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Electric Energy Consumption Forecast and Analysis for Düzce Province

Düzce İli İçin Elektrik Enerjisi Tüketim Tahmini ve Analizi

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Abstract: The purpose of this study is to develop estimation models for the electrical energy consumption values of Düzce Province, Turkey. It has been demonstrated that estimation models were constructed and analyzed for the electrical energy consumption of Düzce between November 2019 and October 2021. To create the dataset, data were obtained monthly from Enerji Piyasaları İşletme A.Ş. (EPİAŞ). Since the data cover two periods (12 months and 24 months) and include seasonality, the Least Squares Method, Fourier Analysis, and Winters' Method were chosen as the estimation models. The evaluation of the models using the Mean Absolute Percentage Error (MAPE) method indicates that Fourier Analysis performs worse than Winters' Method. Winters' Method, which is a multiplicative model, achieved better performance in constructing the electrical energy consumption estimation model in this study. When comparing the two estimation models, no significant difference was observed; however, the analysis results reveal that Winters' Method is more favorable for forecasting electricity consumption values in Düzce for the period between November 2019 and October 2021. These findings demonstrate that Winters' Method outperforms both the Least Squares Method and Fourier Analysis, making it a more reliable option for future studies focused on constructing electricity consumption estimation models. This result emphasizes the importance of using Winters' Method as a reference for future research on electricity demand forecasting.

Keywords: Energy Consumption, Estimation, Winters' Method, Fourier Analysis, Time Series

JEL Classification: C80, C81, H76

Öz: Bu çalışmanın amacı, Türkiye'nin Düzce ili için elektrik enerjisi tüketim değerlerinin tahmin modellerini oluşturmaktır. Kasım 2019 ile Ekim 2021 tarihleri arasında Düzce ili elektrik enerjisi tüketimi için tahmin modellerinin kurulduğunu ve analiz edildiğini kanıtlıyoruz. Veri setini oluşturmak için veriler Enerji Piyasaları İşletme A.Ş. (EPİAŞ) den aylık olarak alındı. Verilerin 12 ay ve 24 ay olmak üzere iki dönemde analiz edilmesi ve mevsimsellik içeriğinden çalışmada tahmin modeli olarak En Küçük Kareler Yöntemi, Fourier Analizi ve Winters Yöntemleri tercih edilmiştir. Modeller arasında Mutlak Hata Yüzdelerinin Değerlendirilmesi (MAPE) yönteminin, Fourier Analizinin Winters yönteminden daha kötü performans gösterdiğini ortaya koymaktadır. Çarpımsal bir model olan Winters Metodunun, bu çalışmadaki elektrik enerjisi tüketim tahmin modelinin oluşturulmasında daha iyi performans gösterdiğine ulaşılmıştır.. İki tahmin modeli karşılaştırıldığında ise anlamlı bir farklılık görülmese de, analiz sonuçları Düzce ili için Kasım 2019 ile Ekim 2021 tarihleri arasındaki elektrik tüketim değerlerinin tahmininde daha iyi sonuçlar verdiği için Winters Yönteminin daha çok tercih edildiğini göstermektedir. Bu sonuç Winters Yönteminin, En Küçük Kareler Yöntemi ile Fourier Analizinden daha iyi performans gösterdiğini kanıtladığından; gelecekte elektrik tüketim değerlerinin tahmin modellerinin oluşturulması konusunda çalışacaklara örnek olarak verilmesi önem arz etmektedir..

Anahtar Kelimeler: Enerji Tüketimi, Tahminleme, Winters' yöntemi, Fourier Analizi, Zaman Serileri

JEL Sınıflandırması: C80, C81, H76

1. Introduction

Electricity is a vital part of today's world and economy. People have been using electricity from past to present in many important basic areas such as lighting and heating. EPİAŞ data demonstrates a consistent increase in electricity consumption over the years in Turkey,

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reflecting its growing significance in meeting daily life demands and supporting industrial operations. These trends highlight how electricity has become indispensable for both individual and societal development (EPIAS, 2023).

Electrical energy consumption is the actual energy demand over the current electricity supply. The concept of demand and supply are the two basic elements of the planning approach for almost all sectors, especially the production sector. Demand is the component of forecast, while supply is the component of determination, decision or execution. In the planning research, firstly demand forecasting should be done correctly. It may not always be possible to accurately calculate demand forecasts. In terms of energy, there are many factors and components that affect the forecasting of electrical energy demand (Haliloğlu and Tutu, 2018).

Considering that no previous electricity consumption forecasting has been conducted for Düzce province, the aim of this study is to obtain electricity consumption values for Düzce and to develop and analyze a forecasting model for the region. As a result of the comparison, it will be observed which estimation method provides better performance.

Accurate forecasting of electricity demand provides insight on investment decisions regarding power generation and supporting infrastructure. Of great interest to energy policymakers, utilities, and private investors, forecasts are also crucial to development professionals. Conversely, overestimating energy demand can result in the development of excess capacity, which effectively translates into resource wastage, particularly financial resources (Kavaklıoğlu et al., 2009). Overestimating or underestimating demand, inaccurate forecasts can have dangerous social and economic consequences for the investor and development. Underestimation of demand leads to shortages of supply and forced blackouts, with serious negative impact on productivity and economic growth (Almeshaiei and Soltan, 2011).

The most used methods for estimating electrical energy consumption data are systems such as Time series, Regression models, Integrated Autoregressive Moving Average (ARIMA) Models, Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Networks (ANN), Gray systems (Bolturk, 2013).

Some of the studies in the literature on electrical energy consumption estimation are summarized below.

Yalçınöz et al. (1991) completed energy forecasts for the years 1991 to 1996 using 5 different forecasting analysis methods; the least squares method is Exponential Analysis, Quadratic Analysis, Moving Average Analysis, Holt's Exponential Smoothing Analysis. They concluded that the estimation method that gives the closest results to actual figures is the moving average method. Ozkan et al. (2020) established an estimation model using the Least Squares (LS) method by performing Fourier Analysis for Turkey's electrical energy consumption. Another prediction model they use is the Winters Method. Fourier analysis using the LS method has shown that as it has a more stable and periodic method, Winters' method is superior in this case.

