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Comparison of Regression Model and Artificial Neural Network Model for the prediction of Electrical Power generated in Nigeria

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ABSTRACT

Energy is the fundamental resource, it gives the ability to transform, transport and manufacture any and all goods and it is vital to the development of any economy. In Nigeria, electricity is one of the oldest energy forms available for daily activities. It is also, unfortunately, grossly inadequate to meet the demands of an ever increasing population. This is largely due to inadequate planning. Efficient energy management necessitates the development and utilization of an energy plan to ensure a balance between demand and supply with any economy. Energy analysis is defined as a particular set of procedures for evaluating the total energy requirements for the supply of a service or project. Energy analysis is an important exercise in the overall energy systems planning and management. Its relevance lies in the generation of forecasts for future energy consumption (demand/supply) patterns, and this is the main objective of the present work. Regression and artificial neural network methods are employed in energy analysis to determine energy requirements up to 2036. We examine in particular the problems of Nigeria's electricity system and based on electricity generation and consumption data we present a conceptual approach aimed at enhancing electricity generation in the country. The predicted values of the responses by ANN and regression models were compared and their closeness with the actual data values was determined.

Key words: Forecasting, Regression models, PHCN, Artificial Neural Network models.

INTRODUCTION

Despite Nigeria's vast oil wealth, much of the country's citizens do not have access to uninterrupted supplies of electricity. Nigeria has approximately 5,900 Megawatts (MW) of installed electric generating capacity. Power outages are frequent and the power sector operates well below its estimated capacity. A fundamental reason offered is the low generating capacity of the Nigerian power sector relative to installed capacity. Consequently, the sector had to undergo some reforms to increase power generation and distribution.

Among the reforms is the setting up of the National Electricity Regulatory Commission (NERC), unbundling of PHCN and entry of Independent Power Producers (IPP) among others. These reforms are expected to increase power generation and distribution and also residential electricity demand in Nigeria. Although much explanation has been offered on the supply of electricity in Nigeria quite a little is known about the fundamentals of residential electricity demand. The quest for more accurate estimates of key electricity demand parameters derives from two factors. First is their critical importance in the projection of future electricity demand. Secondly, the fact that understanding electricity demand dynamics [3,4] is essential for more informed and successful electricity policy decision making and implementation.

To the best of our knowledge, this study is the first to empirically analyze and forecast up to 2036, the residential electricity demand for Nigeria. The empirical analysis is for the period 1973–2007, employing annual data. The choice of this period is due to the availability of data.
Our study makes a methodological contribution to the literature on electricity demand.

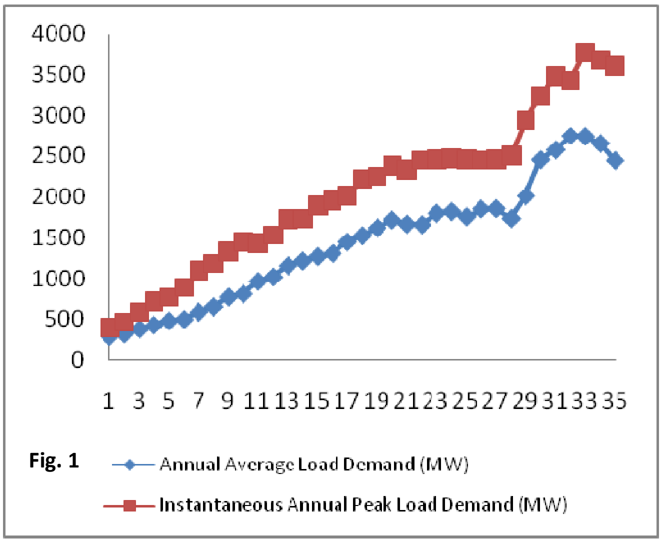

Fig. 1

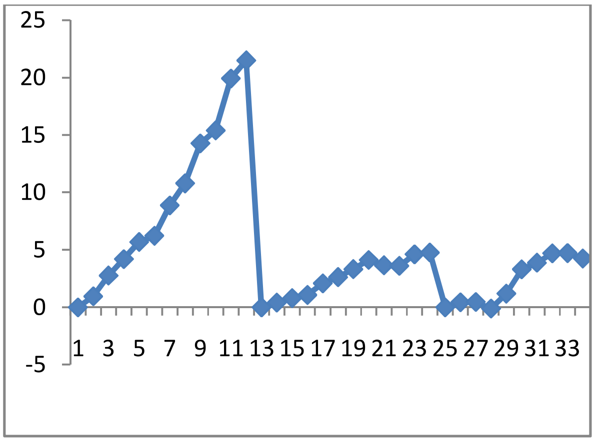

Fig. 2 Power Generation Growth Rate (GGR) in %, as a function of time

2. Objective of Study

The objective of this study is to model the relevant data provided by the Power Holding Company PLC (Appendix A) using the Statistical Technique and the Neural Networks, and then to compare the results of these two techniques.

