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Empirical analysis of electricity demand in Albania. the impact in ecosystem

Valbona Karapici[1,2], Doriana Matraku (Dervishi)[2*], Arsena Gjipali[3]
[1,2]Department of Economics, Faculty of Economy, University of Tirana; valbona.karapici@gmail.com (V.K.)
dorianadervishi@feut.edu.al (D.M.D.).
[3]University of Winnipeg; a.gjipali@uwinnipeg.caa (A.G.)

Abstract: Albania represents the case of a developing country with a volatile demand for power facing an unstable domestic supply, especially during the last decade. Understanding future patterns of electricity usage is crucial in various planning contexts, the most important of which would be security of supply. In this framework, acknowledging the future national demand for electricity is needed for electricity providers for them to plan the sufficient and security of electricity supply. The aim of this paper is electricity demand modelling and forecasting in Albania. The model developed for the determinants of electricity demand for Albania allows understanding of the patterns of consumption behaviour. The main demand drivers of the electric consumption considered here are macroeconomic and demographic factors. The current work empirically estimates that the main determinants of electricity consumption in Albania for the period 1990-2014 are GDP, population and remittances. Results coefficients are then used to forecast electricity consumption for the period 2015-2030. We believe that the main contribution of the proposed estimation forecasts would be for correctly informing policy makers regarding electricity demand patterns in Albania and in forming expectations on a vital sector such as electricity.

Keywords: *Demand, Estimation, Ecosystem, Electricity consumption, Forecast, Green energy.*

1. Introduction

Electricity-supply planning requires efficient management of existing power systems and optimization of the decisions concerning additional capacity. Power System planning starts with electric load (demand) forecasting. Demand prediction is an important aspect in the development of any model for electricity planning. The form of the demand depends on the type of planning and accuracy that is required; hence it can be represented as an annual demand (GWh), a peak demand (MWh), or load duration curves like daily, weekly or annual. Research on electricity consumption forecasting is usually divided into two categories: short-term (see also Soares and Medeiros, 2008), and long term (Meng et al, 2011). The long-term forecasts (five to 20 years) are required for resource planning, utility expansion, and staff hiring. Medium-term forecasts (one month to five years) are used for purchasing fuel and revising electricity tariffs. Short-term load forecasting (STLF) (one hour to one week) is important for scheduling functions, such as generator unit commitment, hydro-thermal coordination, short-term maintenance, fuel allocation, power interchange, transaction evaluation, as well as network analysis functions, such as dispatcher power flow and optimal power flow. In other terms, short-term load forecasts are required for the control and scheduling of power systems. The focus varies from minutes to several hours ahead. The predictions are required as inputs to schedule cost algorithms for the generation and transmission of electricity. This paper is concerned with long term electricity demand forecasting.

Albania represents the case of a developing country with a volatile demand for power facing an unstable domestic supply, especially during the last decade. Hence, understanding future patterns of

* Correspondence: dorianadervishi@feut.edu.al

electricity usage is crucial in various planning contexts, the most important of which would be security of supply. In this framework, acknowledging the future national demand for electricity is needed for electricity providers for them to plan the sufficient and security of electricity supply (Imtiaz et al., 2006 and Soontornrangson et al., 2005).

In modelling the electricity demand function, concentration has centred on income drivers and price drivers. The income drivers are macroeconomic and demographic factors such as GDP growth, growth in household disposable income, population growth, growth in the number of households or the living space per capita, etc. On the other hand, price drivers are related to the price level for electricity and other energy sources that could substitute electricity. The common difficulty to the development of reliable forecasts is the determination of sufficient and necessary information for a good prediction. If the information level is insufficient, a forecasting will be poor; similarly, if information is useless or unnecessary, modelling will be difficult or even skewed.

To build a forecasting model, it is necessary to understand the demand drivers of the electric consumption. Over the past two decades, several studies have applied different econometric models, to estimate the relationship between electricity demand and its determinants, as well as to forecast the electricity demand. An appropriate model of the determinants of electricity demand for Albania would allow the understanding of patterns of consumption behaviour, as well as observe the degree of similarities and/or differences. The value of this would be for correctly informing policy makers regarding different regional demand patterns in the country, in forming expectations on a vital sector such as electricity.

The remainder of this paper is organized as follows. Section 2 reviews the economic literature on electricity demand modelling. Section 3 presents the dataset and the methodology employed in the analysis of electricity demand forecasting in Albania. The influence of economic and demographic variables on the annual electricity consumption in Albania is empirically investigated, with the intention to develop a long-term consumption forecasting model. Section 4 concludes.

