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Kuzey Kıbrıs Türk Cumhuriyeti İçin Orta ve Uzun Vadeli Elektrik Tüketim Tahmin Modelleri

Medium and Long Term Electricity Consumption Prediction Models for Northern Cyprus

Yasemin Merzifonluoğlu

Abstract

Overestimation of energy usage would result wasted capacity and financial loss while underestimation would result devastating power disruptions. The objective is therefore to simultaneously improve the efficiency of energy systems and develop state-of-art techniques which accurately predict future energy demand. This is especially vital for developing regions such as Northern Cyprus. In this study, we provide medium and long term electricity consumption models using varying time-series and associative forecasting techniques. When time series methods are studied, a novel approach of optimizing initial parameters in addition to smoothing parameters is applied. A benchmark study is provided to evaluate the performance of different consumption models in terms of forecast accuracy.

Keywords: *Electricity Consumption, Forecasting, Time Series, Regression Models*

Öz

Enerji kullanımına yönelik tahmin yürütülürken, gerçekleşebilecek düzeyin üzerinde bir tahminde bulunmak, kapasite kullanımı açısından ve finansal yönden kayıplara neden olmaktadır. Kullanımın az olacağı yönünde yapılan tahminler ise istenmeyen elektrik kesintilerine ve buna bağlı olarak ortaya çıkan ekonomik kayıplara neden olmaktadır. Dolayısıyla, sözü edilen iki yönlü kayıpların önüne geçilebilmesi için enerji sistemlerinin iyileştirilmesi ve güvenilir enerji tüketim tahmin modellerinin de geliştirilmesi gerekmektedir. Bahse konu gereksinim, Kuzey Kıbrıs Türk Cumhuriyeti gibi gelişmekte olan bölgeler için daha da önem kazanmaktadır. Bu çalışmada, orta ve uzun vade için zaman serileri ve ekonometrik teknikler kullanılarak, Kuzey Kıbrıs Türk Cumhuriyeti için elektrik tüketim tahmin modelleri geliştirilmiştir. Çalışmada, zaman serileri tekniklerini kullanma bakımından yenilikçi yaklaşımlar uygulanmış, başlangıç ve yumuşatma parametrelerinin optimal değerleri kullanılmış, farklı tüketim modellerinin doğruluk bakımından karşılaştırıldığı sayısal çalışmanın sonuçları ortaya konulmuştur.

Anahtar Kelimeler: *Elektrik Tüketimi, Tahmin, Zaman Serileri, Regresyon Modelleri*

Introduction

Energy management aims to manage generation and consumption of energy minimizing costs and pollutant emissions. Developing environmentally friendly and efficient energy systems will help to reduce fossil fuel use and the pollutant emissions. In this process, energy demand modeling is an important tool drawing common interest of policy makers, electricity power system planners and scientists. Overestimation of energy consumption would cause idle capacity and financial loss while underestimation would cause devastating power disruptions. Thus, accurate energy forecasting can lead to an overall reduction of cost and successful planning of current operations and future installations. The objective is therefore to simultaneously improve the efficiency of energy systems and develop state-of-art techniques which accurately predict future energy demand.

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Energy demand modeling and prediction of future consumption efforts are especially vital for developing markets such as Northern Cyprus. Electricity demand forecasts can be considered in three classes: Short-term forecasts (one hour to one week), medium-term forecasts (one month to one year) and long-term forecasts which are longer than a year. In this study, we provide long and medium term predictions of electricity usage using various forecasting methods. To predict the monthly consumptions, Holt's-Winter's Method is studied due to observed trend and seasonality patterns in the data. As opposed to the traditional application of this method where the model parameters are selected based on trial and error method and regression analysis, this paper follows an innovative approach of optimizing all the model parameters to reach the best results. To predict the annual consumptions, three different approaches have been studied; curve fitting, Holt's method and multiple linear regression with economic variables.

