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Forecasting the Monthly Electricity Demand of Georgia using Competitive Models and Advices for the Strategic Planning

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Abstract

Electricity is a kind of energy that consumption increases rapidly. However, Electricity is used from the residences to the industry everywhere. This non-storable energy needs to be predicted precisely and supplied sufficiently. For this reason in this research electricity demand of Georgia is predicted using comparative models as Box Jenkins and Neural Network. By this way, an accurate model was developed to perform a strategic plan. For the calculation of significance level, MAPE is utilized to see error. It was seen that artificial neural network multilayer perceptron model provided better predictions rather than SARIMA model. Finally, some suggestions are expressed to the government of Georgia for future plans.

Keywords: Strategic Planning, Artificial Neural Networks, Box Jenkins, Forecasting, Georgian Electricity Demand

1. Introduction

Electricity is one of the most important energy resources and welfare parameters of a country. Energy utilization has been increasing from year to year in every country based on use of electrical instruments in manufacturing and industry and residences. Electricity is an energy which is not only used in manufacturing and business sector of country, but also in houses daily. From this point of view, energy demand in a country must be planned accurately in order to supply sufficiently. Electricity demand prediction is one of the most critical parameters. Electricity is not a storable energy and that is why must be planned and investment must be prepared on time and sufficient.

Georgia is located at such a strategic place that has many rivers to produce electricity. “Hydro resources take the first place among the natural riches of Georgia. There are 26 000 rivers on the territory of the country. Their total length is approximately 60 000 km. The entire fresh water supply of Georgia, which is made up of ice, lakes and water reservoirs, is 96.5 km3. Around 300 rivers are significant in terms of energy production; their total annual potential capacity is equivalent to 15000 MW, while the average annual production equals to 50 bln. KWh."(Ministry of Energy). From this point of view, these kinds of natural resources might be used more efficiently to increase welfare of country. However, energy is very important for welfare level of Georgia. On the other hand, electricity production increases importance when it is considered that Georgia doesn't have natural resources as petroleum, gas… etc. Normally, electricity consumption might be thought in three categories as industrial users, commercial users, and residential users but it will be considered as one category for case of Georgia.

Forecasting of demand is important for strategic planning of electricity production. For more accurate predictions, more historical data and the appropriate model is needed. But Georgian data in electricity is not recorded or announced before 2007. So we have only data from 2007 till 2013. For this reason, we will try to find the best model for the current data.

Artificial neural network for the forecasting monthly electricity demand for Georgia is not performed in the literature currently. This makes this research original.

For this research, secondary data was used and this data was collected from the site called reegle.info. When the official sites of Georgia are checked, the information was conformed. Georgian electricity demand data shows that consumption is increasing at yearly basis. On the other hand, consumption is higher in winter terms rather than summer terms. But the next winter, demand will be probably higher than this year. This estimation shows that data has trend at distribution.

2. Literature Review And Hypotheses

2.1. Forecasting the electricity demand and strategic planning

Forecasting and strategic planning are very tightly close to each other (Meng and Sun, 2011). David, (2011) stated that "Forecasts are educated assumptions about future trends and events. Forecasting is a complex activity because of factors such as technological innovation, cultural changes, new products, improved services, stronger competitors, and shifts in government priorities, changing social values, unstable economic conditions, and unforeseen events".

Despite of strategic planning is known as a one of the most critical parameter for success, it is generally issued as perfunctory task. (Cervone, 2014) On the other hand, success without strategic planning is very hard issue.

Strategic planning was defined by Chandler, (1969, 1990) in two aspects;

(a) The identification and expression of long-term goals and
(b) The provisioning of resources to bring those goals to fruition.

This expression shows that long term identification and expression can be performed by forecasting and this forecast may probably will be fruitful in the future.

If anyone wants to plan about the future, s/he must know what is going to happen in the future. For this, many calculations and models might be required for a company, country, society…etc.

“Individuals and organizations have operated for hundreds of years by planning and forecasting in an intuitive manner”. Armstrong, (1983). But in this age, many outstanding models were come out to perform for more accurate designs. But the importance of forecasting at strategic planning never can be ignored.

If a company would like to perform a good strategy, needs strong information about the future.

“High performing firms seems to make more informed decisions with good anticipation of both short- and long-term consequences. In contrast, firms that perform poorly often engage in activities that are shortsighted and do not reflect good forecasting of future conditions.” (David, 2011). From this point, the importance of accurate forecasting is significantly important.

