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Modelling and analysis of future energy scenarios on the sustainability axis

Sürdürülebilirlik ekseninde gelecek enerji senaryoları modellemesi ve analizi

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Modelling and Analysis of Future Energy Scenarios on the Sustainability Axis

Highlights

- *The electricity demand in Turkey is forecasted till 2030 by combining two methods.*
- *A grey prediction with rolling mechanism (GPRM) model is employed to predict the future values of each independent variable, and the predicted values are then used in the artificial neural network (ANN) model.*
- *Four different electricity mix scenarios are built based on the predicted demand for electricity.*
- *The assessment of the sustainability of the four scenarios is conducted using the technique for order preference by similarity to ideal solution (TOPSIS) method.*

Graphical Abstract

An approach for the electricity demand forecasting and multi-criteria decision making (MCDM) is developed to evaluate the sustainability of the Turkey's electricity mix by 2030.

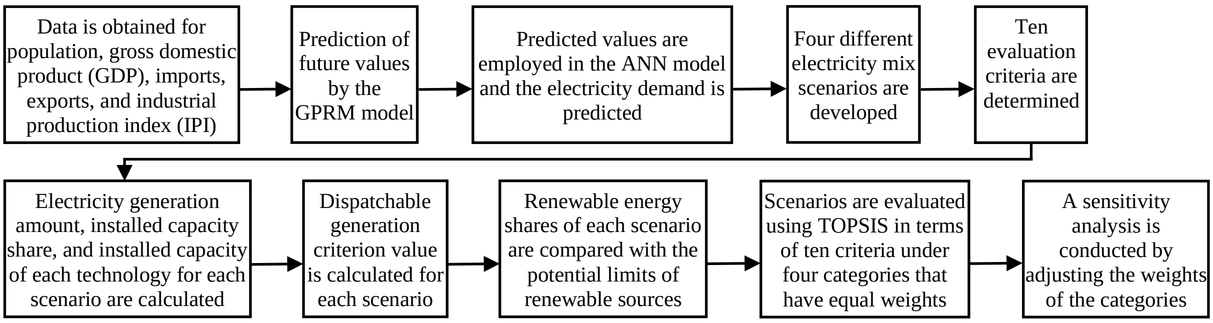

Figure. The flowchart of the developed approach for the sustainability assessment.

Aim

The aim of the paper is to put forward a sustainable electricity mix option for Turkey for the year 2030.

Design & Methodology

The integrated method based on multilayer perceptron (MLP) ANN method and GPRM method are used to forecast the electricity demand. The TOPSIS method is utilized to evaluate the electricity mix scenarios considering ten evaluation criteria.

Originality

First, a sound approach is established based on ANN and GPRM methods for the prediction of long-term electricity demand. Second, as far as we know; there is a limited number of studies that especially consider the electricity mix sustainability in the literature. Therefore, this study is the first approach that employs the TOPSIS method to research the electricity mix sustainability in Turkey for the year 2030. Third, the electricity demand forecasting is integrated into the decision-making process relating the electricity mix.

Findings

Electricity demand of Turkey is forecasted as ≈ 384,569 GWh for the year 2030. Scenario-(C) is found to be most sustainable scenario in that nuclear energy generation has a comparatively higher share.

Conclusion

The combined ANN-GPRM approach proposed in this study is suitable method to predict the long-term electricity demand. Electricity demand forecasting makes possible to determine more practical shares of power generation technologies for the development of the electricity mix scenarios. The evaluation with TOPSIS reveals that the Scenario-(C) is the most sustainable scenario when equal weights are assigned to the criteria categories. On the other hand, the rankings of the scenarios can considerably change when different weight sets are assigned to them in sensitivity analysis.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Modelling and Analysis of Future Energy Scenarios on the Sustainability Axis

Araştırma Makalesi / Research Article

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ABSTRACT

This study aims to propose a sustainable electricity mix option for Turkey by 2030. First, the electricity demand of Turkey by 2030 is estimated by employing a method that comprises MLP ANN and GPRM. Population, GDP, imports, exports, and IPI are considered independent variables used in the ANN model. The future values of each of the independent variables are predicted by a GPRM model based on a univariate time series approach. ANN model is then employed to predict electricity demand based on the future values of independent variables. Secondly, four diverse electricity mix scenarios are developed considering the forecasted electricity demand. The sustainability evaluation of the scenarios is performed using TOPSIS method considering ten different criteria classified into environmental, economic, technical, and social categories. Furthermore, four diverse weight sets are determined for the given categories, and also a sensitivity analysis is carried out. Turkey's electricity demand is found out as ≈ 384,569 GWh according to the prediction for the year 2030. The Scenario-(C), which has a comparatively higher percent of nuclear energy generation, is determined as the most sustainable electricity mix scenario according to evaluation with the TOPSIS method.