Section 2 presents an overview of the current energy systems of Northern Cyprus and future opportunities/investments for the renewable energy production in the area. Section 3 presents a literature review of energy consumption models while Section 4 provides an analysis of monthly electricity consumption patterns in Northern Cyprus. This section also summarizes application steps of the time series method, optimization process for the model parameters and the numerical study evaluating the performance of the selected method. Section 5 focuses on the annual consumption models. In Section 6, conclusion and future research directions are presented.

Energy Systems Overview of Northern Cyprus

Cyprus is the third largest island in the Mediterranean Sea, after the Italian islands of Sicily and Sardinia (both in terms of area and population). It is also the world's 81st largest by area and world's 49th largest by population. It has a total surface area of 9,250 km² and north of island is 3,355 km² (Wikipedia, 2014). The economy of Northern Cyprus is dominated by the services sector which includes the public sector, trade, tourism, agriculture and education. Since 1996, Cyprus Turkish Electricity Authority (Kib-Tek), the local state run utility company, has been fully responsible for energy production, transmission and distribution in north side of the island. The total installed capacity was 60 MW in 1995, 120 MW in 1996, 327.5 MW in 2008 and 346.3 MW in 2012. Table 1 summarizes the power stations installed to date (Özerdem and Biricik, 2011, p.72).

Table 1. Power Stations

Power Stations	Power	Units
Teknecik	2x60MW Steam Turbine	120 MW
Teknecik	1x20 MW Gas Turbine	20 MW
Teknecik	1X10 MW Gas Turbine	10 MW
Dikmen	1x20 MW Gas Turbine	20 MW
Kalecik	4x17.5 MW Diesel Generator	70 MW
Guzelyurt	1.3 MWp Photovoltaic Plant	1.3 MW
Teknecik	6x17.5 MW Diesel Generator	105 MW
	Total Installed Capacity	346.3 MW

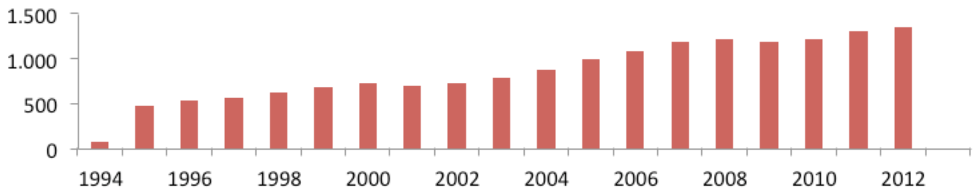

Figure 1. Electricity Generation between years 1997-2011 (KWh)

Figure 1 indicates the electricity generation in Northern Cyprus between 1997 and 2012. As seen Figure 1, electricity generation has been steadily increasing over years, for instance generated electricity was 1,303 KWh in 2011 displaying 7.21% increase compared to 2010 figures.

Current electricity production in Northern Cyprus is entirely dependent on imported oil and petroleum products. In addition to being expensive and resulting dependency, current system is neither sustainable, nor environmentally friendly. That is why Kib-Tek has been exploring possibilities for renewable energy production, especially solar and wind energy. As an initial effort, 1.3 MWp pilot photovoltaic plant was installed in 2010 and became operational in 2011. Cyprus is also suitable for electricity generation from wind having a wind speed of 5-7 m/s. Wind map of the area is currently being developed, the current plan is to construct 5MW wind energy station once studies concluded (Kib-Tek, 2014).

This overview indicates that Kib-Tek needs precise future estimations of power requirements in order to create short and long time oil-petroleum import plans, and to effectively manage future renewable energy investments.

Literature Review

Energy consumption models are developed with the help of statistical analysis and optimization tools. The value of the prediction model is evaluated based on the availability of historical consumption data and on the knowledge about the key affecting parameters on the energy consumption such as: economic, demographic data, and energy prices.

Time-series forecast methods use historical data with the assumption that the future values can be estimated from past values. Analysis of time series data requires identifying the patterns in the series such as trends and seasonal variations. When trend exists in the data, the regression models may search for an equation that will appropriately describe the trend. Trend-adjusted exponential smoothing method is also a widely accepted method as it dynamically updates the trend and level parameters in the model. Various time-series forecasting techniques have been used in energy demand forecasting of Turkey, such as Winters smoothing, cycle analysis and ARIMA and SARIMA (Ediger and Tatlıdil, 2002, p. 473; Aras and Aras, 2004, p. 463; Ediger et al., 2006, p. 3836; Erdoğdu, 2007, p. 1129). To our knowledge, very limited literature exists which focus on energy modeling in Northern Cyprus.

