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LONG TERM FORECAST OF ELECTRICITY CONSUMPTION AND ESTIMATION FOR ACTIVE POWER DEMAND: A CASE STUDY OF BAUCHI, NIGERIA

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Abstract — *Accurate forecast of electricity consumption is important for utility companies because it determines the dynamics and characteristics of future construction of power facilities. Forecasting electricity is vital for power generation companies. It has many applications, including energy production scheduling, maintenance and operation of electric network, elaborate accurate investment and development plans for transmission and distribution networks, negotiation of power purchase agreements (PPAs) and purchasing fuels at optimal costs. In the long term, if the forecasts were too low or high, it could cause a number of adverse events, leading electricity companies in the generation deficit or complex financial problems due to excessive investment in generating facilities that are not fully utilized. This paper presents the results of the forecast energy demand, electricity consumption and estimation for active power of Bauchi metropolis, using the model for Analysis of Energy Demand (MAED). Modeling of base year is done on the basis of available statistical data and trends in individual sectors. Results were compared with forecasts that were prepared using other methods.*

Keywords *- Forecasting; Model for analysis of energy demand; Active power; Annual load growth; Statistical data.*

I. INTRODUCTION

Forecasting of electricity is one of the basic activities during energy sector planning process. Electricity consumption is observed with current and expected/planned development of economy with simultaneous observation of the influence of energy demand on economic development [1]. The precise forecast is important for utilities and electric companies because it determines the dynamics and characteristics of future expansion of power facilities of the system [2]. Precise forecasting requires statistical data, forecaster awareness and experience in total development and policy formulation during forecasting period. Forecasts can be classified into short-term (1 hour to 1 week), mid-term (1 week to 1 year) and long-term (more than 1 year) forecasts with respect to forecasting period [3]. Nowadays several methods and techniques for energy forecast have been developed, giving a large insight into possible applications of the different methodologies [1-4].

Load forecasting techniques can broadly be divided into two categories: parametric or non-parametric techniques. Examples of parametric (statistical) techniques include linear regression, general exponential technique and stochastic time series techniques. Non parametric (artificial intelligence) based techniques include artificial neural network and fuzzy logic. Model for analysis of energy demand (MAED) that requires detailed statistical data for base year while enabling detailed analysis and projection of energy demand for each sector in these circumstances represents a quite acceptable approach [5].

Forecasting models are made for each electricity distribution area and the sum of forecasted energy demand of those areas gives the result for complete model [6]. This approach provides not only information about energy forecast for different administrative areas but also other important information that accommodate the peculiar needs of the other areas.

II. MATERIALS AND METHODS

2.1 MAED Methodology

The need for energy planning has led to development of area end-user models that represent simple mathematical models with detailed structural analysis of demand areas which start from final energy consumption. Final energy consumption comprises both heating and electricity for non-heating, etc. After final energy forecast, total shares in structure is determined. Structural end-user models can be applied based on data analysis of one previous year and do not need, consistent time series for several years like econometrical models. It enables the inclusion of all relevant determinants on energy consumption, such as growth and structure of Gross Domestic Product (GDP), demographic changes, housing standard, population mobility, climatic conditions, and changes in efficiency of energy use, habits and customs [7].

The analysis and forecast are performed for individual consumption sectors. The second level of structural modeling is the type of final energy needs forecasting of future energy demand, which is always performed on the basis of different scenarios. In cases where some determinants have no official surveys of development, it should be estimated by expert analysis based on analogical trends from countries that had already reached that level of socio-economic development. At the very beginning, the end-user model estimates useful energy needs so some identified determinants of consumption from year in future and applied on the specific energy consumption of base year and are corrected afterward to an expected amount in future year.

When using this model, it is necessary to take into account the different set of indicators that reflect the current (base) states, and also define those factors on which it is possible to make predictions in the future. Some of the input parameters are; GDP and GDP growth rate, population size and rate of population growth, the number of people per housing unit, size of residential buildings, urbanization, presence of technology for heating, presence of air conditioners and energy efficiency devices [8].