Keywords: Energy, sustainability assessment, artificial neural network, grey prediction, TOPSIS.

Sürdürülebilirlik Ekseninde Gelecek Enerji Senaryoları Modellemesi ve Analizi

ÖZ

Bu çalışma Türkiye için 2030 yılına ait sürdürülebilir bir elektrik enerjisi karması seçeneği önerilmesini amaçlamaktadır. İlk olarak, MLP ANN ve GPRM'yi kapsayan bir yöntem kullanılarak Türkiye'nin 2030 yılı elektrik enerjisi talebi tahmin edilmiştir. ANN modelinde dikkate alınan bağımsız değişkenler nüfus, GDP, ithalat, ihracat ve IPI olmaktadır. Her bir bağımsız değişkenin gelecekteki değerleri tek değişkenli zaman serisi yaklaşımı temelinde bir GPRM modeli kullanılarak tahmin edilmiştir. ANN modeli daha sonra bağımsız değişkenlerin gelecekteki değerleri temelinde elektrik enerjisi talebinin tahmin edilmesinde kullanılmıştır. İkinci olarak, tahmin edilen elektrik talebi dikkate alınarak dört farklı elektrik karması senaryosu geliştirilmiştir. Senaryoların sürdürülebilirlik değerlendirilmesi TOPSIS kullanılarak çevresel, ekonomik, teknik ve sosyal kategorileri dâhilinde sınıflandırılmış on farklı kritere göre gerçekleştirilmiştir. Buna ek olarak, belirtilen kategoriler için dört farklı ağırlık seti belirlenmiş ve bir duyarlılık analizi de gerçekleştirilmiştir. 2030 yılı için yapılan tahmin işlemine göre Türkiye'nin elektrik enerjisi talebi ≈ 384,569 GWh olarak bulunmuştur. TOPSIS metodu ile yapılan değerlendirmeye göre, karşılaştırmalı olarak daha yüksek nükleer enerji üretim yüzdesine sahip olan Senaryo-(C) en sürdürülebilir elektrik enerjisi karması senaryosu olarak belirlenmiştir.

Anahtar kelimeler: Enerji, sürdürülebilirlik değerlendirmesi, yapay sinir ağı, gri tahmin, TOPSIS

1. INTRODUCTION

To date, electricity has been the most important input for the industrialization in the world. At the outset of the twentieth century, the industry 2.0 began. This era is characterized by the introduction of the electrical energy into the industry and the initiation of the mass production. The production grew significantly in this era, and the standard of the living increased consequently. Electricity has played an important role in the formation of modern lifestyle. Today, electrical energy has become an indispensable component of the modern life. Electricity is used for heating, cooling, lighting, transportation and in the medical devices, home appliances, and office equipment.

Electricity is a secondary energy source that is produced from the energy sources that belong to fossil, nuclear, or renewable categories. There are various electricity generation technologies, such as coal, natural gas, nuclear, hydro, wind, and solar-PV power plants that utilize the energy sources belong to given categories. In general, the fossil fuel technologies are advantageous as they are dispatchable. On the other hand, their environmental impact such as the greenhouse gas emission amount is relatively high. Nuclear power plants (NPPs) are beneficial as they are dispatchable, however the capital costs of these power plants are relatively high. Renewable energy technologies are favoured due to their relatively low environmental impacts, though as a

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drawback, various technologies such as the wind and solar-PV are not dispatchable.

There has been a continued emphasis on the sustainability of the energy systems in recent decades. Research on the energy supply systems is of key importance in terms of sustainability of energy systems. Electricity demand growth necessitates increasing capacity in the electricity supply infrastructure. Right decisions for generation expansion should be taken to supply reliable, secure, and economic electricity considering the increase in energy demand in the future. Therefore, the prediction of future electricity demand is the first task in capacity planning for making right decisions. In fact, none of the generation technologies is solely adequate to maintain the electricity generation in the grid. Hence, electricity demand forecasting and sustainability evaluation based on the priorities in environmental, economic, technical, and social dimensions, and availability of the energy source form the basis for the decision on the shares of the energy technologies in the electricity mix.