Haliloğlu and Tutu (2018), a model that predicts the daily electrical energy consumption in Turkey has been developed. They also preferred the Least Squares Method for demand forecasting. It indicates that the success of short-term electrical energy consumption forecast is directly proportional to the size of the data used. By using daily data and LS method, the threshold temperature difference is taken as an independent variable, while time and electrical energy consumption are taken as dummy variables to create the model.

Çelik (2015), 8 effective criteria have been determined for temperature estimation by conducting a literature review, and the 4 most effective analysis methods or forecasting methods were chosen among them by using AHP and DEMATEL methods with the help of expert opinions. The model was established with the Adaptive Neuro-Fuzzy Inference System (ANFIS) method through selection of the inputs that affect the output the most. To show the effectiveness of the model, the absolute error percentages were calculated using the squared error method. The analysis of the results concluded that the most effective model was the ANFIS and it was more consistent than other models. Bilgen (2018), modelling of the electrical energy consumption for Turkey was aimed. Working on the long range data for the period between 1995-2017, gaussian and triangular forms for the Adaptive Neural Fuzzy Inference System, and quadratic and linear forms from the genetic algorithm have been utilized. As a result of the hypothesis tests, it was revealed that the linear model in genetic algorithms and the triangular model in Adaptive Neural Fuzzy Inference System provided better results.

İpek (2019), it was aimed to predict a chaotic time series on ANFIS based on the data received from the Industry 4.0 production line with sensors. First degree Sugeno determined membership functions using fuzzy inference system method and calculated mean absolute percentages error (MAPE) values with square root of mean squares of errors (RMSE) to evaluate their performance. In addition, the ARIMA models with the Box-Jenkins method was determined and calculated the same performance values for this model. As a result of this study, the first degree Sugeno fuzzy inference system method provided to give the best results on Industry 4.0 data. In addition, it produced the closest prediction values to the actual figure via the ANFIS method. In this study conducted by Wenming Li et al. (2022), two statistical models are discussed: one is a correctly specified model, and the other is a misspecified model that includes some superfluous variables. The paper compares the statistical properties of these models, focusing on the best linear unbiased estimators (BLUE) under both assumptions. It is assumed that one of them is correctly defined while the other is not. By using tools from precision matrix theory and linear bias-free estimators, it is considered various statistical properties of the estimators of each model. This is followed by a discussion of the connections between the estimators and the models and a discussion of the best linear unbiased estimators of unknown parametric vectors based on the two models.

Ok (2010), medium-term electrical energy demand forecasts for Turkey has been done using the Adaptive Neural Fuzzy Inference System model. In order to compare the performance of the model created, he also created a Regression analysis model and evaluated the estimation results over the average absolute percent error. At the end of the study, it is emphasized that the model established with ANFIS gave successful results. Antonella Falini et. al. (2022) conducted a spline Hermite semi-interpolation technique and prediction and anomaly detection model for pre-processing of the imputation and smoothing of single variable time series. This article provides a valid tool based on the Hermite semi-interpolation, which has double use. By performing the opening and straightening operations, the time series considered has been successfully pre-processed. In all of the examples it is evaluated, it has been achieved promising results compared to standard techniques. This is the first step in deeper implementation of the proposed QI plan for time series operation in different contexts. Doğan (2012) utilized fuzzy logic methods and artificial neural networks for demand forecasting in businesses, aiming to improve prediction accuracy and address uncertainties. The parameters were determined by trial and error method, and finally the results of the two methods were compared and examined. Artificial neural networks were established with the help of the WEKA program and the parameters were modified until the most effective results were obtained. It has been observed that the performance of the ARIMA method in weekly demand forecasting is better than the artificial neural networks and ANFIS method, but it has also been stated that ANFIS and ARIMA gave similar results.

Akpınar (2017), consumption for the province of Sakarya was estimated with artificial intelligence and statistics. Taking two different situations, he made monthly demand and dayahead demand forecasts. Winters Exponential Smoothing (WUD) method, Decomposition of Time Series (ZSA), Integrated Autoregressive Moving Average Model (ARIMA) and Seasonal ARIMA (SARIMA) were the methods used. As a result of the study, it has been revealed that the forecast models established for the natural gas demand are applicable without the need for any other variables other than the actual historic data. Yıldırım (2019), sales forecasting in the public procurement sector was conducted using statistical data mining techniques (such as classification and regression techniques). In the application part, the linear model, decision trees and generalized model algorithms (Xgboost Trees and Random Trees) were used with the data for the period of 2007-2018. As a result, DMO has integrated the empirical application model, which was made with the IBM SPSS Modeler application, into the system based on the live dataset on a data mart. Thus, faster and more effective decisions could be taken in the strategic plan.

Es (2013), artificial neural networks and Grey Modelling were examined in order to accurately predict Turkey's energy demand. Working on the dataset between 1970 and 2010, he established the artificial neural network model with the variables of export, import, gross domestic product, population, building area and number of vehicles. In order to measure the performance of the established artificial neural network model, regression and time series models were developed and compared. As a result of these comparisons, it is concluded that the model built with artificial neural networks performed more successful and better performance predictions compared to the regression and time series models. The net energy demand of Turkey was estimated by artificial neural networks for the period of 2011-2025 within the scope of the study.

Finally it is proved that the monthly total energy consumption data of Duzce Province is studied periodically from November 2019 to October 2021. The data set is created through taking the actual monthly data from EPİAŞ (2023), while Fourier Analysis and Winters' Method are discussed using the least squares method. MAPE (Mean Absolute Percentage Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) values are calculated as model success criteria.

The least squares method is a statistical method for finding the best fit for a set of data points by minimizing the sum of the distances or residuals of the points from the plotted curve. Least squares regression is used to predict the behavior of dependent variables and provides the general rationale for fitting the best-fit line between the data points studied. The difference of this method from other methods is that it gives better results in short-term forecasts (Kıran, 2015).

2. Material and Method

It is proved that estimation models will be established through using electrical energy consumption data in time series analysis for Duzce province. For the estimation model, firstly, Fourier Analysis will be performed using the Least Squares (LCS) Method, secondly, Winters' method will be used. Due to its convenience in mathematical operations, the Least Squares method can be used as one of the most effective estimation methods, apart from other regression methods. The first reason for using these methods is to obtain better results in short-term forecasting studies (Alma and Vupa, 2018).