2. Literature Review

Electric energy is a significant driving force for economic development, while the accuracy of demand forecast is an important factor leading to the success of efficiency planning. The concept of electricity demand forecast affects several diverse activities corresponding to different purposes. Demand forecasts are generally required for the expansion, controlling and scheduling of power systems. Thus, investment in electricity generation capacity, whether using fossil-based or renewable energy sources, is largely motivated through the anticipated long-term need for electricity (Ulutaş, 2005; Franssen and Simbeck, 2006).

Forecasting electricity consumption is of national interest to any country. Future electricity forecasts are not only required for short- and long-term power planning activities but also in the structure of the national economy. According to the neoclassical household production theory, electricity can be seen as an input together with electricity-using capital stock into the production of services, such as lighting, cooling, heating and cooking that generate some utility to the consumer. Therefore, the demand of electricity is a derived demand, as it comes from the consumer's optimal choice of a certain service.

There is a vast literature that investigates the role of various aggregate factors that affect the demand for electricity power. Several electricity forecasting models have been developed using economic, social, geographic and demographic factors. Mohamed and Bodger (2005) propose electricity consumption forecasting models based on economic factors for Domestic and Non-Domestic sectors and total consumption for New Zealand, using multiple linear regressions. Investigating the influence of selected economic and demographic variables on the annual electricity consumption in New Zealand, they conclude that a multiple linear regression model using GDP, price and population would provide an appropriate forecasting model for electricity consumption. In this framework, Egelioglu et al. (2001) considered the influence of economic variables on the annual electricity consumption in Northern

Cyprus by using multiple linear regression analysis. It was found that the number of customers, the price of electricity and the number of tourists correlate with annual electricity consumption. Harris and Liu (1993) bring into attention that price plays a major role in explaining conservation behaviour by electricity consumers.

Yan (1998) projected residential electricity consumption using climatic variables for Hong Kong. Ranjan and Jain (1999) expressed energy consumption patterns for Delhi as functions of weather and population while Fung and Tummala (1993) concluded that it was reasonable to use electricity price, gross domestic product (GDP), deflated domestic exports and population to forecast electricity consumption in Hong Kong. Liu et al. (1991) used GDP, real electricity price and population in electricity consumption of Singapore. Instead, besides residential price of electricity and per capita income, Lakhani and Bumb (1978) incorporate also the estimated long run elasticity of demand in forecasting demand for electricity in Maryland. In a dynamic structural model Harris and Lon-Mu (1993) estimated the relationship between electricity consumption and several potentially relevant variables, such as weather, price, and consumer income. They used a 30 year data series from south east USA, finding a high seasonality of electricity demand. Whilst Kamaludin (2013) evaluates electricity consumption in 32 developing countries as dependent variable and independent variables are GDP per capita, price of oil (proxy variable) and lagged electricity consumption.

The literature on forecasting demand for electricity develops various methods. For example, Saab et al. (2001) investigated different univariate modelling methodologies to forecast monthly electric energy consumption in Lebanon. Instead, Al-Ghandoor et al. (2008) presented a model developed to forecast electricity consumption of the Jordanian industrial sector based on multivariate linear regression of time series to identify the main drivers behind electricity consumption. Erdogdu (2007) has proposed a model based on ARIMA (autoregressive integrated moving average) providing an electricity demand estimation and forecast for Turkish electricity demand. Taylor et al. (2006) on the other side, compare the forecast accuracy of six univariate methods, among which consider the multiplicative seasonal ARIMA, artificial neural network, exponential smoothing and a principal component analysis approach for lead times up to a day-ahead. Following similar challenge, Ozoh et al. (2014) introduces a modified Newtons model (MNM) to forecast electricity consumption from historical data. Whilst Almeshaiei and Soltan (2011) presents a pragmatic methodology for the Electricity demand forecasting mainly based on decomposition and segmentation of the load time series. However, these latter studies rely on real daily or other type of frequent load data.

The literature suggests that both directions of the causality between electricity consumption and economic growth are possible and have been observed. Nazlioglu et al. (2014) found that there was bidirectional causality between electricity consumption and economic growth in Turkey. Lee (2005) analysis provides support of a long run cointegration relationship between energy consumption and GDP in eighteen developing countries, using data for the period 1975 to 2001. Their empirical evidence shows that long-run and short-run causalities run from energy consumption to GDP, but not vice versa. Bildirici and Kayikci (2012) estimate the causal relationship between energy consumption and economic growth at per capita and aggregate levels for some transition countries in Europe and find that Albania faces unidirectional causality from economic growth to electricity consumption. Madlener et al. (2008) also aims at analyzing the causal relationship between energy use and economic activity, obtaining indications for a bidirectional causal relationship between electricity consumption and economic growth. The literature regarding less developed economies, produce often results that emphasize the relationship in the energy-growth nexus. However, these mostly highlight the effect of energy consumption (rather than just electricity consumption) to economic growth. For example, Atif and Siddiqi (2010) affirm the existence of unidirectional Granger causality from electricity consumption to economic growth without any feedback effect for Pakistan, whilst Asafu-Adjaye (2000) results indicate that, in the short-run, unidirectional Granger causality runs from energy to income for India and Indonesia, while bidirectional Granger causality runs from energy to income for Thailand and the Philippines, as well as in Guta et al. (2015) for Ethiopia.

