

Smart Forecasting and Clustering of Renewable Energy Capabilities for Smart Grid Planning by Using Machine Learning Model

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ARTICLE INFO

Article history:

Received 28 May 2026

Received in revised form 1 July 2026

Accepted 9 July 2026

Available online 13 July 2026

Keywords:

Renewable energy; Energy efficiency;
Gaussian Mixture Model (GMM); Holt's Linear
Trend method; Machine Learning

ABSTRACT

The quick switch to renewable energy has become essential for powering smart cities and connected infrastructure as the need for intelligent and sustainable energy systems increases globally. This green transition is being accelerated by the climate crisis and resource depletion, necessitating data-driven policies and sophisticated smart grid design. With an emphasis on evaluating Turkey's progress, this study uses computational intelligence to assess the smart transition preparedness and renewable energy efficiency of 201 nations. The Gaussian Mixture Model (GMM) technique was used in a machine learning clustering approach to handle the complicated data related to global energy changes. In order to categorize nations according to their smart energy transition paths, parameters including renewable energy capacity and the renewable percentage of electrical capacity were examined. Additionally, future renewable energy efficiencies were predicted using Holt's Linear Trend technique, a predictive data intelligence tool. The results offer important, data-driven forecasts that can direct infrastructure planners and policymakers in maximizing smart energy investments and smart grid integration in Turkey and elsewhere.

1. Introduction

The dramatic shift to renewable energy infrastructures brought about by the global climate crisis's rapid acceleration has completely changed how smart cities distribute and manage power. In order to maintain grid stability, maximize energy efficiency, and lessen the inherent intermittency of renewable sources, intelligent predictive systems must be integrated as metropolitan areas depend more and more on decentralized energy networks [1-3]. The dynamic complexity of contemporary smart grids cannot be adequately addressed by conventional, static approaches to energy policy and capacity planning, as recent developments in computational intelligence have shown [4-6]. In order to estimate long-term capacity requirements across various geographical regions and model complicated energy transitions, policymakers and urban planners are increasingly utilizing machine learning algorithms [7, 8].

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Accurate benchmarking of national renewable energy capacities is crucial to successfully navigating this green shift. Strong clustering and forecasting models that can handle massive, multidimensional energy information are crucial, according to recent research [9, 10].

In order to find structural parallels in global energy transitions and forecast future infrastructure requirements, data-driven approaches in particular, Gaussian Mixture Models and sophisticated time-series forecasting have become extremely useful [11]. Countries can strategically align their renewable energy policies with global sustainability targets and actively improve the resilience of their respective smart urban ecosystems for future generations by directly utilizing these sophisticated and highly intelligent machine algorithms [12].

Due to numerous factors such as the climate crisis, sudden and extreme weather events, increasing production, consumption, and consequently energy consumption as a result of population growth, and the harmful effects and insufficiency of fossil fuels, energy and the transition to renewable energy are among the most important issues of our time. All countries are increasing their capacity and targets related to this issue, defining policies and strategies to accelerate the energy transition, and speeding up projects. Some studies that evaluate countries' renewable energy processes from different perspectives are as follows.

In their study, Kanzari et al. [13] evaluated the energy environment of African countries and performed clustering analysis to group them according to their similarities. In this study, after performing clustering by considering social, economic and cultural parameters, each cluster was evaluated in terms of renewable energy and strategies were proposed. In another study, key parameters for sustainable transformation and the development of environmental policies in the energy sector were identified using discriminant analysis, and clustering was performed. Countries were examined in terms of decarbonization and climate change through defined cluster groups, and evaluated in terms of the transformation processes and characteristics of their energy sectors [14]. In another study, 30 European countries were grouped using cluster analysis based on their economic structure, energy supply policy, and energy consumption. Historical data for each country was used for this purpose, resulting in 9 clusters. These clusters and countries were evaluated in terms of energy policies and economic development, energy dependence, and renewable energy [15]. Włodarczyk and others examined the relationship between renewable energy development and sustainable development across European Union countries using hierarchical cluster analysis. Based on Eurostat indicators, the study classified EU member states into homogeneous groups according to their renewable energy performance and sustainability characteristics, revealing substantial disparities among countries. The findings highlighted the importance of tailored policy interventions to accelerate renewable energy deployment and achieve the Sustainable Development Goals [21]. Gostkowski et al. [22] investigated sectoral energy consumption patterns in the Visegrad countries and compared them with other European Union members using k-means, hierarchical clustering, and DIANA algorithms. The study demonstrated that countries with similar economic structures exhibit comparable energy consumption profiles, although differences in energy efficiency remain significant. The authors emphasized that cluster analysis provides valuable insights for designing region-specific energy policies. Hutterski et al. [26] evaluated electricity generation from renewable energy sources across EU countries by combining Hellwig's taxonomic development measure with panel data analysis. Their results indicated that economically developed Northern European countries consistently outperformed newer EU members in renewable electricity production. The study further confirmed that GDP per capita and public energy expenditures significantly influence renewable electricity generation. Kosowski [27] analyzed the evolution of primary energy production structures across European countries between 1990 and 2022 using k-means clustering. The research

identified substantial transitions from fossil fuel dependence toward renewable energy systems, while revealing considerable differences in countries' energy security and production profiles. The study highlighted that cluster-based analyses can effectively support energy transition planning and policy development. Döme [28] combined cluster analysis and event history analysis to investigate the global adoption of renewable energy policies, particularly Feed-in Tariffs (FIT) and Renewable Portfolio Standards (RPS). The findings revealed two distinct groups of adopter countries differentiated by income level, governance quality, and environmental pressures. The study concluded that policy diffusion, international cooperation, and institutional characteristics play significant roles in renewable energy policy adoption. van Zanten and Putintseva [29] developed an empirical framework to evaluate governmental policies supporting the Sustainable Development Goals by applying the BIRCH hierarchical clustering algorithm to 84 policy-related indicators. Their analysis classified countries according to the effectiveness of national policies across all 17 SDGs and showed that only a limited number of countries have policy environments strongly supporting sustainable development. The study emphasized the need for integrated policy approaches that exploit synergies among SDGs. Sompolska-Rzechuła et al. [30] assessed renewable energy utilization and environmental degradation in European Union countries using Self-Organizing Maps (SOM). The clustering results revealed clear geographical differences, with Scandinavian countries exhibiting high renewable energy use and relatively low environmental degradation, whereas several Eastern European countries remained less advanced. The study demonstrated the usefulness of artificial neural network-based clustering for identifying spatial sustainability patterns. Georgescu et al. [31] explored the transition toward climate neutrality among European Union member states using k-means cluster analysis. The research grouped countries according to greenhouse gas emissions, renewable energy adoption, and climate-related economic indicators, identifying distinct levels of progress toward climate neutrality. The authors suggested that differentiated policy strategies are necessary to address the heterogeneous transition pathways observed across EU countries.

The current study has several important and distinct points. Unlike others, the clustering process was carried out for all countries in the world, not just a single region. In this study, the latest published data and the most appropriate methods for this data were determined, resulting in realistic and reliable conclusions. Based on the results obtained from this data, a robust projection has been made for Türkiye's future in renewable energy. The main objective of this study is to objectively examine the renewable energy capacities and efficiencies of all countries worldwide using current data, and to analyze Türkiye's current and future situation.