Estimation will be analyzed in 12 and 24 months' periods. The relationship between the division of the data set into two periods and the coefficient of variation in the two periods, along with the success of the prediction models created will be examined. As success criteria, Absolute Error Percentages Mean (MAPE), Mean Squared Mean Error (MSE), Root Mean Squared Deviation (RMSE), Mean Absolute Error (MAE) values will be examined. In the forecasting stage, the data between November 2019 and September 2021 will be evaluated as two periods. The evaluation of these methods will be done with the help of Microsoft Excel, Eviews12 and Minitab19 pack programs.

2.1. Fourier Analysis with the Least Square Method

It is accepted that the method of least squares (LSM) was discovered by the German mathematician Carl Fredrich Gauss in 1794. Squared errors will eliminate the signal problem. Algebraic operation is simple and square acquisition makes large error terms larger (TechTarget. 2020).

Least Squares method, which is one of the regression methods, is a statistical method that aims to minimize the error sum of squares. It is a method that emerged with the aim of solving a (inconsistent) linear equation system that has no solution. The aim of the least squares method is to minimize the prediction error mathematically. The least squares method is a statistical method for finding the best fit for a set of data points by minimizing the sum of the distances or residuals of the points from the plotted curve (Alma and Vupa, 2018).

There are different trend functions in the LS method. These functions can be specified as Linear Trend Functions, Quadratic Trend Functions and Exponential Trend Functions. The linear trend function is calculated as Equation (1) (Akpınar, 2017).

$$T = a + bt + e \tag{1}$$

'a' and 'b' are estimated using the least squares method. 'e' indicates the amount considered as margin of error. 't' represents the time in the time series and 'Y' represents the value of the dependent variable (prediction). The difference between the estimate and the actual value gives the error and is expressed as Equation (2) (Akpınar, 2017).

$$e = Y - T \tag{2}$$

It is aimed to minimize the error (e). On the one hand, the error must be independent and not directional. For this reason, it is tried to obtain the minimum error by using Equation (3) (Akpınar, 2017).

$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} ly_{i-T_{i'}}^2 = \sum_{i=1}^{n} (y_i - a - bt_i)^2 = min \tag{3}$$

This method is called the "Least Squares Method". Having zero derivative means that the equation is minimum. Therefore, in this equation, the derivative with respect to a and b is intended to be zero.

$$\frac{de}{da} = 2\sum_{i=1}^{n} -(y_i - a - b \cdot t_i) = -\sum y + n_a + b\Sigma_t = 0 \tag{4}$$

$$\frac{de}{da} = 2\sum_{i=1}^{n} -t\left(y_i - a - b_{t_i}\right) = -\sum 2 + n_a + b\sum t = 0 \tag{5}$$

$$\overline{\sum t} = na + b\sum t \tag{6}$$

To find a and b, both equations with two unknowns are solved. As a result, an initial cut-off value and b equation trend are found (Akpınar, 2017).

System elements of time series can be revealed with Fourier analysis. Fourier analysis involves the use of discrete time series to empirically approximate functions containing trigonometric terms. In order to apply the Fourier analysis to discrete time series, it must be defined using a limited number of observations (Yalcınoz, 1991).

Fourier analysis is a method of defining periodic waveforms in terms of the 's' trigonometric function 's'. The method takes its name from the French mathematician and physicist Jean Baptiste Joseph, Baron de Fourier, who lived in the 18th and 19th centuries. Fourier analysis can be used in electronics, acoustics and communications. Many waveforms consist of energy at a fundamental frequency as well as harmonic frequencies (multiples of the fundamental frequency). The relative ratios of energy in fundamental and harmonics determine the shape of the wave. The wave function (usually amplitude, frequency or phase-time) can be expressed as the sum of the Fourier series sine and cosine functions, and the Fourier coefficient can be uniquely described with constants known as 's'. If these coefficients are represented by a, a_1, a_2, a_3, ..., a_n, ... and b_1, b_2, b_3, ..., b_n, ... then Fourier series F(x), where x is an argument (usually time), has the form (TechTarget. 2020):

$F\ (x)\ = a/2 + a_1.cosx + b_1.sinx + a2.cos2x + b.sin2x + \ldots + a_n.cosnx + b_n.sinnx + \ldots$ (7)

The aim in Fourier analysis is to calculate the coefficients a, a_1, a_2, a_3, ..., a_n and b_1, b_2, b_3, ..., b_n up to the largest possible value of n. The larger the value of N (i.e., the more terms in the series whose coefficients can be determined), the more accurate the Fourier series representation of the waveform (TechTarget. 2020).

When the problem is considered as a one-dimensional time series, the Fourier series should be determined based on the incremental value of the variable y_t (the observed value at time t) and t (time). This analysis is called "sine function curve fitting". The regression equation in the Fourier Analysis using the LS method is given in the equation (8). $y\hat{}t$; returns the estimated value of t at any time (Turker and Can, 1997).

$$\hat{y}_t = a_0 + 2\sum_{k=1}^{k} \text{acos}(wkt) + 2\sum_{k=1}^{k} b_k \sin(wkt) + e \qquad (8)$$

In the above equation, the absolute error at time t is expressed with the letter "e". K depends on N, which is the number of observations.

The "Matrix of Coefficients" in Equation (9) is expressed by matrix A. The "Measure Matrix" containing the observed data is represented by the G matrix (Yalcınoz, 1991).

$$\begin{vmatrix} 1 & 2cos(wt0) & 2sin(wt0) \\ 1 & 2cos(wt1) & 2sin(wt1) \\ & * & * \\ & * & * \\ & 2cos(wtN-1) & 2sin(wtN-1) \end{vmatrix} \qquad (9)$$

Multiplying the transpose of the coefficient's matrix A by the coefficients matrix A itself gives the matrix N observation numbers.

$$N = A^T.A \qquad (10)$$

Multiplying the transpose of the coefficient's matrix A with the values it is observed, the G measure matrix, gives the matrix n.

$$n = A^T.G \qquad (11)$$

The x matrix, which is called the Unknowns Matrix and contains the necessary coefficients for the estimations, is given as in Equation (12).

$$x = [a_0\ a_1\ b_1\ a_2\ b_2\ \ldots\ a_k\ b_k]^T \qquad (12)$$

There is another method of expressing the unknown matrix. For this, it is necessary to check whether there is a correlation between the observation values. If there is a correlation between the observed data, the x unknown matrix can also be expressed as Equation (13) (Yalcınoz, 1991).

$$x = (A^T.A) - 1.A^T.G \tag{13}$$

2.2. Fourier Analysis with the Least Square Method

The Holt-Winters forecasting method applies a triple exponential smoothing for level, trend and seasonal components. It is a multiplicative model (Pleños, 2022).