Different studies produce analyses that separate electricity consumption according to the user. For example, Dilaver and Hunt (2011) investigate the role of household total final consumption expenditure and residential electricity prices for Turkey which result to be important drivers of residential electricity demand consumption. Bastos et al. (2015) argue that the electricity consumption of the commercial class has been growing more than the consumption of the other classes, e.g. residential, industrial, and others in Brasil. Ubani (2013) revealed that electricity consumption in Nigeria is not affected by sectoral consumption usage (residential, commercial and residential) and that the consumption rate in the region is significantly related to the socio-economic and physical features of the region. On the other side, Kemalbey and Korkmazoglu (2012) discuss the impact of economic growth on annual electricity consumption using gross national product of primary industry, gross national product of secondary industry, gross national product of tertiary industry, installed capacity, electricity production, and government expenditure from 1981 to 2010 for Turkey checking for multicollinearity of the different sectoral output variables.

Electricity demand is estimated using disposable income and electricity price for developed economies such as the case of Madlener et al. (2008) analysis on a group of several OECD member countries. These variables, and especially income, are found to be significant drivers for electricity consumption in the developing economies as well, such as the case for India (Saravanan et al. 2012), countries of South East Europe (Bildirici and Kayikci, 2012), Asian and other Developing countries (Aziz et al., 2013; Asafu-Adjaye, 2000), although the latter refer to the broad energy consumption rather than just the electrical produced energy. Jannuzzi and Shipper (1991) observed that the increase in electricity demand was faster than the income when analyzing the consumption of electrical energy for the residential sector in Brazil. It is explained that this is a typical behaviour of the commercial energy demand (and electricity in particular) in the developing countries. The S-shaped curve often characterizes the increase in electricity demand in the relationship between the GDPs per capita (in the horizontal axis) and the electricity consumption (in kWh per capita in the vertical axis) (OME, 2007).

This paper investigates and forecasts the long-term electricity consumption in Albania based on cointegration and stationary time series. The econometric literature focusing on Albanian electricity consumption is extremely limited. The main studies are provided by the government agencies such as ERE and/or REBIS reports (final report 2004), which mostly concentrate on technical analysis concerning characteristics of the sector rather than on a more comprehensive investigation incorporating aggregate economic indicators. Hence, this paper represents a first attempt to specifically estimate the Albanian electricity consumption forecasting. In this context, an important step in the model development was to select a range of appropriate economic and demographic variables that could potentially affect electricity demand or could be proxies for the patterns observed in the sectors' electricity usage. The next step was then to collect the historical data for these variables, as discussed in the previous section. Potential variables included population, GDP, Remittances, Political instability.

As Bianco et al. (2009) argue, worldwide energy consumption is rising fast because of the increase in human population and continuous pressures for better living standards. We will develop regressions using population as a selected variable to forecast electricity consumption in Albania. Moreover, a simplification is proposed considering regression models using the ratio between other aggregate variables and population (GDP growth and remittances per capita) as independent variables.

Literature on the field suggests that household energy consumption is not only a function of the number of households and the level of heating and cooling comfort, but also of the level of consumer expenditure, which is correlated with household income received from remittances. According to IEA (2004), residential electricity demand growth has primarily been driven by increased use of electric appliances. "Big appliances" such as dishwashers, air-conditioning and other electric home appliances dominated the growth of household expenditures from the 1990's, while much of this growth is attributed to the money received from migration. Thus, different Albanian surveys (Arrehag et al., 2005; Uruci and Gëdeshi, 2003; Gëdeshi, 2000; Kule et al., 2000) indicate that remittances are mainly used for consumption, and then used to improve or build the household dwelling. According to ERE (2014), about 60 percent of electric consumption is registered to be consumed by households.

In addition to growth factors, the demand for electricity depends on the price for electricity and the price of alternative goods. In general, the higher the price for electricity, the lower the overall consumption level will be (ceteris paribus). This reduction in consumption can be a result of energy savings, profitable energy efficiency measures, or substitution of electricity for other energy sources. For example, electric space and water heating can be replaced by other kinds of space and water heating such as district heating, oil, coal or gas. However, as elaborated in Section 3.2, Albanian consumers of energy have limited possibilities to substitute electricity with other alternative power sources. Moreover, as Kamaludin (2013) observes, the demand for electricity is relatively inelastic as the quantity demanded does not change much when the price changes in his analysis on 32 developing countries. The rationale could be that goods and services for which no substitutes exist are generally inelastic since they are necessities. Besides, government regulatory action in controlling the price of electricity in the economy may possibly affect the price of electricity.