2. Methodology

Two different stages and two different methods were used in the study. While the GMM (Gaussian Mixture Model) clustering technique was used to group countries according to their renewable energy efficiency, Holt's Linear Trend technique was used to estimate Turkey's renewable energy capacity until 2035. The methodological flow applied in the study is shown in the Figure 1 below. According to the methodological framework applied in the study, data are first collected and prepared for analysis; in the second stage, the obtained data are clustered using the Gaussian Mixture Model (GMM) technique, and countries are grouped based on the similarities in their renewable energy capacities. In the next stage, future projections for renewable energy capacities in Turkey up to the year 2035 were generated using Holt's linear forecasting technique, based on data from 2015 to 2024. Finally, the results obtained were compared with the future and current situations.

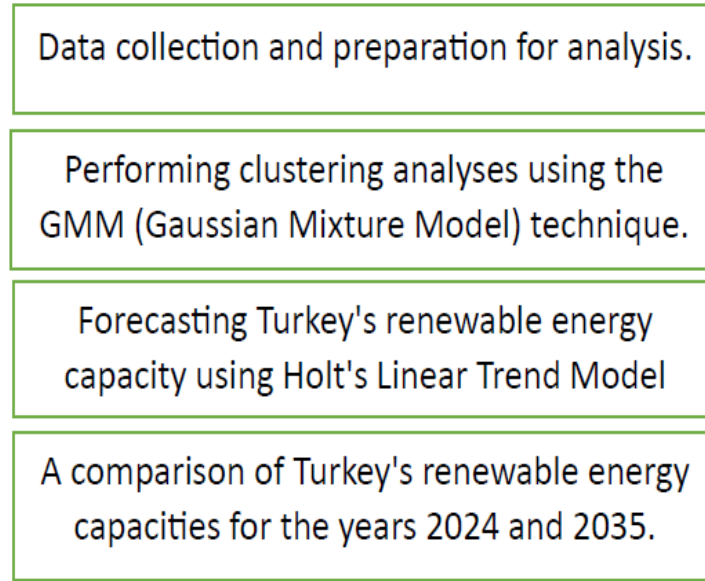


Fig. 1. Methodological flow.

DATA: The dataset created from the source of RENEWABLE ENERGY STATISTICS 2025 from IRENA (International Renewable Energy Agency) [16]. The parameters used in the dataset are; Total Renewable Energy Capacity (MW), Hydropower energy capacity (MW), Wind energy capacity (MW), Solar energy capacity (MW), Bioenergy capacity (MW), Geothermal energy capacity (MW), Renewable energy share of electricity capacity (%) and the number of countries considered is 201. In the study, for clustering the world countries used data belong to term 2024 and for forecasting Turkey's renewable energy capacity used data between term 2015-2024.

Gaussian Mixture Model (GMM):

GMM performs clustering based on the probability that the given data points belong to clusters and the covariances and means of the clusters are considered. Updates are made until the model's log-probability is optimized through expectation maximization. Data points are distributed into clusters with the highest probability of matching. In a clustering with k components, the probability function of data point x is as follows. This method is probability-based and performs flexible clustering compared to other clustering techniques [17].

$$p(x) = \sum_{k=1}^K \pi_k N(x | \mu_k, \Sigma_k) \quad (1)$$

The working principle of a GMM is based on the Expectation-Maximization (EM) algorithm. Initially, the model starts with estimated parameters for each Gaussian component. During the Expectation (E-step), the algorithm calculates the probability that each data point belongs to every Gaussian component, resulting in soft cluster assignments rather than assigning each point to a single cluster. During the Maximization (M-step), the model updates the parameters of each Gaussian using these probabilities to maximize the likelihood of the observed data. These two steps are repeated iteratively until the model converges, meaning that further parameter updates no longer produce significant improvements [18]. Figure 2 depicts the Gaussian Mixture Model [17].

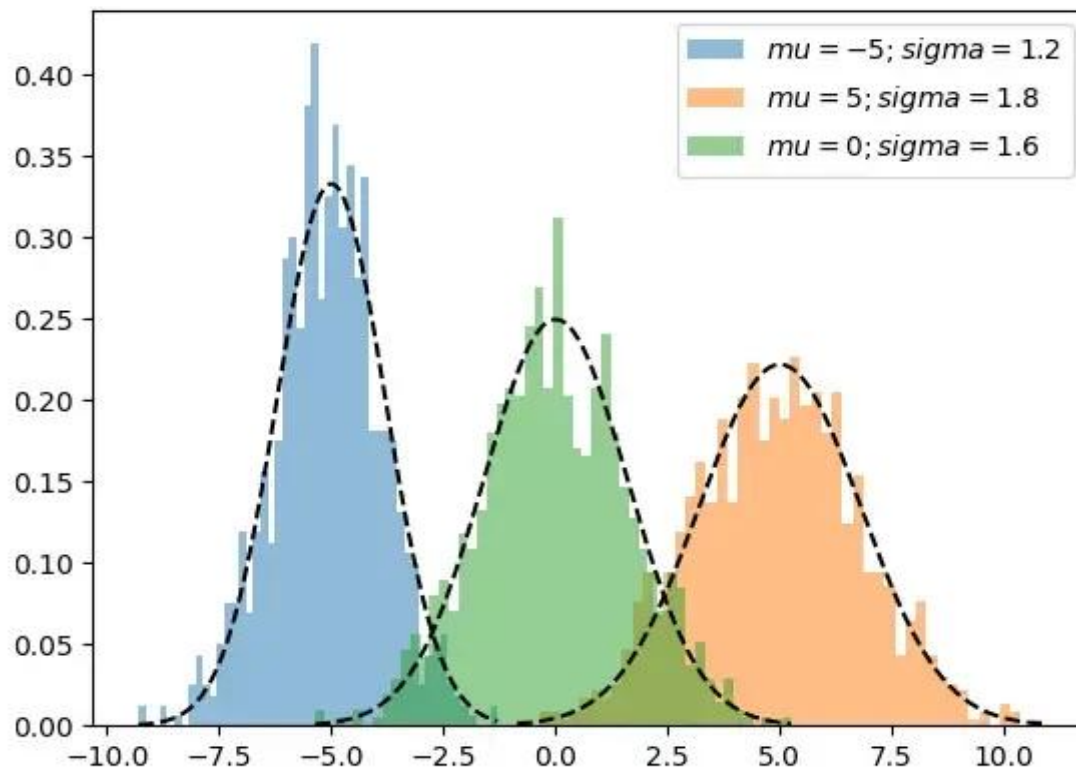


Fig. 2. Gaussian Mixture Model representation [17].

A Gaussian Mixture Model is defined by three main parameters for each Gaussian component. The mean vector (μ) specifies the center of the cluster, the covariance matrix (Σ) determines the spread, shape, and orientation of the distribution, and the mixing weight (π) represents the probability or relative proportion of data generated by that component. Together, these parameters enable GMMs to model clusters with different sizes, shapes, and overlaps, making them more flexible than methods such as K-means clustering, which assigns each data point exclusively to a single cluster [18].