Econometric methods are also widely used to predict future electricity consumptions. In these techniques, a functional relationship is developed between independent variables and the consumption data using regression method. A prior knowledge about system dynamics and dependable future predictions of independent variables are necessary for reliable and robust econometric models. A large number of studies have been published to investigate the functional relationship between energy consumption and economic and demographic factors in Turkey (Altınay and Karagöl, 2004, p. 985; Ceylan and Öztürk, 2004, p. 2525; Sarı and Soytaş, 2004, p. 335). On the other hand, variables affecting electricity consumption may vary from one region to another. Egelioglu et al. (2001, p. 355), investigated the influence of economic variables on the annual electricity consumption in Northern Cyprus for the period of 1988–1997.

Medium Term Consumption Models

In this section, monthly electricity consumption of Northern Cyprus is evaluated then appropriate time series methods are applied with available data. For the period of 1997-2012, monthly electricity consumption data is obtained for different customer segments from KIB-TEK reports Figure 2 presents monthly fluctuations for this period.

Time-series methods use previously observed values to predict future values. Such methods are appropriate when the history is a good indicator of the future. Any observed demand can be seen as a combination of *systematic* and *a random component* because there will always be a random component that cannot be explained by historical demand patterns. The objective of any forecasting technique is to get away from the random component and correctly estimate the systematic component which is the expected value of the demand. There exist two primary methods to estimate the systematic component: static and dynamic methods. Static methods assume that the estimates of "level", "trend", and "seasonality" do not vary in time. Therefore, estimates of these parameters are developed based on historical data and then uses for all future forecasts. On the other hand, adaptive methods update the estimates of level, trend, and seasonality after each new observation (Chopra and Meindl, 2012, p. 203).

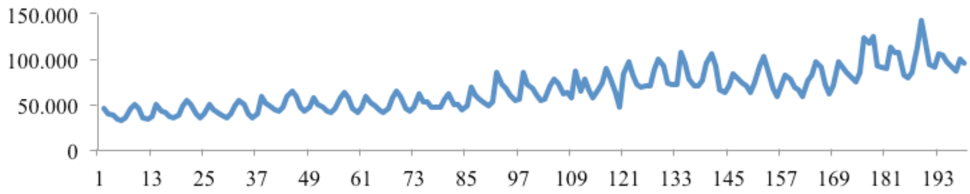

Figure 2. Total Monthly Electricity Consumption of Northern Cyprus (1997-2013)

When demand has no observable trend or seasonality, the systematic component only involves: "level". Moving average or simple exponential smoothing methods are appropriate for this case. When the systematic component involves "level" and "trend", Trend Corrected Exponential Smoothing (Holt's method) is more appropriate. When the systematic component also includes "seasonality", Trend and Seasonality Corrected Exponential Smoothing model (Holt's-Winter's method) is appropriate. There are two variations of this method named "additive" and "multiplicative" version. The additive method is preferred when the seasonal variations are constant through the series, while the multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series (Hyndman and Athanasopoulos, 2013). We believe multiplicative method is more appropriate for the current study.

Let p be the number of seasons per cycle (such as 12 months per year). The forecast equation for Holt-Winters method is the following:

$$F_{t+m} = (L_t + mT_t) * S_{t+m} \tag{1}$$

In the equation above, m denotes the forecast made for period "$t + m$" at time "t" with given estimates of level (L_t), trend (T_t), and seasonal factors (S_t,..., S_{t+p-1}). After observing demand for period $t + 1$ (D_{t+1}), the estimates for level, trend and seasonal factors are updated using following smoothing equations:

$$L_{t+1} = \alpha(D_{t+1}/S_{t+1}) + (1-\alpha)(L_t + T_t) \tag{2}$$

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1-\beta)(T_t) \tag{3}$$

$$S_{t+p+1} = \gamma(D_{t+1}/L_{t+1}) + (1-\gamma)(S_{t+1}) \tag{4}$$

In the formulations above, α is a smoothing constant for the level; β is a smoothing constant for the trend and γ is a smoothing constant for the seasonal factor. To start updating the level, trend and seasonal factors, one need initial estimates of them (L_0, T_0 and S_1,..., S_p).

