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Research Article

A Curve Fitting Modelling Approach to Forecast Long-Term Electrical Energy Consumption: Case Study of Turkey

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Abstract

For Turkey to achieve the targets of Vision 2023 of being in the top ten economies of the world, the eleventh National Development Plan (NDP11) focuses on ensuring uninterrupted, high-quality, sustainable, reliable and affordable energy supply. In this regard medium- and long-term energy supply-demand planning is regarded as a key input to the planning process. Medium and long-term planning is possible only when reliable forecasts are available. Using Turkey's electrical energy consumption data from 1970 to 2015, this study presents novel Gaussian, Fourier and Exponential curve fitting and extrapolation approaches to forecast Turkey's electrical energy consumption up to the year 2025. Major interest is put on how the model forecasts electrical energy consumption for year 2023 because this year marks a century of the establishment of the Republic of Turkey and all strategic plans are focused on how to achieve the targets as outline in Vision 2023. We evaluate the performance of the models on how best they forecast electrical energy consumption for the year 2023. Our forecasts for the year 2023 are 352.7TWh, 377.4 TWh, and 460.1TWh for the Gaussian, Fourier and Exponential models respectively which compare well with NDP11's estimated 375.8 TWh electrical energy consumption in 2023.

Keywords: : energy consumption forecasting, curve fitting, Vision 2023, Turkey

1. Introduction

In the late 20th century, Turkey experienced a dramatic increase in energy consumption. As expected, the energy consumption will continue to rise in the future. Energy is an enabler to the creation and generation of wealth and has great significance in economic development. Thus, for every country, energy is a vital resource. To achieve sustainable development there must be a sustainable supply of energy. Over the last decade, forecasting has become a tool used by many business corporations and governments not only to make better decisions but also gain competitive advantage. Turkey's current energy generation does not meet the existing energy demands that are raising annually by 4-6 percent until 2023 [1]. The operational electric energy sources are composed of coal, liquid fuels, electricity, natural gas, and renewable. Of this coal contributes 37.2%, liquid fuels 0.1%, natural gas 30.3%, Hydroelectricity 19.7% and renewable energy and wastes 12.7% [2]. Of the electricity generated from the above sources, the industrial sector is the biggest consumer with 45.6%, followed by household/domestic sector with 21.1%, commercial 20.4%, others 6.5%, government 4.6% and illumination 1.8% [3]. In regard to energy, the Eleventh National Development Plan (NDP11) focuses on ensuring uninterrupted, high-quality, sustainable, reliable and affordable energy supply. NDP11 further mentions that medium- and long-term energy supply-demand planning will be made. Forecasting energy

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demand is key to supply-demand planning. To show the importance of forecasting, in NDP11 it is estimated that electricity demand will reach 375.8 TWh by the year 2023 [4]. All of the goals that contribute to achieving the high-level national objective of Vision 2023, whose objective is to make Turkey one of the ten greatest economic powers in the world by the year 2023 require a substantial amount of electrical energy supply in the country. Various studies have used different approaches to forecast Turkey's electrical energy demand and consumption. For example, using Artificial Neural Networks (ANN) Yunus and Mo [5] forecasted Turkey's sectoral electrical energy consumption until the year 2023. Gülsüm [6] forecasted regional electrical energy demand using time series, panel data and spatial panel data models. Şule et al [7] used multiple linear regression (MLR) to select independent variables from population, Gross Domestic Product (GDP), exports, imports, employment and natural gas to forecast Turkey's electrical energy consumption for the years 2015-2023 using ANN. The results show that Turkey's electrical energy consumption will vary between 337087.4 and 385006.6 Gwh by 2023. In another study, Aydin [8] used regression analysis taking population and gross domestic product as independent variables to forecast Turkey's primary energy consumption for the years 2010 up to 2025. The forecasts showed that Turkey's future energy consumption would be between 174.65 and 203.13 Million Tons of Oil Equivalent (Mtoe) in the year 2025. Turkey's Ministry of Energy and Natural Resources (MENR) has extensively used the Model for the Analysis of Energy Demand (MAED) to forecast energy demand. For comparison purposes with MAED results, MENR used the "old technique" developed in the mid-20th century to forecast energy demand. This technique simply states that every year energy demand increases by 7% of the previous year's energy consumption. All the previous studies mentioned above use either statistical and computational intelligence forecasting approaches. In either case, both approaches use various independent variables mostly social economic factors as inputs to forecast electrical energy consumption. Therefore, future values of the independent variables have to be obtained, mainly through forecasting so that electric energy can be forecasted. This means that the accuracy of electric energy forecasts depend on the accuracy the forecasted independent variables. If the independent variables are poorly forecasted, the electric energy forecasts too are going to be poor. Thus, in this study we present a novel Gaussian, Fourier and Exponential curve fitting and extrapolation approaches to forecast Turkey's electrical energy consumption up to the year 2025. The Least Squares Algorithm was used to find optimal parameters of the models. As seen in all the previous studies, we also compare results with the "old technique" used by MENR to forecast energy demand. In section 2 we present related work while section 3 discusses the methods and materials. Section 4 presents the results and we make a conclusion in section 5.