Holt's Linear Trend Method:

This method is one of the classical time series methods that produces fairly good forecasting with a small amount of data that has a linear trend.

Forecast equation	$\hat{y}_{t+h t} = \ell_t + hb_t$	
Level equation	$\ell_t = \alpha y_t + (1 - \alpha)(\ell_{t-1} + b_{t-1})$	(2)
Trend equation	$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1}$	

Single Exponential Smoothing (SES) is an effective forecasting method for stationary time series but performs poorly when the data exhibit a trend. To overcome this limitation, Holt's Linear Trend Method extends SES by incorporating both the level and trend components of the series, making it more suitable for forecasting non-stationary data with linear trends. The method consists of two smoothing equations, two smoothing parameters, and one forecasting equation. Despite its advantages, Holt's Linear Trend Method has several limitations. It cannot effectively model seasonal

or cyclical patterns, assumes that the current trend will continue into the future, making it more appropriate for short-term forecasting, and generally provides less accurate forecasts when applied to small datasets [19]. It is better to use for short term forecasting as it is based on the assumption that future trend will follow the current trend [20].

3. Results

GMM uses two metrics to determine the optimum number of clusters: AIC and BIC. These metrics generate a penalty score corresponding to an excess component. The point where the score value is lowest for both metrics gives the optimum number of clusters. As seen in the graph in Figure 3, the optimum number of clusters for this data is determined to be 5 for both metrics.

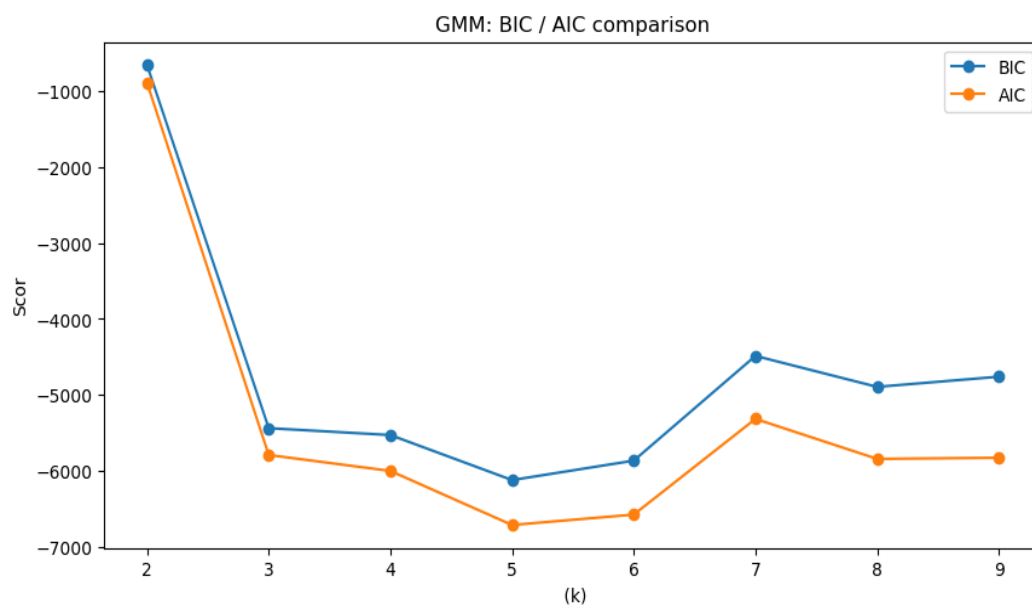


Fig.3. Determining optimum number of clusters using BIC and AIC.

AIC (Akaike Information Criterion) = $2k - 2\ln(L)$

BIC (Bayesian Information Criterion) = $k\ln(n) - 2\ln(L)$

k: number of parameters of the model, L: maximum likelihood value of the model, n: number of data

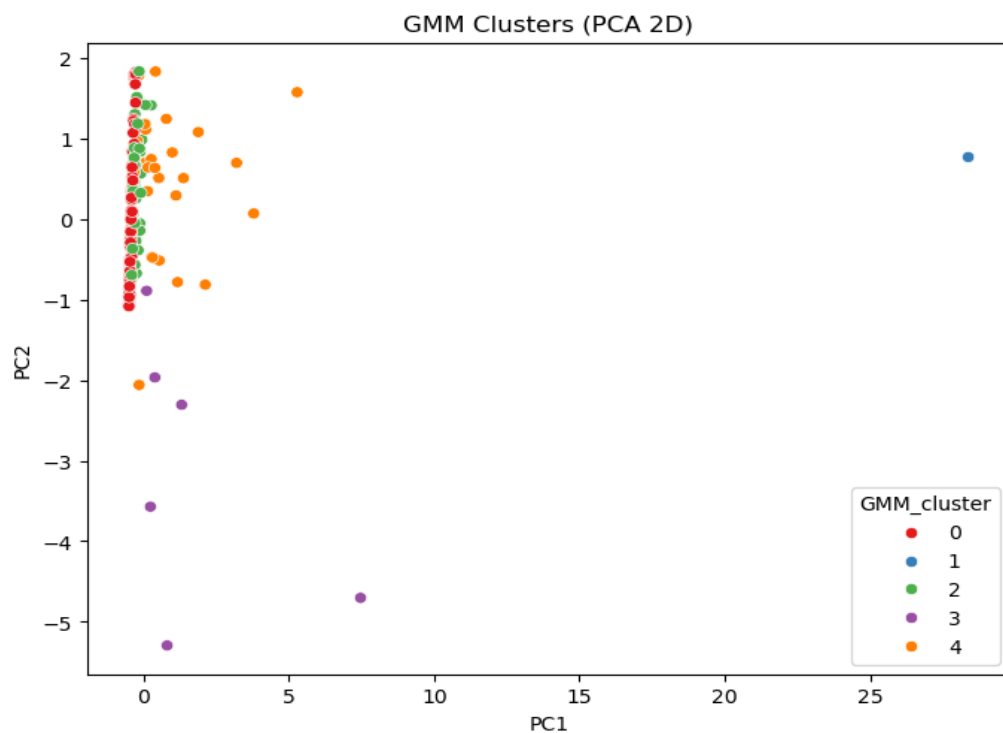


Fig. 4. GMM clusters representation in two-dimensional space.