(Steiner, 1979) stated the importance of forecasting by expressing that an organization can improve effectiveness by forecasting the environment, anticipate problems and respond to those problems. It doesn’t have to be only a company, it can be a government that is predicting the problem or upcoming situation and it doesn’t have to be the problem forecasting but it can be a demand forecasting, too.

Forecasting is important only when it has accuracy. On the other hand, accuracy can be reached by the right data and right model combination. From this point, artificial neural network models are broadly used to perform forecasting in short, medium, and long term predictions. (Jhee & Lee, 1993; Chiang, Urban, & Baldridge, 1996; Stern, 1996; Hill, O’Connor, & Remus, 1996; Kohzadi, Boyd, Kermanshahi, & Kaastra, 1996; Indro, Jiang, Patuwo, & Zhang, 1999; Nayak, Sudheer, Rangan, & Ramasastri, 2004; Karunasinghe & Liong, 2006; Oliveira & Meira, 2006; Gareta, Romeo, & Gil, 2006. For example, Peng et al. (1992) utilized minimum-distance-based identification for the appropriate load data and degree of temperature used for training of the ANN. Dillon et al. (1991) proved that artificial neural network has learning capability based on input, factors, and output sets. It is proved by one another author also that artificial neural network models have learning ability(Kalogirou, 2000) and with this ability these models perform much better than other classical model many times. May be that is why Dillon et al. (1991) and Peng et al. (1992) didn’t compare the outcomes comparatively. Moreover, wavelet transformation and neural network model was utilized by Yao et al. (2000) in order to forecast electrical load. Aydinalp et al., (2002) has used artificial neural network to forecast loads of Canadian residences. Their approach in this study was time-consuming. Hsu & Chen, (2003) used artificial neural network model in order to forecast peak loads of Taiwan. In this study they have compared artificial neural network with the regression models. Ozdemir, (2014) also proposed artificial neural network models in order to predict energy intensity of Turkey.

SARIMA models are also broadly used in the literature. Demir, (2014) proposed SARIMA model in order to analyse future expectations of Northern-Iraq. Moreover, Rallapalli and Ghosh, (2012) proposed MSARIMA model in order to perform a forecast at monthly peak demand of electricity in India.

There are also some studies that have utilized artificial neural network with other computational models. For example, Kheirkhah, et. Al. (2012) proposed artificial neural network and compared the model with Principal Component Analysis (PCA), Data Envelopment Analysis (DEA) and ANOVA methods to estimate and predict electricity demand for seasonal and monthly changes in electricity consumption. They made an accurate prediction for Iranian electricity demand by these computational models. In this study also we will use computational models as comparing SARIMA and artificial neural network.

Most of the studies, in that artificial neural network models are proposed, feed-forward neural network is utilized. The reason might be this model has back-propagation training algorithm and model recognizes and learns the previous patterns which will show the similarity with the similar parameters patterns. On the other hand, this model is not utilized for the case of Georgia. In order to enlighten whether multilayer perceptron will work for the case of Georgia or not, in this study also we have proposed multilayer perceptron section of artificial neural network in order to forecast future demand of Georgia. This is the originality of this paper.

3. Methodology

In this research, we used the data which consist of electricity demand of Georgia as a secondary data and downloaded from the Georgian sites. The aim of this research is to find a good model to perform a good forecasting in order to determine the future expectations of Georgian electricity demand and perform the forecasting using the best model among competitive models. For this aim, SARIMA models are proposed to check the error level of the forecasting. Although there exists the electricity demand of Georgia Between 2007-2013, only 2007-2012 monthly electricity actual demand data was used in order to perform training. Remaining 2013 year monthly electricity data was used for the test forecasting in order to check the error levels second time to see if it the error was decreasing or increasing. Based on these calculations, two different SARIMA models were proposed to check the level of error. After getting the results of the forecasting by SARIMA models, Artificial Neural Network model is used to perform the same forecast. The error level of this model also checked as other models in two periods as preliminarily at the training part and then at the testing part. The best model among two SARIMA and Artificial Neural Network models was chosen to perform the real forecasting. Finally, the results were concluded to make some suggestions to the government of Georgia for the strategic planning based on the forecasts that was performed in this paper.