2.2 The State Estimator Problem Formation

Given the system measurements described by the linear equation

$$\underline{Z} = H\underline{\theta} + \underline{v} \tag{1}$$

Where Z is an m × 1 measurement vector of system measurements (known), $\underline{\theta}$ is an n × 1 vector of parameters to be estimated (unknown), H is an m × n matrix describing the states of measurements and v is the residual vector. M is number of measurements and n is number of states. The following are the main steps involved in the Soliman and Christensen LAV algorithm, unconstrained problem. For a least absolute value estimator based on linear programming:

Step 1 Calculate the LES solution using the equation

$$\underline{\hat{\theta}} = [H^T H]^{-1} H^T \underline{Z} \tag{2}$$

Step 2 Calculate the LES residuals generated from this solution as

$$v_i = Z_i - H_i \underline{\hat{\theta}} \tag{3}$$

Step 3 Calculate the standard deviation of the calculated residuals as

$$\sigma^2 = \frac{1}{m-n+1} \sum_{i=1}^{m} (v_i - v_{av})^2 = variance \tag{4}$$

$$\sigma = \sqrt{variance} = \left[\frac{1}{m-n+1} \sum_{i=1}^{m} (v_i - v_{av})^2\right]^{\frac{1}{2}} \tag{5}$$

Step 4 Reject the outliers with residuals greater than the standard deviation σ, providing that the system is observable.

Step 5 Recalculate the new LES estimates using the remaining measurements and calculate the new corresponding residuals for these measurements.

Step 6 Select the n measurements that correspond to the smallest least error squares residual and from the corresponding $\underline{\hat{Z}}$ and $\hat{H}$.

Step 7 Solve for the least absolute value estimate, $\underline{\theta}^*$ using

$$\underline{\theta}^* = \left[\hat{H}\right]^{-1} \underline{\hat{Z}} \tag{6}$$

2.3 Annual Load Growth

To maximize the accuracy of next year's load-demand estimation, an estimate of annual load growth as an adjusting factor is employed. It is evident that there is a very strong dependence of the load demand on time. Typical load profiles of successive years reveal very strong correlation at certain periodic intervals. Moreover, there is an average and a clear load increase over the previous years.

This increase amounts to annual load growth at that hour as a function of time (weeks) throughout the whole year. The load growth is modeled as the difference between the load curves of two successive years as a function of time.

A third-order polynomial is utilized to model the load as a function of time at the kth hour as a function of the load of previous hour. The regression model is given by equation (7):

$$Y(t) = a_0(t) + a_1(t)P(t) + a_2(t)P^2(t) + a_3(t)P^3(t) + a_4(t)P(t-1) + a_5(t)P(t-2) + a_6(t)P(t-3) + a_7(t)M(t) + a_8(t)M(t-1) + a_9(t)M(t-2) \tag{7}$$

Where:

$Y(t)$ = Load at time t, t = 1, 2…

$P(t)$ = Population deviation at time t;

$M(t)$ = Total number of paying consumers at time t;

$a_0(t)$ = Base load at time t;

$a_1(t)$, $a_2(t)$ … $a_9(t)$ are the regression parameters to be estimated at time t.

III. RESULTS AND DISCUSSION

Everyday readings of transformers T3 and T4 located at Zaria bypass that supply Bauchi metropolis were taken from year 1997 to year 2015. The monthly energy consumption and yearly energy consumption are then calculated.

Everyday energy consumptions are taken both in industrial users and the residential consumers, from which the monthly and yearly energy consumption were calculated.

A bar chart is plotted using energy against time. This shows the relationship between least absolute value (LAV) and Least Error square (LES) as shown in Figure 2.

The energy estimated graph is now drawn to show the actual energy consumed with respect to time as shown in Figure 1.

The graph of estimation error was also plotted using the record of the annual energy consumption (MWH) and the year as shown in Figure 3.

A plot of the graphs of estimation error means and that of standard deviation using the record of annual energy consumption (MWH) and the year (time) would show that LAV has less percentage error than the LES method and also the LAV standard deviation is less than the standard deviation of the LES method. This can be seen from the estimated error mean and standard deviation table as shown in Table 7.

This clearly shows that the LAV method of simulation is better than the LES method.

Table 1: Collected Data – Annual Average Energy Consumption, Industrial Users and Paying Consumers in Bauchi.

