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Characterization Of Electricity Generation Data For A Nigerian Utility Industry

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***Abstract*—The attainment of organization goals require careful planning by a way of proper allocation of available time among competing resources in an optimal manner. This can be successfully achieved by making forecast of future activities and taking the appropriate action stemming from these forecasts. This study presents an exquisite decomposition analysis of a set of 132 months electricity generation time series data (1996-2006) from Sapele Power Station in Ogorode, Delta State, Nigeria. The multiplicative version of the decomposition model was employed to characterize the data obtained into its various components such as Noise, Trends, Cyclical Component, and Seasonal Index. Our results showed a negative trend, with high seasonality, noise and cyclical activities. The implication is that generation is constantly decreasing over the years. This paper however, presents a veritable tool that will add as guide and adjudged intriguing and intuitively appealing for the maintenance managers in order to come up with better maintenance and operation policies that can cub the up and down nature of the present operation and maintenance (O & M).**

Keywords—Trend; Seasonality; Decomposition; Noise; Cyclical Activity.

I. Introduction

The major objective of the electricity Power industry in Nigeria is to provide regular and uninterrupted power supply to the consumers of electricity nationwide. However, the industry has experienced a great deal of setback which has led to almost near collapse of several utilities in the country. This situation has compelled the Federal Government of Nigeria, the electricity industry and the academia, to look for various means of tackling these problems. Several reports have shown that all is not well with the entire electricity market in Nigeria. The Federal Government of Nigeria has set targets to overcome the electricity challenges facing the country, but such attempts only ended in futility. The Problem has been compounded by ever growing population; maintenance neglect and the ineptitude of the utility agency responsible for the provision of public power supply and a political culture that is deep rooted in lopsided institutionalism. Electricity generation targets are far from realization as a result of wrong forecasting approach. Electricity generation data like most time series data is associated with trend, seasonal influences, cyclical activities and noise, which are the inherent component of the data. However, Industrial Managers are often faced with the challenge of getting the required information which will enable them operates optimally. Understanding what is hidden in the set of electricity data is needful and insightful into the design of the solution to most of the prevailing problems. Meanwhile, a good and accurate forecast of the electricity generation data is needed so as to help in production planning as well as workforce scheduling. Failure to employ scientific approach to set goal often leads to production losses. Besides, there appears to be a dearth of statistical forecasts in most of the electricity industries in Nigeria. Most of the forecasts have been based on human judgment which basically focuses on information available at the time of forecast. Forecasting based on human judgment has been investigated by some researchers and found to lack the ability to match load with the appropriate work force size. Notable example includes [1]. This is because such forecasting is based on mental representation of the information available to them at the time of forecast. However, there appears to be a better approach whereby statistical forecast is employed using the expert's weighting or weighing technique from an automatic assessment of expert's past performance [2]. The decomposition model employed in this research has been proven to be a robust model for handling problems associated with the estimation of seasonal influences, trend, noise and cyclical activities [3]. [4] Combined the theory of forecast accuracy. Similar work was carried out by [5] to compare forecast accuracy of different forecasting models in electric load forecasting. [6] Also made use of this algorithm to solve problems in Brazillian residential electricity consumption. Furthermore, similar experimental work carried out by [7] which combined decomposition with other methods to improve the logarithm Mean Division Index (LMDI) method, was applied to find factors affecting Indonesian Power Sector evaluation particularly in the household sector. Other works carried out in this area include those carried out by [8, 9, 10, 11] and so many others. Recent research on this subject also includes: [12, 13 and 14].

II. Methodology

This model analyzed time series data of 132 months energy generation in MWh, obtained from Sapele Power generation station. The expression for the multiplicative version of decomposition model employed is shown in equation (1).

$$Y_t = T_r * S_t * C_I * I_I \qquad (1)$$

where, T_r = Trend

S_t = Seasonal Index

C_I = Cyclical Component

I_I = Noise / Irregular Activities

The decomposition model consists of the following procedures:

A. *Step 1*

Six (6) months Moving Totals (MT) were computed and the Centre Moving Totals (CMT) were computed from the equation (2)

$$CMT = \frac{(MT_1 + MT_{1+1})}{12} \quad (2)$$

B. *Step 2*

The next step is the determination of Ratios to Moving Average (RMA).These were computed by dividing each observation by the corresponding Centre Moving Total (CMT) as shown in equation (3)

$$RMA = Y_t / CMT \quad (3)$$

C. *Step 3*

Following the above step is the determination of Seasonal Index. The ratios obtained in step 2 above are considered to be unrefined seasonal factors. The refinement is presented in table 1. The sum of the Ratios to Moving Average (RMA) entries and each average values were obtained for each month. The seasonal Index (S_t) for a month is, obtained by taking an average for the month such that their sum equals 12. This is shown in equation (4).

$$S_I = \left(\frac{x_1}{x}\right)*12 \quad (4)$$

I = 1, 2, 3, 4 12

where, x is the grand sum

x_1 is the grand average.

D. *Step 4*

The step following is the computation of deseasonalized value, d_t. This is obtained by dividing each observation y_t, by the seasonal index as shown in equation (5).

$$d_t = y_t / S_t \quad (5)$$

E. *Step 5*

This step is the computation of Trend (T). The trend is computed from the formula shown in (6).

$$T_1 = b_0 + b_1 t \quad (6)$$

where, $$b_1 = \frac{\sum td_t - \frac{(\sum t)(\sum d_t)}{T}}{\sum t^2 - \frac{\sum t^2}{T}}$$

F. *Step 6*

This step is the computation of cyclical activity C_I, which is obtained by a 3 month moving average as shown in equation (7).

$$C_I = d_t / T_t \quad (7)$$

G. *Step 7*

The final step is the computation of noise I_1, otherwise known as irregular activities. This is shown in equation (8).

$$I_1 = y_t / (S_t . d_t . C_1) \quad (8)$$

The final decomposition is thus obtained by substituting the computed values into equation (1)

III. RESULTS AND DISCUSSION

The plot obtained from the sample data for the electricity generation station revealed a highly fluctuating sinusoidal pattern which appears to be quite cumbersome to analyze. Tables 1 and figures 1 to 5 show the decomposition results obtained for Sapele power station. From the results, Sapele power station was found to have a linear decreasing trend as shown in figure 1. Results also show that generation from this station shows cyclical activities and boisterous noise coupled with white noise as seen in figures 2 and 3. There are also seasonal effects in the generation. As seen in figure 4, the months of January, March, may, June, July and December shows a positive seasonal index. While, the months of December and May recorded the highest index of the same value, the months of February, April, August, September, October and November, recorded a negative seasonal index. On the other hand, the months of January and October almost had no seasonal effect. However, figure 5 show that the months of February, May and October recorded low cyclical activities while the months of December recorded the highest cyclical activities. In addition, the result also shows that Sapele power station is characterized by white noise. Usually the Sapele power generating station energy generation is based on load allocation provided their generating turbines are not faulty. In particular the hydro power generating stations carry out their maintenance activities during the dry season which is usually between October and March while the thermal stations carry out their maintenance during the rainy season which is between March and August. When the thermal stations are on maintenance the hydro generation stations are tasked with the duty of taken care of the nation's generation and vice versa. However, the high energy generation peak noticeable in December in this result stems from the fact that electricity consumption in Nigeria is usually high in the dry season due to excessive heat. This leads to high electricity demand since fans, and air conditioners are heavily put to use at this period.

Furthermore, it is instructive to note that this research study is limited to only the Electricity generation station in Ogorode, Delta state, Nigeria (SAPELE POWER STATION) and the electricity generation data employed were those made available by the Sapele station data bank.

