

Forecasting Electricity Consumption of Türkiye via Time Series Analysis with Fuzzy C-Means Clustering and Markov Chain

BahadırYörür

Industrial Engineering Department
Kütahya Dumlupınar University, Kütahya, Türkiye
bahadir.yorur@dpu.edu.tr

Mustafa Ünver

Industrial Engineering Department
Maltepe University, İstanbul, Türkiye
mustafaunver@maltepe.edu.tr

Nihal Erginel

Industrial Engineering Department
Eskişehir Technical University, Eskişehir, Türkiye
nerginel@eskisehir.edu.tr

Abstract

Nowadays, energy consumption prediction has become crucial to address rising energy demand, guide energy investment policies, utilize resources efficiently, and facilitate energy planning. Energy consumption is primarily in the form of electricity. Electricity consumption predictions are made using historical data with several techniques, including artificial intelligence methods, machine learning algorithms, and classical regression and time-series methods. In time series methods, the seasonal effect is a constant, such as monthly, yearly, or quarterly. But the seasons do not have to be in the same period. It is important to capture values that exhibit the same behavior and to determine the transition situation among seasons. So, clustering algorithms can capture these values. In this study, seasons are determined using the Fuzzy C-means clustering method, and transitions are calculated using a Markov transition matrix. In addition, because expressing a country's electricity consumption in crisp numbers is not inherently true, fuzzy numbers are used to classify values. More accurate forecasts can be achieved by using comprehensive clusters and distribution numbers to summarize the reported data within consumption data. This study considered Türkiye's monthly electricity consumption between 2019 and 2024. The MAPE value is used to compare similar studies in the literature. In conclusion, this study presents a relevant and practical approach to estimating electricity consumption using fuzzy C-means clustering and Markov chain-based time series analysis.

Keywords

Electricity consumption, Fuzzy C-means classification, Markov matrix, Time series analysis, Seasonal effect.

1. Introduction

The accuracy of electricity consumption prediction will also enable the accurate planning of electricity generation resources and investments for countries. Consumption prediction can provide a reference for energy investment companies to develop future plans and help governments set strategic goals for the energy industry (Li et al. 2022).

The energy planning process is also crucial for countries' energy security and sustainable development. Electricity consumption forecasts are particularly prominent in countries' long-term renewable energy investment planning. Long-term electricity consumption forecasting studies are widespread worldwide. Kaytez et al. (2015) used regression analysis, neural networks, and support vector machines in electricity consumption forecasting and compared the results. Khan et al. (2020) improved forecasting performance using machine learning techniques for the Organization of Petroleum Exporting Countries (OPEC). Velasquez et al. (2022) used a time series analysis model to forecast Brazil's electricity consumption. Toktarova, et al. (2019) used regression models, Du et al. (2023), Pu et al. (2021) used methods such as the gray system method to estimate electricity consumption.

Unlike long-term consumption forecasting, medium-term electricity consumption forecasting requires consideration of various parameters, such as seasonal effects. Taking seasonal effects into account in electricity consumption forecasting is critical to improving prediction accuracy. This is because electricity demand is not constant throughout the year; weather conditions, day length, economic activity, and consumer behavior vary seasonally. Therefore, seasonal effects are one of the strongest determinants of electricity demand, and ignoring them significantly reduces forecast accuracy.

Determining the seasonal effect depends on how and when seasonal transitions occur. Furthermore, electricity consumption can exhibit significant variability at hourly, daily, and monthly time scales, and many factors can affect consumption. Therefore, fuzzy approaches are used in electricity consumption forecasting to improve model performance and better manage uncertainty. In this study, data will be clustered using Fuzzy C-means algorithm as four clusters for a time series forecast for Türkiye's monthly electrical energy forecast, which includes uncertainties. Transitions between sets are calculated using Markov transition matrices, which specify the probability of a system transitioning from its current state to the next.

1.1 Objectives

This study aims to: (i) classify the seasons with Fuzzy C-means classifying method (ii) consider the fuzzy electrical consumptions that represent the real-world values instead of crisp values (iii) obtain the transition matrix among clusters (iv) predict the electrical consumptions by using monthly 6 years data for Türkiye (v) show the effectiveness of proposed methods compare performance indicators to studies in literature. Review of the literature is presented in the next section. Next, the Fuzzy C-means classifying method and proposed method are introduced. Then, proposed models are applied and followed by the results and discussion. Finally, the conclusion is presented.