3. A Historical Perspective

In 1972 the popular National Electric Power Authority (NEPA) came into existence by law in Nigeria [9], and was mandated to develop and maintain an efficient, co-ordinated and economical system of electricity supply for all parts of Nigeria. However over the years due to lack of maintenance of equipments, inadequate planning and growth in population, NEPA could not cope and became inefficient at generating and distributing electricity. The incessant power outages which clearly resulted from the difference between the Annual Average Load Demand

(ALD) and the Instantaneous Annual Peak Load Demand (IAPLD) as seen in Fig.1, was indicative of the fact that over the thirty five years depicted, the electricity company could not meet up, perhaps because of the rapid population growth. Furthermore the fluctuating Power Generation Growth Rate (GGR %) in Fig.2, also reflects this fact. The erratic nature of power supply eventually made Nigerians to coin the phrase '**N**ever **E**xpect **P**ower **A**lways' as an acceptance of the inadequacies of the electricity company.

In 1988, the National Electric Power Authority was partially commercialized, supported by an upward review in tariffs. As part of the restructuring effort of the power sector, the Electric Power Sector Reform Act 2005 was enacted. Consequently, the defunct National Electric Power Authority (NEPA) is now known as Power Holding Company of Nigeria (PHCN). The law paved the way for the unbundling of NEPA into the 18 companies– 6 generating companies, 1 transmission company and 11 distributing companies. The generating companies are made up of 2 hydro and 4 thermal (gas based) stations.

A summary of the generating stations, types and capacity is given in Table 1. The Nigerian power sector is marked by low generating capacity relative to installed capacity and much of the country's citizens do not have access to uninterrupted supplies of electricity.

Table 1

Power Station /Location	Type	Year Commissioned	Generation Capacity (MW)	Remarks
Lagos Station at Egbin	Thermal (gas)	1985-1987	1,320	6×220MW reheat steam turboelectric unit
Sapele station at Ogorode	Thermal (gas)	1978-1990	1020	6×120 MW steam and 4×75 MW
Delta TV at Ugheli	Thermal (gas)	1966-1990	832	Including 6×100 MW
Afam	Thermal (gas)	1975-1982	710	
Oji	Thermal (coal)	1956	30	Not functional
Ijora Station Lagos	Thermal (gas)	1978	60	3 units × 20 MW (2 units working)
Lagos IPP (Enron AES)	Thermal		170	Maximum planned is 270 MW
Abuja IPP	Thermal		30	
Rivers IPP (Trans-Amadi)	Thermal	2000-2002	30	
Kainji	Hydro	1968,1976, 1978	760	Some generators require major overhaul
Jebba	Hydro	1986	540	All units available
Shiroro	Hydro	1990	600	Some units require repairs

4. Artificial Neural Network Model

Artificial neural network models are based on the neural structure of the brain. The brain learns from experience and so do artificial neural networks. Previous research has shown that artificial neural networks are suitable for pattern recognition and pattern classification tasks due to their nonlinear nonparametric adaptive-learning properties. As a useful analytical tool, ANN is widely applied in analyzing the business data stored in database or data warehouse nowadays. One critical step in neural network application is network training. Generally, data in a company's database or data warehouse is selected and refined to form training data sets. Artificial Neural Network is widely used in various branches of engineering and science and their unique property of being able to approximate complex and nonlinear equations makes it a useful tool in quantitative analysis.

