Real Measure of a Transmission Line Data with Load Fore-cast Model for The Future

M. Yilmaz

***Abstract*— In this study, an electric transmission line taken hourly data of feeders, belonging to the 1990-2017 year in Turkey by using actual consumption value, load forecasting analysis was done for the future. Short-medium-long term forecast range that results in hourly resolution, presented a mathematical approach to versatile applications. A statistical prediction tool that is called Exponentially Weighted Moving Average (EWMA) is used to predict the next year's demand for transmission in Turkey. In addition to this method, the estimated value of load factors near future, within a few years also has been shown to successfully predict the hour as possible. To load demand will increase in the future, it was presented solutions to be taking precautions.**

***Index Terms*— Power grids, microgrids, power transmission, power system management, smart grids.**

I. Introduction

ELECTRICITY DEMAND is constantly increasing. The way to meet this increasing demand for energy in the most appropriate way possible by making the right forward planning. In order to meet energy demand and realize production at low cost, load estimation analysis is a very important issue. Some studies Show us, the power plants do not use the power of 5-10%, while 20% say that the value is used only 1-2 hours in a day.

For these reasons, it is important to predict in advance. Load forecast analysis is the first step in planning electrical energy. For a good system planning, the energy demand and peak load values must be estimated with the least number of errors. The installation of joints and / or new power plants to be made to the power plants is determined to meet the foreseen energy demand, taking into account the peak load values. According to the load estimation results, the capacity additions to the transmission - distribution systems together with the production and the investment costs related to them are determined.

The inability to store the electric energy increases the importance of the accuracy of the demand estimate. The accuracy of the load demand forecast; reliability and efficiency of electrical power systems, optimization between power plant units, hydrothermal coordination and fuel harvesting affect the operating characteristics of the energy system.

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Faults in the load forecast can cause significant problems in future power system planning. If the estimated value is below the future value, the system is overloaded, the energy quality is decreased and if the forecast is high, the cost is increased and the system is operating at low capacity. In order for the system not to work this way, as the available data increases, the estimates and corresponding plans must be renewed.

Studies on predicting the consumption of electricity is usually done by term load estimates (covering periods from one hour to one month), medium term load estimates (covering periods from one month to one year), long term load estimates (covering periods longer than one year).

The short-term load forecasting analysis determines the load sharing between the power plants and the commissioning status of the production units. Generally, the peak load values in the daily load curve are tried to be predicted in real time. Maintenance programs are prepared, river flow conditions for hydraulic power plants and water quantity to be kept in water reservoir are determined, the amount of fuel is determined in thermal power plants, data related to steam flow are determined and load of the plant units is provided according to estimated load values.

Mid-term load estimation is very important because it covers the planning of physical equipment. At this stage, the transmission system is expanded and transmission, distribution systems and units that can be taken over soon are determined. It is also used in planning distribution systems, collective planning studies and economic reviews to determine sales tariffs, maintenance periods and fuel sources.

In the long-term load forecasting, planning strategies are determined first. In addition to this, issues such as the need for fuel and the determination of fuel resources and the provision of capital are also realized in this period. The most needed long-term load estimate in practice. Because, at this stage, very important decisions are taken and high capital is used and production plans are made.

Load forecasting is important to industry and society in where and when needed, the electrical energy sufficient to meet the need for reliable and not necessary to determine the amount of more or less. In the realization of the electricity energy plans, each plant must be provided with the primary energy source, selection of site, feasibility studies, financing, execution without interruption, operation of the operation teams.

Since there are a lot of uncertainties in long-term load estimates, it is not possible to make a precise and precise estimate. When performing load estimation analysis; accurate determination of the variables affecting the change of the load, generalization with the mathematical load model and methods of obtaining the model parameters, the conditions in the input variables should be taken into consideration.