2. Literature Review

Studies for Türkiye, in the literature, have included long-term forecasts and generally employ artificial intelligence methods more frequently. Kavaklioglu (2011) used the Support Vector Regression (SVR) methodology to model and forecast Türkiye's electricity consumption. To facilitate future electricity consumption forecasts, a separate SVR model was created for each input variable using current and past values, and these models were combined to obtain consumption forecasts. Toksarı (2016) presents a hybrid algorithm based on Ant Colony Optimization (ACO) and Iterative Local Search (ILS) algorithms to forecast Türkiye's local electricity consumption. These study aims to combine the advantages of these two algorithms to achieve successful forecasts. The proposed algorithm is linear and quadratic. The study found that the quadratic algorithm better reflects the variations in indicators and produces better results. Pençe et al. (2019) used a feedforward artificial neural network method for forecasting in their study. Forty-seven annual data sets covering electricity consumption in industrial areas between 1970 and 2016 were used in the study. A one-out cross-validation method was used for model validation. A grid search method with various numbers of neurons in the hidden layers was used to determine the appropriate parameters. Kaytez (2020) proposes a hybrid model based on a least-squares support vector machine and an autoregressive integrated moving average. The forecast results of this hybrid approach are compared with similar studies in the literature, such as the multiple linear regression approach and a single autoregressive integrated moving average model. It is also noted that their proposed model responded better to some unexpected responses in time series. Nebati et al. (2021) conducted a demand forecast analysis for 2035 using regression analysis and time series techniques. The analysis results were compared with TurkStat data, and the obtained results were observed to be close to each other.

Aslan and Beşkirli (2022) used the Arithmetic Optimization Algorithm (AOA), a stochastic metaheuristic algorithm, to solve the energy demand problem. Because the existing location update rules of AOA were not robust enough to solve the problem addressed in this study, they performed the analyses with an improved version, called IAOA, by

incorporating a new location update rule into the basic AOA to improve AOA's exploration and exploitation capabilities. Es (2021) used four different gray models for Turkey's total energy demand and compared the results. The study used the time series models GM(1,1) as well as the cause-and-effect models GM(0,N) and GM(1,N). The purpose of using these two forecasting structures is to capture the recent trend in the time series and to obtain reliable and robust forecasts by capturing the change in energy demand through a cause-and-effect relationship. Yörür et al. (2024) proposed the multivariate triangular intuitionistic fuzzy grey model (TIFGM(1,N)) for predicting the electric consumption for nine regions of Türkiye.

However, it appears that the inability to accurately determine electricity consumption values in historical data, and the uncertainties in the collected data, are not sufficiently reflected in the forecasting models and forecasting results. Studies addressing these uncertainties are based on fuzzy sets. Fuzzy sets and numbers are commonly used as triangular fuzzy numbers or trapezoidal fuzzy numbers, and fuzzy numbers with and without members are expressed intuitively. intuitionistic fuzzy numbers are very useful in providing a flexible model for detailing uncertainty in real-world problems. intuitionistic fuzzy sets were introduced as an extension of fuzzy sets in 1983 by Atanassov (1986). Fuzzy studies on forecasting are also available in the literature. Nishad et al. (2023) proposed a high-order fuzzy time series model using a two-factor fuzzy relationship aggregation operator. They used this model to forecast stock values. Phamtoan et al. (2024) proposed a fuzzy time series model based on the Bidirectional Long Short-term Memory model. In their study, the number of clusters was determined using the self-updating clustering algorithm, clustering was performed using fuzzy relationships between elements, rules were then generated, and finally, forecasting was performed using the Bidirectional Long Short-term Memory model, and model performance was discussed. The model was applied to Vietnamese stock data. As seen in the literature, accurate electricity consumption forecasting in the coming years is crucial for planning electricity investments and formulating management policies. Furthermore, methods based on fuzzy approaches that consider the uncertainties in the data are needed for forecasting.

Zhang et al. (2025) propose a high-order hesitant fuzzy time series model based on an improved cumulative probability distribution approach and weighted fuzzy logic relation to increase the reliability and prediction accuracy of the fuzzy time series model. A mixed-order univariate intuitionistic fuzzy time-series forecasting framework was introduced by Cansu et al. (2026), incorporating an artificial neural network, an intuitionistic fuzzy c-means algorithm, and a gray wolf optimization algorithm. In another study, an integrated forecasting method based on hesitant fuzzy time series and multi-objective optimization was developed for predicting natural gas futures prices (Gao et al. 2026). The integration of fuzzy clustering methods with forecasting methods has become increasingly common recently. This study, which emphasizes that model performance improves when the fuzzy clustering approach is integrated with forecasting methods, uses a hybrid time-series forecasting approach combining fuzzy clustering and machine learning (Alsalam 2025). Nguyen et al. (2026) propose a novel time series forecasting model based on a kernel-based fuzzy clustering algorithm. In the first stage of the proposed fuzzy clustering model, the optimal number of clusters is determined based on the clustering problem. In the second stage, the algorithm establishes fuzzy relationships between elements using a kernel-based fuzzy c-means algorithm, then removes fuzzification using a proposed mathematical rule, and finally forecasts the time series. When examining studies that integrate prediction methods with clustering, the unique aspect of this study lies in obtaining inter-cluster transitions via the Markov transition matrix.