TABLE I. RESULTS OF DECOMPOSITION ANALYSIS OF SAPELE POWER STATION GENERATION DATA

t	Month t	Generation Y_t	CMA	S_t	Trend	C_i	I1	Final Decomposition
1	Jan	101152		1.141	150477.52			
2	Feb	162855		0.957	149727.52	0.872	1.30338	162855
3	Mar	115804		0.874	148977.52	1.026	0.86685	115804
4	Apr	154749	132042.5	0.993	148227.52	0.938	1.120849	154749
5	May	126905	133471.2	0.985	147477.52	0.849	1.028985	126905
6	Jun	116204	134116.9	1.275	146727.52	0.806	0.770663	116204
7	Jul	130324	133740.5	0.962	145977.52	0.857	1.082885	130324
8	Aug	150827	129452.7	1.017	145227.52	0.96	1.063746	150827
9	Sep	135581	127994	1.007	144477.52	1.036	0.899517	135581
10	Oct	130455	126250.8	0.786	143727.52	0.954	1.210458	130455
11	Nov	99745	119059.6	0.899	142977.52	0.935	0.82995	99745
12	Dec	125860	108966.8	1.011	142227.52	0.756	1.157794	125860
13	Jan	99750	101838.8	1.141	141477.52	0.733	0.843016	99750
14	Feb	95106	99695.9	0.957	140727.52	0.633	1.115612	95106
15	Mar	70188	97974.3	0.874	139977.52	0.693	0.827866	70188
16	Apr	110313	96540.8	0.993	139227.52	0.687	1.161437	110313
17	May	94172	96435.3	0.985	138477.52	0.706	0.977916	94172
18	Jun	110773	101468.2	1.275	137727.52	0.687	0.918219	110773
19	Jul	97636	109436.8	0.962	136977.52	0.688	1.076954	97636
20	Aug	95954	113731	1.017	136227.52	0.795	0.871185	95954
21	Sep	129734	115065.9	1.007	135477.52	1.009	0.942467	129734
22	Oct	146390	120427.4	0.786	134727.52	1.081	1.278812	146390
23	Nov	109626	128506.9	0.899	133977.52	1.04	0.875162	109626
24	Dec	111338	130050.8	1.011	133227.52	0.935	0.88407	111338
25	Jan	161409	125393.1	1.141	132477.52	0.973	1.097456	161409
26	Feb	129135	123362.8	0.957	131727.52	1.032	0.992604	129135
27	Mar	115079	126193.8	0.874	130977.52	0.948	1.060424	115079
28	Apr	105153	127589.8	0.993	130227.52	0.937	0.867821	105153
29	May	126499	128225.2	0.985	129477.52	0.863	1.149333	126499
30	Jun	128438	126252.1	1.275	128727.52	1.028	0.761235	128438
31	Jul	161061	119477.2	0.962	127977.52	1.05	1.245926	161061
32	Aug	137107	111953.6	1.017	127227.52	1.008	1.051228	137107
33	Sep	83430	106040.3	1.007	126477.52	0.759	0.863053	83430
34	Oct	55503	101932.3	0.786	125727.52	0.66	0.850981	55503