A Holt-Winters model is defined by three order parameters, namely, alpha, beta, and gamma, where alpha specifies the level smoothing coefficient, beta indicates the trend smoothing coefficient, and gamma indicates the seasonal smoothing coefficient. There is also a parameter for the seasonality type: Additive seasonality, where each season changes by a fixed number, and Multiplicative seasonality, where each season changes by a factor. This method only works on numerical time series. There are two variations of this method that differ in the nature of the seasonal component. The addition method is preferred when the seasonal variation is approximately constant in the whole series, and the multiplication method is preferred when the seasonal variation changes proportionally with the series level. In the scale of the observed series by the addition method, the seasonal component is expressed as absolute, and the seasonal component is subtracted from the level equation while the series is seasonally adjusted. Within each year, the seasonal component will reach approximately zero. In the multiplicative method, the seasonal component is expressed in relative terms (percentages), and the series is seasonally adjusted by dividing the seasonal component (RapidMiner. 2020).

The Holt-Winters method itself is a combination of 3 much simpler components, all of which are smoothing methods. These components are given below.

1.Simple Exponential Correction (SES): Simple exponential smoothing assumes no change in the level of the time series. Therefore, it cannot be used in series with trend, seasonality, or both [24].

2.Holt's Exponential Retracement (HES): Holt's exponential retracement is one step above the simple exponential retracement as it allows time series data to have a trend component. Holt's exponential correction is still not good at dealing with seasonal data (Analytics Vidhya. 2020).

3.Winters' Exponential Correction (WES): Winters' exponential smoothing is an extension of Holt's exponential smoothing, eventually allowing seasonality to be included. What is called the Holt-Winters method is Winter's exponential smoothing in other words.

Therefore, the Holt-Winters method is often referred to as triple exponential smoothing, as it is literally a combination of 3 smoothing methods built on top of each other (Analytics Vidhya. 2020).

In this study, the 3rd component, Winters' Exponential Correction (WES), will be discussed. The equations of the Winters' Method multiplicative model are given below (BOLTURK, 2013).

$$y_t' = \alpha \cdot \frac{y_t}{It-L} + (1-\alpha) \cdot (y_{t-1}^1 + bt - 1) \quad (14)$$

$$b_t = \gamma(y_t^1 - y_{t-1}^1) + (1-\gamma) \cdot b_{t-1} \quad (15)$$

$$I_t = \beta \frac{y_t}{y_t^1} + (1-\beta) \cdot I_{t-L} \quad (16)$$

where $y_t{}^1$ is the smoothing value for period t, and b_t is the period t gives the trend prediction value. t-1 shows the relevant parameter values for the previous period, while t_L shows the forecast parameter values for the previous period. L in the equation is the length of the season in a given period, I is the seasonal correction factor. α, β and γ components are respectively; the correction factor of the model (0< ∝ <1), the correction coefficient for the trend (0 <β < 1), and the seasonal correction constant (0 <γ < 1) (Yalcınoz, 1991).

The equation of the multiplicative Winters' Method estimation model is given in Equation (18).

$$\hat{y}_{t-m} = (y_t^1 + b + m) \cdot I_{t-L+m} \quad (17)$$

2.3. Fourier Analysis with the Least Square Method

The relationship between dividing the data set into two periods and the success of the forecasting models will be examined. Mean Absolute Error Percentages (MAPE), Square Mean Error (MSE), Root Mean Squared Deviation (RMSE), Mean Absolute Error (MAE) values will be examined as success criteria.

Absolute percent error is used to measure the accuracy of predictions in time series and regression models. The error percentage cannot exceed 100% for values with very low estimation, but there is no upper limit for values with very high estimation. The problem that arises when using MAPE to compare the accuracy of prediction models is that it systematically chooses methods with very low estimates (Veribilimcisi, 2017).

$$\mathrm{MAPE} = \frac{\mathbf{100}}{\mathbf{n}} \sum_{\mathbf{j}} \frac{|\mathbf{e_j}|}{|\mathbf{A_j}|} \quad (18)$$

The mean square error indicates how close the regression curve is to a set of points. MSE measures the performance of the predictive model, an always positive machine learning model. As the mean squared error approaches zero, the performance of the prediction model increases. (RapidMiner, 2020).

$$\mathbf{MSE}=\frac{1}{n}\sum_{J=1}^{n} e_j^2 \tag{19}$$

The RMSE is the standard deviation of the prediction error (residual error), a measure of the distance between the regression line and the data point. It allows to find the density of the data around the line that best fits the data. The RMSE value ranges from 0 to ∞ (Veribilimcisi, 2017).

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{J=1}^{n} e_j^2}{n}} \tag{20}$$

$$\boldsymbol{RMSE} = \sqrt{MSE} \tag{21}$$

The mean absolute error is the average vertical distance between each actual value and the line to fit the data, a measure of the difference between two continuous variables. It is also the average horizontal distance between each data point and the best fit line. The MAE value can range from 0 to ∞. When the scores are negative, that is, the lower the values, the prediction models give better results (Veribilimcisi, 2017).

$$\boldsymbol{MAE} = \frac{1}{n}\sum_{j=1}^{n} |e_j| \tag{22}$$

3. Results

The forecasting models in this study have been evaluated using Microsoft Excel, Minitab19, and Eviews12 software packages (Microsoft**,** 2019; Minitab, 2018; Eview, 2021). The data required for the electricity energy consumption analysis were obtained from the EPİAŞ Transparency platform for Duzce (EPIAS, 2023). The time series used for forecasting includes 24-month period from November 2019 to October 2021. The data were analyzed in two periods, namely, 12 and 24 months. The regression equation was obtained by performing matrix operations on Microsoft Excel for Fourier analysis with the least squares method. As a result of the obtained equation, a prediction model was obtained and graphics were created. For the Winters' method, which is another estimation method, the necessary alpha, beta and gamma parameters were calculated with the Eviews12 program, the graph was created with the help of the Minitab19 program, and the estimation model was obtained.