3. Methods

Used two methods Fuzzy C means and proposed algorithms for prediction with Markov transition matrix are given as flows, respectively:

3.1 Fuzzy C-Means Algorithm

The fuzzy C-Means method was coded and analyzed as explained below. FCM was developed as an extension of the classical k-means algorithm and allows each data point to calculate the membership values of more than one cluster Bezdek (1998), Pal and Bezdek (1995). This approach provides a great advantage, especially in identifying clusters that are not separated by sharp boundaries in real-world data.

The aim of the FCM algorithms is to minimize the following objective function:

$$\text{Min } J_m = \sum_{i=1}^n \sum_{j=1}^c u_{ij}^m \|x_i - c_j\|^2 \quad (1)$$

Where n is the number of data, c is the number of clusters, $x_i \in \mathbb{R}^d$ i. data, c_j is the center of j . cluster, $u_{ij} \in [0,1]$ is the membership degree, $m > 1$ (commonly set to 2) is the constant of fuzzy and $\| \cdot \|$ is the Euclidean norm.

The FCM algorithm divides the dataset into c cluster centers and calculates the membership degree of u_{ij} for each data point x_i with each cluster j . These membership values range from 0 to 1, and the sum of memberships across all clusters for each data point equals 1.

$$\sum_{j=1}^c U_{ij} = 1 \text{ for } \forall i \quad (2)$$

$$0 \leq U_{ij} \leq 1 \text{ for } \forall ij \quad (3)$$

$$0 < \sum_{i=1}^n u_{ij} < n \text{ for } \forall i \quad (4)$$

In each iteration, membership degrees are updated and normalized with the following formulas:

$$u_{ij} = \frac{1}{\sum_{k=1}^c (\|x_i - c_j\| / \|x_i - c_k\|)^{\frac{2}{m-1}}} \quad (5)$$

$$v_j = \frac{\sum_{i=1}^n u_{ij}^m x_j}{\sum_{i=1}^n u_{ij}^m} \text{ for } \forall j \quad (6)$$

$$|u_{ik}^{new} - u_{ik}^{prev}| < \varepsilon \text{ then stop} \quad (7)$$

3.2 Proposed Method for Predicting Electric Consumption

The steps of the proposed method for predicting electric consumption are briefly presented as follows:

Step 1: Clustering of data using the fuzzy C-means method

The fuzzy c-means method is applied to the raw time series data to determine the number of clusters the data is clustered into. Following this step, the cluster centers and membership values of the relevant data for each cluster are calculated.

Step 2: Fuzzification of time series data

Each data point is considered to belong to the cluster with the highest membership value. This way, fuzzy time series are obtained by adding each observation to a corresponding fuzzy set (Çakır 2023).

Step 3: Obtaining fuzzy logical relationships

The transition between the clusters to which the data belong is examined in creating fuzzy logical relationships. As a result of this analysis, fuzzy logical groups are created. For example, relationships are defined as $C1 \rightarrow C1$, $C1 \rightarrow C2$ / $C2 \rightarrow C3$, $C2 \rightarrow C4$.

Step 4: Obtaining the Markov transition matrix

When determining the transition distribution between clusters, the number of occurrences of a specific fuzzy logical relation and the occurrence rate of the total logical relation are used, as in the classical probability approach (Efendi et al. 2013).

Let $C_i \rightarrow C_i$, C_j , C_k ($i, j, k = 1, 2, \dots, p$) be a group of fuzzy logical relations, and let C_i have n_1 relations with itself, n_2 relations with C_j , and n_3 relations with C_k ; where n_1 , n_2 , and n_3 represent the recurrence numbers of the fuzzy logical relation. Therefore, the weights of fuzzy logical relations can be calculated by equation (8). Equation 4 is detailed in equations (9) and (10).

$$w_m = \frac{\text{number of repetitions of } C_i}{\text{total number of fuzzy logical relation}} \quad (8)$$

$$w_1 = \frac{n_1}{n_1 + n_2 + n_3}, w_2 = \frac{n_2}{n_1 + n_2 + n_3}, w_3 = \frac{n_3}{n_1 + n_2 + n_3} \quad (9)$$

$$\sum_{m=1}^3 w_m = \frac{n_1}{n_1+n_2+n_3} + \frac{n_2}{n_1+n_2+n_3} + \frac{n_3}{n_1+n_2+n_3} = 1 \quad (10)$$

A weight matrix W containing transition weight elements of fuzzy logical relations can be expressed as follows:

$$W(C_i) = w_{(t)} = [w_1 \ w_2 \ \dots \ w_q] \quad (11)$$

Step 5: Calculating the defuzzified forecast values

A prediction model based on the obtained cluster centers and transition weights is used to calculate fuzzy prediction values. The defuzzified matrix M (t) is constructed by cluster centers.

$$M(t) = [v_{cj1}^*, v_{cj2}^*, \dots, v_{cjk}^*] \quad (12)$$

Let us assume that the corresponding weights for $C_{j1}, C_{j2}, \dots, C_{jk}$ are $w_1, w_2, \dots, w_k$, respectively.