Different methods have been utilized for the electricity demand forecasting that can be categorized into the following three categories. Traditional approaches category includes regression, time series, and Box-Jenkins methods. Soft computing approaches category comprises the methods such as the genetic algorithms, fuzzy logic, and ANNs. Third category is the emerging techniques, namely, particle swarm optimization, ant colony optimization, and support vector machines. The factors that affect the electricity demand in forecasting are claimed to depend upon whether the time horizon of the forecast is short-term or long-term [1]. Furthermore, there may exist non-linear relationships between some factors and the electricity demand for the considered time horizon. In the electricity demand forecasting models, the independent variables stand for the factors that influence electricity demand, and dependent variable stands for the electricity demand. As the generally non-linear relationship exists between dependent and independent variables, the ANNs are powerful to capture the non-linear nexuses [2]. Electricity generation process is a fundamental component of the electricity supply chain [3]. The evaluation of the sustainability of the electricity generation mix including various types of power generation technologies is a sophisticated subject that necessitates to deal with the multiple dimensions of sustainability. The MCDM is a practical approach for comparing different options according to the various criteria. Many MCDM methods have been developed. Some of these methods are the TOPSIS, Visekriterijumsko Kompromisno Rangiranje (VIKOR), analytic network process (ANP), multi-attribute value theory (MAVT), and analytic hierarchy process (AHP). The MCDM methods are basically classified according to the solution set structure type or the problem type. The first group is the discrete MCDM, which has a finite solution set, according to solution set structure type. The second group is the continuous MCDM, which has an infinite solution set. The problem type can be the choice, decision, sorting, or ranking. The problem type is a key factor for specifying a suitable MCDM method.

In this study, an MLP ANN model is developed based on the social and economic factors; population, GDP, imports, exports, and IPI. A time series model drawing upon the GPRM method is adopted with a purpose of forecasting the values of the independent variables on an individual basis. The values, which are estimated until 2030, are used in the ANN model for performing prediction of Turkey's electricity demand by 2030. A kind of MCDM method; TOPSIS is employed in this study with the purpose of comparing different electricity mix scenarios and to decide on the most sustainable option. Four diverse electricity mix scenarios with different share structures are built considering the recent electricity mix of Turkey [4,5], NPP related situation for Turkey [6], and electricity demand forecast by 2030. Ten common indicators are selected based on the literature survey, which are arranged into economic, technical, social, and environmental categories. Equal weights are assigned to each category. A sensitivity analysis is undertaken through setting diverse weight sets for the categories. This research makes various contributions to the energy supply systems related research field. First, a viable approach drawing upon the ANN and GPRM techniques is developed to perform a long-term electricity demand forecast. Secondly, so far as we know, a limited range of studies specifically focus on the sustainability of the electricity mix in the literature, and this is the first study that explores the electricity mix sustainability of Turkey by 2030 by using the TOPSIS method. Thirdly, the electricity demand forecasting is incorporated into the electricity mix decision making in the research's scope.

In this paper, a comprehensive literature review on the methods used in the proposed approach is concisely presented in Section 2. The forecasting methods and TOPSIS method are briefly described in Section 3. Forecasting of electricity demand with ANN and GPRM models and the TOPSIS model for evaluating mix scenarios are laid out through Section 4. Interpretation of the study's findings is provided by Section 5.

2. LITERATURE REVIEW

A concise synopsis of the literature comprising the forecasting with the ANN method and the grey prediction (GP) method, and the evaluation of the energy systems with the MCDM approach is presented.

In recent studies, the ANN approach has been used for both electricity and energy demand prediction in the long-term. These studies differ in some aspects, such as the architecture of the ANNs and set of the independent variables used in the models. Forecasting of long-term electricity consumption of Turkey has been explored by a variety of studies, in which the researchers compared the forecasting performances of the models they developed as follows. Kavaklioglu et al. [2] developed

ANN models with different input settings. Çunkaş and Altun [1] proposed two models that have different ANN structures. Kaytez et al. [7] developed models by employing the ANN, support vector machines, and regression analysis techniques. Besides, there are studies regarding the electricity consumption forecasting in different countries. Hsu and Chen [8] established a model with the ANN technique with an aim of forecasting the regional peak load in Taiwan, and the researchers compared the model with a regression model. Tso and Yau [9] compared the performances of the ANN, decision tree, and regression analysis approaches in forecasting the Hong Kong's electricity consumption. Several studies on the forecasting of the energy consumption of Turkey have been undertaken in recent years, such as the following. In their study, Sözen, Arcaklioğlu and Özkaymak [10] developed two ANN models with different independent variables and compared these models in forecasting net energy consumption. Sözen, Akçayol, and Arcaklioğlu [11] established an ANN model to forecast the net energy consumption. Sözen and Arcaklioglu [12] built three ANN models with different independent variables to predict the net energy consumption, and researchers compared the models. Sözen, Arcaklioglu and Tekiner [13] developed three models by employing the ANN method to estimate the net energy consumption and they compared these models. Sözen and Arcaklioğlu [14] used the ANN technique to develop models to estimate the consumption of various energy sources. Kankal et al. [15] examined the forecasting performances of the ANN and regression techniques for the models with different independent variable configurations. Uzlu et al. [16] established two ANN models by using different training techniques, and they made a comparison to forecast the performances of the models. The ANN technique also has been applied to forecast energy consumption in various countries. Researchers developed various ANN, exponential, and regression models with a purpose of estimating the energy demand in South Korea in [17], and they compared the results obtained from these models.