3.1. Outlier Test

The data summary for the 12-month period is shown in the Figure 1 below. In the data summary, Anderson-Darling Normality Test, mean, standard deviation, variance, median is observed for 0.5 confidence interval.

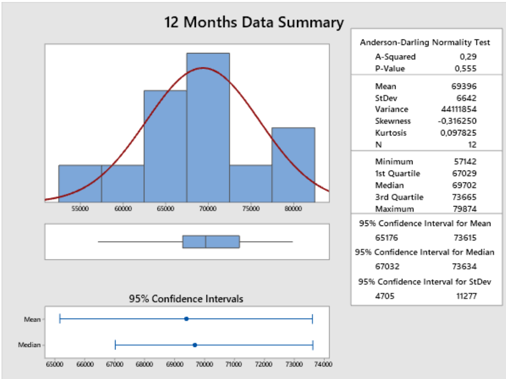

Figure 1. 12 Months Data Summary

Grubbs' test is used to find single outliers in normally distributed data sets. This test finds whether the minimum or maximum value is an outlier (Leys at al, 2013).

Table 1. Grubbs' Test for 12 Months Data

Variable	**N**	**Mean**	**StDev**	**Min**	**Max**	**G**	**P**
Data (y)	12	69396	6642	57142	79874	1,84	0,571

Outliers represent observations that consist of extreme values found in our data during statistical analysis. Depending on the general structure of our data, observations that are too high or too low can be defined as outliers. These exaggerated values may be observed due to certain external factors, special circumstances or incorrect data entry (Leys at al, 2013).

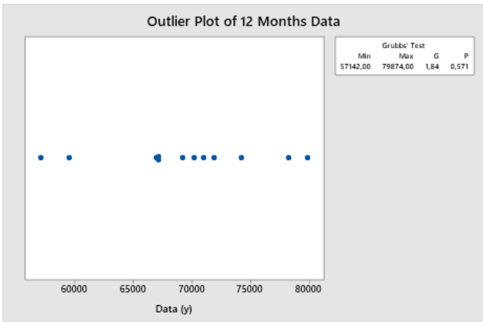

Figure 2. Outlier Test For 12 Months Data

For the 12 months data: the mean of the sample is 69396. The G statistic indicates that the smallest data value, 57142, is 2.5 standard deviations less than the mean. The p-value indicates that, if all values are truly from the same, normally distributed population, then the probability of obtaining a minimum value that small is only 0.571. Because the p-value of

0.571 is more than the significance level (denoted as α or alpha) of 0.05, the fact that it is shows that there is no outlier.

The data summary for the 24 months period is shown in the Figure 3 below. In the data summary, Anderson-Darling Normality Test, mean, standard deviation, variance, median is observed for 0.5 confidence interval.

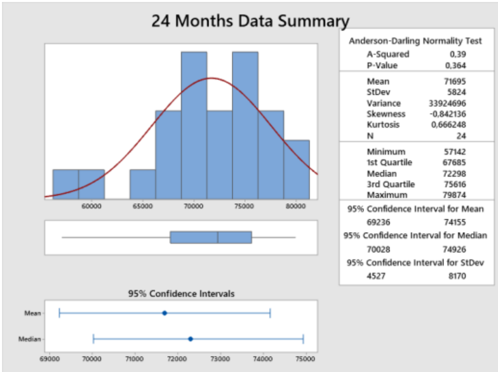

Figure 3**.** 24 Months Data Summary

Grubss Test for the 24 months period is shown in the Table 2 below. It is determined whether the minimum or maximum value is contrary to this test result.

Table 2. Grubbs' Test for 24 Months Data

Variable	**N**	**Mean**	**StDev**	**Min**	**Max**	**G**	**P**
Data (y)	24	71695	5824	57142	79874	2,50	0,178

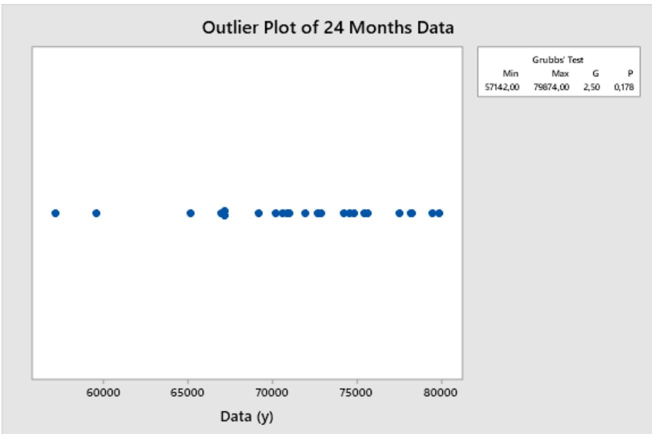

Figure 4. Outlier Test For 24 Months Data

For the 12 months data: the mean of the sample is 71695. The G statistic indicates that the smallest data value, 57142, is 2.5 standard deviations less than the mean. The p-value indicates that, if all values are truly from the same, normally distributed population, then the probability of obtaining a minimum value that small is only 0.178. Because the p-value of

0.178 is more than the significance level (denoted as α or alpha) of 0.05, the fact that it is shows that there is no outlier.

3.2. Period 1: 12-Month Forecast Models

The Matrix of Coefficients A in Equation (9) has been calculated for Fourier analysis using the least squares method. A Matrix of Coefficients is a 12x3 matrix as our estimation period is 12 months. Matrix operations are performed by taking t = 12 and t = 0,1,..,11.

$A =$		2	0	
		1.73205	1	
	0808		1.73205	
	1	1	0808	
	1	1,22515	2	
	1E-16		-	
	1	-1	1,732050808	
	1	.	.	
	.	.	.	
	.	0	-2	
	1	1	-	
	1	1.73205	1,732050808	
	10808		-1	2*3

In order to find the matrix N, which is the Number of Observations Matrix in Equation (10), the transpose of the matrix A is multiplied by the matrix A.