The forecast error for period t is given by the following equation:

$$E_t = F_t - D_t \tag{5}$$

When studying accuracy of forecasting methods, following measures are generally analyzed: The Mean Squared Error (MSE), Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE). These measures are defined by the following equations:

$$MSE = \frac{1}{N}\sum_{t=1}^{N} E_t^2 \tag{6}$$

$$MAD = \frac{1}{N}\sum_{t=1}^{N} |E_t| \tag{7}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N} \left|\frac{E_t}{D_t}\right| \text{x}100 \tag{8}$$

MSE can be used to estimate the variance of the forecast error. Similarly, 1.25*MAD can be used to estimate the standard deviation of the forecast error (assuming it is normally distributed). The literature concluded that MAD is more appropriate than MSE if the error is not symmetrically distributed. MAD is also better measure than MSE if the cost of the forecast error increases linearly with the size of the error. On the other hand, if this relationship is not linear (cost of a large error is much larger than gains of a small error), utilizing MSE would be a better option as MSE penalizes large errors much more significantly than small errors because all errors are squared. The MAPE is a good measure when the forecast has significant seasonality and demand varies considerably from one period to the next (Chopra and Meindl, 2012, p. 215).

Optimizing Smoothing Constants and Initial Values of Level, Trend and Seasonality

When the Holt's-Winter's method is applied, one needs to find the best smoothing parameters (α, β, and γ) to minimize the forecast error measure that is selected (MSE, MAD or MAPE). Initial values for level and trends (L_0, T_0) are generally obtained by a regression analysis. Initial values for the seasonal factors (S_1, ... , S_p) are also obtained by analyzing seasonal patterns of the data. On the other hand, a recent study showed that the prediction model can further be improved by optimizing the initial values for level, trend and seasonal factors (Rasmussen, 2004, p. 115). We next present a Nonlinear Programming Model (NLP) which can be utilized for this purpose.

Minimize (6) or (7) or (8)

Subject to

$$F_t = (L_{t-1} + T_{t-1}) * S_t, \quad t = 1,\dots,N \tag{9}$$

$$L_t = \alpha(D_t/S_t) + (1-\alpha)(L_{t-1} + T_{t-1}) \quad t = 1,\dots,N \tag{10}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)(T_{t-1}) \quad t = 1,\dots,N \tag{11}$$

$$S_{t+p} = \gamma(D_t/L_t) + (1-\gamma)(S_t) \quad t = 1,\dots,N \tag{12}$$

$$E_t = F_t - D_t, \quad t = 1,\dots,N \tag{13}$$

$$0 \le \alpha, \beta, \gamma \le 1 \tag{14}$$

The model above assumes that the demand data is available for periods 1 to N. Given this data, the objective function minimizes the chosen error measure (MSE, MAD or MAPE). This model provides the optimal levels of smoothing constants (α, β, γ) together with optimal levels of initial values for level, trend and seasonality factors (L_0, T_0, S_1, ... ,S_p)). If the recent data is more representative for the future, one can only involve the last segments of it instead of employing the whole data set. Commercial NLP solvers can be utilized to accurately solve the models above.

Even though specific forecasting software is available, the flexibility, ease of use and graphing capabilities of spreadsheets make spreadsheets attractive for analysts to perform time series analysis. When such models applied, it is also becoming common practice to find optimal smoothing constants using Solver. Recently, Rasmussen (2004, p. 115) also suggested optimizing the starting parameters together with smoothing constants using Solver due to its practicality on spreadsheet models. In this study we also adopt Solver. On the other hand, with several decision variables in non-linear models, solver may find a local optimal solution based on the initial values of the decision variables. That is why it is suggested to select the multi-start option in Solver settings.