The predicted values are obtained by calculating the product of the defuzzified matrix M(t) and the transpose of the weight matrix W(t) as follows.

$$F(t+1) = M(t) \cdot w_{(t)}^T \quad (13)$$

Here F(t+1) is the prediction for the next period, M(t) is a $1 \times k$ matrix and $W(t)^T$ is a $k \times 1$ matrix.

Step 6: Evaluation of forecast performance

The mean absolute percentage error (MAPE) criterion was used to evaluate the prediction performance. The calculation of the relevant criterion is given in equation (14).

$$MAPE = \frac{1}{n} \sum_{k=1}^n \frac{|\hat{X}^{(0)}(k) - X^{(0)}(k)|}{X^{(0)}(k)} \times 100\% \quad (14)$$

4. Model Application for Predicting Electric Consumption for Türkiye

To demonstrate the applicability of the proposed method, monthly data from Türkiye for the last six years were used. A total of 72 months of data (2019-2024) was obtained in GWh (Gigawatt-hours) from the Production-Transmission Statistics of the Turkish Electricity Transmission Corporation (TEİAŞ). Monthly consumption values were calculated using the monthly production, export, import, and loss values (TEİAŞ 2025).

Some of the data from 2019 onwards is presented in Table 1. The data was divided into 4 clusters using the fuzzy C-means algorithm for a time series with uncertainty. The last four columns in Table 1 show the membership degree of each cluster.

Step 1: Using the Fuzzy C-Means model

Fuzzy C-Means, a version of the traditional k-means rollout, calculates membership degrees that do not represent the probability that each observation belongs to specific clusters. Thus, instead of a sharp change, the month is represented by similar generality values across different clusters. The Fuzzy C-mean library was used in this study in the Python environment, and the number of clusters was set to four. The data is exported directly to the products without being normalized in GWh. Figure 2 shows the clusters of data with different colors.

The analysis yielded four distinct consumption clusters:

1. Very low consumption cluster: The cluster center is approximately 24,400 GWh. It generally represents the spring months and low demand periods during the pandemic.
2. Low/medium consumption cluster: The cluster center is approximately 26,900 GWh. This cluster includes periods with moderate consumption during the spring and winter months.

3. Medium/high consumption cluster: The cluster center is approximately 28,900 GWh. It represents the average consumption during the winter months and mid-year.
4. High consumption cluster: The cluster center was found to be approximately 33,500 GWh. It was formed due to the increased electricity demand, particularly during the summer months.

Table 1. Türkiye's monthly electric consumption between 2019-2024

Year	Month	GWh	Cluster1	Cluster2	Cluster 3	Cluster4
2019	1	25949.25	0.0657	0.0105	0.6479	0.2759
2019	2	23376.28	0.0329	0.01	0.0826	0.8745
2019	3	24838.57	0.0078	0.0018	0.031	0.9595
2019	4	23635.41	0.0219	0.0064	0.0583	0.9134
2019	5	24822.67	0.0071	0.0016	0.0281	0.9632
2019	6	24256.99	0.0019	0.0005	0.0061	0.9915
2019	7	28773.09	0.982	0.002	0.0135	0.0025
2019	8	27730.72	0.2779	0.0131	0.6676	0.0414
2019	9	25379.77	0.0449	0.0088	0.2473	0.699
2019	10	24115.43	0.005	0.0013	0.0152	0.9784
2019	11	24105.89	0.0053	0.0014	0.0159	0.9774
2019	12	26336.33	0.0417	0.0057	0.8688	0.0839
2020	1	27031.51	0.0033	0.0003	0.9944	0.002
2020	2	25109.73	0.0238	0.005	0.1096	0.8616
2020	3	24871.31	0.0093	0.0021	0.0375	0.9511
2020	4	20363.64	0.1318	0.0565	0.2284	0.5833
2020	5	21027.75	0.1163	0.0471	0.2125	0.6241
2020	6	23825.09	0.0144	0.0041	0.0403	0.9412
2020	7	28683.18	0.9619	0.0039	0.0292	0.0051
2020	8	29296.84	0.9749	0.0051	0.0162	0.0039
2020	9	27578.27	0.1714	0.0096	0.7837	0.0353
...	...	...	...	...	...	...

The distribution of all data for 2019-2024 is given in Figure 1.