N		1	0	0	
$= A^T.A$	2		24,00000	0	
		0	001	24,00000	
		0	0	001	*3

In order to obtain the Matrix n in Equation (11), the transpose of the coefficient's matrix A is multiplied by the G Measure Matrix. The G matrix is a matrix we get from our data. Since it has been covered the 12-month period in this title, the first 12 months in our data will form the G matrix.

$$n = A^T.G = \begin{vmatrix} 832{,}746 \\ 86.33190 \\ 5 \\ - \\ 4.6683385 \end{vmatrix}_{3*1}$$

The x Unknowns Matrix in Equation (12) and Equation (13) contains the estimation coefficients necessary for us to make predictions. By inverting the multiplication of the transpose of matrix A by itself, it is again obtained by multiplying the transpose of matrix A and the measure matrix G. Or in short, it is said that N is obtained by multiplying the matrix of the number of observations with the matrix n.

$$x = N^{-1}.n \begin{vmatrix} 69395.5 \\ 3{,}5971627 \\ 1 \\ - \\ 0.1945141 \end{vmatrix}_{3*1}$$

Thus, for the 12-month period, the regression equation in the Fourier analysis is obtained by substituting the above coefficients with the LS method given in Equation (8).

$$\hat{y}t = 69.395{,}5 + (7{,}1943254).cos(wt) + (-0{,}3890282).sin(wt) \quad (23)$$

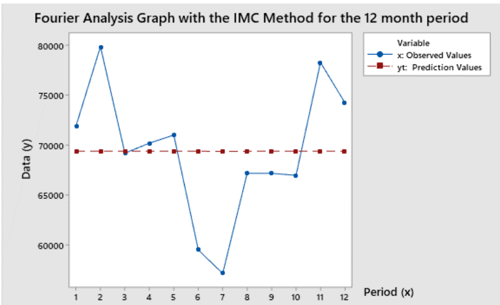

Figure 5. Fourier Analysis Graph with the IMC Method for the 12 months period

Figure 5, there is a graph of the estimation results of Fourier Analysis made with the Least Squares (Least Squares) Method for 12-month data with the help of Microsoft Excel program. ŷt: Prediction Values and x: Observed Values. In Figure 5, a 12-month period from November 2019 to October 2020 is discussed. The estimation results of the Fourier Analysis obtained by LS are given in Table 3.

Table 3. Fourier Analysis with LS Method for the First 12 Months Period

Month	**Period(x)**	**Data(y)** (MWh)	$\hat{y}t$ (MWh)	**Error (e) (MWh)**
November 2019	1	71918	69402,69	2515
December 2019	2	79874	69401,54	10472
January 2020	3	69203	69398,71	-196
February 2020	4	70201	69394,92	806
March 2020	5	71014	69391,12	1623
April 2020	6	59526	69388,3	-9862
May 2020	7	57142	69387,14	-12245
June 2020	8	67179	69387,91	-2209
July 2020	9	67179	69390,35	-2211
August 2020	10	66979	69393,75	-2415
September 2020	11	78284	69397,15	8887
October 2020	12	74247	69399,59	4847

Another estimation method it is used in this study is the Winters' Method. Winters' Method model, which works only in numerical time series and includes multiplicative seasonality in which each season changes according to a criterion, includes three different parameters as alpha, beta and gamma (RapidMiner, 2020). In order to calculate these three parameters, many literature studies have been done and are being done. Parameters, which can also be found by parameter optimization in Excel, were calculated in this study by entering the data into the Eviews12 program, which is a statistical program and is also used in econometric analysis.

Parameters:	Alpha		0.6200
	Beta		0,20
	Gamma		0,20
Sum of Squared Residuals			4.89E+08
Root Mean Squared Error			6381.066
End of Period Levels:	Mean		73452.45
	Trend		-140.8438
	Seasonals:	9	1.010149
		10	0.987643
		11	0.980887
		12	1.021321

Figure 6. Finding Alpha, Beta, Gamma Parameters for 12 Months with Eviews12 Program

It is build the winters' model by applying the optimized alpha, beta and gamma values found in Figure 6 in the Minitab19 package program.

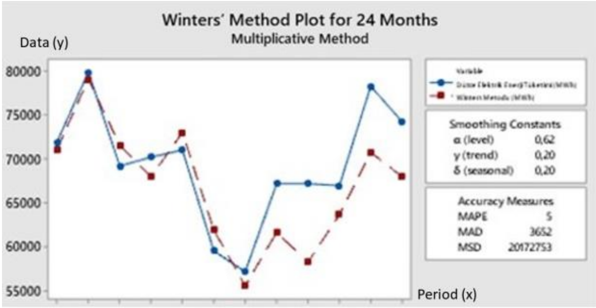

Figure 7. Winters' Method Graph for the 12-Month Period

Figure 7 shows the graph of the estimation results made with the Winters' Method with the help of Minitab19 program. In Figure 7, a 12-month period from November 2019 to October 2020 is discussed. As can be seen from the figure, after the seventh month, the estimated values of electricity consumption were higher than the actual values. The estimation results obtained by Winters' Method are given in Table 4.

In Table 4, the prediction values and residual error values created with the Minitab19 program at the 95% confidence interval are given. The above values were obtained as a result of Winters' Method parameters entered as alpha 0.62, beta 0.20 and gamma 0.20.

Table 4. Winters' Method Estimate Values for the 12-Month Period

Month	**Data(y)** (MWh)	**Softening** (MWh)	$\hat{y}t$ (MWh)	**Error (e)** (MWh)
November 2019	71918	73406,5	71083,68	834,32
December 2019	79874	81623,8	79093,75	780,25
January 2020	69203	73844	71586,02	-2383
February 2020	70201	70550,3	67980,71	2220,29
March 2020	71014	75526,2	73027,90	-2013,9
April 2020	59526	64350,2	61886,55	-2360,6
May 2020	57142	58194,3	55539,64	1602,36
June 2020	67179	64437,7	61638,32	5540,68
July 2020	67179	60184,2	58230,60	8948,4
August 2020	66979	64503,2	63649,64	3329,36
September 2020	78284	71232,8	70755,04	7528,96
October 2020	74247	67560	67968,36	6278,64

3.3. Period 2: 24 Months Forecast Models

In order to establish the 24-month forecasting model, we need to obtain the Coefficients matrix A in Equation (9) again. A Matrix of Coefficients will be a 24x3 matrix as our estimation period is 24 months. Matrix operations are repeated by taking t=24 and t=0,1,2, …,23.

$A =$

2	
1.732050	
808	1
1	1.732050
1,22515	808
E-16	2
.	.
.	.
0	-2
1	-
1.732050	1,732050808
808	-1

24*3

In order to find the matrix N, which is the Number of Observations Matrix in Equation (10), the transpose of the matrix A is multiplied by the matrix A.