The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contains non-linear characteristics. In this paper, one model of neural network is selected among the main network architectures used in engineering. The basis of the model is neuron structure as shown in Fig. 2. These neurons act like parallel processing units. An artificial neuron is a unit that performs a simple mathematical operation on its inputs and imitates the functions of biological neurons and their unique process of learning. From Fig. 3 will have,

$$v_k = \sum_{j=1}^{m} x_j w_{kj} + b_k$$

The neuron output will be

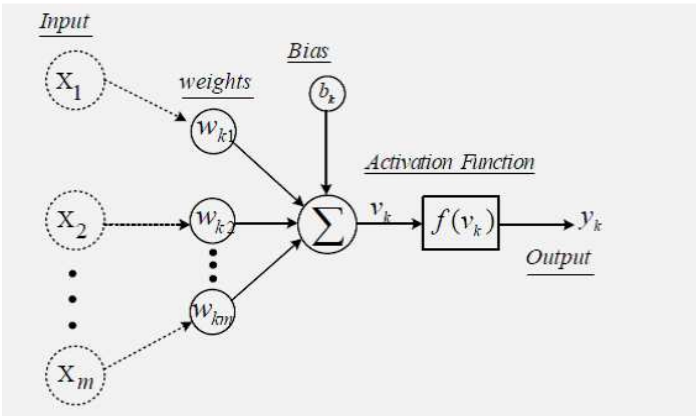

Fig.3 Mathematical structure of ANN

5. Multi-Layer Perception

Artificial Neural Network can be viewed as a mathematical model or computational model that is inspired by the structure or functional aspects of biological neural networks. They are characterized in principle by a network topology, a connection pattern, neural activation properties, training strategy and ability to process data. The most common neural network model is the Multilayer Perceptron [6,8,11]. This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. Fig. 4 shows the block diagram of a single hidden layer multiplayer perceptron (MLP). The inputs are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the hidden layer. Within the hidden layer, they get summed then processed by a nonlinear function (usually the hyperbolic tangent). If more than a single hidden layer exists then, as the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer and so on. Finally the data is multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output. To perform any task, a set of experiments of an input output mapping is needed to train the neural network. These data are one of the most important factors to obtain reliable results from any trained ANN. Thus, the training sample data have to be fairly large to contain all the required information and must include a wide variety of data from different experimental conditions and process parameters.

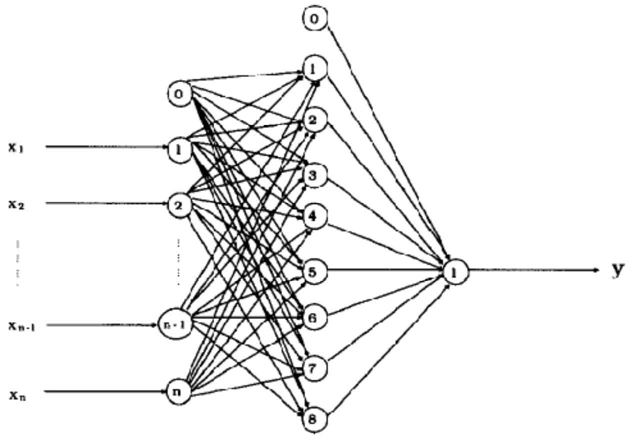

Fig. 4 Structure of the Multilayered Perceptron network with single hidden layer. Node 0 is bias.

5. Learning by Gradient Descent Error Minimization

The Perceptron learning rule is an algorithm that adjusts the network weights w_{mn} to minimize the difference between the actual outputs y_{ki} and the target outputs t_{ki}. We can quantify this difference by defining the *sum squared error* function, summed over all output units *i* and all training patterns *m*:

$$E(w_{mn}) = \frac{1}{2}\sum_{k=1}^{m}\sum_{i=1}^{n}(t_{ki} - y_{ki})^2$$

It is the general aim of network ***learning*** to minimize this error by adjusting the weights w_{mn}.

Typically we make a series of small adjustments to the weights $w_{mn} \to w_{mn} + \Delta w_{mn}$ until the error $E(w_{mn})$ is 'small enough'. We can determine which direction to change the weights in by looking at the gradients (i.e. partial derivatives) of E with respect to each weight w_{mn}.

Then the *gradient descent update equation* (with positive learning rate η) is given by

$$\Delta w_{kl} = -\eta \frac{\partial E(w_{mn})}{\partial w_{kl}}$$

. which can be applied iteratively to minimize the error.

For the present study, the output is the forecasted Electrical Power Generated (*PG*) (Output). The independent variables are the Annual Average Load Demand (*ALD*) and Instantaneous Annual Peak Load Demand (*IAPD*) (Inputs).