Application of the Model on Northern Cyprus Consumption Data

As observed in Figure 2, monthly electricity consumption involves both an increasing trend and seasonality. Therefore, Holt's-Winter's method will be applied to model the consumption. The discussion on error measures suggests that when seasonality exists MAPE is an appropriate measure. That is why MAPE is chosen when defining the objective function of the optimization model. We analyzed four different models. We first minimize the objective to find optimal smoothing constants (α, β, γ), the results for this case is presented under the heading HW-SC in Table 2. In this case initial level and trend values (L_0 and T_0) are determined using linear regression and seasonal factors (S_1,..., S_p) are determined by analyzing seasonal patterns of the data. In the second model (HW-SC-LT), we also consider L_0 and T_0 as decision variables in the model and use Solver to find their optimal values. In the third model (HW-SC-LTS), the initial seasonality factors (S_1,..., S_p) are also assumed to be decision variables of the model and optimized.

Table 2. Model Results

Model	α	β	γ	MSE	MAD	MAPE
HW-SC	0.570	0.029	0.000	30,228,003	3,433	4.55%
HW-SC-LT	0.542	0.031	0.000	29,771,073	3,382	4.43%
HW-SC-LTS	0.541	0.034	0.000	29,368,479	3,277	4.27%
HW-SC-LTS-Dα	0.539	0.035	0.000	29,270,861	3,268	4.26%

McClain (1981, p. 53) introduced the "*declining alpha*" technique for exponential smoothing. He suggests that for a long-term smoothing constant of α, one can start with $\alpha_0 = 1$ and update the smoothing constant as follows: $\alpha_t = \frac{\alpha}{1-(1-\alpha)^t}$ .This allows to start with large smoothing constant and (give more importance to recent data) and decrease over time. In the long run, the smoothing constant will converge to α with the forecast becoming more stable. We refer to this model as SC-LTS-Dα and Table 2 also summarizes the results of this approach.

Interestingly, smoothing constant for the seasonality is 0 suggesting seasonality influence on consumption does not change much in time. Optimizing parameters of the model has helped to decrease the MAPE from 4.55% to 4.27%. Although applying "declining alpha" approach has not improved the model considerably, SC-LTS-Dα model still provides the best results in terms of MSE, MAD and MAPE. Figure 3 illustrates the actual consumption versus forecasts obtained by the suggested technique (SC-LTS-Dα).

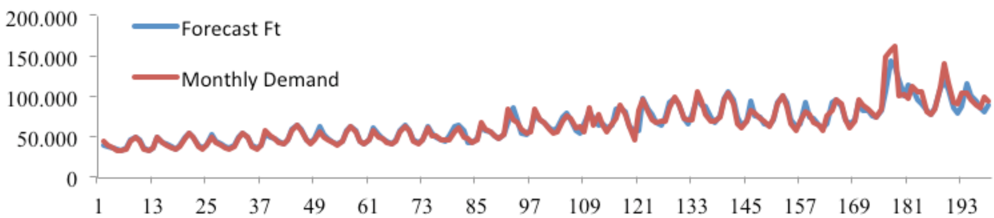

Figure 3. Monthly Electricity Consumption versus Forecast (SC-LTS-D)

Long Term Consumption Models

In this section we will focus on annual electricity consumption models since a longer range of annual data is available for annual consumption (between 1977 and 2012). Our main objective is to gain insights on annual consumption patterns. These insights can also be used to forecast monthly consumption by taking into seasonality. Figure 4 indicates the annual electricity consumption of Northern Cyprus.