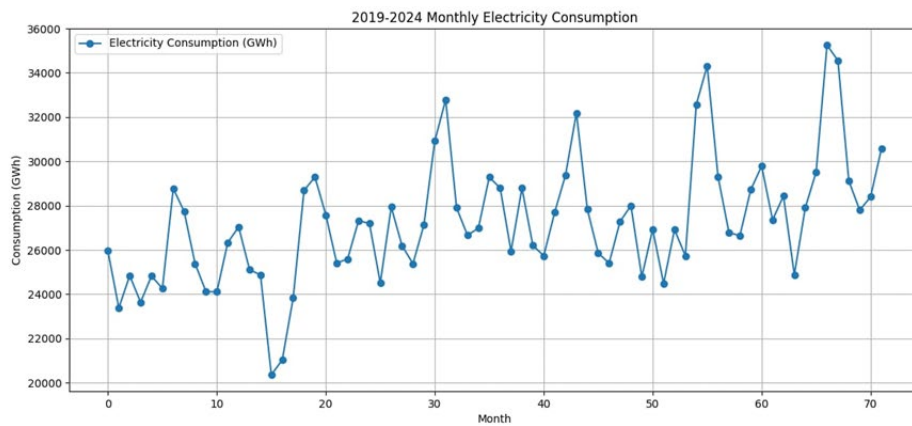


Figure 1. The 2019-2024 monthly electricity consumption of Türkiye

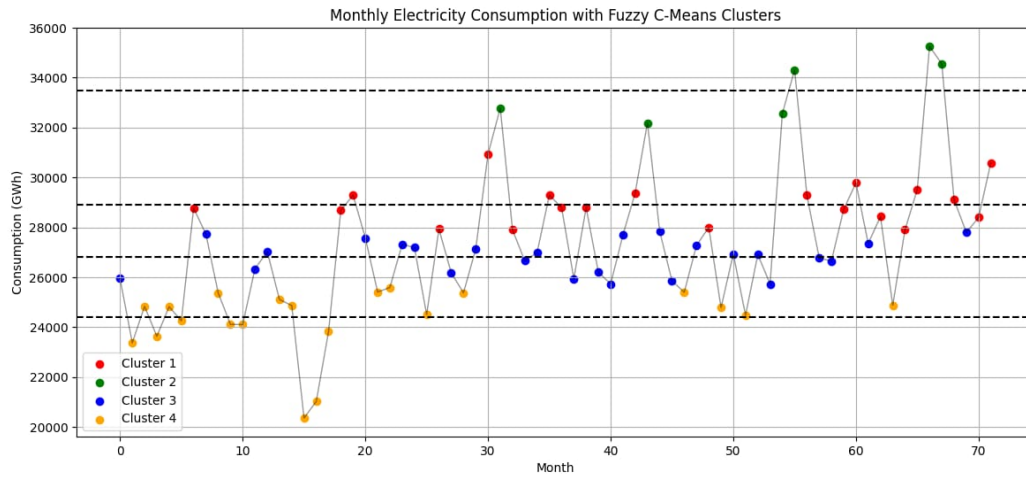


Figure 2. The clusters of data with different colors

In Figure 2, the distribution of data relative to the four cluster centers is represented in different colors.

Step 2: Fuzzification of time series data

Data are associated with these clusters based on the membership degree calculated in Step 1. The results show that cluster 1 contains 16 data points, cluster 2 contains 6 data points, cluster 3 contains 28 data points, and cluster 4 contains 21 data points.

Step 3: Creation of Fuzzy Logical Relationships and Groups

As can be seen from Figure 2, the transition between the cluster data shown in different colors were examined, and blurred logical relationships were created. Table 2 shows relationship groups and transition weights.

Table 2. Fuzzy logical relationship and transition weights

Group	Fuzzy Logical Relationships	Repetition number	Weights
1	C1→C1	4	0.25
	C1→C2	3	0.1875
	C1→C3	7	0.4375
	C1→C4	2	0.125
2	C2→C1	2	0.3333
	C2→C2	2	0.3333
	C2→C3	2	0.3333
	C2→C4	-	No weight
3	C3→C1	9	0.3214
	C3→C2	1	0.0357
	C3→C3	10	0.3571
	C3→C4	8	0.2857
4	C4→C1	2	0.0952
	C4→C2	-	No weight
	C4→C3	8	0.3810
	C4→C4	11	0.5238

Step 4: Calculating the Markov weights

The weight values for each group's fuzzy logical relationship were calculated using Equation (8). The resulting weights are shown in Table 3.

Table 3.The transition matrix

	C1	C2	C3	C4
C1	0.25	0.1875	0.4375	0.125
C2	0.3333	0.3333	0.3333	0
C3	0.3214	0.0357	0.3571	0.2857
C4	0.0952	0	0.3810	0.5238

Step 5: Obtaining the defuzzified forecast values

We calculate monthly fuzzy electricity consumption forecasts using Equation (13). The cluster center values used in the equation were obtained as (28990.61, 33541.24, 26917.82, 24464.89), respectively. The resulting transition probability weight matrix is summarized in Table 3.