Remark:

i) For our analysis we used the ANN algorithm built into SPSS17 software [13]. The algorithm implements automatically the Multi Layer Perceptron neural network with gradient descent learning.

ii) In addition the software displays the following useful information in the output:

- **Network Structure.** Displays summary information about the neural network.
- **Description.** Displays information about the neural network, including the dependent variables, number of input and output units, number of hidden layers and units, and activation functions.
- **Diagram.** Displays the network diagram as a non-editable chart. We note that as the number of covariates and factor levels increases, the diagram becomes more difficult to interpret.
- **Synaptic weights.** Displays the coefficient estimates that show the relationship between the units in a given layer to the units in the following layer. The synaptic weights are based on the training sample even if the active dataset is partitioned into training, testing, and holdout data. Note that the number of synaptic weights can become rather large and that these weights are generally not used for interpreting network results.
- **Network Performance.** Displays results used to determine whether the model is "good". We note that charts in this group are based on the combined training and testing samples or only on the training sample if there is no testing sample.
- **Model summary.** Displays a summary of the neural network results by partition and overall, including the error, the relative error or percentage of incorrect predictions, the stopping rule used to stop training, and the training time. The error is the sum-of-squares error when the identity, sigmoid, or hyperbolic tangent activation function is applied to the output layer. It is the cross-entropy error when the softmax activation function is applied to the output layer. Relative errors or percentages of incorrect predictions are displayed depending on the dependent variable measurement levels. If any dependent variable has scale measurement level, then the average overall relative error (relative to the mean model) is displayed. If all dependent variables are categorical, then the average percentage of incorrect predictions is displayed. Relative errors or percentages of incorrect predictions are also displayed for individual dependent variables.

iii) Depending on preferences, numerous other network information can also be displayed.

5. Statistical Technique

Regression method is one of the most widely used statistical techniques[7,10]. Multiple regression analysis is a multivariate statistical technique used to examine the relationship between a single dependent variable and a set of independent variables. The objective of the multiple regression analysis is to use independent variables whose values are known to predict the single dependent variable. The effect of *independent variables* on the *response* is expressed mathematically be the regression or response function *f*:

$$y = f(x_1, x_2, \dots, x_n; \beta_1, \beta_1, \dots, \beta_n)$$

y - dependent variable.

$\beta_1, \beta_1, \dots, \beta_n$- *regression parameters* (unknown!)
f - the form is usually assumed to be known

The regression model for the observed response variable is written

$$z = y + \varepsilon = f(x_1, x_2, \dots, x_n; \beta_1, \beta_2, \dots, \beta_m) + \varepsilon$$

ε- error in observed value z.

To find *unknown regression parameters* $\{\beta_1, \beta_2, \dots, \beta_m\}$, the *method of least squares* **[**4**]** can be applied:

$$E(\beta_1, \beta_2, \dots, \beta_m) = \sum_{j=1}^{n} (z_j - y_j)^2 = \sum_{j=1}^{n} \left(z_j - f(x_1, x_2, \dots, x_n; \beta_1, \beta_2, \dots, \beta_m)\right)^2$$

where $E(\beta_1, \beta_2, \dots, \beta_m)$ is the error function or sum of squares of the deviations.

To estimate $\beta_1, \beta_1, \dots \beta_m$ we minimize E by solving the system of equations:

$$\frac{\partial E}{\partial \beta_i} = 0, \quad i = 1,2, \dots, m$$

6. Model Specification and Analysis

The regression model to consider in this study takes the Annual Average Load Demand (*ALD*) and Instantaneous Annual Peak Load Demand (*IAPD*) as the explanatory variables and Electrical Power Generated (*PG*) as dependent variable. This is used to obtain a reliable parameter estimates in the regression.

The model to be used can be specified as

$$PG = f(ALD, IAPD)$$

More precisely;

$$PG = \beta_0 + \beta_1\, ALD + \beta_2\, IAPD$$

$\beta_0,\ \beta_1,\ \beta_2 > 0.$

RESULTS AND DISCUSSION

Table 2 is obtained from the SPSS output for the analysis of the multiple linear regression relating the Electrical Power Generated (*PG*) as a function of the Annual Average Load Demand (*ALD*) and the Instantaneous Annual Peak Load Demand (*IAPD*). The standard error for each of the variables are indicated in the brackets below the equation as well as the goodness of fit R^2.