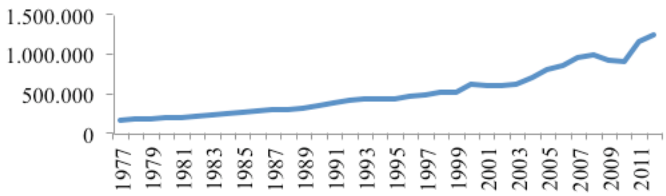

Figure 4. Annual Electricity Consumption of Northern Cyprus (1977-2012)

Fitting a Curve

Minimizing the sum of the squares of the errors is a mathematical procedure for finding the best-fitting curve to a given set of demand points. Let R^2 be the sum of the squares of the vertical deviations of the curve from a set of N data points.

$$R^2 = \sum_{t=1}^{N} \left(D_t - F_t(\beta_0, \beta_1, \dots, \beta_k)\right) \qquad (15)$$

The condition for R^2 to be a minimum is that $\frac{\partial R^2}{\partial \beta_j} = 0$ for all $j=0,1, \dots, k$.

Table 3 denotes the three different curves studied for the available data. The observed trend is best described with an exponential curve model where consumption is described by the following function: $F_t = 152{,}808\ e^{0.056(t-1976)}$ where t denotes years. R^2 value for this curve is calculated as 0.99. Figure 5 illustrates the forecasted values using the exponential curve together with actual observations.

Table 3. Annual Electric Consumption Models based on Least Square Method

Model	Annual Electric Consumption Model	R^2
Linear	$F_t = 26{,}905\ (t\text{-}1976) + 10{,}910$	0.91
Polynomial	$F_t = 26.411\ (t\text{-}1976)^3 - 675.42\ (t\text{-}1976)^2 + 19{,}652\ (t\text{-}1976) + 123{,}716$	0.98
Exponential	$F_t = 152{,}808\ e^{0.056}\ (t\text{-}1976)$	0.99

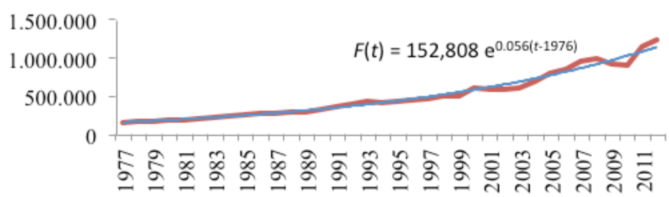

Figure 5. Annual Electricity Consumption versus Forecast (Exponential Curve)

Trend Corrected Exponential Smoothing (Holt's method)

Trend Corrected Exponential Smoothing (Holt's method) is also an appropriate forecasting method for annual electricity consumption when data involves trend. This method suggests the following forecast equation:

$$F_{t+m} = (L_t + mT_t) \qquad (16)$$

In the equation above, denotes the forecast made for period "$t + m$" at time "t". After observing demand for period t+1 (D_{t+1}), the estimates for level, trend and seasonal factors are updated using following smoothing equations:

$$L_{t+1} = \alpha(D_{t+1}) + (1-\alpha)(L_t + T_t) \quad (17)$$

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1-\beta)(T_t) \quad (18)$$

The optimal smoothing parameters have to be determined (α and β) to minimize the forecast error measure that is selected (MSE, MAD or MAPE). Initial values for level (L_0) and trends (T_0) are traditionally obtained by a regression analysis. The forecasting model can further be fine-tuned by optimizing the initial values for level and trend as discussed earlier in Section 4.

Table 4. Holt's Forecast Model Results for the Annual Electricity Consumption

Model	α	β	MSE	MAD	MAPE
H-SC-mse	1	0	2,881,171,490	33,887	7.56 %
H-SC-mape	1	0	2,881,171,490	33,887	7.56 %
H-SC-LTS-mse	1	0	2,486,316,460	31,883	6.07 %
H-SC-LTS-mape	1	0.06	2,535,268,540	27,479	4.15 %

We analyzed four different models, in the first two models (H-SC-MSE and H-SC-MAPE) we find the optimal smoothing constants (α, β) by minimizing MSE and MAPE respectively. For these models, L_0 and T_0 are determined using the regression method.

In the last two models (H-SC-LTS-MSE and H-SC-LTS-MAPE), L_0, T_0, S_t,…, S_{t+p-1} are optimized too. Table 4 summarizes the results of this approach and Figure 7 presents the annual consumption versus H-SC-LTS-MAPE forecast.