There are many approaches to load estimation. What is important is to determine the most accurate and most accurate values. When applying these approaches, the answer to the question of whether peak demand or load must be estimated separately is the direct calculation of the first option peak load. In this case, the result can go directly; but economic changes are ignored. The second option is to determine the load by estimating the load. This option means that the load factor is also calculated. In this alternative the energy is more uniform as it is determined by the load, and the population-dependent and economic factors are not neglected; but irregularly varying load factors can lead to erroneous predictions. In this case, a new question emerges. When making load estimates, should the past data be done as a whole or separately for each consumer group? In answer to this question; it is appropriate to make separate estimations for each group by dividing the consumers into separate groups. Finally, all these estimates are combined to determine the total load needed. As a result, misdirection of prediction is prevented. Another option is to estimate the total burden as a whole. This option has ease of use and a more comfortable observation of the growth tendency. Another question is; Should the upper boundary be used or the middle should be used? Based on the weather reports from the past when planning, it is based on the estimation of the load components. In this method, it is necessary to make some adjustments because the air changes do not have a regular course. Finally, detailed and precise mathematical calculations need to be made when estimating. The mathematical method is determined by the structure of the load. Before choosing a particular method, all possible methods should be tried and found to be the most appropriate.

In the literature, the main methods used for short-term load prediction analysis are: regression-based methods [2], Box Jenkins model [3] time series approach [4-5], Kalman filter [6], YSA models [7] hybrid approaches [8]. Recently, methods of using statistical methods and other artificial intelligence approaches as hybrids have also been suggested for solving this problem. Bayesian inference [9], self-organizing maps [10], wavelet transforms [11], and particle swarm optimization [12].

Medium and long term load forecasting analyzes are also very important in planning power systems. Time series approaches [13] and Fourier series (FS) [14] approaches were used for medium term load estimation. The long-term load estimate is important for long-term planning and for determining the peak loads during the year. The most important methods used in long-term load estimation are time series analysis [4-5], hierarchical artificial neural networks [15] and support vector machines [16].

II. Estimating Methods

The selection of the forecasting technique to be used is important in determining future demand for freight. Depending on the nature of the load changes, one method may outperform the other. Before choosing a particular method, it is necessary to examine the behavior of the load. It can be understood that it is appropriate to select a suitable curve or a stochastic model for the behavior of the load. Since the electric networks show different characteristics, the structure of the existing system should be examined. It is important to know the advantages and disadvantages of different systems in order to select the most appropriate technique according to the system examined. Basically there are two estimation methods, extrapolation and correlation. Extrapolation is made by assuming that the past data and the forces influencing this data will increase in the same way as in the past. There are many extrapolation methods. Some of these are made up of the interpretation of mathematical growth curves. The others are for years to be used for the growth averages of the past years. Correlation is the loading of loads through other factors (such as weather or economic conditions). The most important advantage of correlation is to evaluate the factors that affect growth according to their importance. For example, air is the digitization of the relationship between conditioning and load. The correlation method also helps in determining the cause if the estimates deviate from the true values. Some of the estimation methods used are:

Fourier series, Particle flock optimization, Hybrid, Fuzzy logic, Fuzzy logic, Kalman filter, Bayesian inference, Self-organizing maps, Time series analysis, Box Jenkins models and their derivatives, Artificial neural networks models and other methods.

III. Mathematical Modeling And Application

The mathematical model developed for load prediction analysis is an approach that allows short, medium, and long-term hourly load prediction analysis, unlike previous studies [17]. This model TEİAŞ in Turkey (Turkish Electricity Transmission Company) received the diagnosis hour remaining four years have been found using a total of twenty-six years of actual load data consists of annual value. The proposed method consists of three sub-sections that are intertwined. First part; modeling of annual load values, second part; the modeling of monthly load values during the year, the last part; Modeling of hourly load changes using 3D mathematical notation. A statistical prediction tool that is called Exponentially Weighted Moving Average (EWMA) is used to predict the next year's demand for transmission in Turkey.

In order to use hourly load data in a meaningful way, these data should be analyzed first and their dynamics should be understood. Load values have a dynamic structure and show similarities. But besides this, some unexpected situations, power plant failure, holiday periods, weather conditions and some other factors affect the change of load values. Another observation of load values is that there are two oscillations in the monthly and hourly periods, respectively. However, non-random parts of the load values, in other words portions of the oscillations showing similar variations, can be modeled using wave patterns or mathematical models. In addition, when the average load values of each year are examined, it is seen that the load values increase significantly with years.

One-year total energy values for each day were measured to see the daily variations of the requested load values during the year and the times when the demand was highest and lowest. In these measurements, a daily change of different seasons and periods is given in Figure 1. When analyzes are made, interim valuations are made to eliminate sudden falls (due to electrical failures, failures, etc.). This interim evaluation was done by taking the average of the values of the previous month and the next month of the relevant time. The seasonal changes can be easily observed from Fig 2. As can be seen, electrical demand is at most winter months. Although not as much as the winter months, there are more demanding requests in July and August. In spring months, especially in May and June, the demanded value falls. In addition, it is seen that the demanded load values increased due to the annual increase. The hourly load values for the year 2017 are shown in 3D in Fig 3.

