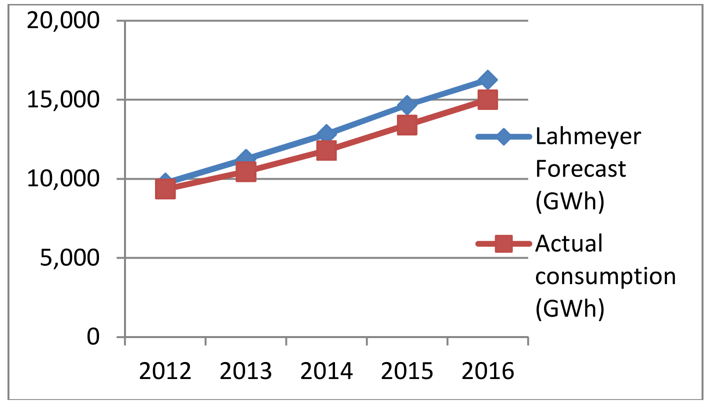

Fig.18. A comparison between Lahmeyer Load Forecast and Actual Load Consumption for Period 2012- 2016

By comparing forecasted load consumption by Lahmeyer and actual load consumption in Table 7and Figure 18, it is clear that there is over estimation in Lahmeyer study. Table 8 shows the error percentage between Lahmeyer load forecast and actual load consumption for period 2012 - 2016.

Table 6. Deviation Percentage between Lehmeyer Load Forecast Study and Actual Load Consumption for Period 2012 - 2016

Year	Lahmeyer Forecast (GWh)	Actual consumption (GWh)	Error %
2012	9,742	9,360	4.1
2013	11,241	10,454	7.5
2014	12,819	11,794	8.7
2015	14,662	13,409	9.3
2016	16,262	15,011	8.3

7. Load Forecast Comparison between Lahmeyer Study and The Paper Load Forecast for Period 2017 – 2031

Table 7 shows the comparison between Lahmeyer load forecast and load forecast done in this paper.

Table 7. A comparison between Lahmeyer Load Forecast and Load Forecast of This Paper for Period 2017- 2031

Year	Lahmeyer Forecast (GWh)	Growth %	Research Forecast (GWh)	Growth%
2017	19,808	22	15,935	6.2
2018	21,333	8	17,305	8.6
2019	22,957	7	18,857	8.7
2020	24,496	6	19,867	5.3
2021	26,066	6	21,042	5.9

2022	27,592	5	22,422	6.6
2023	29,104	5	23,789	6.1
2024	30,555	4	24,935	4.8
2025	31,995	5	26,094	4.6
2026	33,448	5	27,473	5.3
2027	34,929	4	28,853	5
2028	36,405	4	29,990	3.9
2029	37,902	4	31,150	3.9
2030	39,431	4	32,530	4.4
2031	40,990	4	33,908	4.2

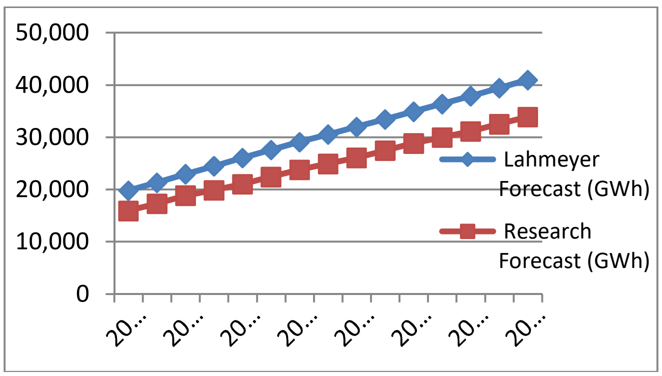

Fig.19. A comparison Between Lahmeyer Load Forecast and Load Forecast of This Paper for Period 2017- 2031

Load forecast values which obtained in this paper took in consideration actual values for load consumption for period up to 2016; meanwhile Lahmeyer study applied actual load consumption values up to 2011. This indicates that load forecast values obtained in this paper are much reliable and reasonable.

8. Actual Load Consumption versus Load Forecasts in 2017

In comparing the actual load consumption in Sudan grid for 2017 between Lahmeyer study and this study forecast are shown in the following table 8.

Table 8. A Comparisons between Actual Load Forecast for 2017

Actual Generation + Interchange 2017	16,138,009 MWh
This Study Load Forecast for 2017	15,934,992 MWh
Lahmeyer Load Forecast Study for 2017	19,808,000 MWh

Table 9 shows that the deviation between actual load consumption, Lahmeyer load forecast and this study load forecast. This comparison indicates that the deviation for this study in only 1.26%, while for Lahmeyer Load forecast is 22.74%.

Table 9. Deviation from Actual Load Consumption, Lahmeyer Load Forecast Study, and This Study Load Forecast for 2017

	Deviation from Actual Energy in 2017
Lahmeyer Study	22.74% (plus)
This Study	1.26% (minus)

CONCLUSION

From the above, the following conclusions can be summarized:

1. Electrical load forecasting is an important process that enables utilities to understand the future load demand, which has important roles in guiding plans, programs and policies. A good forecast leads to better planning and rational policy in term of energy production.
2. In the absence of causal relationships between variables or insufficient information about explanatory variables, the time series method is more accurate in forecasting process.
3. The reslts obtained for load forecast in this study is accurate an dclose to the actual load as in 2017. However this load forecast study should be updated frequently using most recent load consumption to obtain much accurate results.

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