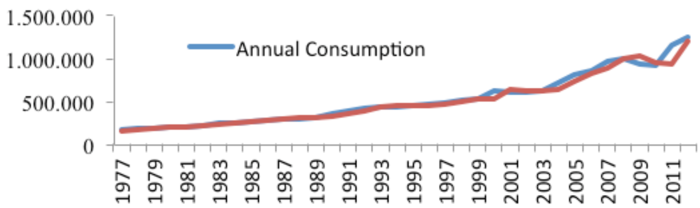

Figure 6. Annual Electricity Consumption versus Forecast (H-SC-LTS-mape)

Our results indicated that H-SC-LTS-MSE model performs favorably compared to the H-SC-MSE model. Similarly, H-SC-LTS-MAPE model performs much better than H-SC-MAPE model. H-SC-LTS-MASE model provides a considerable improvement on MAPE value compared to that of H-SC-LTS-MSE model while it results a slightly higher MSE value. That is why, among four models discussed in this section, we suggest to use H-SC-LTS-MAPE model to predict the annual electricity consumption of the region.

Multiple Linear Regression Analysis Considering Socio-economic Variables

Multiple linear regression analysis is used for modeling the annual energy consumption in Northern Cyprus. The initial model taking different socio-economic variables into consideration is:

$$F(P, GNP, HDD, CDD, I, E) = \beta_0 + \beta_1 GNP + \beta_2 P + \beta_3 I + \beta_4 E + \beta_5 T \qquad (19)$$

Where represents the estimated energy consumption; and $\beta_0 - \beta_5$ values are the regression coefficients. Five independent variables are used as the predictors of the consumption (i.e., GNP for GNP per Capita ($), P for population, I for imports (Million $), E for exports (Million $) and T for tourists). In order to test the energy consumption model of Northern Cyprus, data is collected from State Planning and Organization Department (Devplan, 2014). Table 5 denotes the regression coefficients and adjusted R^2 values for the regression model. So the final regression model is as follows:

$$\mathrm{F(P, GNP, HDD, CDD, I, E)} = -152{,}876 + 3.98\mathrm{GNP} + 2.34\mathrm{P} + 3.46_3\mathrm{I} - 1.44\mathrm{E} + 0.636 \qquad (20)$$

Table 5. Regression Results

β_0	β_1	β_2	β_3	β_4	β_5	F	Adjusted R^2
-152,876	3.98	2.34	3.46	-1.44	0.636	223.207	0.9711

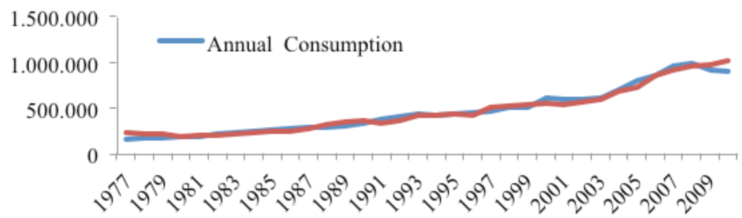

Figure 7. Annual Electricity Consumption versus Multiple Linear Regression Model

The *F*-ratio for the model is 223.207 indicating that it is highly significant. Figure 7 plots the historical predicted values from the regression model versus the actual values of annual electricity consumption for the period of study. Although the model performs favorably with a high R^2 score, its success relies on the availability of accurate forecasts for the independent variables.

Monthly Consumption Modeling Based on the Annual Models and Seasonality

Table 6 provides a comparison of the three models suggested for the prediction of the annual electricity consumption in terms of MSE, MAD and MAPE. According to these results, we conclude that the "Exponential" model best describes the annual electricity consumption of Northern Cyprus.