So far, the GP has been employed in time series related forecasting research comprising subjects such as the energy and economy. There are also studies in the literature which used the variants of the GP. Akay and Atak [18] forecasted Turkey's industrial and total electricity demand by employing the GPRM. Boran [19] forecasted Turkey's natural gas consumption utilizing the GPRM. Li et al. [20] used an improved GP model with an aim of forecasting the consumption of primary energy, GDP, and population in China. Pao, Fu and Tseng [21] used an improved version of the non-linear grey Bernoulli model with a purpose of prediction of CO_2 emissions, energy consumption, and real GDP in China. Wang and Hsu [22] developed a combined GP and genetic algorithm model and predicted Taiwan's high technology industry output.

Previous studies that pertain to energy system evaluation with the MCDM especially dealt with the power plants and energy sources in Turkey as follows. Boran, Boran and Dizdar [23] evaluated hydropower, solar power, fossil fuels, wind power, nuclear power, and natural gas alternatives by applying axiomatic design approach. Boran et al. [24] used a modified version of the TOPSIS method to analyse various options for the electricity generation based on the type of the energy source. Boran [25] used fuzzy TOPSIS method with a purpose of evaluating different type of power plants. Boran [26] employed the intuitionistic fuzzy VIKOR method to rank various renewable energy options. Atmaca and Basar [27] employed ANP for evaluating various power plant types. Atilgan and Azapagic [28] assessed the sustainability of various electricity generation technologies drawing upon MAVT. Kuleli Pak, Albayrak and Erensal [29] evaluated different energy sources drawing on a combined approach that includes ANP. So far, the MCDM approach has been utilized for the evaluation of energy sources, energy projects, electricity generation technologies, and electricity mix alternatives in different countries as follows. Shen et al. [30] utilized fuzzy AHP to evaluate Taiwan's renewable energy sources. San Cristóbal [31] took an approach based on the AHP and VIKOR methods with a purpose of selecting a project on renewable power generation among different options in Spain. Ribeiro, Ferreira and Araújo [32] introduced a tool for multi criteria assessment and assessed different power generation scenarios for Portugal through this tool. Hong, Bradshaw, and Brook [33] carried out an analysis of four different electricity mix scenarios for Japan in accordance with the MCDM approach. Santoyo-Castelazo and Azapagic [34] used the MAVT method to evaluate various electricity mix scenarios for Mexico from a sustainability perspective. Brand and Missaoui [35] analysed various scenarios relating to Tunisia's electricity mix by using the TOPSIS method coupled with a market model for electricity. Moreover, some studies pertinent to energy systems evaluation have been conducted without referring a particular energy system. Kaya and Kahraman [36] put forward a fuzzy approach with modification to apply the TOPSIS method to choose the better power generation technology among several options. Maxim [37] evaluated several types of power generation technologies by using an approach that combines multi-attribute utility method and weighted sum method.

3. PRELIMINARIES

The proposed approach in this study is undertaken in two steps. First, the ANN and GPRM methods are employed with a goal of electricity demand forecasting. Next, the TOPSIS method, whereby the electricity mix scenarios are evaluated, is used.

3.1. ANN Method

An ANN model is characterized by several attributes, such as the architecture, topology, and the training method that need to be determined. For an ANN model, the architecture delineates the arrangement of neurons with regard to each other, and the topology describes the structural combination possibilities for a specific architecture [38]. An MLP ANN includes three types of layers: an input layer, one hidden layer at minimum, and one output layer, and the neurons are found on the layers [39]. A general structure of an MLP ANN model with 'n' independent variables and one dependent variable is illustrated in Figure 1.

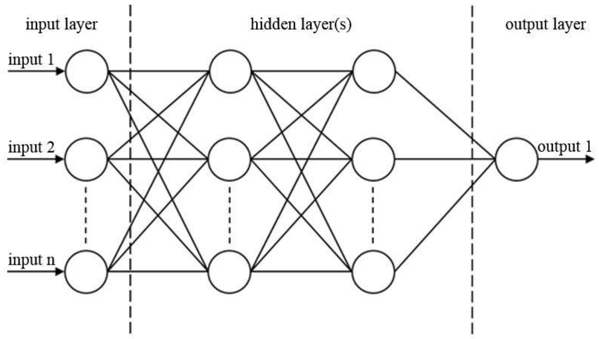

Figure 1. The structure of an MLP ANN model

The neurons are the units that process information, and the activation function is one of the fundamental elements of a neuron that ensures to limit the amplitude relating to neuron's output [40]. Various types of activation functions are used in the ANN models. Two of the most common types are the hyperbolic tangent sigmoid (1) and linear (2) activation functions [41].

$$a = \frac{e^n - e^{-n}}{e^n + e^{-n}} \tag{1}$$

$$a = n \tag{2}$$

The ANN model is trained in order to examine its performance. The backpropagation algorithm is advantageous in the training of the MLP models regarding engineering applications [15]. Levenberg-Marquardt (LM) algorithm is one of the faster variants of the backpropagation algorithm, and scaled conjugate gradient (SCG) is another faster variant as well [14]. The count of hidden layers and the count of each hidden layer's neurons are both critical parameters. On the other hand, there's not a common rule to specify the number of the hidden layers for the backpropagation models, to this end, the trial and error approach can be employed [8].