2. Related work

Electrical energy forecasting is fundamentally important to many players in the generation, transmission and distribution of energy. These include among others governments, energy suppliers, and participants in energy markets. Energy forecasts are divided into short-term forecasting, medium-term forecasting and long-term forecasting. Short-term forecasting is from one hour to one week. The forecast results of short-term forecasting are mainly useful for load balancing and pricing. Medium-term forecasting is used to forecast energy from one week to one year while long-term forecasting is for longer periods ranging from one year to up to thirty years or more. The long-term forecasting results are useful for capacity investment decisions, planning for expansion, revenue analysis and corporate budgeting,[9]. Kuster et al.,[10] in their review of electrical load forecasting models notes that despite their simplicity, regression methods are still in common use for long-term and very long-term forecasting. In contrast to regression, other statistical methods such as time series analysis are also used. Besides statistical methods, computational intelligence methods have found rich applicability in forecasting. Commonly used methods include Support Vector Machines (SVM), and artificial neural networks which are mostly used for short and very short-term forecasting. All methods take some form of historical data is used. In Barran et al.,[11] Random Forest Regression (RFR), Gradient Boosted Regression (GBR) and Extreme Gradient Boosting (XGB) were used to study wind energy prediction and solar radiation globally and locally. Their experiments showed that predictions using Support Vector Regression (SVR) for individual wind farms is greatly improved by these ensemble methods. [12] proposes a novel approach that is more accurate to forecast electricity load using Recurrent Extreme Learning Machine (RELM). The study adapts a method for training single hidden layer feed forward neural network to train the Jordan recurrent network. A comparative analysis of results with linear regression, traditional ELM, generalized regression neural network and other commonly used machine learning methods showed that RELM had achieved tremendous success in electricity load forecasting. Jinliang et al.,[13] asserts that much as short term electricity load forecasting is important for market participants, it is to a great extent influenced by both natural and social factors which make it more challenging. They thus proposed a hybrid model based on Autoregressive Integrated Moving Average (ARIMA), Wavelet Neural Network (WNN) and Improved Empirical Mode Decomposition (IEMD). To optimize the model, the fruit fly optimization algorithm (FOA) is used. The optimized model is then used to forecast short term electricity loads. Comparison of results of proposed model with other models showed that the hybrid model performed better in electricity load forecasting. SVR with a radial basis function (SVR-RBF), a multilayer feed-forward neural network (MLFFNN) and a Particle Swarm optimized adaptive neuro-fuzzy inference system (ANFIS-PSO) are implemented in,[14] to predict the speed and direction of wind and the resulting power output of a wind turbine. Using statistical indices to compare the observed and predicted values showed that the SVR-RBF model was better than the MLFFNN and ANFIS-PSO models. Unler, [15] proposed a model to forecast energy demand of Turkey based on particle swarm optimization (PSOEDF). The model takes population, GDP, imports and exports of Turkey were used as independent variables. Kankal et. al,[16] studied how a teaching-learning-based optimized artificial neural network (ANN-TLBO) performs when modelling Turkey's electric energy demand (EED). This model uses population, imports, exports and GDP as independent variables. Back-propagation optimized ANN (ANN-BP) and Artificial Bee Colony algorithm optimized ANN (ANN-ABC) were compared with ANN-TLBO. The results showed that the ANN-TLBO models performed better than the ANN-ABC and ANN-BP models to estimate EED. An analysis of the changes in electricity generation policies by revisiting the dynamics Turkey's electricity generation resources is done in,[17]. A Multiple Attribute Decision Making (MADM) based on an integrated method composed of Monte Carlo simulation, Borda count and entropy were used to evaluate solar photovoltaic (PV), hydro, wind, biomass, coal, nuclear and oil alternatives. The evaluation results showed that the primary sources for generating electrical energy in Turkey should be mainly composed of sources that are renewable. Kaytez,[18] proposed a model that hybridizes least-square SVM and ARIMA to forecast net electrical energy consumption for Turkey until 2022. The study results show that the hybridized SVM-ARIMA generates more reliable and realistic forecasts. Çevik et al.,[19] in their study used ANN and Particle Swarm Optimization (PSO) techniques to forecast electricity load for 24 hours of next day. ANN weights of ANN were updated in the learning phase by PSO. ANN inputs were past values of consumed electrical load data, season, and daily average air temperature data. Turkey's monthly electrical demand between 2015 and 2018 were predicted by modelling seasonality and trend effects in [20]. They developed four different ANN models out of which the best model was selected. The best ANN model was compared with Seasonal Autoregressive Integrated Moving Average (SARIMA) model. Çeribaşı, and Çalışkan [21] estimated prospective long-term and short-term energy that can be generated by Adasu Regulator and Hydroelectric Energy Plant and Pamukova Hydroelectric Energy Plant in Sakarya Basin of Turkey. To make short-term estimates, ANN was used while long term estimates were obtained using the Innovative Sen Method. Farahat and Talaat,[22] presented a Curve Fitting prediction approach to forecast short-term load in which the optimal parameters of Gaussian model are obtained using a genetic algorithm that takes the error between actual and forecasted load as the cost function. In [23], linear regression and polynomial curve fitting are used to forecast wind and solar power production. Results showed that the R-squared and adjusted R-squared values obtained from the polynomial curve fitting model were better than those of the regression model, hence concluding that the polynomial curve fitting model is a better model.