Table 2

Variable	Coefficient	Std. Error	*t*-statistic	Prob
ALD	8.740	2.136	4.092	.000
IAPD	.152	1.718	.088	.930
Constant	-534.070	874.979	-.610	.546

$$PG = -534.07 + 8.740\,ALD + 0.152\,IAPD$$
$$(874.979) \quad (2.136) \qquad (1.718)$$
$$R^2 = 0.934$$

7.1 Computer results for the MLP Network Model
Model Summary

Table 3 Dependent Variable: PG

Training	Sum of Squares Error	.011
	Relative Error	.001
	Stopping Rule Used	Training error ratio criterion (.001) achieved
	Training Time	0:00:00.000
Testing	Sum of Squares Error	.010
	Relative Error	.002

a. Error computations are based on the testing sample

Table 4 Hidden Layer parameters

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1		Output Layer
		H(1:1)	H(1:2)	PG
Input Layer	(Bias)	-.148	.174	
	ALD	.363	-.259	
	IAPD	.020	.-096	
Hidden Layer 1	(Bias)			.435
	H(1:1)			1.378
	H(1:2)			-1.608

Summary

The table 5 shows a summary of the results obtained for the statistical and neural network analysis of the electricity data for the prediction of the Electrical Power Generation (PG) of Nigeria. The forecasting ability of the two models is accessed using Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). The results clearly show that Neural Networks, when trained with sufficient data and proper inputs, can better predict the PG. Statistical technique is well established, however their forecasting ability is reduced as the data becomes more complex.