Selection of the independent variables representing the factors influencing the electricity demand is an essential process of the establishment of a forecasting model. A period exceeding one year is classified as long-term in the electricity demand forecasting, and the factors such as the economic ones are mooted to affect the long-term electricity demand [1].

A more efficient ANN training process could be ensured by applying data normalization. The min-max technique given by (3) is one of the data normalization approaches that finds widespread use in the development of ANN models.

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

3.2. GPRM Method

In 1982, Ju-Long propounded the theory of grey systems [42]. Relevant to the time series prediction, GP is an application field of this theory, which essentially takes into consideration the systems with insufficient information characteristics and a single variable differential model, GM(1,1), whose procedure is outlined below [43,44].

Step 1. The time sequence data is represented as

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)) \quad n \geq 4 \tag{4}$$

Monotonically increasing $x^{(1)}$ is obtained through accumulated generating operator.

$$x^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)\right), \quad n \geq 4 \tag{5}$$

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \quad k = 1,2,3, \dots, n \tag{6}$$

Step 2. Mean operation is applied to $x^{(1)}$ to generate $z^{(1)}$ sequence.

$$z^{(1)} = (z^{(1)}(1), z^{(1)}(2), \dots, z^{(1)}(n)) \tag{7}$$

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1), \\ k = 2,3, \dots, n \tag{8}$$

Step 3. GM(1,1) is achieved through a differential equation that is

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{9}$$

Step 4. The sequence of parameters $[a, b]^T$ of the equation given in (9) is obtained by using least squares method as

$$\begin{bmatrix} a \\ b \end{bmatrix} = [B^T B]^{-1} B^T Y \tag{10}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & 1 \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{11}$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{12}$$

Step 5. Based on the obtained parameters a and b, equation (13) is solved to obtain GP equation given in (14).

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{13}$$

$$\hat{x}^{(1)}(k+1) = \left[x^{(1)}(0) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \tag{14}$$

Using the inverse accumulating generating operator, the predicted values are acquired

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k+1), \quad k = 2,3,\dots,n \quad (15)$$

GPRM is an improved version of the GP. The GPRM procedure is defined as follows [18, 19]. The rolling mechanism provides a better prediction accuracy by considering relatively most recent data. In the forecasting with GM(1,1), whole time sequence data is utilized; whereas in the GPRM, GM(1,1) is applied to $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(k))$, where $k < n$, in order to predict $x^{(0)}(k+1)$. The procedure is performed again by adding the predicted new data $x^{(0)}(k+1)$ to the data set ending, and discarding the oldest one that is $x^{(0)}(1)$. Thereafter, $x^{(0)}(k+2)$ is predicted by utilizing $x^{(0)} = (x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(k+1))$. Given $k = l, l+1, \dots, n-1$, for the time instant $(k+1)$ the mean absolute percentage error (MAPE) is described as

$$er(k+1) = \left|\frac{x^{(0)}(k+1) - \hat{x}^{(0)}(k+1)}{x^{(0)}(k+1)}\right| \times 100\% \quad (16)$$

Where $k+1 \leq n$,

The average rolling error is expressed as

$$er = \frac{1}{n-l}\sum_{k=l}^{n-1} er(k+1) \times 100\% \quad (17)$$

3.3. TOPSIS Method

The TOPSIS technique is based on a procedure that comprises six consecutive steps for evaluating different alternatives, and at the end of the procedure, the option that is most distant from negative-ideal solution but closest to ideal solution is selected depending on the concept of technique [45].

The criteria; C_j $(j = 1,2,\dots,n)$ and alternatives; A_i $(i = 1,2,\dots,m)$ are presented by a decision matrix denoted by D for the evaluation with the TOPSIS.

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \quad (18)$$

Step 1. Construction of normalized decision matrix

Normalization facilitates comparing different criteria by providing them a non-dimensional characteristic. The normalized decision matrix is denoted by R and the calculation of r_{ij} entry of the R is given as

$$r_{ij} = x_{ij} \Big/ \sqrt{\sum_{i=1}^{m} x_{ij}^2} \quad (19)$$

Step 2. Weighted normalized decision matrix formation.

A weight set is determined; $w = (w_1, w_2, \dots, w_j, w_m)$, $\sum_{j=1}^{n} w_j = 1$. Each of the weights w_j in the set is multiplied with the corresponding columns of the matrix R to obtain normalized decision matrix denoted by V as follows.

$$v_{ij} = r_{ij}(.)w_j \quad (20)$$

Step 3. Negative-ideal solution and ideal solution determination.