The target of the following section is to identify the demand drivers of electricity consumption and provide an appropriate model for electricity consumption forecasting.

3. Electricity Demand Forecast for Albania: Data and Methodology

This Section presents a pragmatic methodology that can be used as a guide to construct electric consumption and load forecasting models. The influence of economic and demographic variables on the annual electricity consumption in Albania has been investigated with the intention to develop a long-term consumption forecasting model. As observed in the previous section, different regression models have been developed, using historical electricity consumption, gross domestic product (GDP), gross domestic product per capita (GDP per capita), population, and income. In the following Section 3.1 the rationale, under which the demand drivers for estimating and forecasting the electricity demand are considered, is explained in more details. Section 3.2 describes the methodology to be used for the estimation, which results are provided in Section 3.3.

3.1. Data and the Selection of Proper Economic Factors

A very important component of the regression modelling involves the collection of appropriate data for the relevant variables required. Economic growth is a key determinant of electricity demand. Although there is not a one-to one relationship between GDP growth rates and electricity demand growth rates, there is a strong positive correlation. This means that electricity consumption typically increases with increasing GDP growth. GDP growth indicates increased economic activity and available income, both of which are correlated positively with electricity consumption.

As REBIS (2004) suggests, it is almost impossible to discern the influence of price during the 1990s when there were so many other economic changes under way in the economies of Central and Eastern Europe. This does not imply that electricity prices do not have influence but rather that electricity prices and general economic reforms tend to happen simultaneously, and it is impossible to separate their effects. For this reason, and mainly because the price of electricity is set at the national level by the energy regulatory authority (ERE), the electricity price in Albania is considered to be relatively rigid. Hence, we do not incorporate price as an explanation variable in the estimating model of electricity demand. In this context, even the international prices of energy in times of large import levels would generate no variances in the price to the final consumer. The regulatory agency smoothest variability effects of the utility price.

An important step in the model development is to select a range of appropriate economic and demographic variables that could potentially affect electricity demand or could be proxies for the patterns observed in the sectors' electricity usage. The next step is then to collect the historical data for these variables, as discussed in the previous section. Potential variables include population, GDP and Remittances. We use the annual data of electric power consumption (kWh), GDP (measured in 1000000

$US), population (in thousands) and remittances (measured in 1000000 $US) during the period 1990-2014 to estimate regressor parameters that affect electricity power consumption in Albania. The data were taken from the World Development Indicators of World Bank. Descriptive statistics for these variables are presented in Table 1. As can be observed, real variable values display a relatively high variance, shown by the Standard Deviation indicator. Hence, there is the rationale, as explained in the following Methodology subsection, to use the natural logarithm values of the variables which are calculated for empirical estimation. The minimum value for the population variable corresponds to year 2014, whilst the lowest value for GDP corresponds to year 1992.

Table 1.
Descriptive statistics.

	GDP	Population	Personal remittances	Electricity consumption
Mean	6520	3064	23.6	5636
Median	4450	3051	4.1	6070
Max	1340	3286.5	191.0	7701
Min	7090	2894	4.1	2790
Std. dev.	4620	128	49.5	1466

Note: GDP is in 1000000 $US; Population is in thousands; Remittances are in 1000000 $US.

Figure 1 indicates the trend of all the variables of interest in Albania during the period under study. The general path is a rise of the overall electricity consumption, with a faster increase in 1992-1996 and then during 2009-2013. The very first couple of years after the fall of the central system, and the period after 2013 reveal a decrease in the electric consumption. Referring to the GDP, the fastest and most considerable increase is noticed for the period 2002-2008, although the time span of the GDP rise is larger than that, with ups and downs especially during the first decade and also the third decade after the economic system transformation. Population only decreases from 1990, whilst personal remittances show an almost steady rise up to 2007-2008, after which there is a falling trend. The peak is related to the world financial crises, to which the emigrant's income and hence their money transfers to home destination are correlated. Although thought as relevant, we do not involve estimation of any effects of the political instability, as the dummy variable which would be added would not be able to identify between the general and the local elections, if a value of one is put for each year when elections, either general or local evolved.