35	Nov	85866	95911.2	0.899	124977.52	0.702	1.088661	85866
36	Dec	98112	92473.4	1.011	124227.52	0.851	0.91796	98112
37	Jan	142091	98983.8	1.141	123477.52	0.832	1.212187	142091
38	Feb	83023	110980.6	0.957	122727.52	0.873	0.809711	83023
39	Mar	96261	119628.3	0.874	121977.52	0.873	1.034296	96261
40	Apr	121596	123279.6	0.993	121227.52	1.098	0.919955	121596
41	May	163735	129488	0.985	120477.52	1.067	1.293108	163735
42	Jun	124015	136967.2	1.275	119727.52	1.197	0.678697	124015
43	Jul	160004	138386.3	0.962	118977.52	1.124	1.243726	160004
44	Aug	139611	133331.4	1.017	118227.52	1.218	0.953307	139611
45	Sep	129423	131895.8	1.007	117477.52	1.135	0.963899	129423
46	Oct	105463	130433.3	0.786	116727.52	1.129	1.018147	105463
47	Nov	119210	126192.5	0.899	115977.52	1.197	0.95518	119210
48	Dec	151312	122525.7	1.011	115227.52	1.108	1.172266	151312
49	Jan	115158	119626.7	1.141	114477.52	1.136	0.776086	115158
50	Feb	133567	118708.1	0.957	113727.52	1.012	1.212666	133567
51	Mar	91465	184770.4	0.874	112977.52	1.043	0.888111	91465
52	Apr	108633	253831.8	0.993	112227.52	0.952	1.023944	108633
53	May	105017	255767.3	0.985	111477.52	2.906	0.32911	105017
54	Jun	958253	256831.1	1.275	110727.52	3.013	2.252762	958253
55	Jul	136950	256620.8	0.962	109977.52	3.099	0.417697	136950
56	Aug	135001	254732.4	1.017	109227.52	1.15	1.056784	135001
57	Sep	102800	181162.8	1.007	108477.52	1.092	0.86179	102800
58	Oct	94775	108326.7	0.786	107727.52	1.02	1.097348	94775
59	Nov	96214	105686.7	0.899	106977.52	0.968	1.033501	96214
60	Dec	84220	103036.4	1.011	106227.52	0.974	0.805134	84220
61	Jan	136950	106052.7	1.141	105477.52	0.984	1.156435	136950
62	Feb	103321	111863.8	0.957	104727.52	1.1	0.93718	103321
63	Mar	102677	118933.1	0.874	103977.52	1.147	0.985051	102677
64	Apr	131093	120593.6	0.993	103227.52	1.231	1.038907	131093
65	May	129629	121794.5	0.985	102477.52	1.203	1.067509	129629
66	Jun	135637	124631.3	1.275	101727.52	1.139	0.918133	135637
67	Jul	105459	120288.8	0.962	100977.52	1.198	0.906206	105459
68	Aug	149223	110839.3	1.017	100227.52	1.152	1.270795	149223
69	Sep	90817	101409.4	1.007	99477.52	1.18	0.7683	90817
70	Oct	90843	983755	0.786	98727.52	0.906	1.292119	90843