Negative-ideal solution set $A^- = \{v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-\}$ and ideal solution set $A^* = \{v_1^*, v_2^*, \dots, v_j^*, \dots, v_n^*\}$ are formed by determining least and most favoured values respectively on the cost-benefit grounds for each criterion.

Step 4. Computation of separation measure

Through Euclidean distances calculation considering ideal and negative-ideal solutions, separation values denoted by S_{i*} and S_{i-} are found, respectively, as follows.

$$S_{i*} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^*\right)^2} \quad i = 1,2,\dots,m \quad (21)$$

$$S_{i-} = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \quad i = 1,2,\dots,m \quad (22)$$

Step 5. Closeness coefficient computation

The closeness coefficient is computed as follows for each of the alternatives.

$$C_{i*} = S_{i-}/(S_{i*} + S_{i-}) \quad i = 1,2,\dots,m \quad (23)$$

Step 6. Ranking process

The alternatives are ranked considering the descending order pertinent to C_{i*}.

4. PROPOSED APPROACH FOR DETERMINATION OF ELECTRICITY MIX SCENARIOS

The approaches for developing the combined ANN-GPRM model and the TOPSIS model, and the properties of these models are presented in this section.

4.1. Combined ANN-GPRM Model for Forecasting Turkey's Electricity Demand for 2030

A social factor; population, and economic factors, namely, GDP, imports, exports, and IPI are considered for establishing the model for forecasting the dependent variable represented by the electricity demand in this framework. The ANN model is developed by using a data set of variables covering years 1970-2017.

The population affect the energy consumption [46] and the electricity consumption; ergo, population increase leads to electricity consumption increase [2]. Herein, data of population is obtained from the Turkish Statistical Institute (TURKSTAT) [47]. In the obtained data set, the population data for the years 1970, 1975, 1980, 1985, 1990, and 2000 is available based on the census results. In addition, data from 2007 to 2018 is available based on the Address Based Population Registration System. Missing values for the years in the population data are calculated drawing upon the natural increase formula (24) [48].

$$P_n = P_o \times e^{rn} \tag{24}$$

Economic growth-energy consumption nexus has been explored in Turkey by considering especially GDP. Soytas and Sari [49] asserted that the causality direction was from energy consumption towards GDP, and Lise and Van Montfort [50] claimed a causality existence running in the opposite direction for the 1950-1992 period and 1970-2003 period, respectively. Altinay and Karagol [51] and Yalta [52] considering the energy consumption and real GDP, found no nexus pertinent to 1950-2000 period and 1950-2006 period, respectively. Altinay and Karagol [53] contended that the direction of the causation was from the consumption of electricity towards real GDP during period of 1950-2000, while the study of Aslan [54] reveals presence of two-way causality nexus between them regarding the 1968-2008 period. Previous studies show that there exists a variety of findings regarding both energy consumption-GDP and electricity consumption-GDP nexus. The GDP per capita is used in the model developed in the present study and the related data is gathered from OECD [55].

The trade may have an impact on the consumption of energy in terms of composition, technique, and scale effects [56]. Huang et al. [46] claimed that net export affected the energy consumption in China over the period of 1980-2014. Dedeoğlu and Kaya [57] explored the nexus between energy usage-imports and energy usage-exports for 25 countries from OECD during the period of 1980-2010 and found a two-way causal nexus between both sets. Topcu and Payne [56] examined trade-energy usage nexus for 34 countries from OECD over the 1990-2015 period, and the researchers discovered that there existed non-linear and linear relationships between them as inverted U-Shape and cross-sectional dependence, respectively. The imports and exports data is collected from the TURKSTAT [58] in the present study.

The IPI is selected as an independent variable, since the industrial sector corresponds to the highest electricity consumption proportion for Turkey in the last decade as shown in Table 1 [59].

Table 1. Turkey's net electricity consumption shares per sector for the 2008-2017 period [59]

Year	Total (GWh)	Household (%)	Commercial (%)	Government (%)	Industrial (%)	Illumination (%)	Other (%)
2008	161,948	24.4	14.8	4.5	46.2	2.5	7.6
2009	156,894	25.0	15.9	4.5	44.9	2.5	7.2
2010	172,051	24.1	16.1	4.1	46.1	2.2	7.4
2011	186,100	23.8	16.4	3.9	47.3	2.1	6.5
2012	194,923	23.3	16.3	4.5	47.4	2.0	6.5
2013	198,045	22.7	18.9	4.1	47.1	1.9	5.3
2014	207,375	22.3	19.2	3.9	47.2	1.9	5.5
2015	217,312	22.0	19.1	3.7	47.6	1.9	5.7
2016	231,204	22.2	18.8	3.9	46.9	1.8	6.4
2017	249,023	21.8	19.8	4.1	46.8	1.8	5.7

According to Soytas and Sari [60] electricity is an indispensable element in the manufacturing industry of Turkey, and researchers found that a causality existed towards manufacturing value added from electricity consumption over the period 1968-2002 in Turkey. Sun and Anwar [61] asserted the presence of a causation towards industrial production from electricity consumption in Singapore over the period January 1983-February 2014. Herein, the IPI data of manufacturing drawn from the OECD with a base year of 2015 is utilized [62].