3. Methods and materials

Electricity is the most commonly used form of secondary energy; therefore, we have developed models for electricity consumption for Turkey. In this study we develop four models to forecast electricity demand for Turkey and compare our results with the old technique used by MENR. First, we describe the "old technique" used by MENR.

3.1. The Old Technique

In the middle of 20th century, a very basic and simple technique was used in order to predict energy demand. This technique simply states that every year energy demand increases by 7% of the previous year’s energy consumption, “as shown in Equation 1”.

$$a_t = a_0 * (1.07)^{t-t_0} TWh \tag{1}$$

where a_t is the consumption for year t, a_0 is the known consumption of year t_0. Using this technique, if we take the consumption of 263TWh for year 2015, we find that the consumption for the year 2023 is 458.88TWh, “as shown in Equation 2”.

$$a_{2023} = 263 * (1.07)^{2023-2015} = 458.88\, TWh \tag{2}$$

3.2. The proposed approach

In this study we propose a novel approach of curve fitting to long-term electrical energy forecasting. Curve fitting is involves finding an appropriate or optimal function that can be used to fit a model to a given dataset. It is not a necessary requirement that the function has to pass through all of the points, the focus is to model the data with the minimum possible error between the observed data points and the fitted curve. Curve fitting is done in two phases, in the first phase a functional relation involving undetermined parameters is selected and in the second phase best estimates of the values of the parameters is made. In curve fitting, we examine whether one or more predictors (independent variables) are related to a response variable (dependent variable). The goal is to define a "best fitting model" that describes the relationship. In our study, the year was taken as the independent variable and historical load was taken as the dependent variable. The curve fitting procedure finds the specific coefficients which make that function match given dataset as closely as possible. Any type of function can be used for curve fitting. The curve fitting procedure is shown in the Fig. 1 below.