71	Nov	56484	95444.1	0.899	97977.52	0.928	0.691021	56484
72	Dec	95624	93895.3	1.011	97227.52	0.868	1.120745	95624
73	Jan	109065	97730.3	1.141	96477.52	1.056	0.938231	109065
74	Feb	110440	104319.5	0.957	95727.52	1.178	1.023369	110440
75	Mar	111014	110433.8	0.874	94977.52	1.263	1.058869	111014
76	Apr	116666	110536.2	0.993	94227.52	1.259	0.990357	116666
77	May	109732	108265.3	0.985	93477.52	1.139	1.046324	109732
78	Jun	115747	102610.7	1.275	92727.52	1.063	0.920996	115747
79	Jul	90171	94781	0.962	91977.52	1.033	0.986529	90171
80	Aug	102084	90411.1	1.017	91227.52	0.895	1.229385	102084
81	Sep	51514	85652.7	1.007	90477.52	0.944	0.59894	51514
82	Oct	82210	81462	0.786	89727.52	0.959	1.215508	82210
83	Nov	91749	78114.4	0.899	88977.52	1.057	1.085141	91749
84	Dec	76629	76440.1	1.011	88227.52	0.933	0.920781	76629
85	Jan	79001	77628.4	1.141	87477.52	0.844	0.937795	79001
86	Feb	73083	75645.3	0.957	86727.52	0.825	1.067317	73083
87	Mar	60423	74009	0.874	85977.52	0.906	0.887519	60423
88	Apr	87561	75823.5	0.993	85227.52	0.864	1.197479	87561
89	May	62600	77128.2	0.985	84477.52	0.865	0.869723	62600
90	Jun	86143	79333.1	1.275	83727.52	0.901	0.895606	86143
91	Jul	91261	79759.6	0.962	82977.52	0.955	1.197144	91261
92	Aug	76479	77542.8	1.017	82227.52	1.025	0.892237	76479
93	Sep	83486	76396.5	1.007	81477.52	1.01	1.007453	83486
94	Oct	69616	76290.8	0.786	80727.52	0.955	1.148845	69616
95	Nov	53944	77797.2	0.899	79977.52	0.953	0.787268	53944
96	Dec	81043	80480.2	1.011	79227.52	0.941	1.075223	81043
97	Jan	95092	83775.3	1.141	78477.52	1.098	0.967188	95092
98	Feb	90725	90774.8	0.957	77727.52	1.263	0.965688	90725
99	Mar	101436	94314.8	0.874	76977.52	1.311	1.150043	101436
100	Apr	91208	88744.4	0.993	76227.52	1.426	0.844992	91208
101	May	116345	82461.5	0.985	75477.52	1.137	1.376364	116345
102	Jun	61123	78766.3	1.275	74727.52	0.961	0.66756	61123
103	Jul	48167	75644.3	0.962	73977.52	0.718	0.94265	48167
104	Aug	62255	72330.9	1.017	73227.52	0.895	0.934019	62255
105	Sep	85564	72463.4	1.007	72477.52	1.081	1.084508	85564
106	Oct	69616	77927.8	0.786	71727.52	1.315	0.93902	69616
107	Nov	98176	82559.3	0.899	70977.52	1.304	1.179906	98176
108	Dec	80882	85483.4	1.011	70227.52	1.288	0.884459	80882
109	Jan	93980	90025.6	1.141	69477.52	1.142	1.0381	93980
110	Feb	72501	92058.8	0.957	68727.52	1.379	0.79935	72501
111	Mar	109927	93273.8	0.874	67977.52	1.402	1.319713	109927
112	Apr	99759	95098.8	0.993	67227.52	1.585	0.942815	99759
113	May	92431	96740.9	0.985	66477.52	1.371	1.029601	92431
114	Jun	101207	95486.2	1.275	65727.52	1.383	0.873235	101207
115	Jul	95555	86114.5	0.962	64977.52	1.375	1.111764	95555
116	Aug	90632	73902.5	1.017	64227.52	1.372	1.011312	90632
117	Sep	76739	59862.6	1.007	63477.52	1.001	1.199313	76739
118	Oct	20487	43465.8	0.786	62727.52	0.689	0.603085	20487
119	Nov	25159	27950.2	0.899	61977.52	0.289	1.562434	25159
120	Dec	0	14002.6	1.011	61227.52	0.151	0	0
121	Jan	0	5900.4	1.141	60477.52	0	0	0
122	Feb	0	2096.6	0.957	59727.52	0	0	0
123	Mar	0	0	0.874	58977.52	0	0	0
124	Apr	0	0	0.993	58227.52	0	0	0
125	May	0	1441.4	0.985	57477.52	0	0	0
126	Jun	0	6353.5	1.275	56727.52	0	0	0
127	Jul	0	13570.9	0.962	55977.52	0.103	0	0
128	Aug	17297	20911.8	1.017	55227.52	0.356	0.865056	17297
129	Sep	41648	27676.2	1.007	54477.52	0.711	1.06777	41648
130	Oct	44961		0.786	53727.52	0.91	1.169971	44961
131	Nov	43129		0.899	52977.52	0.897	1.009545	43129
132	Dec	38044		1.011	52227.52			0
SUM		13369493	13751538	130.977				