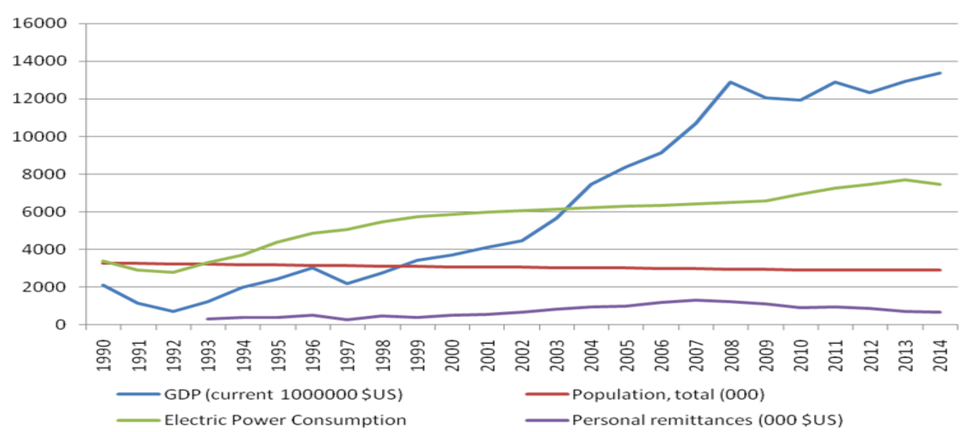

Figure 1.
Trends of the interested variables.
Source: World Bank (2015).

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3.2. Methodology

Demand pattern is almost very complex due to the deregulation of energy markets, making the finding of the appropriate forecasting model for a specific electricity network a challenging task. Although many forecasting methods were developed, none can be generalized for all demand patterns. Thus, forecasting electricity consumption has been applied using many theoretical methods including growth curves (Mohamed and Bodger, 2005), multiple linear regression methods that use economic, social, geographic and demographic factors (Liu, et al., 1991) as well as Box-Jenkins autoregressive integrated moving average (ARIMA) techniques (Saab et al., 2001).

To investigate the influence of the economic variables on annual electricity consumption, the multiple regression method is used, according to the following model equation:

$$ElCons_t = c + b_1 GDP_t + b_2 Pop_t + b_3 Remit_t + e_t \quad (1)$$

Where $ElCons_t$ represents the annual electrical energy consumption, b values are regression coefficients and e is the unknown disturbance term (i.e., error or residuals). Measurement error for the dependent and independent variables, and effect of possible omitted variables are generally the main sources of random disturbance.

A great advantage while applying estimations with big variable values accrues by using the natural logarithm. Frequently, the local variance of the series is larger when the level of the series is higher. Hence, taking logarithm of the macroeconomic data would be useful as the time series could be heteroscedastic. It is likely that a stationary or integrated model can be fitted after the transformation. Moreover, the small changes in the natural logarithm of a variable are directly interpretable as percentage changes, to a very close approximation. In this context, the regression coefficient of the log-transformed data is interpreted as a percent change of the energy consumption with a percent change in each of the regressors, all other variables kept constant. So, the natural logarithm of each of the variables described above is used, instead of their absolute value (*LnX*).

The variables used in time series analysis should be stationary to avoid causing possible spurious relationships among the variables. Cointegration analysis has thus increasingly become the favoured methodological approach for analyzing time series data containing stochastic trends. In this context, if the data generating processes underlying the time series are integrated of order one, $I(1)$ (which is the case for most economic variables), or higher, usual regression analysis can lead to spurious results. A common solution is to take first differences of the data. Therefore, we have tested common unit root process by Augmented Dickey Fuller (ADF) (1979) test. Accordingly, we found that the time series were not stationary at the level [I(0)]. First and second difference of the series is then considered. The *LnGDP* series becomes stationary at [I(1)], and so the *LnRemit* and *LnElCons* by taking the first difference of the natural logarithm of the respective variables. The variable LnPop becomes stationary only after taking the second order difference. Because the dependent variable itself exhibits non-stationarity, the first difference of this variable is also included as a regressor to explain the long-run behaviour of the electricity consumption. Augmented Dickey Fuller tests for the explanatory variables at first order difference of their natural logarithm and (for the LnPop) the second order difference are presented in the Appendix A1.

Given the above, the equation form we produce for estimating electricity consumption during 1990-2014, which form will also be used to forecast the dependent variable for the 2015-2030 period, is:

$$lnElCons_t = c + b_1 LnGDP_{t-1} + b_2 LnPop_{t-2} + b_3 LnRemit_{t-1} + lnY_{t-1} + e_t \quad (2)$$