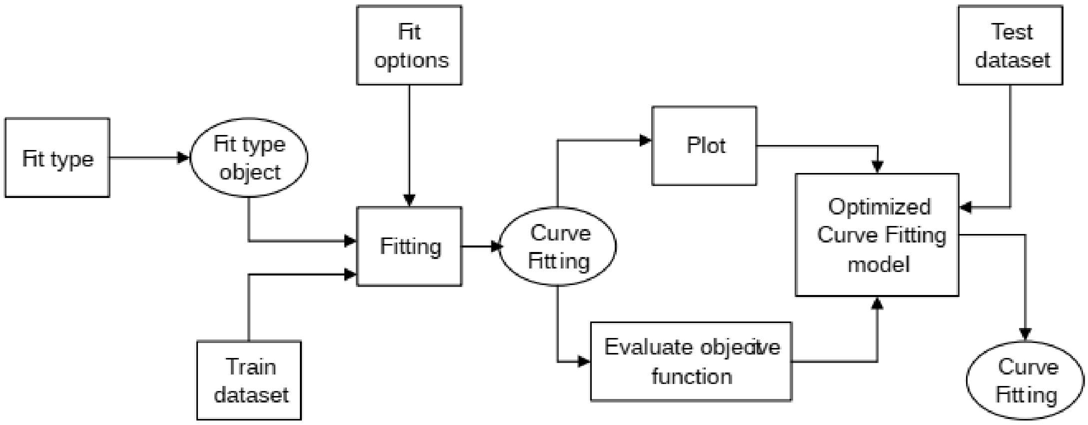

Figure 1 Typical curve fitting approach for prediction

The curve fitting process begins with choosing a fit type. When a fit type is chosen a fit type, object is created. The fit type object together with the train dataset and fit options create a new object Fitting which is passed on to the curve fitting process. The fit options include among others the fitting method, fitting algorithm, convergence criteria and starting lower and upper bounds for coefficients to be determined. During the curve fitting process, the objective function is evaluated and the plot is a visual representation of the process. Since we are using non-linear curves for fit our data, this is an iterative process which results into an optimized curve. Test data is used on the optimized curve fitting model to evaluate its performance. The optimized model is finally used to predict the future. In this study, we developed three curve fitting models using Gauss, Exponential and Fourier functions. The models are shown in the "Equations 3, 4 and 5" respectively.

$$f(x) = a_1 exp^{-(\frac{x-b_1}{c_1})^2} \tag{3}$$

$$f(x) = aexp^{bx} \tag{4}$$

$$f(x) = a_0 + a_1 coswx + b_1 sinwx \tag{5}$$

By exploring various parametric and non-parametric fits, the objective is to find appropriate coefficients for the best fit to the data. In this optimization problem, the sum of squared errors (SSE) between the actual value and the predicted value is minimized. Our objective function is thus "as shown in the Equation 6".

$$\min SSE = \sum_{i=1}^{n} (Actual\ Load - Predicted\ Load)^2 \tag{6}$$

where n is the number of data points. The goal is to identify the coefficients such that the curve fits the data well. We use the least squares algorithm to solve this optimization problem.

3.2.1. The Least Squares Algorithm

In the least squares fitting process, the summed square of residuals is minimized. The 'best' curve is the one that has minimum error i.e., summed squared error, between data points and the curve. From elementary calculus, the slope of a function is represented by its derivative and the minimum of a function occurs at a point where the slope of the function is zero. Therefore, the least squares algorithm determines the coefficients of the curve fitting function by differentiating the summed squares of residuals with respect to each coefficient, and the result is set equal to zero. In the next paragraphs we describe how the least squares algorithm can be used to determine the coefficients of curve $y = f(x; \beta)$ given the data points (x_i, y_i). Here x is the independent variable whose values are presumed precisely known, and the βj are the n coefficients to be determined.

Let $(x_i, y_i), i = 1,2, \dots, m,$ be a set of data points, and let $y = f(x; \beta)$ a curve to be fitted to this data. At the point $x = x_i$ the experimental value of y is y_i , thus the value that corresponds to the curve to be fitted is $f(x_i; \beta)$: If e_i is the residual of approximated value at $x = x_i$ then $e_i = y_i - f(x_i; \beta)$. The summed square of the residuals S can be written as

$$S = \sum_{I=1}^{m}(y_i - f(x_i, \beta))^2 = \sum_{i=1}^{m} e_i{}^2 \tag{7}$$

Substituting values of y_i and $f(x_i)$ at each x_i in "Equation 7" above, we get S as a function of the coefficients β to be determined. From the theory of calculus, we can determine the minimum of S by taking the partial derivative of S with respect to β_j and equating them to zero, i.e.

$$\frac{\partial S}{\partial \beta_j} = 0 \tag{8}$$

The result is a system of equations having n unknowns. The solution to these equations are the coefficients of the curve/polynomial fitting to the data.

3.2.2. Procedure of the Proposed Model

The method that is proposed is used to find an accurate long-term electrical energy forecasting model for Turkey. The actual annual electrical energy consumption data from 1970 to 2015 was taken from the Turkish Electricity Transmission Company (TETC). Data for the years 1970 to 2005 was used as training data and data the years 2006 to 2015 was used as testing data. Forecasting long term electrical energy consumption is affected by many factors which make it exhibit many non-linearities. Fitting a linear model becomes difficult because the coefficients cannot be estimated using simple matrix techniques. Therefore, the procedure of the least squares' algorithm used for the Gaussian, Fourier, and Exponential models developed in this study follows an iterative process as outlined below.