Drawing upon the min-max normalization technique, the input data is normalized into [0-1] range. The data set is split at random into three portions; seventy percent, fifteen percent, fifteen percent, and these portions are allocated for training, testing, and validation processes, respectively. In this study, a number of ANN models with different number of layers and neurons that use various combinations of different activation functions and training algorithms are developed and trialled. The MATLAB software is used for designing the ANN model.

The MLP type of architecture is chosen for the forecasting model in this study. Following the determination of the architecture of the neural network, an appropriate topology is explored with an aim of obtaining the best performance. The highest performance is achieved when hyperbolic tangent sigmoid and linear type activation functions are applied to the hidden layer and output layer, respectively. The LM, Bayesian regularization, and SCG algorithms are trialled for the training of the neural network. Neural network models containing one, two, or three hidden layers are established. A range of 2 to 20 neurons is trialled for these layers.

The performances of such models are compared by using coefficient of correlation (R) and mean squared error (MSE) measures. It's found that the performance of the neural network with the LM algorithm is better compared with other algorithms. According to the trial and error process results, the model containing one hidden layer with six neurons illustrated in Figure 2 exhibits the best performance, which is achieved at epoch 13 as shown in Figure 3. This model has the highest R values as illustrated in Figure 4. The MSE and R values of the selected model are presented in Table 2. The model is found to be appropriate for forecasting as it has very low MSE values and its R values are close to 1.

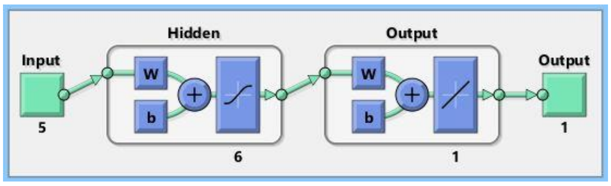

Figure 2. Schematic of the ANN model architecture

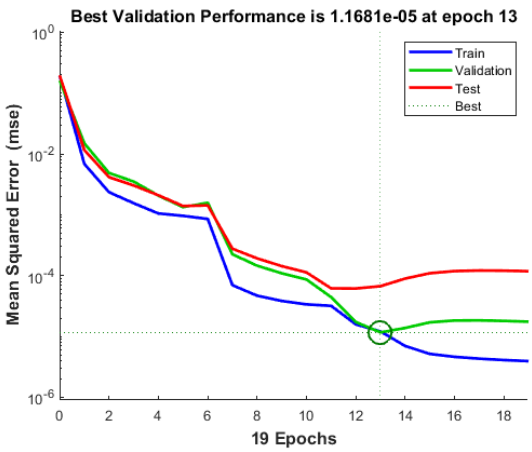

Figure 3. ANN model's performance graph

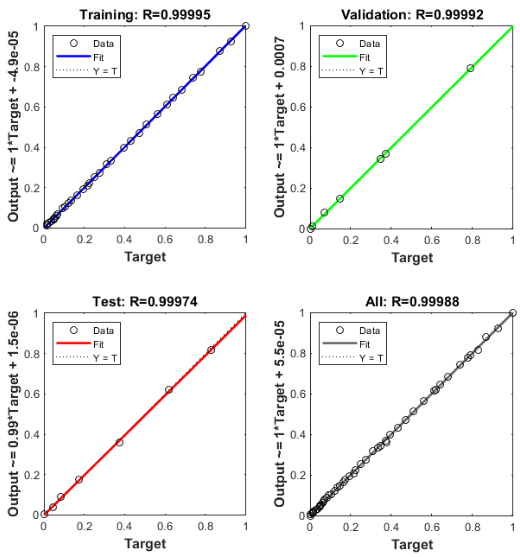

Figure 4. Regression graph of the ANN model

Table 2. MSE and R values for the selected ANN model

Process	MSE	R
Training	1.2123×10^{-5}	0.99995
Validation	1.1681×10^{-5}	0.99992
Testing	6.7173×10^{-5}	0.99974

The GPRM method is utilized for each of the independent variables to predict its values for the 2019-2030 period by using its values over the period of 1970-2018. Firstly, corresponding MAPE values for different time point values for each independent variable are examined through a trial and error process to ascertain the lowest MAPE value. Table 3 demonstrates obtained lowest MAPE values and their corresponding time points. Secondly, future values of each of the independent variables are predicted, taking into consideration its determined time point value.