The transition prediction value of the months from the data belonging to the C1, C2, C3 and C4 clusters, respectively, was calculated as given below.

The transition prediction value of the months from the data belonging to the C1, C2, C3 and C4 clusters, respectively, was calculated as given below.

$$F(C1) = [28990.61 \ 33541.24 \ 26917.82 \ 24464.89] \cdot [0.25 \ 0.1875 \ 0.4375 \ 0.125]^T = 28371.29$$

$$F(C2) = [[28990.61 \ 33541.24 \ 26917.82 \ 24464.89] \cdot [0.3333 \ 0.3333 \ 0.3333 \ 0]^T = 29816.56$$

$$F(C3) = [28990.61 \ 33541.24 \ 26917.82 \ 24464.89] \cdot [0.3214 \ 0.0357 \ 0.3571 \ 0.2857]^T = 27119.79$$

$$F(C4) = [[28990.61 \ 33541.24 \ 26917.82 \ 24464.89] \cdot [0.0952 \ 0 \ 0.3810 \ 0.5238]^T = 25830.36$$

Step 6: Evaluation of forecast performance

The MAPE calculation, most commonly used in the literature and given in equation 14, was performed to evaluate forecast performance. According to the forecast results, the MAPE value was calculated as 7.12%. According to the MAPE evaluation, values less than 10% indicate excellent accuracy, and values between 10% and 20% indicate good prediction (Liu et al, 2016)

5. Results and Discussion

Electricity consumption values are used for different time periods. Various variables, particularly seasonal effects, can affect monthly consumption values. The estimated and actual values obtained from applying the proposed method using six years of data are presented in Figure 3.

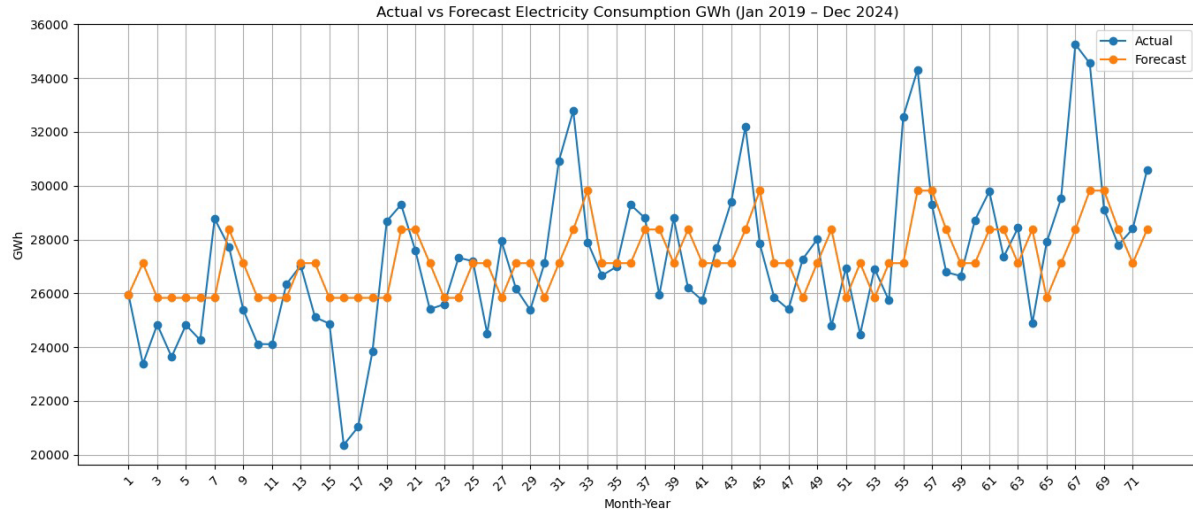


Figure 3. Actual and forecast monthly electricity consumption values

According to the membership degrees, it was observed that some months transitioned between two or more clusters, meaning they were neither entirely low nor entirely high consumption groups. This demonstrates that the FCM algorithm provides a more flexible classification compared to the classical k-means method.

The results reveal a significant seasonality in electricity consumption. Increased air conditioning use in the summer months pushes consumption into the upper cluster, while consumption is concentrated in lower clusters in the spring. Furthermore, due to the impact of the COVID-19 pandemic in April and May 2020, consumption dropped significantly, shifting to the lower cluster.

This analysis demonstrates that the Fuzzy C-Means algorithm is a successful method for revealing seasonal trends and clusters in electricity consumption data. The resulting four cluster centers provide reference values for energy demand management and future forecasting models.

6. Conclusion

Estimating electricity consumption is crucial for accurate capacity planning and efficient utilization. Monthly electricity consumption forecasts, in particular, exhibit seasonality, which requires careful attention. This research aims to present a method for medium-term monthly electricity consumption data estimation, particularly those that take into account seasonality. The proposed method is based on a hybrid methodology that combines the fuzzy C-means method and defuzzified time series.