1. For each coefficient, make and an initial estimate. For our forecasting models, we use random values on the interval [-1,1].
2. For the current set of coefficients, produce the fitted curve.
3. By using a fitting algorithm, we adjust the coefficients to find out if the fit improves. For our study we chose the Levenberg-Marquardt algorithm of the curve fitting toolbox in MATLAB.
4. By returning to step (2), we iterate the process until we reach the specified convergence criteria for our fit.

Various fits are evaluated numerically or graphically to find the best fit. The commonly used performance metrics are based on residuals between the actual and forecasted values. Common metrics include R-Squared, Root Mean Square Error (RMSE), Mean Average Percentage Value (MAPE), Mean Square Error (MSE) and Mean Average Error (MAE) [24]. For this study we evaluate the various fits to the models using R-Squared and RSME. R-squared is also known as the coefficient of determination. R-squared is calculated as shown in the "Equation 9".

$$R^2 = 1 - \frac{SS_E}{SS_X} \tag{9}$$

Where $SS_E$and SS_X are the sum of squares of residuals and errors and given by "Equations 10 and 11", respectively.

$$SS_E = \sum_{i=1}^{n}(x_i - \hat{x_i})^2 \quad (10)$$

$$SS_x = \sum_{i=1}^{n}(x_i - \bar{x})^2 \quad (11)$$

Where x_i is the actual value, $\hat{x_i}$ is the forecasted value, and $\bar{x}$ is the mean of the actual values. We use extrapolation to obtain the forecasts.

RMSE is calculated using the formular in "Equation 12" below

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}|x_i - \hat{x}_i|^2}{n}} \quad (12)$$

4. Results

In this study, Gaussian, Fourier and Exponential curve fitting models for long term electricity forecasting were developed. Performance metrics and confidence intervals on fitted coefficients were used to determine how good our models are able to forecast. The performance metrics helped to determine the ability of the curve to fit the data. Descriptively, a high performance metric represents suitability of a certain model is suitable. On the predictive side, a high performance metric implies that the model performs well. The performance metrics (using train data) for the models are shown in the "Table 1".

Table 1 Performance metrics for the forecast models

Model	**Performance metric**			
	SSE	**R-Square**	**Adjusted R-Square**	**RMSE**
Gauss	617.5	0.9978	0.9977	3.79
Fourier	668.8	0.9976	0.9975	3.99
Exponential	3602	0.9872	0.9869	9.047

Because long term energy forecasting is characterized with lots of uncertainties which affect the accuracy of forecasts, we tried to capture these uncertainties by taking 95% confidence bounds when finding coefficients of curve fitting models. The obtained coefficients are shown in "Table 2".

Table 2 Coefficients of curve fitting models

Model	**Coefficients (with 95% confidence bounds)**
Guass	a_1 = 433.4 (361.3, 505.4)
	b_1 = 2039 (2034, 2045)
	c_1 = 34.85 (32.16, 37.54)
Fourier	a_0 = 1.1e+008 (-2.8e+013, 2.8e+013)
	a_1 = -1.0e+008 (-2.8e+013, 2.8e+013)
	b_1 = 1.0e+007 (-1.4e+012, 1.4e+012)
	w = -5.1e-005 (-6.7, 6.7)
Exponential	a = 2.6e-052 (-1.2e-051, 1.7e-051)
	b = 0.062 (0.059, 0.065)

Using the optimized coefficients shown in "Table 2", "Equations 3, 4 and 5" become:

$$f(x) = 433.4 \ exp^{-(\frac{x-2039}{34.85})^2} \quad (13)$$

$$f(x) = 2.6 * 10^{-52} \ exp^{0.062x} \quad (14)$$

$$f(x) = 1.0 * 10^8 - 1.0 * 10^8 \cos(-5.1 * 10^{-5})\, x + 1.0 * 10^7 sin(-5.1 * 10^{-5}) x \quad (15)$$

The graphs in "Figures 2, 3 and 4" show the Gaussian, Fourier and Exponential curve fits to the data and extrapolations to the 2025, with the consumption in the year 2023 highlighted. We highlight the consumption for the year 2023, because it is the year to which all targets of NDP11 focus on. It is the year the Turkish Republic is making 100 years since its establishment.