Estimation results are explained in the following subsection. From the regression of the Serial Correlation, the LM test statistic for the null of "*no serial correlation*" indicates that there is no serial correlation in the residuals. Thus, the equation could be used for hypothesis testing and forecasting. Moreover, given the goodness of fit of this regression estimation, we are able to use this form of equation for forecasting the electricity consumption up to year 2030. As we suspected that the series used exhibited non-stationarity, next step consists on the identification of what of kind of ARIMA model to use for forecasting. We check the nature of the correlation between current values and their past values for each of the variables considered in the analysis, build a series of residuals and look at

autocorrelation properties. The instrument used is the correlogram view produced *Eviews 7* program. According to the Box and Jenkins (1970), if the autocorrelation function dies off smoothly at a geometric rate, and the partial autocorrelations decline geometrically, a first-order autoregressive model is appropriate, as is the case of each independent variables. Alternatively, as the autocorrelations were zero after one lag, and the partial autocorrelations declines geometrically, a first-order moving average process seemed appropriate for the variable indicating Population (LnPop), hence, MA(1). Instead, LnRemit and LnGDP display MA(2) and MA(5) orders respectively.
So, considering LnRemit AR(1) MA(2), LnPop AR(1) MA (1) and LnGDP AR(1) MA(5), the values of the regressors are forecasted up to year 2030. These will serve the purpose of overall forecast of the electricity consumption. Next subsection provides the results of the equation 2 estimation as well as the forecasting evaluations.

3.3. Results

Estimation results of equation (2) are presented in table 2. As explained earlier, the dependent variables for estimation are the first (GDP, Remit and ElCons) and second (Pop) differenced values of the natural logarithm of the real values of the variables of interest. The variable coefficients are significant and of the expected sign, except for the GDP. Electricity consumption is significantly explained by the trend of its previous values at the lag of one difference. Moreover, there is a positive relationship between the consumption of electricity and population as well as personal remittances. Although the empirical literature indicates that GDP positively explains electricity consumption, while it is used as a proxy for the income, the same is not found in case of Albania. It could be that the best proxy for income are the personal remittances, which as elaborated in Subsection 3.1 have served to fuel overall consumption of Albanian families for more than two decades. Thus, income effect on electricity consumption seems to be larger through the purchases of electrical-using appliances and their usage rather than through greater economic activities. Hence, we expect that the forecasted electricity consumption will be mostly affected by the trend of population and remittances. On the other side, unless the Albanian economy performs at considerable direct investments, the GDP will not perform at considerable variation to positively and significantly affect electricity consumption trend.

Table 2.
Equation estimation results.

Variables	(1)		(2)		(3)	
LnGDP (-1)	-0.001				0.027	*
	(0.029)				(0.016)	
LnPop (-2)	0.102	***	0.102	***	0.053	***
	(0.027)		(0.025)		(0.018)	
LnRemit (-1)	0.017	**	0.017	**		
	(0.008)		(0.007)			
LnElCons(-1)	0.819	***	0.815	***	0.834	***
	(0.098)		(0.048)		(0.006)	

Note: The value in brackets below coefficients indicates the standard error. In equation (3) observations are for 2000-2014. *** significant at 1% level; ** significant at 5% level.

Table 2 coefficients of equation 2 are displayed in two columns, with the GDP variable included and not as an explanatory regressor. Coefficient results as well as standard errors are quite similar in both cases. Hence, we focus on the first equation estimation to interpret coefficients. These express the elasticity of each of the electricity consumption with respect to lagged GDP and remittances, as well as second difference of population. The exact percentage change is computed using the formula: $100[\exp(\beta)-1]$, where β represents regression coefficient. Accordingly, an increase in population by 1 percentage, leads to an increase in electricity consumption by about 10 percentages. The effect of

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personal remittances is 1.7 percent. Previous period (year) electricity consumption stimulates the largest percentage change, calculated at about 127 percent. E-views output of coefficients' estimation is presented in Appendix A2 (panel A).

Based on equation estimation as in column one of Table 2, and forecasted regressors up to year 2030 according to the ARIMA model, electricity consumption forecast is derived. Figure 2 displays the general picture, projecting a smooth performance of the electricity consumption level at a slightly falling trend for the next 15 years. This is shown by the red and green lines which represent two scenarios of electricity consumption forecast. The red line projection is based on coefficients estimated as in column 1 of Table 2. The second projection is obtained by taking into consideration only years 2000 to 2014 in estimating equation 2 for building the forecasting trend. Eviews output is in Appendix A2 (panel B). In this exercise, all the variables are again natural logarithm of their real values, and the GDP and personal remittances are first differenced. The variables are again of the expected sign and significant, and the coefficients are shown in column 3 of Table 2. The rationale for conducting estimations only for the period 2000-2014 is that all the variables are less affected by the radical socio-economic changes that characterize the first decade after the transformation of the economic system in Albania. In this case, remittances are not included. In order to estimate the forecasted values of all the variables according to the ARIMA model, stationary and correlogram tests conducted suggested: for lnGDP, AR(1) MA(1); for lnPop, AR(1) MA(2); for LnRemit, AR(1) MA(1); lnElCons, AR(1) MA(2)