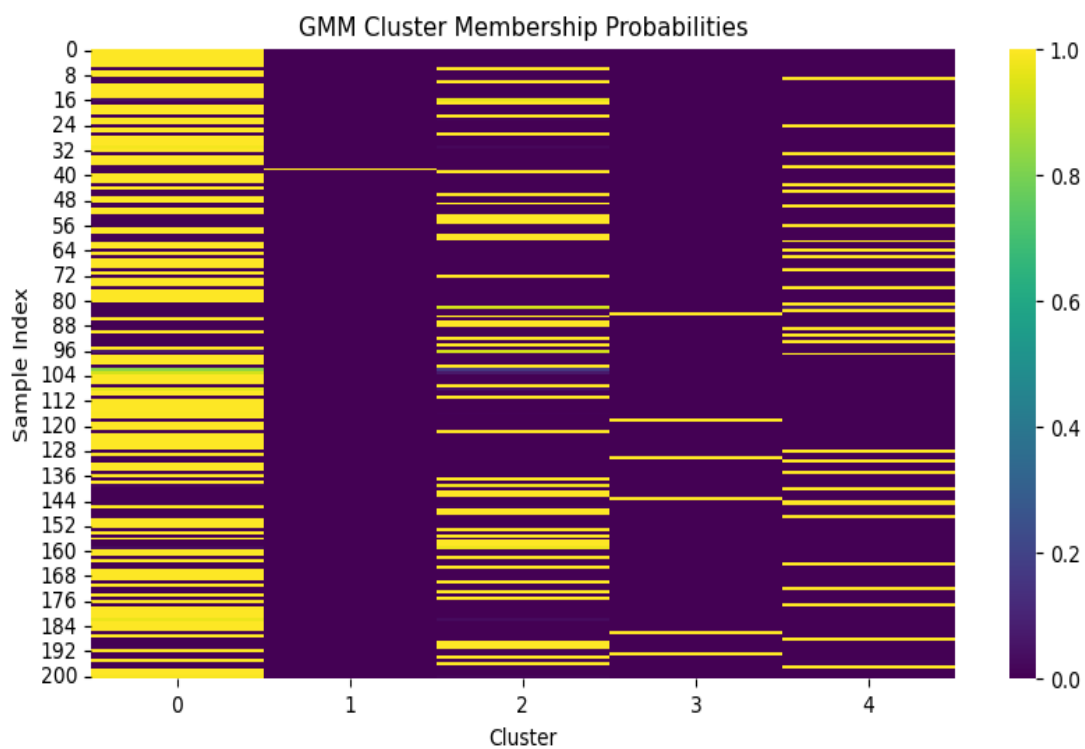


Fig. 5. GMM cluster membership probabilities.

When we examine the cluster points in a two-dimensional graph in Figure 4, it is seen that there is not a very clear separation. This is generally because the correlation between the parameters in the data is low. However, in Figure 5, the colored cluster probability graph clearly shows us that the clustering has been done quite well. In other words, we can say that the elements of each cluster belong to the clusters they are in with a high probability. In Figure 6, there is a map representation of the clustering results. each cluster is indicated by a color. The most notable cluster on this map, shown in red, is China, which forms a cluster on its own as in many other areas. China has a capacity far above the entire world in renewable energy.

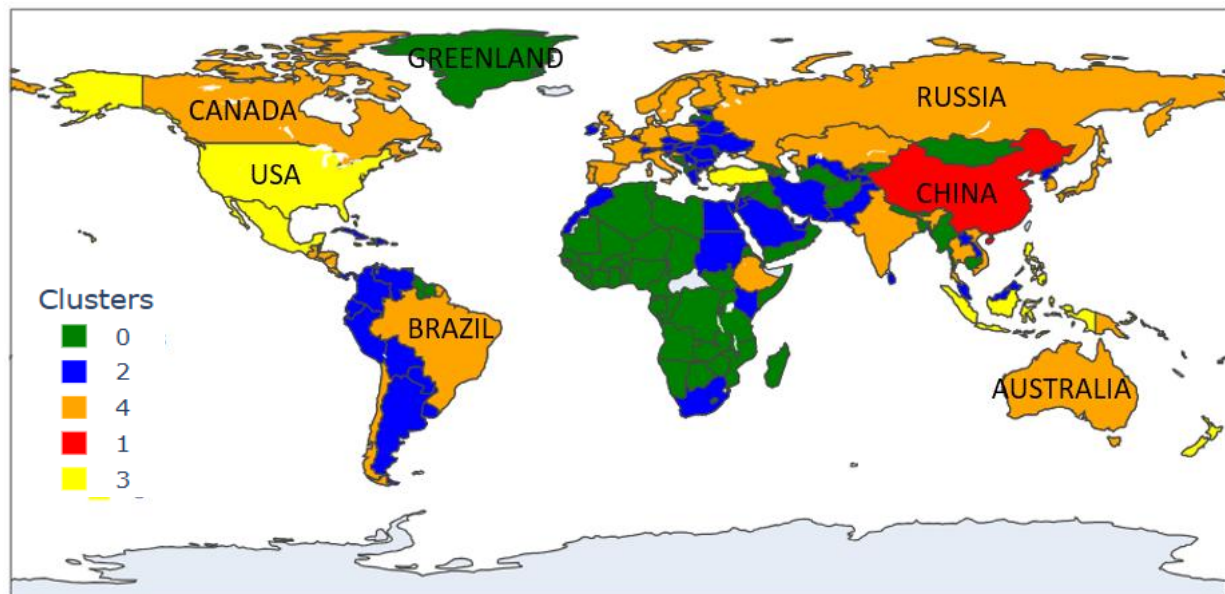


Fig. 6. Colored map graph for clusters.

Table 1 presents the results of the clustering performed on 201 countries based on their 2024 renewable energy capacities, using the GMM clustering technique. The data obtained in Table 2 shows the average values for each cluster on a parameter basis. In light of the data in the table, the highest average capacity across all energy sources with the exception of geothermal energy belongs to Cluster 1, that is, China. The second-highest average capacity belongs to Cluster 3, which includes Türkiye.

Table 1

Cluster contents for each cluster.