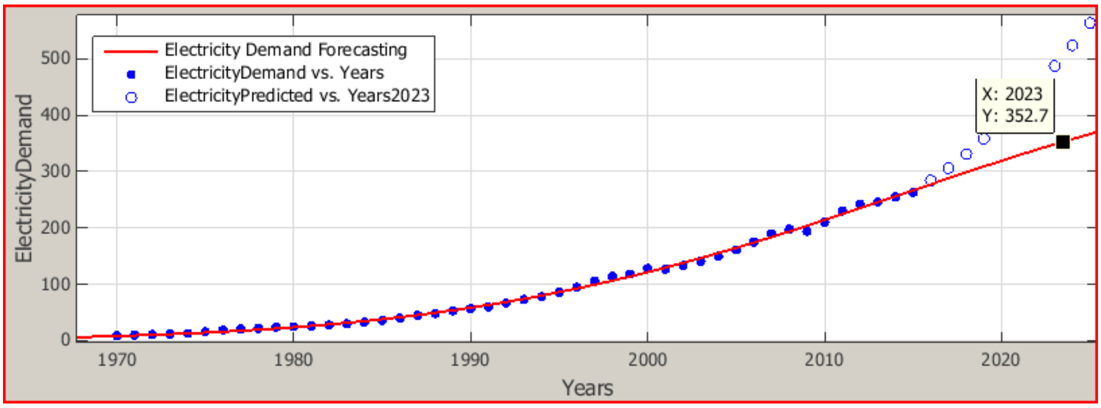

Figure 2 The prediction of electricity demand (TWh) in 2023 using Gaussian Curve Fitting

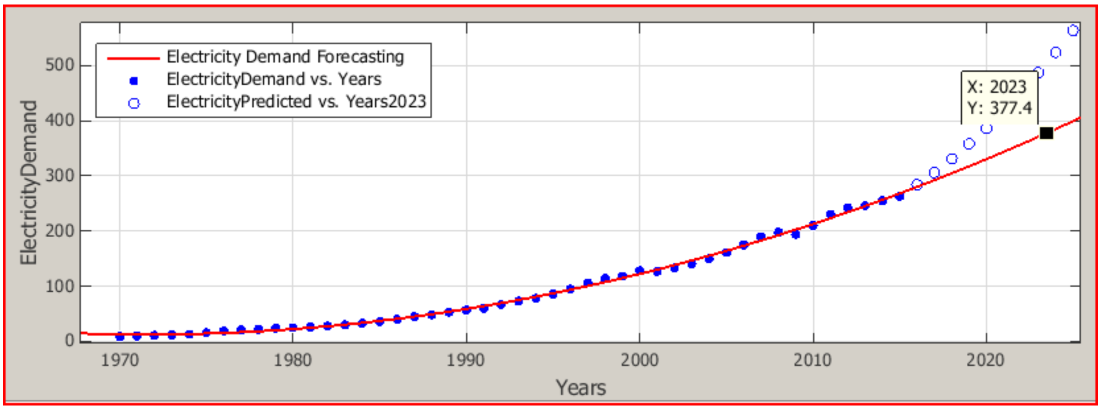

Figure 3 The prediction of electricity demand (TWh) in 2023 Fourier Curve Fitting

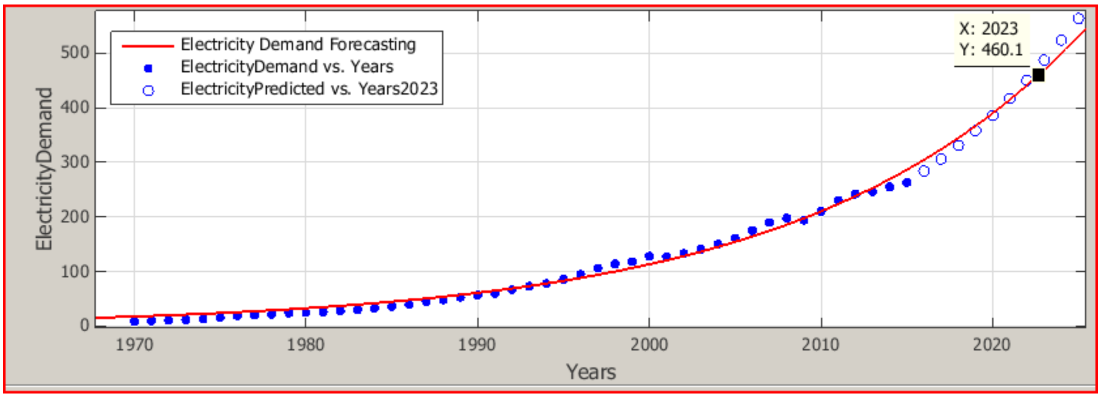

Figure 4 The prediction of electricity demand (TWh) in 2023 Exponential Curve Fitting

The results of the long-term electricity consumption for Turkey are shown in the "Table 3".