There are 72 data for training and 12 data for testing. Monthly index, month, and year is used as factor to decrease forecast error. However, IBM SPSS is utilized for these operations. First of all, load distribution data is shown on the figure below;

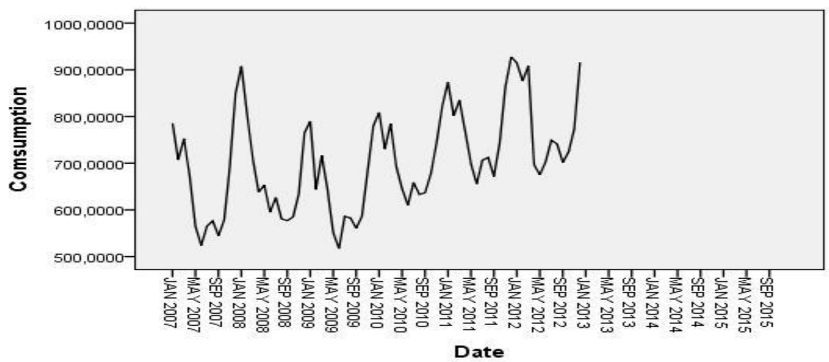

Figure 1: Monthly consumption data distribution between the years 2007 and 2012

Data distribution can be seen as sequence from the figure 1. it seems that there is an interesting impulse at January, 2008. It will be hard for programs to estimate this impulse. That is why some factors might be used to add more importance to this abnormal consumption data at January, 2008. On the other hand, beside this impulse, it is obvious that there is seasonality, trend, and fluctuation on the data. For this reason, natural log, difference and seasonal difference taken data was represented on the figure 2;

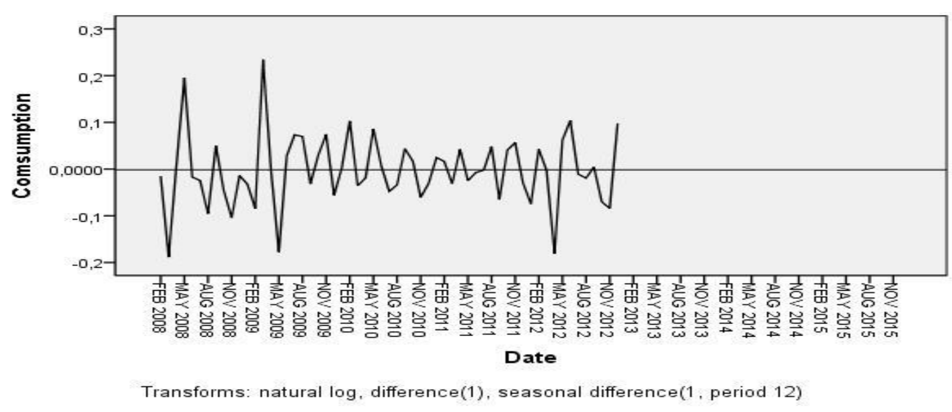

Figure 2: representation of “Monthly consumption data distribution between the years 2007 and 2012” after transformations

It can be seen that data is stationary after all these transformations. Furthermore, autocorrelation and partial autocorrelation functions are determined below in order to define the best model for seasonal autoregressive integrated moving average SARIMA.

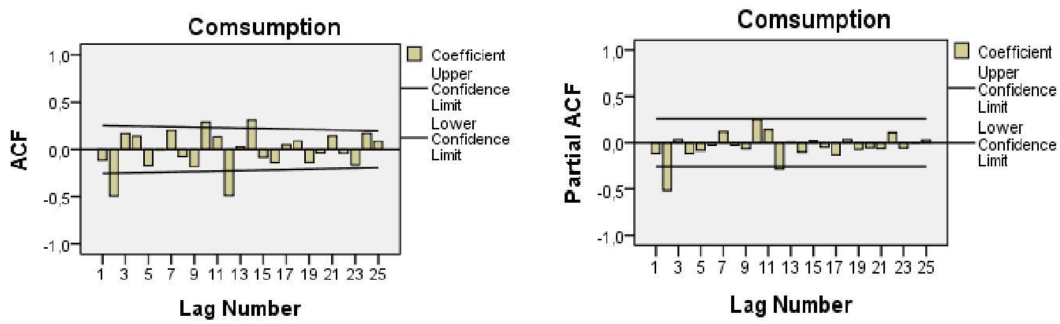

Figure 3: autocorrelation and partial autocorrelation functions of the transformed data

It can be said looking at ACF that autoregressive for the data is 4. Moreover, difference and seasonal difference of the data has already been taken. That is why, (4,1,1)*(0,1,1) and (4,1,0)*(0,1,1) models will be compared to see results. Best model will be selected from the lower MAPE and MAE level. There are the results of models on table 1;

SARIMA (p, d, q)*(P,D,Q)$_{12}$	MAPE	MAE
SARIMA (4,1,0)*(0,1,1)$_{12}$	3.847	28.606
SARIMA (4,1,1)*(0,1,1)$_{12}$	3.610	26.185

Table 1: Models results for performing forecasting

There are MAPE and MAE levels of each model on the table 1. It is known that the lower MAPE or MAE level means more accurate model than one another that has higher MAPE level. According to this comparison, model (4, 1, 1)*(0, 1, 1)$_{12}$ seems better performing based on MAPE and MAE levels.