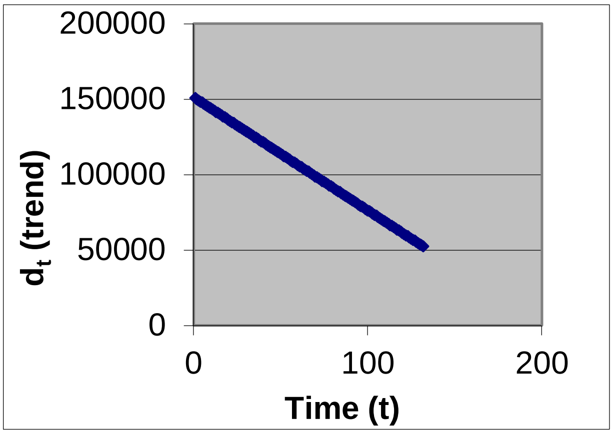

Fig. 2. Plot of Trend against time

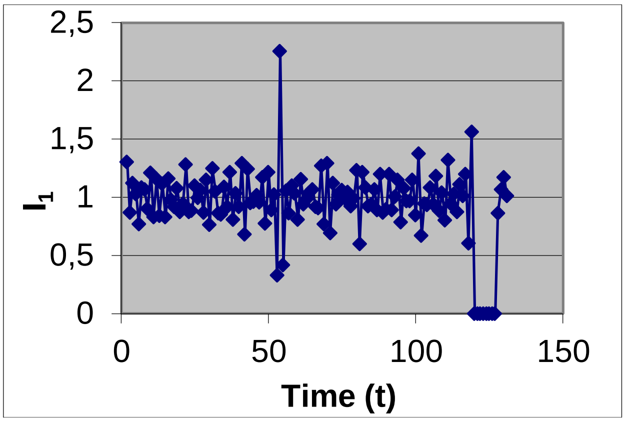

Fig. 1. Plot of Seasonality against time

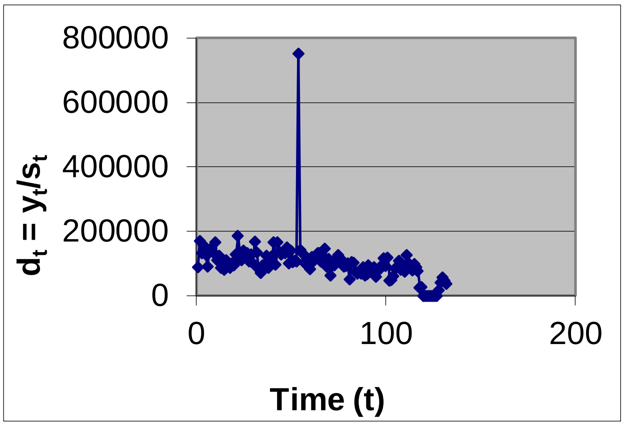

Fig. 3. Plot of Deseasonalized value against time

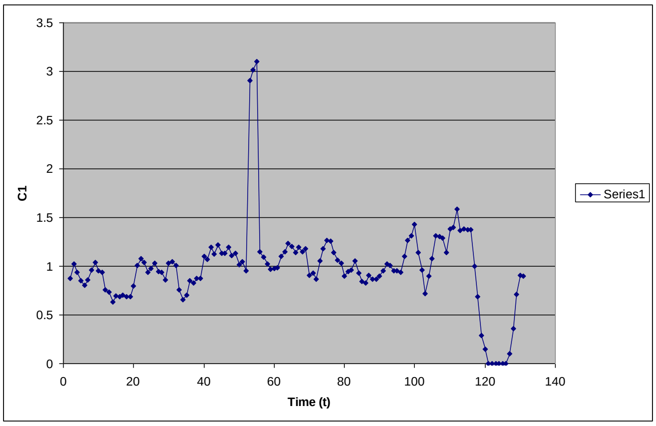

Fig. 4. Plot of Seasonal Index against time

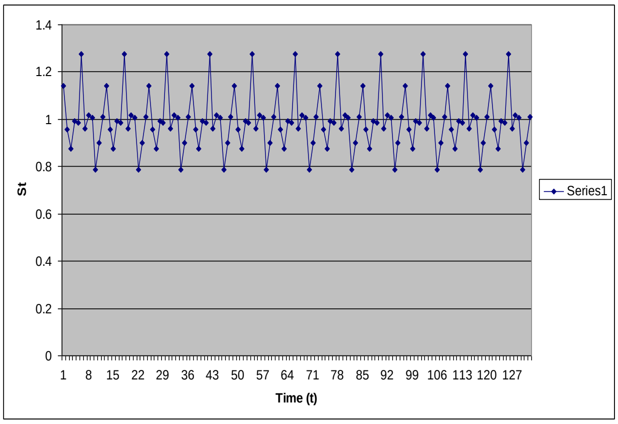

Fig. 5. Plot of Noise against time

IV. CONCLUSION

We have been able to successfully break Sapele Power Station electricity generation data into its varying components thereby revealing the underlying inherent property of the energy generation data. The model employed was able to characterize the monthly generation output data into its various components and replicate the original data in spite of the fluctuations, coupled with the noise, trend, cyclical activity and seasonal influences. This is evident from the results obtained in the final decomposition shown in table 1, column 9 as compared to the original electricity generation data in column 3. From the results, it is clearly seen that the operation and maintenance of this power generating station appear not to be in conformity with standard practices steaming from poor maintenance culture and policies. However, a good understanding of these results can help reverse the steady downward trend of electricity generation observed in this high esteemed power generation station. Also all these signals will help in articulating maintenance planning stemming from the fact that the cost and logistics involved in setting up a power plant is quite cumbersome and as such, requires articulate and careful planning as well as good maintenance culture to keep the plant in operation.

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