$N = A^T.A$

	2.267949	
	192	-1
24	43,00000	1,732050
2.267949	001	808
192	-	47.00000
-1	1,732050808	01

*3

$n = A^T.G =$

1720,685
260,28847
-82,116571

3*1

In order to obtain the Matrix n in Equation (11), the transpose of the coefficients matrix A is multiplied by the G Measure Matrix. The G matrix is a matrix we get from our data. Since we consider the 24-month period in this title, all of our data will form the G matrix.

The x Unknowns Matrix in Equation (12) and Equation (13) contains the estimation coefficients necessary for us to make predictions. It is obtained by multiplying the matrix of N observations with the matrix n.

$$x = N^{-1}.n \begin{vmatrix} 71474{,}0307 \\ 2.27772514 \\ -0.142498 \end{vmatrix}_{3*1}$$

Thus, for the 24-month period, the regression equation in the Fourier analysis is obtained by substituting the above coefficients with the LS method given in Equation (8).

$$\hat{y}t = 71.474{,}03 + (4{,}55545).cos(wt) + (-0{,}285).sin(wt)$$

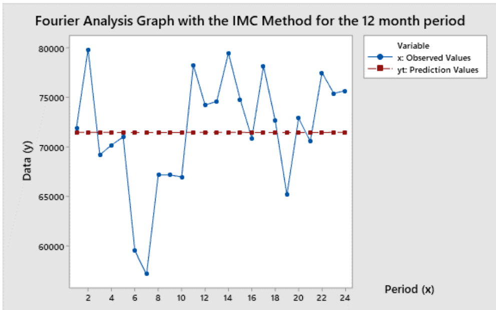

Figure 8. Fourier Analysis Graph with the IMC Method for the 24 months period

Figure 8 shows the graph of the Fourier Analysis estimation results with the Least Squares Method for the 24-month data set with the help of Microsoft Excel program. ŷt: Prediction Values and x: Observed Values. In Figure 8, a 24-month period from November 2019 to October 2021 is discussed. The estimation results of Fourier Analysis obtained by LS are given in Table 5.

Table 5. Fourier Analysis with LS Method for the 24 Months Period

Month	**Period(x)**	**Data(y)** (MWh)	**ŷt** (MWh)	**Error (e)** (MWh)	**Month**	**Period(x)**	**Data(y)** (MWh)	**ŷt** (MWh)	**Error (e)** (MWh)
November 2019	1	71918	71478,59	439,4138	November 2020	13	74603	71476,88	3126,12
December 2019	2	79874	71477,83	8396,167	December 2020	14	79484	71476,12	8007,88
January 2020	3	69203	71476,02	-2273,02	January 2021	15	74822	71474,31	3347,69
February 2020	4	70201	71473,6	-1272,6	February 2021	16	70891	71471,89	-580,89
March 2020	5	71014	71471,18	-457,183	March 2021	17	78179	71469,47	6709,53
April 2020	6	59526	71469,37	-11943,4	April 2021	18	72677	71467,66	1209,34
May 2020	7	57142	71468,62	-14326,6	May 2021	19	65163	71466,91	-6303,91
June 2020	8	67179	71469,09	-4290,09	June 2021	20	72913	71467,38	1445,62
July 2020	9	67179	71470,61	-4291,61	July 2021	21	70589	71468,9	-879,90
August 2020	10	66979	71472,75	-4493,75	August 2021	22	77516	71471,04	6044,96
September 2020	11	78284	71474,88	6809,12	September 2021	23	75421	71474,7	3946,30
October 2020	12	74247	71476,41	2770,59	October 2021	24	75681	71473,17	4207,83

Winters' Method parameters (alpha, beta and gamma), which we used as the other estimation method in this study, were obtained with the help of Eviews12 program for 24-month period estimation.

Parameters:	Alpha			0.5700
	Beta			0,20
	Gamma			0,20
Sum of Squared Residuals				7.32E+08
Root Mean Squared Error				5523.493
End of Period Levels:		Mean		75169.17
		Trend		-15.68182
		Seasonals:	23	0.991791
			24	1.008209

Figure 9. Finding Alpha, Beta, Gamma Parameters for 24 Months with Eviews12 Program

Seasonal forecasting methods use alpha, beta, and gamma parameters: Alpha (α) is the smoothing parameter for the level component of the forecast, and its value can be any number between 0 and 1. Beta (β) is the smoothing parameter for the trend component of the forecast, and its value can also be any number between 0 and 1. Gamma (γ) is the smoothing parameter for the seasonality component of the forecast where its value can be any number between 0 and 1. Each seasonal forecasting method uses some or all of these parameters depending on the situation. The Winters' model can be created by uploading the alpha, beta and gamma values found to the Minitab19 package program with the data.

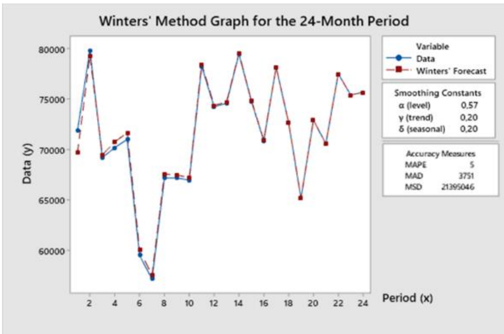

Figure 10. Winters' Method Graph for the 24-Month Period

Figure 10 shows the graph of the estimation results made with the Winters' Method with the help of Minitab19 program. In Figure 10, a 24-month period from November 2019 to October 2021 is discussed. The estimation results obtained by Winters' Method are given in Table 6.