Monthly electricity consumption values covering the years 2019-2024 were used in the study. Data were divided into four clusters using the fuzzy C-means method, assigned to the relevant clusters based on the highest membership degree, and then the predicted values were calculated by calculating the Markov transition weights between the clusters.

The mean absolute error percentage (MAPE) of the obtained prediction values was 7.12% and this value shows that the proposed method gives successful results. In conclusion, the integrated system proposed in this study demonstrates robust forecasting performance under varying seasonal load conditions. It can be considered a practical and effective decision-support tool for power system management and offers valuable insights for power grid planning and development.

In models that measure seasonal effects, it is assumed that past seasonal patterns will persist. Overcoming this problem requires longer historical data covering more seasonal cycles. Furthermore, unusual events such as extreme weather, epidemics, power outages, or unexpected economic developments may not be well captured by seasonal models. To overcome these limitations, artificial neural networks or clustering using intuitionistic or spherical fuzzy numbers can be employed.

References

- Alsalam, K., A hybrid time series forecasting approach integrating fuzzy clustering and machine learning for enhanced power consumption prediction, *Scientific Reports*, vol. 15, 6447, 2025.
- Aslan, M. and Beşkirli, M., Realization of Turkey's energy demand forecast with the improved arithmetic optimization algorithm, *Energy Reports*, vol. 8, pp. 18-32, 2022.
- Atanassov, K., Intuitionistic fuzzy set, *Fuzzy Sets and Systems*, vol. 20, pp. 87-96, 1986.
- Bezdek, J. C., Pattern Recognition with Fuzzy Objective Function Algorithms. Plenum Press, New York, 1981.
- Cansu, T., Bas, E. and Egrioglu, E., Mixed order single variable intuitionistic fuzzy time series forecasting method based on a new artificial neural network and grey wolf optimization algorithm, *Scientific Reports*, vol. 16, 15682, 2026.
- Çakır, S., Renewable energy generation forecasting in Turkey via intuitionistic fuzzy time series approach, *Renewable Energy*, vol. 214, pp. 194-200, 2023.
- Du, X., Wu, D. and Yan, Y., Prediction of electricity consumption based on GM(1, N_r) model in Jiangsu province, China, *Energy*, vol. 262, 125439, 2023.
- Dunn, J. C., A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters. *Journal of Cybernetics*, vol. 3, pp.32-57, 1973.
- Efendi, R., Ismail, Z. and Deris, M. M., Improved weight fuzzy time series as used in the exchange rates forecasting of us dollar to ringgit Malaysia, *International Journal of Computational Intelligence and Applications*, vol. 12, no. 1, 135005, 2013.
- Es, H. A., Monthly natural gas demand forecasting by adjusted seasonal grey forecasting model, *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 43, no. 1, pp. 54-69, 2021.
- Gao, Y., Yang, H., Yi, Y. and Wang, J., A novel forecasting framework based on hesitant fuzzy time series and multi-objective optimization algorithm for natural gas future price, *Energy*, vol. 345, 140168, 2026.
- Kavaklioglu, K., Modeling and prediction of Turkey's electricity consumption using Support Vector Regression, *Applied Energy*, vol. 88, no. 1, pp. 368-375, 2011.
- Kaytez, F., Toplamacioglu, M. C., Cam, E. and Hardalac, F., Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines, *Electrical Power and Energy Systems*, vol. 67, pp. 431-438, 2015.
- Kaytez, F., A hybrid approach based on autoregressive integrated moving average and least-square support vector machine for long-term forecasting of net electricity consumption, *Energy*, vol. 197, 117200, 2020.
- Khan, A., Chiroma, H., Imran, M., Khan, A., Bangash, J. I., Asim, M., Hamza M. F. and Aljuaied, H., Forecasting electricity consumption based on machine learning to improve performance: A case study for the organization of petroleum exporting countries (OPEC), *Computers and Electrical Engineering*, vol. 86, 106737, 2020.
- Li, J., Luo, Y. and Wei, S., Long-term electricity consumption forecasting method based on system dynamics under the carbon-neutral target, *Energy*, vol. 244, 122572, 2022.
- Liu, L., Wang, Q., Wang, J. and Liu, M., A rolling grey model optimized by particle swarm optimization in economic prediction, *Computational Intelligence*, vol. 32, no. 3, pp. 391-419, 2016.
- Nebati, E. E., Taş, M. and Ertaş, G., Türkiye'de elektrik tüketiminde talep tahmini: Zaman serisi ve regresyon analizi ile karşılaştırma (Translate: Demand Forecasting in Electricity Consumption in Türkiye: Comparison with Time Series and Regression Analysis), *European Journal of Science and Technology*, vol. 31, no. 1, pp. 348-357, 2021.
- Nguyen, Q-D., Phamtoan, D., Phan, N-M. and Vu, T. Q., A robust kernel-based fuzzy clustering algorithm for time series forecasting, *International Journal of Information Technology*, vol. 18, no. 1, pp. 373-388, 2026.
- Nishad A. K., Aggarwal G. and Abhishekh, Hesitant fuzzy time series forecasting model of higher order based on one and two-factor aggregate logical relationship, *Engineering Applications of Artificial Intelligence*, vol. 126, 106897, 2023.
- Pal, N. R. and Bezdek, J. C., On Cluster Validity for the Fuzzy C-Means Model, *IEEE Transactions on Fuzzy Systems*, vol. 3, no. 3, pp.370-379, 1995.
- Pençe, İ., Kalkan, A. and Çeşmeli, M. Ş., Türkiye sanayi elektrik enerjisi tüketiminin 2017-2023 dönemi için yapay sinir ağları ile tahmini (translate: Forecasting Türkiye's Industrial Electricity Consumption for the Period 2017-2023 Using Artificial Neural Networks), *Journal of Applied Sciences of Mehmet Akif Ersoy University*, vol. 3, no. 2, pp. 206-2028, 2019.
- Phamtoan, D., VoThiHang, N. and PhamThi, B., Improving forecasting model for fuzzy time series using the Self-updating clustering and Bi-directional Long Short Term Memory algorithm, *Expert Systems with Applications*, vol. 241, 122767, 2024.