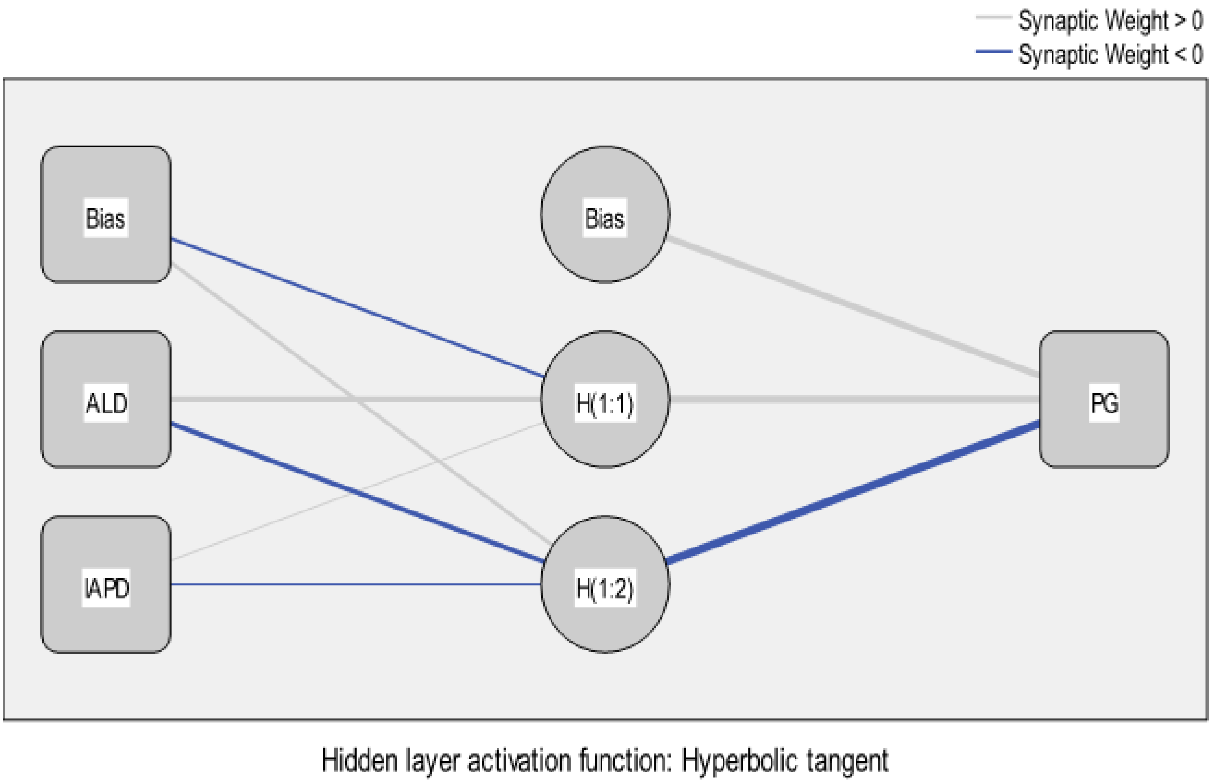

Fig. 5

Table 5 Comparison of models

	No of Obs	MAE	MSE	RMSE
Regression	35	0.056	0.003	0.076
ANN	35	0.049	0.0012	0.062

CONCLUSION

In this paper, two techniques for modeling and forecasting the electrical power generated of Nigeria: Neural Network and Statistical Technique. The forecasting ability of these models is accessed on the basis of MSE, MAE and RMSE. We have discovered the fact that Neural Networks outperform Statistical technique in forecasting.

The field of neural networks is very diverse and opportunities for future research exist in many aspects, including data pre-processing and representation, architecture selection, and application [1,2,8,12]. The next logical step for the research is to improve further the performance of Neural Networks, for this application, perhaps through better training methods, better architecture selection, or better input.

The study also explored the association between electrical power generated, annual average load demand and instantaneous annual peak load demand in Nigeria (R^2 = 0.934).

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Appendix A

Energy consumed in relation to generation growth rate and population growth rate [NCC,PHCN, 1993, Census Department, Bureau of Census (for Nigeria) International Data Base]

Year	EPG (GWh)	AALD (MW)	IAPLD (MW)	PE ($\times 10^5$)	GGR (%)	PGR (%)
1973	2493	284.7	387	54226	0	0
1974	2780	317.55	457	55865	0.9594	0.2519
1975	3322	379.23	579	57905	2.7711	0.5038
1976	3750	428.25	708	59143	4.2018	0.7558
1977	4195	479.07	767	60782	5.6893	1.0075
1978	4359	497.8	887	62421	6.2375	1.2592
1979	5151	588.24	1095	64060	8.8849	1.5117
1980	5724	653.68	1181	65699	10.8002	1.7633
1981	6766	772.68	1323	67782.1	14.2833	2.0833
1982	7102	811.05	1448	69865.2	15.4067	2.4033
1983	8456	965.68	1434	71948.3	19.9325	2.7233
1984	8927	1019.46	1532	74031.4	21.5067	3.0433
1985	10155	1159.7	1720	76114.5	0	0
1986	10665	1217.94	1730	78197.6	0.4185	0.2456
1987	11141	1272.3	1885	80280.7	0.8091	0.4561
1988	11147	1309.99	1952	82363.8	1.0799	0.6842
1989	12700	1450.34	2008	84446.9	2.0885	0.9132
1990	13364	1526.17	2219	86530	2.6333	1.1403
1991	14212	1623.01	2246	89263	3.3292	1.4396

Year	EPG (GWh)	AALD (MW)	IAPLD (MW)	PE ($\times 10^5$)	GGR (%)	PGR (%)
1992	15066	1720.54	2382	92057	4.13	1.7455
1993	14617	1669.26	2330	94934	3.6616	2.0604
1994	14557	1662.46	2446	97900	3.6123	2.3851
1995	15793	1803.56	2452	100959	4.6266	2.7201
1996	15971	1823.84	2470	104095	4.7727	3.0634
1997	15416	1760.51	2457	107286	0	0
1998	16253	1856.09	2448	110532	0.4525	0.2521
1999	16291	1860.43	2458	113829	0.473	0.5082
2000	15227	1738.92	2499	117171	-0.1022	0.7678
2001	17637	2014.15	2934	120481.3	1.2006	1.0249
2002	21544	2460.32	3233	123791.6	3.3126	1.2821
2003	22612	2582.29	3479	127101.9	3.8899	1.5392
2004	24132	2755.87	3428	130412.2	4.7116	1.7963
2005	24177	2749.59	3774	133722.5	4.7359	2.0534
2006	23300	2660.86	3682	137032.8	4.2618	2.3106
2007	23187	2450.61	3599			

EPG=Electric Power Generated, **AALD**=Annual Average Load Demand, **IAPLD**=Instantaneous Annual Peak Load Demand
PE=Population Estimate, **GGR**=Generation Growth Rate, **PGR**=Population Growth Rate.