YEAR	ENERGY CONSUMPTION (MWH)	PAYING INDUSTRIAL USERS	NUMBER OF PAYING CONSUMERS
(t)	(EY)	(MD)	(PP)
1997	12707.45	1538	106786
1998	13455.2	1606	126667
1999	11310.75	1625	151905
2000	9677	1607	176000
2001	12601	1515	200417
2002	17660.2	1376	132917
2003	15589.7	1364	148148
2004	14733.15	1281	141667
2005	12839.75	1249	155000
2006	13543.4	1196	130000
2007	17936.85	1242	50000
2008	17379.25	1467	112222
2009	16170.15	1536	118571
2010	13455.2	1576	129333
2011	11310.75	1676	130000
2012	10177	1624	178333
2013	8601	1564	160000
2014	9710.2	1426	130000
2015	12812.15	1356	135324

Table 2: Parameters

Parameter	symbol	Formula
YEAR (t)	(t)	-
ENERGY CONSUMPTION (MWH)	EY	-
PAYING INDUSTRIAL USERS	MD	-
NUMBER OF PAYING CONSUMERS	PP	-
3 YEAR CONSUMER AVERAGE	PA	PA(t)=[PP(t) + PP(t+1) + PP(t+2)]/3
PAYING CONSUMER DEVIATION	P(t)	P(t) =[PP(t)-PA(t)]/800
INDUSTRIAL USERS DEVIATION	M(t)	M(t)={[180000-PP(t)]*[MD(t)^0.5]}/1000000
Least Absolute Value ENERGY	LAV	
Least Error Squares ENERGY	LES	

Table 3: Calculated Regression Parameters (A0 – A9)

YEAR	ANNUAL AVERAGE ENERGY (MWH)	Paying industrial users	Number of Paying Consumers	population average (3 YEARS AHEAD)	=(PP-PA)/800	=((180000-PP)*(MD^0.5))/1000000	A0	A1	A2	A3	A4	A5	A6	A7	A8	A9
(t)	(EY)	(MD)	(PP)	(PA)	P(t)	M(t)	(x 10)	P(t)	$P(t)^2$	$P(t)^3$	P(t-1)	P(t-2)	P(t-3)	M(t)	M(t-1)	M(t-2)
1997	12707.45	1538	106786	106786.0	0.0	2.9	10	0.0	0.0	0.0	-	-	-	2.9	-	-
1998	13455.2	1606	126667	116726.5	12.4	2.1	10	12.4	154.4	1918.5	0.0	-	-	2.1	2.9	-
1999	11310.75	1625	151905	128452.7	29.3	1.1	10	29.3	859.4	25193.5	12.4	0.0	-	1.1	2.1	2.9
2000	9677	1607	176000	151524.0	30.6	0.2	10	30.6	936.1	28638.6	29.3	12.4	0.0	0.2	1.1	2.1
2001	12601	1515	200417	176107.3	30.4	-0.8	10	30.4	923.4	28058.7	30.6	29.3	12.4	-0.8	0.2	1.1
2002	17660.2	1376	132917	169778.0	-46.1	1.7	10	-46.1	2123.0	-97820.8	30.4	30.6	29.3	1.7	-0.8	0.2
2003	15589.7	1364	148148	160494.0	-15.4	1.2	10	-15.4	238.2	-3675.4	-46.1	30.4	30.6	1.2	1.7	-0.8
2004	14733.15	1281	141667	140910.7	0.9	1.4	10	0.9	0.89381	0.8	-15.4	-46.1	30.4	1.4	1.2	1.7
2005	12839.75	1249	155000	148271.7	8.4	0.9	10	8.4	70.7	594.9	0.9	-15.4	-46.1	0.9	1.4	1.2
2006	13543.4	1196	130000	142222.3	-15.3	1.7	10	-15.3	233.4	-3566.1	8.4	0.9	-15.4	1.7	0.9	1.4
2007	17936.85	1242	50000	111666.7	-77.1	4.6	10	-77.1	5941.8	-458016.9	-15.3	8.4	0.9	4.6	1.7	0.9
2008	17379.25	1467	112222	97407.3	18.5	2.6	10	18.5	342.9	6350.5	-77.1	-15.3	8.4	2.6	4.6	1.7

2009	16170.15	1536	118571	93597.7	31.2	2.4	10	31.2	974.5	30420.0	18.5	-77.1	-15.3	2.4	2.6	4.6
2010	13455.2	1576	129333	120042.0	11.6	2.0	10	11.6	134.9	1566.5	31.2	18.5	-77.1	2.0	2.4	2.6
2011	11310.75	1676	130000	125968.0	5.0	2.0	10	5.0	25.4	128.0	11.6	31.2	18.5	2.0	2.0	2.4
2012	10177	1624	178333	145888.7	40.6	0.1	10	40.6	1644.7	66703.2	5.0	11.6	31.2	0.1	2.0	2.0
2013	8601	1564	160000	156111.0	4.9	0.8	10	4.9	23.6	114.9	40.6	5.0	11.6	0.8	0.1	2.0
2014	9710.2	1426	130000	156111.0	-32.6	1.9	10	-32.6	1065.3	-34769.7	4.9	40.6	5.0	1.9	0.8	0.1
2015	12812.15	1356	135324	141774.7	-8.1	1.6	10	-8.1	65.0	-524.3	-32.6	4.9	40.6	1.6	1.9	0.8