In "Table 4", we compare our results with those of previous studies. Looking at the comparisons in the "Table 4", the numerical values of the percentage errors are small for the previous studies but they are negative, meaning that the methods forecast less as compared to the actual. Our study gives bigger forecast errors in comparison to the actual, but they are positive. For planning purposes, it is better to have excess than deficit. This is what makes our study better than the previous studies.

Table 3 Results of forecast models and the actual electricity consumption (TWh)

Years	Actual	GAUSSIAN	FOURIER	EXP	MENR
2015	217.3	277.7	274.9	267.9	267.9
2016	231.2	291.3	286.8	295.3	285.7
2017	249.0	301.1	298.9	319.2	305.7
2018	258.2	310.5	311.4	342.3	327.1
2019	304.3	318.2	326.6	360.5	345.0
2020		323.1	342.2	383.7	374.5
2021		330.9	352.5	407.3	400.7
2022		343.6	360.4	427.3	428.7
2023		**352.7**	**377.4**	**460.1**	**458.6**
2024		360.8	397.9	507.3	490.9
2025		374.3	409.7	520.1	525.2

Table 4 Comparison of our results with previous studies

Year		2015	2016	2017	2018	2019	2015	2016	2017	2018	2019
		Consumption (TWh)					% Forecast error				
Actual		217.3	231.2	249.0	258.2	304.3					
MENR		267.9	285.7	305.7	327.1	345.0	23.3	23.6	22.8	26.7	13.4
Kavaklioglu et al, [25]		212.2	217.7	223.2	228.7	234.3	-2.4	-5.9	-10.4	-11.4	-23.0
Kavaklioglu, [26]		184.1	193.2	199.6	207.6	215.9	-15.3	-16.4	-19.8	-19.6	-29.0
Toksari, [27]		201.5	204.2	206.9	209.5	212.1	-7.3	-11.7	-16.9	-18.9	-30.3
Kiran et al, [28]		249.5	261.2	273.8	287.4	302.1	14.8	13.0	10.0	11.3	-0.7
Our Study	**Guassian**	277.7	291.3	301.1	310.5	318.2	27.8	26.0	20.9	20.3	4.6
	Fourier	274.9	286.8	298.9	311.4	326.6	26.5	24.0	20.0	20.6	7.3
	Exponential	267.9	295.3	319.2	342.3	360.5	23.3	27.7	28.2	32.6	18.5

5. Conclusion

In this study, we have developed models for electrical energy demand forecasting based on a novel curve fitting approach. The study focused on designing a simple yet compact, fast and accurate long term electrical energy forecasting models that can be used for policy formulation and planning especially in the energy sector. Our approach was guided by the principle of finding the minimum error between the observed data and the predicted data. We developed three forecasting models, i.e., Gaussian, Fourier and Exponential curve fitting models. The forecasting models presented in this paper take the year as the independent variable and electrical energy consumption as the dependent variable. The simplicity of the curve fitting models and using only one independent variable results into very low times for both training and forecasting. We used the coefficient of determination (R-Squared) as a measure of forecast accuracy performance. The accuracy of the proposed models is excellent. Accordingly, the Gaussian model gave better results (R-squared = 0.9978) followed by the Fourier (R-squared = 0.9976) and Exponential (R-squared = 0.9872) models respectively. We have been able to capture uncertainties that exist in every forecasting model by taking 95% confidence values for the coefficients of the Gaussian, Fourier and Exponential models to get a lower and upper bound forecast. Accordingly, our forecasts from the Gaussian, Fourier and Exponential models for the target year 2023 are 352.7 TWh, 377.4TWh and 460.1 TWh respectively. Except for the Exponential model, the forecasts for the Gaussian and Fourier models are close to and in agreement with the estimated 375.8 TWh energy demand in NDP11.

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