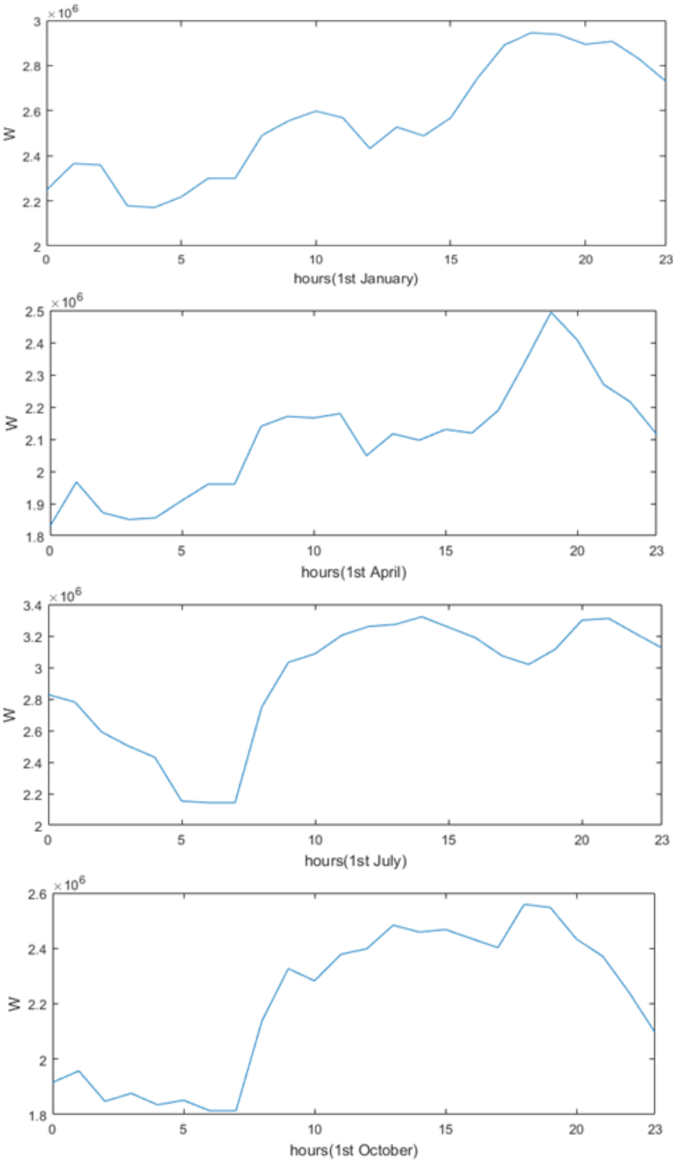

Figure 1. Daily energy demand values for some months of the 2017

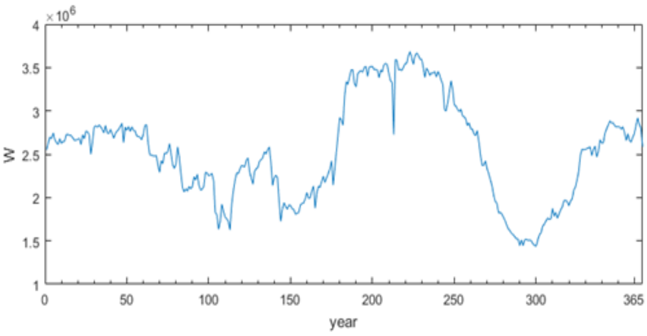

Figure 2. Annual average energy demand per day

The reason for the 3D representation of the load values, the combination of time and day-dependent changes of this representation; in other words, it has a compact visual property. As can be seen from the figures, the 3D representation has more information and information on the change of load values. Because of the relative nature of the load changes, the mathematical modeling of Figure 3 is extremely complex. On the other hand, if the change in 3D graphics from one day to the next is separated by 3D matrix display, it will be possible to display this less complex model.