Table 6. Winters' Method Estimate Values for the 24-Month Period

Month	Data(y) (MWh)	Softening (MWh)	$\hat{y}_t$ (MWh)	Error (e) (MWh)	Month	Data(y) (MWh)	Softening (MWh)	$\hat{y}_t$ (MWh)	Error (e) (MWh)
November 2019	71918	74295,2	71944,3	-26,29	November 2020	74603	69518,9	70559,3	4043,68
December 2019	79874	80047,6	77427,9	2446,07	December 2020	79484	81916,3	83604,2	-4120,2
January 2020	69203	74084,6	71884,5	-2681,5	January 2021	74822	76165,5	77307,4	-2485,4
February 2020	70201	71221,9	68685,3	1515,73	February 2021	70891	76632,6	77499,5	-6608,5
March 2020	71014	73701,7	71196.8	-182,75	March 2021	78179	78476,7	78597,6	-418,57
April 2020	59526	66128,1	63778,7	-4252,7	April 2021	72677	72111,3	72178,6	498,36
May 2020	57142	58783,2	56067,8	1074,22	May 2021	65163	69855,7	69975,4	-4812,4
June 2020	67179	63247,6	60354,2	6824,84	June 2021	72913	74897,7	74419,8	-1506,8
July 2020	67179	60024,8	58048,4	9130,63	July 2021	70589	69059,7	68449,9	2139,12
August 2020	66979	64362,2	63410,3	3568,75	August 2021	77516	70005,1	69637,4	7878,64
September 2020	78284	69206,8	68630,3	9653,68	September 2021	75421	79474	80042,6	-4621,6
October 2020	74247	68560,3	69044,9	5202,07	October 2021	75681	71311,3	71349,8	4331,2

Table 6 shows the prediction values and random errors created with the Minitab19 package program at 95% confidence interval. The above values were obtained as a result of Winters' Method parameters entered as alpha 0.57, beta 0.20 and gamma 0.20.

3.4. Model Success Criteria

Table 7. Electric Energy Estimation Models Success Criteria

Fourier Anaysis with LSM						**Winters' Method**					
Period Range	**t**	**MAPE**	**(MSE)^2**	**RMSE**	**MAE**	**Period Range**	**t**	**MAPE**	**(MSE)^2**	**RMSE**	**MAE**
2019 November - 2020 October	12	0.07199	40383597,3823	6354,8090	4857,4278	**2019 November - 2020 October**	12	0.052467	20172753,1289	4491,4088	3651,7270
2019 November - 2021 October	24	0.064672	32541013,5598	5704,47312	4482,2296	**2019 November - 2021 October**	24	0.052415	21394945,0846	4625,4670	3750,9875

In Table 7, the success criteria of the prediction models concluded are given. Calculated MAPE, MSE^{2,} RMSE and MAE values were found as 0.0719, 40383597.3823, 6354.8090, and 4857.4278, respectively, for the model created with the Least Squares Method for the 12-month data set. These values were calculated with 95% confidence interval and 1\10,000 detail. For the 24-month data set, the success criterion values for the model established with the Least Squares Method were found to be 0.0646, 32541013.5598, 5704.47312, and 4482.2296, respectively. These values are calculated at the 95% confidence interval and based on 4 decimal places.

The MAPE, MSE^2, RMSE and MAE values calculated for the Winters' Method were found to be 0.052, 20,172,753.1289, 4,491.4088 and 3,651,7270 for the 12-month period, respectively. For the 24-month period, it was found as 0.0524, 21,394,945.0846, 4.625.4670 and 3,750.9875 respectively. These values were calculated with 95% confidence interval and 1\10,000 detail.

As another success criterion, when the Coefficient of Variation (Coefficient of Variation), which is a statistical measure of the distribution of data points around the mean, is examined, the C_v values were found to be 0.1229 for the 12-month period and 0.1251 for the 24-month period.

4. Discussion and Conclusion

The coefficient of variation is the ratio of the standard deviation to the mean. The higher it is, the higher the degree of dispersion around the mean. It has no units, so it can be used as an alternative to standard deviation to compare the variability of data measured by different instruments. It is used for samples that do not have the same unit of measure or ratio. The coefficient of variation compares the standard deviation with the mean of each sample (Arachchige et al., 2022).

In this study, prediction models for electrical energy consumption for Duzce province between November 2019 and October 2021 were established and analysed. Since the data analysed in two periods, 12 months and 24 months, contain seasonality, Fourier Analysis with the Least Squares Method and Winters' Method were preferred as the estimation model. These two estimation methods are actually quite different from each other. It is also known as the Fourier sinusoidal curve fitting method. Winters' is also known as seasonal multiplicative exponential smoothing estimation method. Although the two estimation methods are different from each other, it is seen that there is not much difference in working on the same data set.

For example, a similar study in the literature Ozkan et al. (2020) stated in their study that it is more useful to create prediction models for 2020 with the Winters' Method by looking at the Absolute Percentages of Error (MAPE) values. They emphasized that (LS) and Fourier analysis method can also form the basis of the decision plan. Fourier analysis using the LS method showed that it has a more stable and periodic method and showed that Winters' method is better.

According to the data obtained, the difference in absolute square errors between the two methods was found to be 0.0073. Although there is not a big difference between the two estimation models, when the results of the analysis are examined, it is seen that Winters'

Method is more preferable considering that it gives better results in the electricity consumption demand estimation between November 2019 and October 2021 for Duzce province. This result can be used as an example showing that Winters' Method will outperform the Fourier Analysis with LS Method in establishing electricity consumption estimation models for Duzce province and in the future.

When it is looked at the Absolute Percent Error Rates (MAPE) among the models, the MAPE value of LSM and Fourier Analysis shows that it gives lower performance than Winters' Method. Looking at these values, it is seen that Winters' Method, which is actually a multiplicative model, gives a better performance in establishing the electrical energy consumption estimation model. At the same time, when it is examined other success criterion values, it is observed that Winters' Method gives more successful results than LSM and Fourier Analysis.

addition, when the coefficients of variation between the data, namely C_v values, are considered, the coefficient of variation for the 12-month period is 0.1229 and the coefficient of variation for the 24-month period is 0.1251. When the success criteria of the models are examined in Table 7, the increase in the coefficient of variability causes the low performance of both estimation models as it increases the degree of distribution around the mean.

Since a similar study is not found in the literature for Duzce with this study, these results will be an example that Winters' Method can be used more primarily in establishing an electrical energy consumption estimation model for a different province, as well as in establishing estimation models with regression in electrical energy consumption in Duzce and it is believed that a research that makes a difference has been conducted.

Obtained models can be suggested for use in electrical energy consumption estimations and analyses on similar data sets. In addition, if larger data sets are obtained as an additional study to the literature, it may be suggested to recalculate the success criteria between the two estimation methods and compare them with other estimation models.

In the study of Haliloglu and Tutu (2018), unlike the studies in the literature, daily frequency data were used and threshold temperature was used. By doing a similar study in the future studies the different variables can be defined for the estimation of energy consumption.

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