CLUSTER 0	CLUSTER 1
'Afghanistan', 'Albania', 'Algeria', 'Andorra', 'Angola', 'Antigua Barb', 'Armenia', 'Aruba', 'Azerbaijan', 'Bahamas', 'Bahrain', 'Bangladesh', 'Barbados', 'Belize', 'Benin', 'Bhutan', 'Bosnia Herzg', 'Botswana', 'British Virgin Islandlands', 'Brunei Darsm', 'Burkina Faso', 'Burundi', 'Cabo Verde', 'Cambodia', 'Cameroon', 'Cayman Island', 'Cent Afr Rep', 'Chad', 'Comoros', 'Congo DR', 'Congo Rep', 'Cote d Ivoire', 'Curacao', 'Cyprus', 'Djibouti', 'Dominica', 'Equatorial Guinea', 'Eritrea', 'Faroe Islandlands', 'Fiji', 'Fr Guiana', 'Gabon', 'Gambia', 'Georgia', 'Ghana', 'Greenland', 'Grenada', 'Guam', 'Guinea', 'Guinea Bissau', 'Guyana', 'Haiti', 'Iraq', 'Jamaica', 'Kiribati', 'Kosovo*', 'Kuwait', 'Kyrgyzstan', 'Latvia', 'Lebanon', 'Lesotho', 'Liberia', 'Libya', 'Luxembourg', 'Madagascar', 'Malawi', 'Maldives', 'Mali', 'Malta', 'Marshall Island', 'Mauritania', 'Mauritius', 'Moldova Rep', 'Mongolia', 'Montenegro', 'Mozambique', 'Myanmar', 'Namibia', 'Nauru', 'Nepal', 'New Caledon', 'Niger', 'Nigeria', 'North Macedonia', 'Oman', 'Palau', 'Puerto Rico', 'Rwanda', 'Samoa', 'Sao Tome Prn', 'Senegal', 'Sierra Leone', 'Solomon Island', 'Somalia', 'South Sudan', 'St Kitts Nevis', 'St Lucia', 'St Martin', 'St Vincent Gren', 'Suriname', 'Syrian AR', 'Tanzania', 'Timor Leste', 'Togo', 'Tonga', 'Trinidad Tobago', 'Tunisia', 'Turkmenistan', 'Turks Caicos', 'Tuvalu', 'Uganda', 'US Virgin Island', 'Vanuatu', 'Yemen', 'Zambia', 'Zimbabwe'	'China'
	CLUSTER 2
	'Argentina', 'Austria', 'Belarus', 'Belgium', 'Bolivia', 'Bulgaria', 'Colombia', 'Cuba', 'Czechia', 'Dominican Rep', 'Ecuador', 'Egypt', 'Estonia', 'Eswatini', 'Greece', 'Hungary', 'Iran IR', 'Ireland', 'Israel', 'Jordan', 'Kenya', 'Korea DPR', 'Lao PDR', 'Lithuania', 'Malaysia', 'Morocco', 'Pakistan', 'Panama', 'Paraguay', 'Peru', 'Qatar', 'Romania', 'Saudi Arabia', 'Serbia', 'Singapore', 'Slovakia', 'Slovenia', 'South Africa', 'Sri Lanka', 'Sudan', 'Switzerland', 'Tajikistan', 'Ukraine', 'United Arab Em', 'Uruguay', 'Uzbekistan', 'Venezuela'
	CLUSTER 3
	'Indonesia', 'Mexico', 'New Zealand', 'Philippines', 'Turkey', 'USA'
	CLUSTER 4
	'Australia', 'Brazil', 'Canada', 'Chile', 'Costa Rica', 'Croatia', 'Denmark', 'El Salvador', 'Ethiopia', 'Finland', 'France', 'Germany', 'Guatemala', 'Honduras', 'India', 'Italy', 'Japan', 'Kazakhstan', 'Korea Rep', 'Netherlands', 'Nicaragua', 'Norway', 'Papua N Guin', 'Poland', 'Portugal', 'Russian Fed', 'Spain', 'Sweden', 'Thailand', 'UK', 'Viet Nam'

Table 2

The parameter means for each cluster.

	TOTAL	hydropower	wind	solar	bioenergy \
cluster					
0.0	674.147	505.638	22.802	133.250	12.526
1.0	1827270.000	385000.000	521746.000	887930.000	32564.000
2.0	7533.298	3780.957	1036.468	2465.340	224.064
3.0	93992.167	24238.667	29216.833	35616.833	3027.667
4.0	51587.774	16509.258	12271.774	19907.290	2799.032
geothermal	Renewable energy share of electricity capacity				
cluster					
0.0	0.000	34.227			
1.0	26.000	54.500			
2.0	0.064	47.030			
3.0	1891.833	41.283			
4.0	102.806	58.681			

Table 3 presents Türkiye's annual renewable energy capacities between 2015 and 2024. Based on this data, a forecast regarding future renewable energy capacity expansion has been generated for Türkiye.

Table 3

Renewable energy capacities (MW) for Turkey between 2015-2024.

YEAR	Total	hydropower	wind	solar	bioenergy	geothermal	R.E share of electricity capacity (%)
2015	31 516	25 868	4 503	250	271	624	43.1
2016	34 446	26 681	5 751	834	359	821	43.9
2017	38 746	27 273	6 516	3 422	472	1 064	45.5
2018	42 230	28 291	7 005	5 064	587	1 283	47.7
2019	44 389	28 503	7 591	5 996	784	1 515	48.6
2020	49 195	30 984	8 832	6 668	1 097	1 613	51.3
2021	53 175	31 493	10 607	7 817	1 583	1 676	53.3
2022	55 946	31 571	11 396	9 426	1 861	1 691	53.9
2023	58 764	31 962	11 806	11 293	2 010	1 691	55.1
2024	68 984	32 386	12 973	19 883	2 006	1 734	59.3

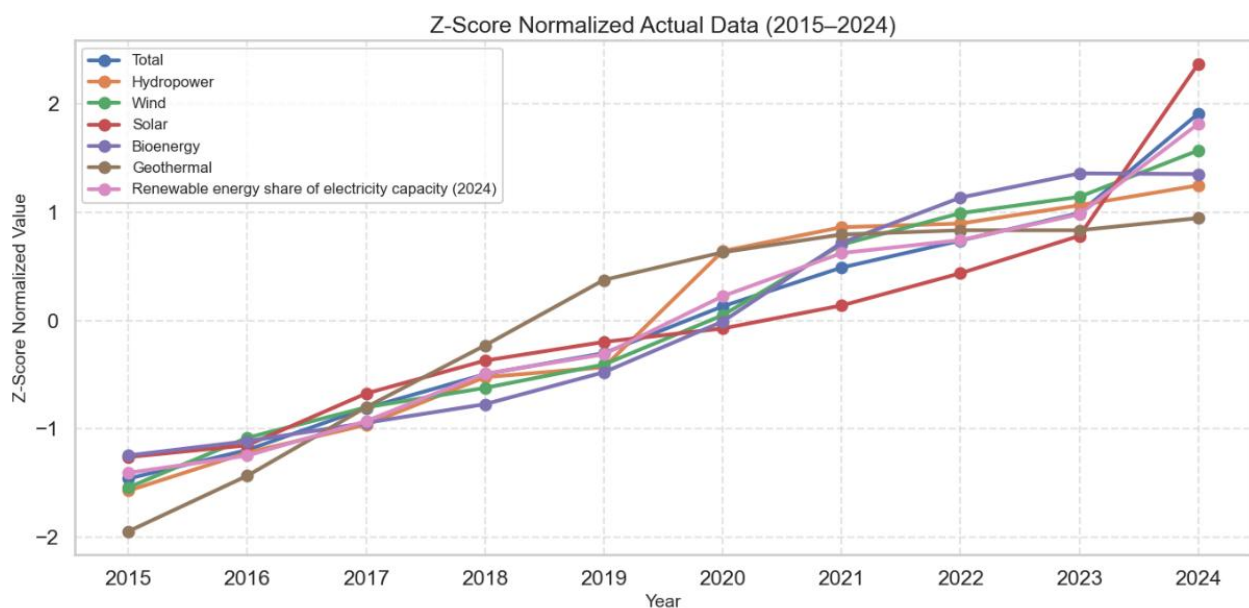


Fig. 7. Z-score normalized data between 2015-2024 term.

The graph in Figure 7 shows the normalized values of renewable energy capacities separately (Hydropower, Wind, Solar, Bioenergy, Geothermal, Total) and renewable energy share of electricity capacity for year 2024. According to the graph capacity growth across all renewable energy sources has continued with an upward trend from 2015 to 2024. In addition, a much higher increase in solar energy compared to other sources has been observed, particularly between 2023 and 2024. These graphs below show the forecasts made for each parameter using Holt's Linear Trend technique.

According to the graphs, each source maintains an increasing trend until 2035, and it can be said that it produced quite successful predictions for a data base of 10 units.