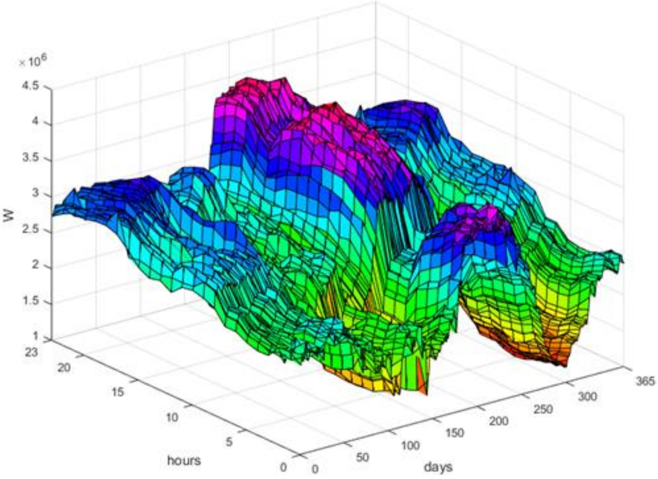

Figure 3. 3D representation of hourly demand data in 2017

In the method proposed in this study, the load values are modeled as three internal parts. The first part is the modeling of the annual mean load values. The second part is modeling the monthly residual load values within a year. The third part is the modeling of hourly variations within a month. This model is also modeled using matlab. This interstitial structure is shown in Fig.3.

IV. Modeling Of Annual Load Values

Turkey is a country constantly increasing demand for electricity. According to TEİAŞ' data, electricity demand is increasing continuously between 1996-2016. The changes in annual load values are given in Fig. 4. The total chart for the years 1996-2016 is given in Figure 5.

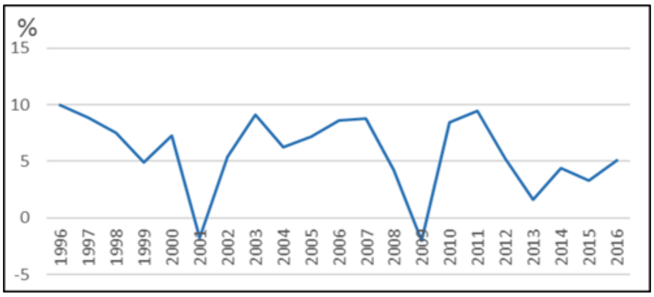

Figure 4. Turkey' electiricty demand changes between the years 1996-2016.

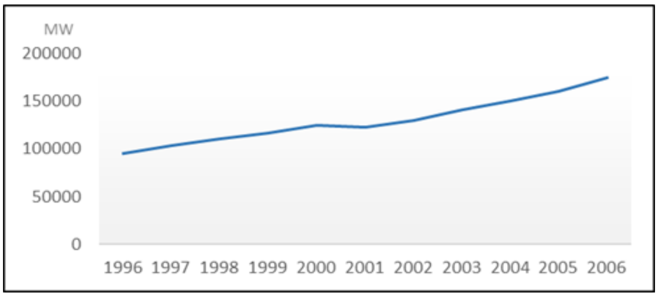

Figure 5. Turkey's electricity demand between the years 1996-2016

To be able to model, this graph can be examined by dividing into two parts. In this way, both the continuously increasing state (Figure 5) and the year-over-year changes (oscillations) can be modeled (functional difference between Figure 1 and Figure 2).

As know EWMA is a time series based statistical tool. To express EWMA, firstly we should define a time series and moving average [2].

A time series can be considered as x_t, t= 1,2,3, … , i then the average of it can be calculated. If i is selected large, then an integer n which is selected smaller than i, x_t can calculated a set of averages, or simple moving averages (of order n) [2]:

$$\bar{x}_{t.1} = \frac{1}{n}\sum_{t=1}^{n} x_t \quad (1)$$

$$\bar{x}_{t.2} = \frac{1}{n}\sum_{t=2}^{n+1} x_t \quad (2)$$

$$\bar{x}_{t.i-n+1} = \frac{1}{n}\sum_{t=i-n+1}^{t} x_t \quad (3)$$

Where $2 \leq n \leq i$ the each calculation of the average of the values over an interval of n data becomes as follows [2],