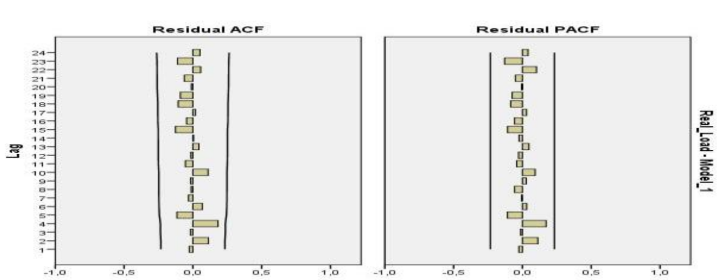

Figure 4: autocorrelation and partial autocorrelation functions of the selected model

It seems the model is suitable looking at residuals that none of them are significant (greater than 0.05) and model is proved. The next step is to check if model is adequate or not. For this purpose, a Ljung-Box Q-test result, which shows the significance of selected model, was proposed. According to the results;

H0: model is adequate

H_1: model is not adequate

Ljung-Box Q-test		
Statistics	DF	Sig.
9.459	12	0.663

Table 2: Ljung-Box Q-test for proving that the model is adequate

It is blatant that the result of portmanteau test that the model is adequate looking at the significance level of the model (0.663) is greater than 0.05. Therefore, model is accepted.

3.1. Comparing with the Artificial Neural Network (Multilayer Perceptron)

In this part, multilayer perceptron model of artificial neural network was utilized in order to compare and decrease the error level. IBM SPSS 20 software is utilized for these operations. Partition includes 72 data which occupies 66.67 percent of the whole data including holdout.

Testing part consist of 12 data which has the portion of 11.11 percent. Holdout part is consisting of 24 data which is 22.22 percent of total amount of data. Totally 108 data is operated including in-sample and out-sample sets.

Multilayer perceptron has input, hidden and output layers. Input layer consists of 3 neurons called as Monthly_Index, Years, and SARIMA (4, 1, 1)*(0, 1, 1). Hidden layer consists of 3 neurons and output layer has only one neuron which represents the monthly demand forecasts of Georgia. Parameters of the supervised learning model for the forecasting are set as;

Training criteria	Mini-batch
Optimization algorithm	Gradient decent
Initial learning Rate	0.3
Lower boundary of the learning rate	0.001
Interval center	0
Interval offset	±0.5
Learning rate reduction, in Epochs	10
Momentum	0.0001

Table 3: parameters of multilayer perceptron model

Parameter Estimates

Predictor		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	Real_Load
Input Layer	(Bias)	,729	,190	,286	
	Monthly_Index	-,496	,079	-,223	
	YEAR_	-,382	,043	-,014	
	SARIMA_4_1_1_0_1_1	,204	,359	,194	
Hidden Layer 1	(Bias)				,535
	H(1:1)				-1,530
	H(1:2)				1,476

H(1:3)				,372

Table 4: Parameter Estimates

Here are the results as coefficient estimates that show the relationship between the units in a given layer to the units in the following layer.
Test forecast results are shown on the table below;

Date	Real_Demand	SARIMA	Error	MLP	ERROR
January-2013	941.836	934.220	7.616	944.767	2.931
February-2013	791.546	846.204	54.658	817.316	25.77
March-2013	864.821	856.986	7.835	879.796	14.975
April-2013	766.835	740.333	26.502	779.426	12.591
May-2013	689.969	691.534	1.565	708.794	18.825
Jun-2013	724.313	687.367	36.946	726.596	2.283
July-2013	788.400	806.400	18.000	810.199	21.799
August-2013	785.958	756.752	29.206	799.213	13.255
September-2013	732.786	753.254	20.468	755.019	22.233
October-2013	803.222	772.73	30.492	810.830	7.608
Nowember-2013	810.880	882.535	71.655	835.830	24.95
December-2013	989.647	920.711	68.936	980.094	9.553