The graphs presented above Figures 8, 9, 10, 11, 12 and 13 show the values recorded between 2015 and 2024, as well as the projected values for the 2025–2035 period, for each renewable energy source individually. Holt's linear forecasting technique was employed for these projections. As expected, all the graphs exhibit an upward trend, and capacities are forecast to increase rapidly in the future. Similarly in Figure 14 shows the actual and forecasted values using Holt's Linear method between years 2015 and 2035 for the parameter Renewable energy share of electricity capacity.

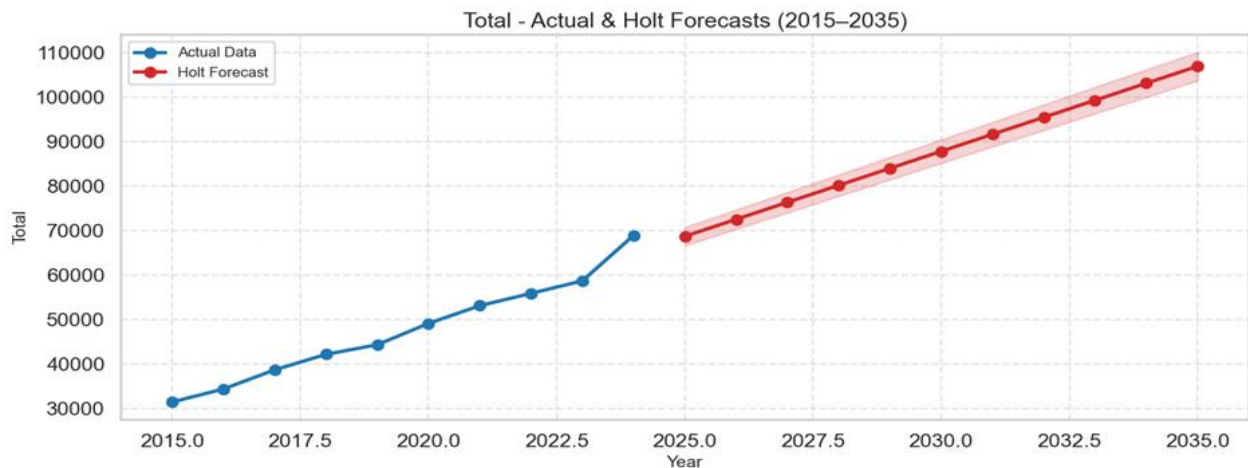


Fig. 8. Actual and forecast graph for Total capacity (MW)

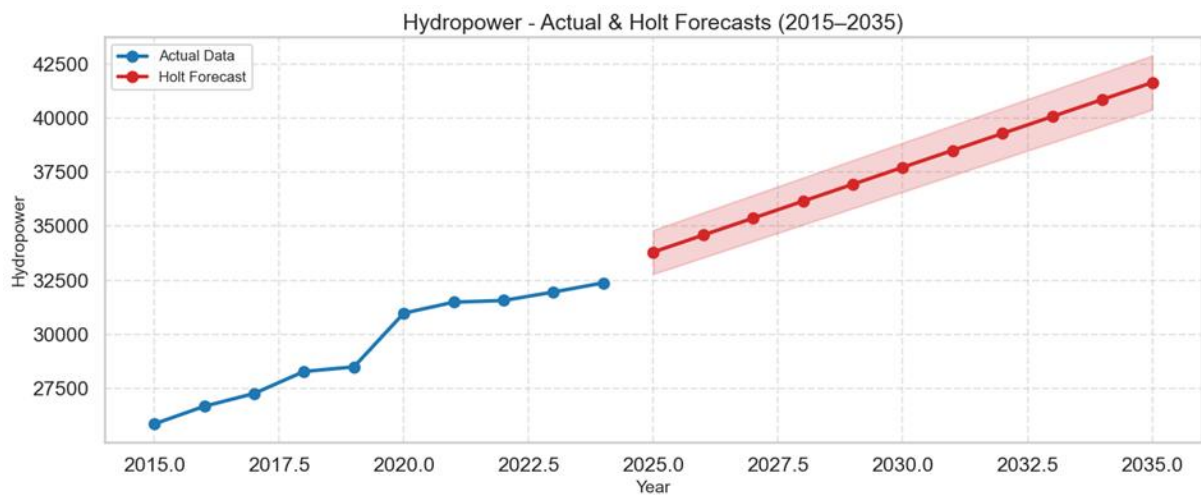


Fig. 9. Actual and forecast graph for Hydropower capacity (MW)

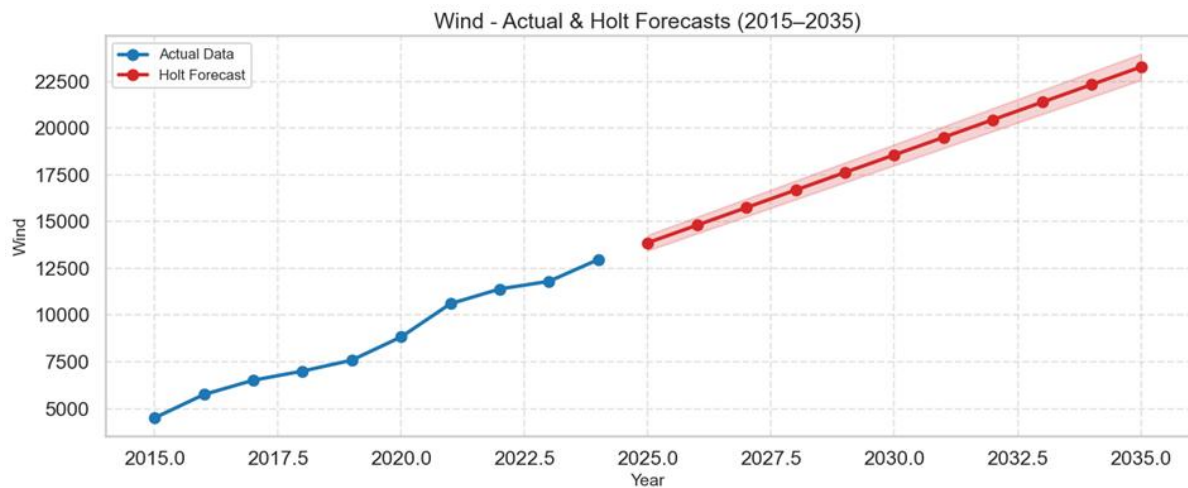


Fig. 10. Actual and forecast graph for Wind energy capacity (MW)