- Pu, B., Nan, F., Zhu, N., Yuan Y. and Xie W., UFNBM(1,1): A novel unbiased fractional grey Bernoulli model with Whale Optimization Algorithm and its application to electricity consumption forecasting in China, *Energy Reports*, vol. 7, pp. 7405-7423, 2021.
- Toksari, M. D., A hybrid algorithm of Ant Colony Optimization (ACO) and Iterated Local Search (ILS) for estimating electricity domestic consumption. Case of Turkey, *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 776-782, 2016.
- Toktarova, A., Gruber, L., Hlusiak, M., Bogdanov, D. and Breyer, C., Long term load projection in high resolution for all countries globally, *International Journal of Electrical Power & Energy System*, vol. 11, pp. 160-181, 2019.
- TEİAŞ, Available: <https://www.teias.gov.tr/turkiye-elektrik-uretim-iletim-istatistikleri>, Accessed on May 10, 2025.
- Velasquez, C. E., Zocatelli, M., Estanislau, F. B. and Castro, V. F., Analysis of time series models for Brazilian electricity demand forecasting, *Energy*, vol. 247, 123483, 2022.
- Yorur B., Erginel N. and Şentürk S., A Multivariate Intuitionistic Fuzzy Grey Model for Forecasting Electricity Consumption, *Journal of Intelligent Systems in Current Computer Engineering*, vol. 3, no. 1, 2025.
- Zhang, C., Sun, D., Pang, K., Zou, L. and Martines, L., A high-order hesitancy fuzzy time series model based on improved cumulative probability distribution approach and weighted fuzzy logic relationship, *Information Sciences*, vol. 717, 122262, 2025.

Biographies

Yörür, B., works at the Department of Industrial Engineering, Kütahya Dumlupınar University in Türkiye. She received her bachelor's and master's degrees in industrial engineering from the same university. She received her PhD from Eskişehir Technical University in 2025. Her research focuses on multi-criteria decision making, optimization, and forecasting. She also conducts research on renewable energy and electricity consumption forecasting.

Ünver, M. received a B.Sc. degree in Industrial Engineering in 2009. His Ph.D. (2023) degree is also in Industrial Engineering from Eskişehir Technical University. He worked as an Assistant Specialist of Scientific Programs in TÜBİTAK (The Scientific and Technological Research Council of Türkiye) for a while and researcher position at several Universities. He is currently working in the Department of Industrial Engineering at Maltepe University as an assistant professor. He specializes in fields such as Artificial Learning, Natural Language Processing (NLP), Fuzzy Sets, and Systems. Interested in both academic research and industrial applications of these areas, Dr. Ünver operates in a wide range of subfields such as Clustering Analysis, Machine Learning, Text Mining, Pattern Recognition, Computational Intelligence, Feature Selection, and Data Science.

Erginel, N. is a professor in the Industrial Engineering Department at the Eskişehir Technical University. She graduated from Anadolu University, Industrial Engineering Department. She took her BS degree from Anadolu University, and PhD (1999) is from Eskişehir Osmangazi University in Turkey, Industrial Engineering Department. She worked Arcelik refrigerator factory that is an appliance firm between 1995 and 2001. She has Black Belt Certificate and expert on ISO9001. Her interested area and courses are probability, statistics, quality control, six sigma, and fuzzy set theory. Also she is interested in clustering and text mining on big data.