Table 4: Calculated Regression Co-Efficient Using Matlab Script

REGRESSION CO-EFFICIENT	A0	A1	A2	A3	A4	A5	A6	A7	A8	A9
LAV (q)	1464.762	483.1552	1.8156109	0.003789	-274.176	37.8233	-54.1912	10239.01	-10944	-1208.32
LES (O)	1489.535	537.4643	2.208967245	0.017231	-314.137	76.38644	-91.5601	12512.91	-13289.7	-819.686

Table 5: Calculated Results Using the New Regression Co-Efficient

YR	EY	LAV RESULT (MWH)	LES RESULT (MWH)
1997	12707.45	44046.47	50823.158
1998	13455.2	11399.61	10533.578
1999	11310.75	11796.41	12494.017
2000	9677	10334.83	10843.62
2001	12601	11898.94	12237.853
2002	17660.2	13492.74	15526.198
2003	15589.7	13625.33	13218.27
2004	14733.15	15010.92	14053.753
2005	12839.75	13105.93	14183.118
2006	13543.4	12620.18	14751.747
2007	17936.85	17830.89	17677.464
2008	17379.25	18693.72	18172.553
2009	16170.15	15153.84	15912.97
2010	13455.2	7938.79	11173.867
2011	11310.75	10158.94	11611.782
2012	10177	10702.43	9909.1082
2013	8601	10371.62	11470.385
2014	9710.2	11203.58	13275.907
2015	12812.15	13028.02	12451.903

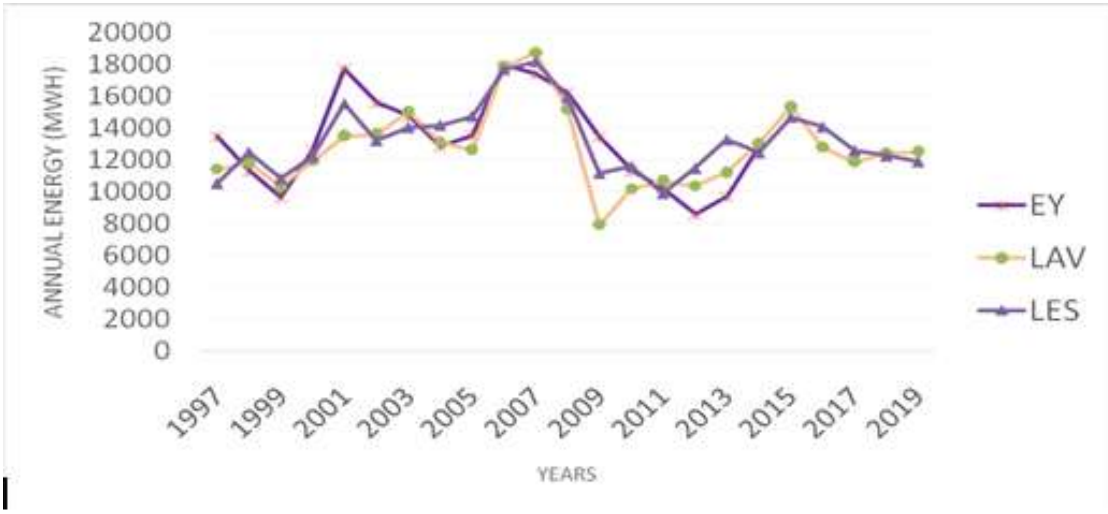

Figure 1: Energy Estimation Chart.

Figure 2: Energy Estimation Bar Graph.