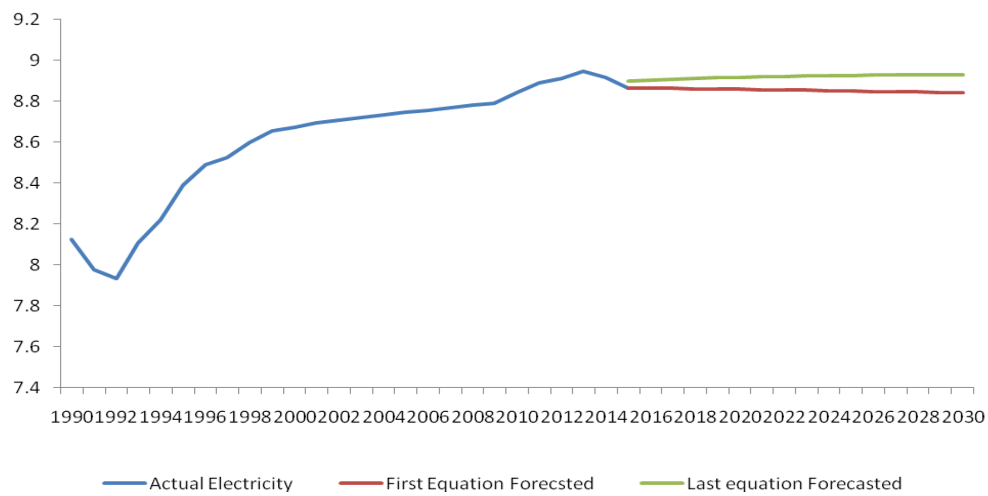

Figure 1.
Actual and forecasted electricity consumption.

The trend found according to both scenarios is relatively similar. Although one should be cautious in considering long-term forecast relying on limited number of observations in past time series, anticipated estimations of electricity consumption produced here are thought to be close to the real expected consumption. There is some rationale behind these findings. Overall, according to the estimated coefficients, the effect of Population and Personal Remittances is robust and positive. Both these two variables display a falling tendency. Hence, the red line reflects mostly the trends of these two variables. On the contrary, the green line representing a better prospect of the electricity consumption is produced reflecting more weight to the GDP as compared to the first specification. A clearer view on the trend of the actual and forecasted electricity consumption based on estimations beginning from 2000 is shown in the Appendix A3.

4. Conclusions

This paper provides an attempt to model and forecast the electricity demand for Albania for the period 2015-2030. The literature reviewed suggested that the inputs to provide good predictions of the electricity demand are mainly related to economic and demographic drivers as well as other conditions related to weather and political stability. Among these, GDP, remittances and population were shown to be the variables that mostly impact the electricity demand in Albania. Accordingly, ARIMA model was used to forecast electricity consumption based on its own historical past values as well as the other independent variables with the help of the E-Views package.

Two equations were estimated; one based on the period 1990-2014, and the other from 2000 to 2014, due to relatively large variations of the variables used in the first decade of the economic transformation changes. Consequently, two trends were produced that project the electrical demand up to year 2030. The first one, based on the longer series, reflects a smooth development of the electricity demand, as compared to the second one, which reflects a more significant effect of the GDP while the remittance variable is omitted. There are certain explanations for such trends. Under the current conditions of the economic growth not being expected significantly higher than the near past (referring to 2015), with the populations merely shrinking due to migration and lower fertility rate than before, the first model is believed to make a projection closer to the current developments in the electricity sector. There are also explanations that relate to the performance of the distribution process of the electricity produced, regarding mainly to the recent reforms in the sector. Accordingly, bill collections have increased improving financial performance of the Electric Distribution Company in Albania. Moreover, the corresponding company has as well been engaged in reducing financial and technical loss. Given the overall performance of the sector, the expectations are that public will reflect by consuming electricity rationally and efficiently. That meaning that since they will have to pay all the energy they consume, public will not use electricity as the only mean of energy source and will take care of being more rationale towards electricity consumption and alternative sources. On the other side, the cost of alternative electricity supply (such as solar energy) is sharply falling and may reduce demand for electricity from the grid.

Electricity projections based on GDP rather than remittances, mirror the GDP trends. For the policy makers to assure the security of supply, associated investments in the electricity sector and power generation would be needed in case of relevant investments in other sectors which boost the economy. Albania is an emerging developing country which should consider such opportunities soon.

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Appendix A1.

Augmented Augmented Dickey Fuller tests of the independent variables.