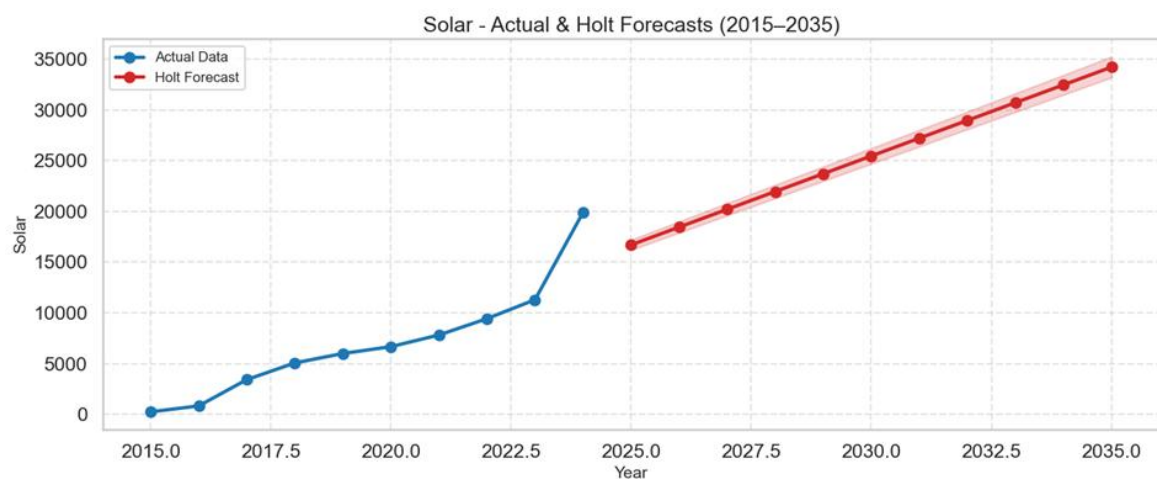


Fig. 11. Actual and forecast graph for Solar energy capacity (MW)

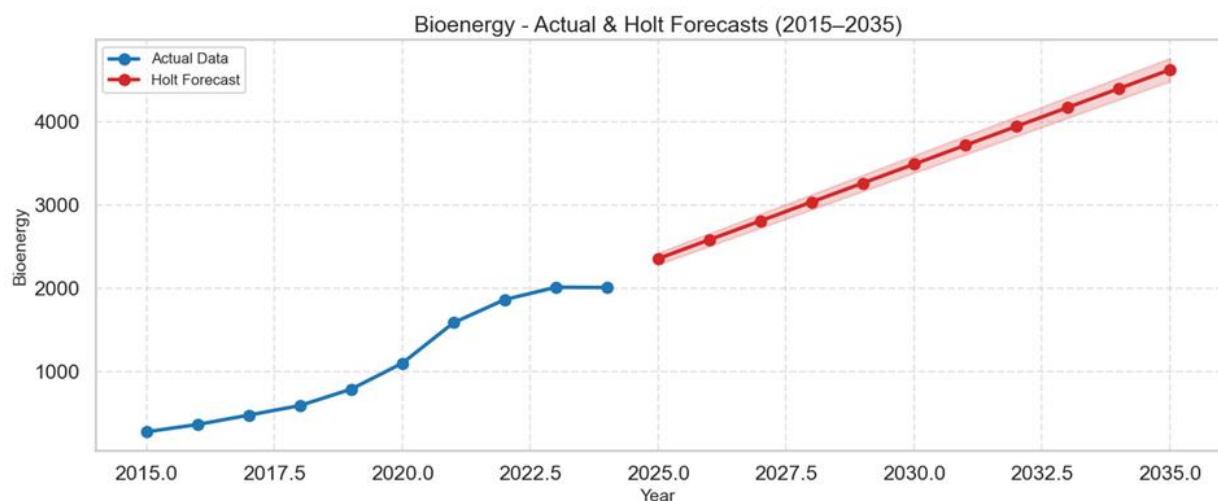


Fig. 12. Actual and forecast graph for Bioenergy capacity (MW)

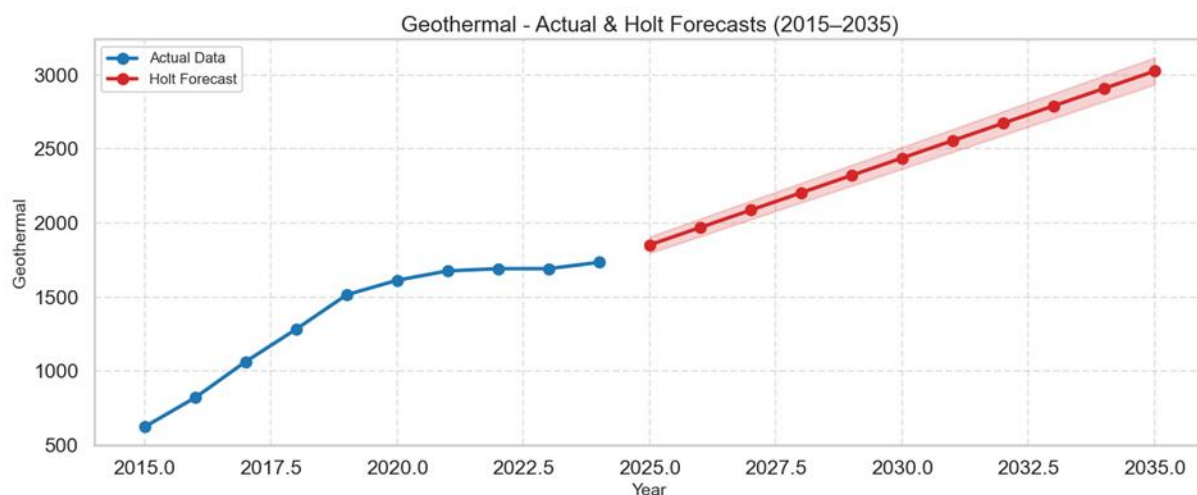


Fig. 13. Actual and forecast graph for Geothermal energy capacity (MW)

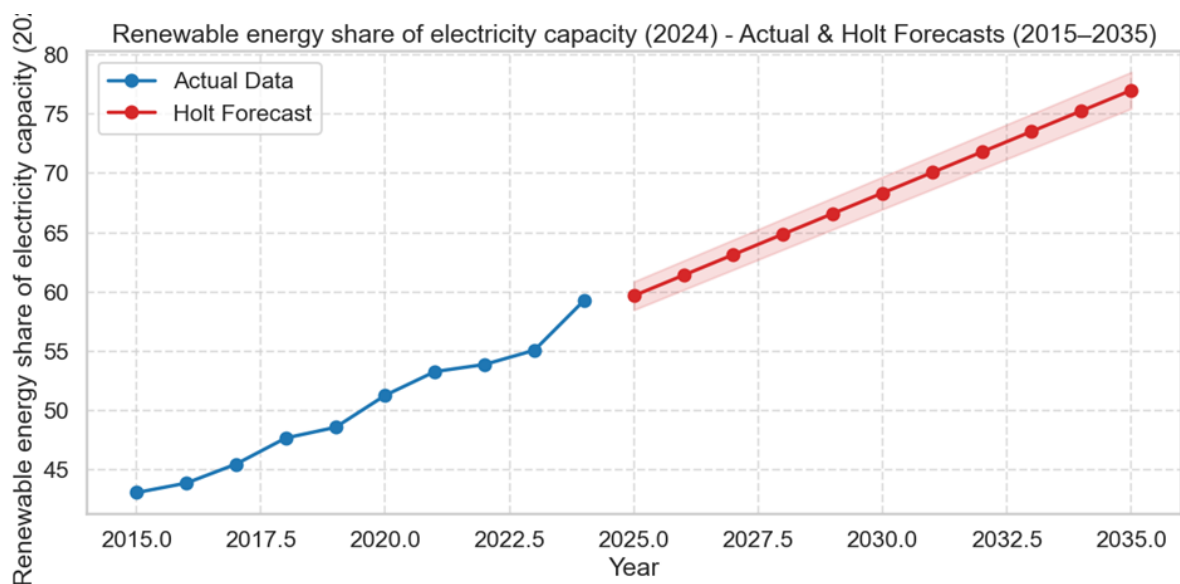


Fig. 14. Actual and forecast graph for renewable energy share of electricity capacity (%)