Table 5: Forecast results of 2013 year for 12 month

Finally, the comparison table between SARIMA and Multilayer perceptron are shown on the following table;

Model	Error Type	In-Sample	Out-of-Sample
SARIMA	MAPE	2.93	3.86
	MAE	25.174	31.157
MLP	MAPE	2.05	1.82
	MAE	17.635	14.731

Table 6: Comparison table between SARIMA and MLP

4. Conclusion

As a first conclusion, it obviously can be said that multilayer perceptron “feed forward model” decreased the error at the electricity consumption data. This means that the ministry of energy, strategic planning foundations of energy those are in Georgia, and electricity energy related institutions might use this model to perform and outstanding forecasting to predict expectations in the future. Data of electricity energy demand is analyzed and found adequate to be forecasted using feed forward model, artificial neural networks. On the other hand, this result consists of only electricity demand data and not others. However, it doesn’t mean the same results will be seen at other data types. It is seen that the monthly index has a very important impact on data accuracy from the learning point of view. But for the future researches, lags, seasonal indexes, population factors etc. parameters might be included into the model to improve and develop more accurate results.

As second conclusion, this model and result has an important part from the strategic plan point of view. Below there is a figure shows the future expectations from the electricity demand of Georgia;

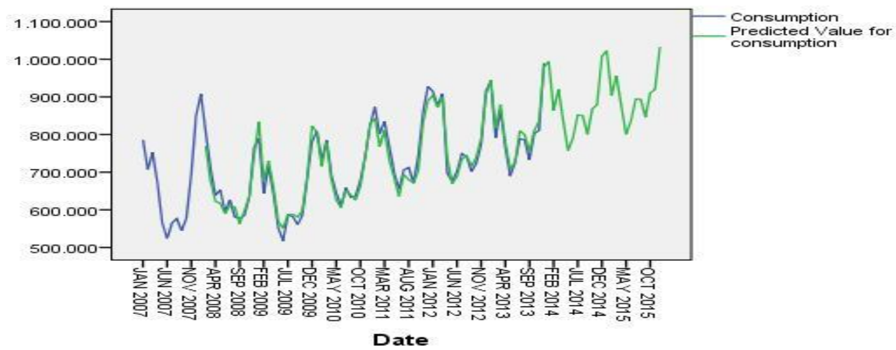

Figure 5: consumption data sequence of electricity demand of Georgia

The figure shows that the consumption is increasing year by year. It is estimated from the graph that after two years, electricity demand will be above 1000 MW in winter times. The table below will help to see the exact numbers about the future;

Date	Demand (MW)	Date	Demand (MW)
Jan-14	993.919	Jan-15	1.022.438
Feb-14	863.585	Feb-15	903.763
Mar-14	920.263	Mar-15	956.166
Apr-14	835.47	Apr-15	877.249
May-14	757.136	May-15	800.378
Jun-14	791.113	Jun-15	836.378
Jul-14	852.028	Jul-15	894.425
Aug-14	850.601	Aug-15	893.887
Sep-14	800.492	Sep-15	845.916
Oct-14	868.269	Oct-15	911.016
Nov-14	879.376	Nov-15	920.089
Dec-14	1.008.169	Dec-15	1.033.278

Table 7: Forecasted electricity demand of Georgia including 2014 and 2015

As it can be seen on the table above, the electricity demand is increasing to the peak in December and January every year. From this point, Georgia needs extra investment on electricity energy load to satisfy the demand of consumption. In 2014 and 2015 years electricity demand is above 1000 MW in December and January. According to the information taken from the official site of Ministry of Economy and Sustainable Development (Georgia) (2013), "*Mikheil Janelidze, Deputy Minister of Economy and Sustainable Development of Georgia received the representatives of the Chinese company - Guo Din Sinzian Electricity on July 10.The Chinese side expressed its interest to invest in Georgian energy sector. Guo Din Sinzian Electricity is studying several projects of building of power stations with total capacity of 1170 megawatts."*

This meeting might be a good opportunity from the point of fitting the future demand of electricity in Georgia. However, rivers also are a good opportunity for Georgia to utilize in order to generate electricity from.

Finally, Georgia needs to operate new investments on electricity demand to increase electricity load in order to satisfy the market demand. Ministry of Economy and Sustainable Development of Georgia might get use of this research from the strategic planning point of view. By this way this will be the contribution of this academic research to the practical life.

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