Table 6: Estimation Error (In Percentage) LAV Error = (LAV-EY)*100/LAV

YR	EY	LAV	LES	LAV error	LES error
1997	12707.45	44046.47	50823.158	71.1499	74.99673
1998	13455.2	11399.61	10533.578	-18.0321	-27.7363
1999	11310.75	11796.41	12494.017	4.117035	9.47067
2000	9677	10334.83	10843.62	6.36521	10.75859
2001	12601	11898.94	12237.853	-5.90016	-2.96741
2002	17660.2	13492.74	15526.198	-30.8867	-13.7445
2003	15589.7	13625.33	13218.27	-14.417	-17.9405
2004	14733.15	15010.92	14053.753	1.850437	-4.83427
2005	12839.75	13105.93	14183.118	2.030997	9.471601
2006	13543.4	12620.18	14751.747	-7.31547	8.191216
2007	17936.85	17830.89	17677.464	-0.59424	-1.46732
2008	17379.25	18693.72	18172.553	7.031594	4.365392
2009	16170.15	15153.84	15912.97	-6.70659	-1.61617
2010	13455.2	7938.79	11173.867	-69.4868	-20.4167

2011	11310.75	10158.94	11611.782	-11.3379	2.59247
2012	10177	10702.43	9909.1082	4.909451	-2.70349
2013	8601	10371.62	11470.385	17.07176	25.01559
2014	9710.2	11203.58	13275.907	13.32952	26.85848
2015	12812.15	13028.02	12451.903	1.656995	-2.89311
2016		15309.95	14682.461		
2017		12774.43	14078.685		
2018		11884.08	12601.111		
2019		12405.32	12258.181		
2020		12503.52	11902.224		

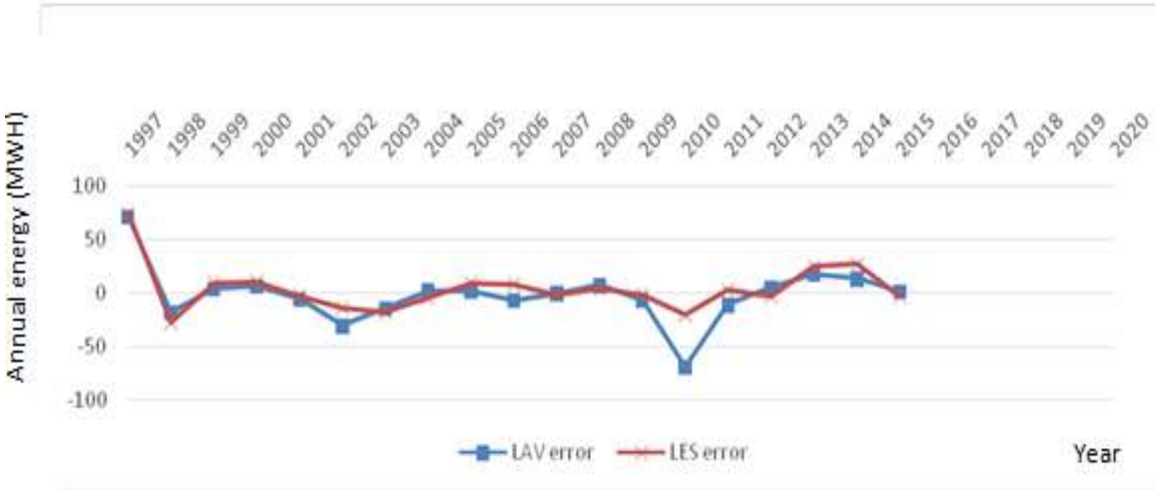

Figure 3: Estimation Error.

Table 7: Estimation Error Mean and Standard Deviation Table

	LAV	LES
error mean	-1.85074	3.968471
STD	1123.18	1687.461

Table 7 shows that both the error mean and standard deviation of the LAV estimation are lower than that of the LES. This shows that the LAV method gives a better estimation.

IV. CONCLUSION

This paper presents the results of long-term forecast of energy sources, electricity and active power for Bauchi metropolis in Nigeria. The least absolute value static state estimation and the least error squares estimation model were used as the forecasting techniques.

The sum of individual forecasts in the end was quite close to the results obtained from the model forecast for the whole area, and the results were compared with predictions by other methods applied by other authors. In comparison to other methods, this approach allows sectorial planning and forecasting, and in addition to information about energy needs in the future. Other important information about the energy intensity in certain sectors can be obtained which may indicate the need for systematic measures in these sectors.

Records of population of Bauchi town were taken. The birth rates and the death rates were taken into consideration. Other considerations include the Gross Domestic Product (GDP), growth rate, the number of people per housing unit, size of residential buildings, urbanization, presence of the technology for heating, presence of air conditioners, energy efficiency devices. The weather parameters such as temperature, wind speed, humidity, amount of rainfall were all taken into consideration in the forecasting process.

The model used provides additional information about the forecasted values of energy needs by individual consumer trends which can be easily compared with socio-economic environment in other neighboring cities.

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