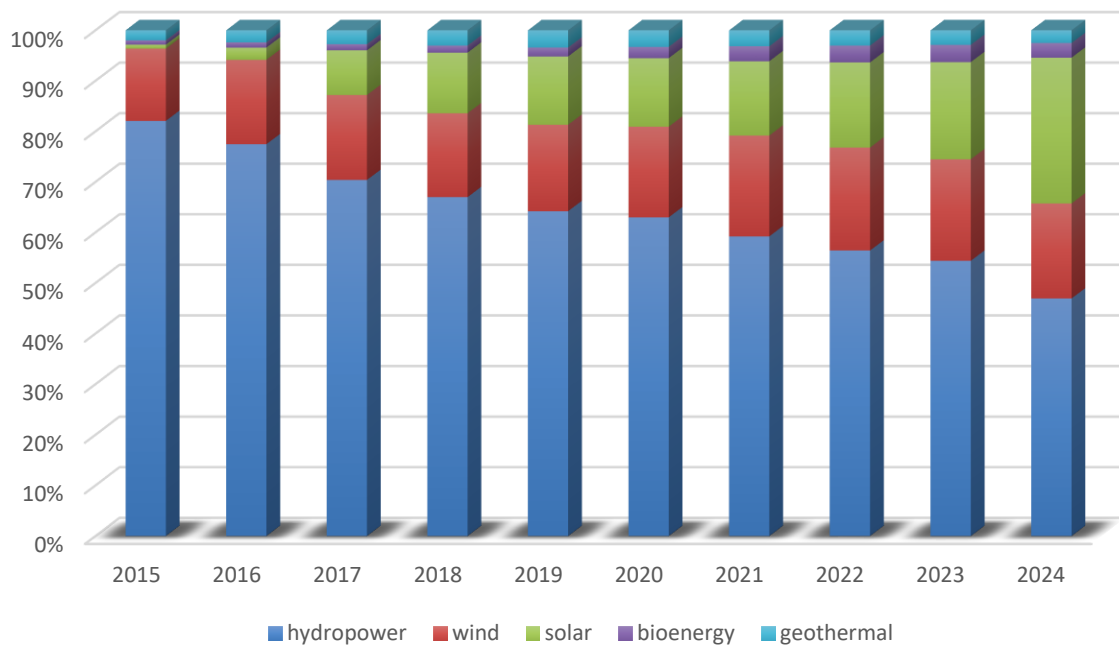


Fig. 15. Shares of renewable energy sources in electricity generation by year (%).

The graph in Figure 15 shows the change over the years based on the percentage values of the parameters. It is clearly seen here that there has been a linear increase in all renewable energy capacities. However, it is noteworthy that the increase in solar energy between 2023 and 2024 was quite high compared to other sources. This situation can be explained by increased government support and investments, as well as many other factors.

4. Conclusions

Global warming, population growth, the rapid pace of production and consumption, economic factors, and nature are just some of the many important reasons that demonstrate the importance of renewable energy year after year through various events and developments. The importance of this issue makes the research conducted so valuable.

This study groups countries around the world according to their renewable energy efficiency and capacity, using data from 2024. For this purpose, GMM, a probability-based and flexible clustering technique, was used. According to the clustering results, China was identified as the country with the highest renewable energy capacity (excluding geothermal) in the world and forms a cluster (cluster 1) all by itself. Considering the average parameters, Turkey is among the second cluster (cluster 3) with the highest capacity. In analyses conducted using data from 2015 and 2024 for Türkiye, renewable energy capacity was forecasted from the past to the future, and the results were evaluated. The projections cover the period from 2025 to 2035, and the current state of renewable energy and the projected state in 2035 have been compared.

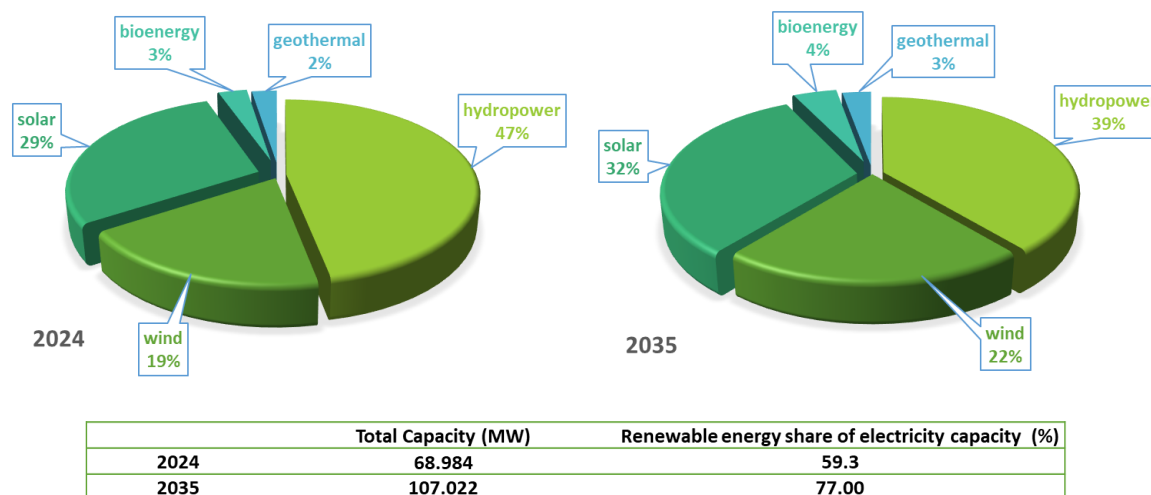


Fig. 16. The share of renewable energy by source as percent for year 2024 and 2035.

In these graphs, the share of renewable energy resources is compared with the current situation in 2024 and the projected situation for 2035. As can be seen from the graphs and predictions, solar and wind energy are expected to replace hydroelectricity over the years. Figure 16 shows the current situation for total capacity and the share of renewable energy in electricity generation in 2024 and the projected situation for 2035. Significant increase is observed in these parameters as well. In future studies, recent artificial intelligence tools can be adopted [23-25].

Author Contributions

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used “Conceptualization, Y.Ş. and E.Ş.; methodology, Y.Ş.; software, Y.Ş.; validation, Y.Ş., E.Ş.; formal analysis, Y.Ş.; resources, Y.Ş., E.Ş.; data curation, Y.Ş.; writing original draft preparation, Y.Ş.; writing review and editing, Y.Ş., E.Ş.; visualization, Y.Ş.; supervision, E.Ş.; project administration, Y.Ş., E.Ş. All authors have read and agreed to the published version of the manuscript.” Authorship must be limited to those who have contributed substantially to the work reported.

Data Availability Statement

Not applicable.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

Not applicable. This publication is based on a paper previously presented at the 5th International World Energy Conference held at Erciyes University in December 2025.

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