$$\bar{x}_t = \frac{1}{n}\sum_{t=t-n+1}^{t} x_t. \quad (4)$$

This reveals that the average estimation at time t is the simple average of the n values at time t and the leading up to n-1 time steps. If weights are applied that decrease the number of n that are next in time, the moving average will be called as exponentially smoothed. Therefore Moving averages are usually provided forecasting information about at a series time t+1, St+1, is considered as the moving average for the period of including time t, e.g. today's forecast is based on an average of earlier values. Using (4) all n's are equally weighted. These equal to weights assumed as μ_t, every n weights would equal 1/n, so the sum of the weights would be 1, where $\mu_t = 1/n$, then the (4) turns into [2]

$$\bar{x}_t = \sum_{t=t-n+1}^{t} \mu_t x_t. \quad (5)$$

Using exponentially weighted moving averages the contribution to the mean value from n's that are more removed in time is planned decreased, so emphasizing more local events. Basically a smoothing parameter is $0<\mu<1$. Where $0<\mu<0.5$ designates more weight than to the prior (x_t). If $0.5<\mu<1$ less weight is assigned to x_{t-1} and more to x_t . In exponential smoothing it is needed to use a set of weights that sum to 1 to reduce in size geometrically [2]. The weights are used would be [2]

$$\mu(1-\mu)^k, \quad (6)$$

where k= 1,2,3,…. After some mathematical operations and reduction, the moving average that weighted with (5), (6) becomes [2]

$$\bar{x}_t = \sum_{k=1}^{n} \mu(1-\mu)^{k-1} x_{t-k+1}. \quad (7)$$

Then (5) can be written as a repeated smoothed relation [2]

$$S_t = \mu x_t + (1-\mu) x_{t-1} \quad (8)$$

In (8), x_{t-1} is indicated annual percentage growth rate of 1996 and x_t is indicated annual percentage growth rate of 2016 [2].

Modeling the hourly load values: In order to create a smooth hourly model of a year, a 'monthly model' was created using data from 2006. In order to find the monthly model, averages of the values of 12 months were taken. The hourly chart within a month is similar to the other days of the year. The arithmetic average for these 12 months represents the symbolic (nominal) monthly average. Before the average is taken, the total energy of the hourly curves of each month is normalized to normalize the active energy demand and to avoid the effects of increases and decreases within a year. As a result, the total energy of the created model is equal to the individual. The normalized hourly load changes are given in Figure 6.

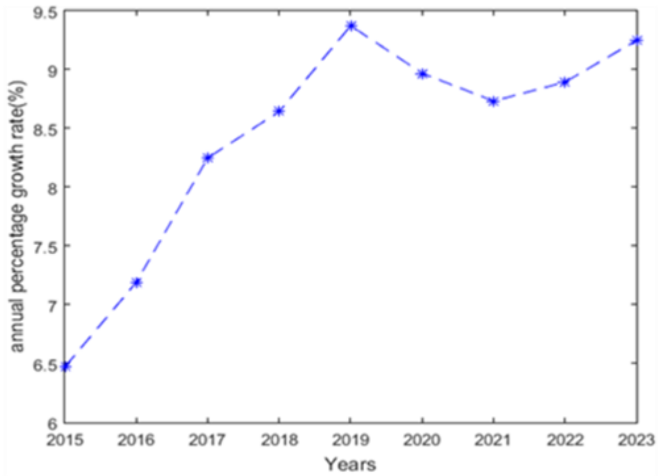

Figure 6. EWMA is used to predict next years' loads.

V. CONCLUSION

The success of the load estimation analysis depends on the accuracy and accuracy of the statistical data of the current system. In this study, electric power generation, has been tested using the proposed method and the data presented in Turkey for energy transmission and distribution companies and financial units, which is a very important issue in terms of load forecasting analysis. Unlike other hourly load estimation methods, this method can estimate for several years. It has been observed that the estimation results obtained by the mathematical model consisting of subdivided subsegments give successful results on an hourly basis.

To create awareness about management of electric energy demand for next years the electrical load that will affect the electrical grid is shown firstly. Turkey is one of the developing countries. Therefore, the energy and technology demand of the country is increasing continuously. It will be needed a power plant investment due to electric demands in Turkey that dependents on foreign energy. To overcome these problems existing power plants should be optimized which can be occurred by smart grid. The aim of the smart grids is to generate efficient and reliable energy and control the generation of power, consumption, storage, distribution and transmission in a flexible way by using of information technologies. If Turkey does not employ the smart grid in electrical power system, it cannot benefit from its renewable energy resources, and its external dependence on energy will increase.

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