(First order difference for lnRemittances and lnGDP variables and (for the LnPop) the second order difference)

Null Hypothesis: D(Personal_Remittances) has a unit root			
Exogenous: Constant, Linear Trend			
Lag Length: 5 (Automatic - based on SIC, maxlag=5)			
		t-statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-4.335157	0.0155
Test critical values:	1% level	-4.571559	
	5% level	-3.690814	
	10% level	-3.286909	
*MacKinnon (1996) one-sided p-values.			
Warning: Probabilities and critical values calculated for 20 observations			
and may not be accurate for a sample size of 18			

Null Hypothesis: D(LN_POP,2) has a unit root				
Exogenous: None				
Lag Length: 0 (Automatic - based on SIC, maxlag=5)				
			t-statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-5.484177	0.0000
Test critical values:	1% level		-2.674290	
	5% level		-1.957204	
	10% level		-1.608175	
*MacKinnon (1996) one-sided p-values.				
Null Hypothesis: D(LN_GDP) has a unit root				
Exogenous: Constant				
Lag Length: 0 (Automatic - based on SIC, maxlag=9)				
			t-statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-5.722153	0.0000

Test critical values:	1% level	-3.610453	
	5% level	-2.938987	
	10% level	-2.607932	
*MacKinnon (1996) one-sided p-values.			
Null Hypothesis: D(LN) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=5)			
		t-statistic	**Prob.***
Augmented Dickey-Fuller test statistic		-3.773571	0.0095
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	
*MacKinnon (1996) one-sided p-values.			

Appendix A2.
E-view output.

A- Dependent variable: *Ln*ElConsum
Method: Least squares
Date: 12/23/15 Time: 12:56
Sample (adjusted): 1992 2014
Included observations: 23 after adjustments

Variable	Coefficient	Std. error	t-statistic	Prob.
LN_GDP(-1)	-0.001424	0.028663	-0.049672	0.9609
LN_POP(-2)	0.102325	0.026679	3.835455	0.0011
LNREMIT(-1)	0.016980	0.007988	2.125604	0.0469
LNElConsum (-1)	0.819069	0.098023	8.355880	0.0000
R-squared	0.977193	Mean dependent var		8.645112
Adjusted R-squared	0.973592	S.D. dependent var		0.262869
S.E. of regression	0.042718	Akaike info criterion		-3.311644
Sum squared resid	0.034671	Schwarz criterion		-3.114167
Log likelihood	42.08391	Hannan-Quinn criter.		-3.261979
Durbin-Watson stat	2.210042			

B - Dependent Variable: *Ln*ElConsum
Method: Least Squares
Date: 01/11/16 Time: 12:45
Sample (adjusted): 2002 2030
Included observations: 29 after adjustments

Variable	Coefficient	Std. error	t-statistic	Prob.
LN_GDP(-1)	0.027842	0.016398	1.697935	0.1015
LN_POP(-2)	0.053531	0.018512	2.891662	0.0076
LNElConsum(-1)	0.838338	0.061851	13.55419	0.0000
R-squared	0.964721	Mean dependent var		8.868777
Adjusted R-squared	0.962007	S.D. dependent var		0.076597
S.E. of regression	0.014930	Akaike info criterion		-5.473183
Sum squared resid	0.005796	Schwarz criterion		-5.331738
Log likelihood	82.36115	Hannan-Quinn criter.		-5.428884
Durbin-Watson stat	1.243855			

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Appendix A3 Estimated actual and forecasted electricity consumption

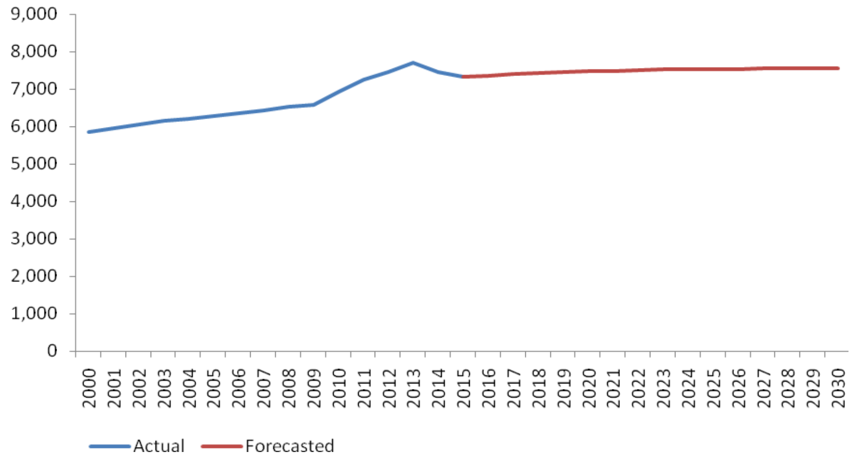

Figure A3.
Actual and forecasted electricity consumption (Scenario according to the third column in Table 2).

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