Table 6. Performance Comparison of Annual Consumption Prediction Models

Model	MSE	MAD	MAPE
Exponential	1,441,608,883	25,715	4.52%
H-SC-LT-MAPE	2,535,268,540	27,479	4.15 %
MLR	1,508,516,295	30,148	8.10%

Table 7. Historical Average of Consumption Percentages of Each Month

Month	January	February	March	April	May	June
s_{month}	9.67%	8.50%	8.06%	7.25%	6.85%	7.56%
Month	July	August	September	October	November	December
s_{month}	9.58%	10.49%	9.53%	7.65%	7.03%	7.85%

We next develop another model (Exponential-M) that uses the predictions of "Exponential" model for the annual electricity consumption and consumption percentages of each month (S_{month}) as inputs and produce monthly consumption forecasts. Table 7 indicates the consumption percentages for each month.

$$F_t(month) = \left(152{,}808\ e^{0.056(t-1976)}\right) s_{month} \qquad (21)$$

Table 8. Comparison of HW-SC-LTS-D and Exponential-M Models for Monthly Consumption

Model	MSE	MAD	MAPE
HW-SC-LTS-Dα	29,270,861	3,268	4.26%
Exponential-M	45,592,555	5,023	7.36%

Table 8 provides a comparison of the selected time series method for monthly consumption and "Exponential-M" method. Results confirmed that optimized Holt's and Winter's method with "declining alpha" (HW-SC-LTS-Dα) still provides the best results to predict the monthly electricity demand consumption.

Conclusion

Reliable forecast of energy consumption is vital for policy development and improvement of production and distribution facilities. Currently, electricity production in Northern Cyprus is completely dependent on imported oil and petroleum products. That is why, policy makers have been exploring possibilities for renewable energy production. Considering the need to plan expensive oil-petroleum imports, and to manage future renewable energy investments, there is an indispensable need to precisely estimate future power requirements of the region. A large variety of mathematical methods have been developed for electricity consumption forecasting. In this study, we discuss various approaches for medium and long-term electricity demand forecasting.

For monthly predictions (medium-term forecasts), we have used the optimized Winter's method which is a novel technique in which smoothing and initial parameters are found by minimizing the selected error measure (MSE, MAPE or MAD). We analyzed four different models. In the first model, we minimized MAPE to find the optimal smoothing constants (α, β, γ). In the second model, we also consider L_0 and T_0 as decision variables in the model and in the third model the initial seasonality factors ($S_1, \dots, S_p$) are also assumed to be decision variables. In the fourth model, we incorporated the "declining alpha" approach in our optimized Holt's and Winter's method. Our numerical study showed that the optimized Winter's method produces very promising results to predict monthly electricity consumption of Northern Cyprus. Current study also demonstrates that optimization of smoothing constants and starting parameters is vital when Winter's method is employed. Another conclusion is that required optimization process is not necessarily difficult when spreadsheets are effectively utilized. On the other hand, "declining alpha" method did not improve the forecasting accuracy much, so one may avoid this approach to avoid extra computational complexity.

Current study also analyzes the behavior of annual demand fluctuations of the region. We first studied optimized Holt's method analyzing four different models; in the first two models, optimal smoothing constants are found by minimizing MSE and MAPE. In the last two models, initial level and trend are optimized too. In addition to Holt's method, we studied four different curves to fit the observed data. Observed trend is best described with an exponential curve. Lastly, a multiple linear regression analysis is applied for modeling the annual energy consumption in Northern Cyprus. Five independent variables are used as the predictors of the consumption (i.e., GNP per Capita, population, imports, exports and tourists). Multiple linear regression method is very useful as it explains the effect of other variables rather than only using the historical data. On the other hand, the results provided by this method could be limited mainly due to two reasons. First, one may not include all the contributing factors into the model and second, the relationship between dependent and independent variables may not be linear and difficult to describe in reality. In addition to forecast accuracy, a forecaster may not choose this method as it is necessary to know or accurately forecast the future values of all predictor variables. Therefore this approach is the most demanding one in terms of data and computing effort and not suggested for this case. The forecasting model to be selected depends on the available data, provided forecast accuracy and required computational complexity. Among these three approaches, it is found that an exponential curve describes the annual electricity consumption of the region most accurately. Fitting a curve method is also the most practical and simple one among others.

Exponential Smoothing and ARIMA models are the two most common time series forecasting approaches. In this study we mostly used Exponential Smoothing which is based on a description of trend and seasonality in the data. ARIMA models aim to describe the autocorrelations in the data. A future researcher may apply ARIMA models to predict the electricity consumption of Northern Cyprus.

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