Table 3. Lowest MAPE value and corresponding time point for each of the independent variables

Independent variables	MAPE (%)	Time point
Population	0.1585	4
GDP	5.3512	4
Imports	15.4458	10
Exports	11.6037	8
IPI	5.4004	13

Existing values of the independent variables for 2018 and predicted values of the independent variables obtained by using GPRM method for 2019-2030 are inserted in the ANN model. Therefore, the electricity demand from 2018 to 2030 are obtained as given in Table 4. Turkey's electricity demand for 2030 is found as ≈ 384,569 GWh according to the prediction with the proposed ANN model. Furthermore, considering the ratio of total consumption to supplied electrical energy for Turkey, an average ratio of ≈ 0.8543 is calculated depending on the values for the years 2005, 2010, 2015, and 2016 [63]. Therefore, the gross electricity production amount is found as ≈ 450,157 GWh.

Table 4. Predicted values for the independent variables and dependent variable

Year	Population	GDP (US dollars/capita)	Exports (Thousand US dollars)	Imports (Thousand US dollars)	IPI (manufacturing, 2015=100)	Electricity demand (GWh)
2018	82,003,882	28,454.63156	167,920,613.5	223,047,094.5	113.8667	246,976.5227
2019	83,089,837	29,705.7001	159,528,783.9	225,079,179.6	124.07793	294,756.6377
2020	84,272,020	30,326.72069	162,773,925.1	213,651,654.6	133.17336	322,618.8445
2021	85,415,036	31,408.08259	166,559,935.2	210,609,500	142.54037	348,814.561
2022	86,609,424	32,224.75568	173,378,760.7	207,157,508.1	150.36526	361,652.651
2023	87,795,160	33,260.8163	176,957,889	209,029,367	158.81464	372,618.682
2024	89,012,561	34,195.00806	177,796,571.2	212,386,939.1	168.66851	379,341.5827
2025	90,235,078	35,242.48153	180,376,538	209,485,406	178.91346	382,507.6448
2026	91,480,727	36,261.1341	186,152,918.9	202,153,375.6	189.96463	383,916.6158
2027	92,737,830	37,346.83994	189,852,842.1	201,445,596.8	201.82375	384,467.6527
2028	94,014,499	38,436.99634	193,254,394.1	199,748,847.6	214.60907	384,632.5831
2029	95,305,662	39,574.58548	196,350,668	199,715,857.5	227.77213	384,616.3791
2030	96,615,039	40,732.29511	200,325,853.8	198,287,227.5	242.28974	384,569.0158

4.2. Evaluation of Sustainability of Electricity Mix Scenarios for Turkey for 2030

This study focuses especially on the electricity mix sustainability and aims to determine the best option among four different scenarios comprising a similar sort of power generation technologies. As mentioned in Section 1, the recent power generation structure of Turkey as given by Table 5 and Table 6 is considered as a basis for developing these electricity mix scenarios [4,5].

Table 5. Shares of energy resources in gross electricity generation for Turkey, 2018 [4]

Resource	Electricity generation (GWh)	Contribution (%)
Imported coal	62,988.5	20.67
Hard coal+Asphaltite	5,173.1	1.70
Lignite	45,087.0	14.79
Natural gas	92,482.8	30.34
Liquid fuels	329.1	0.11
Dam	40,972.1	13.44
N. Lake and Run of River	18,966.4	6.22
Wind	19,949.2	6.54
Renewable+Waste+Waste Heat	3,622.9	1.19
Geothermal	7,431.0	2.44
Solar	7,799.8	2.56
Total	304,801.9	100.00

Table 6. Shares of energy resources in installed capacity for Turkey, 2018 [5]

Resource	Installed power (MW)	Contribution (%)
Imported coal	8,793.85	9.93
Hard coal+Asphaltite	782.50	0.88
Lignite	9456.09	10.68
Liquid fuels	370.60	0.42
Multi fuel fired	5,206.83	5.88
Waste heat	197.03	0.22
Natural gas	21,479.89	24.26
Renw. Waste+Waste	621.87	0.70
Wind	7,005.39	7.91
Solar	5,062.84	5.72
Dam	20,536.10	23.19
N. Lake and Run of River	7,755.29	8.76
Geothermal	1,282.52	1.45
Total	88,550.78	100

So far, there has been no NPP in the operational phase in Turkey, however, commissioning of three NPPs are planned for the period of 2023-2035 [6]. Basically two factors, amount of share in the electricity mix and availability of criteria data are considered in the selection process of existing power technologies from the recent electricity mix of Turkey. The power generation technologies which have relatively high shares are selected.

Both coal and lignite make up significant proportions of the recent electricity mix of Turkey. Criteria data is not sufficient for the lignite in the literature. For this reason, these two technologies are represented by the coal option. Hydropower plants can be classified according to construction type or installed capacity, and there's not a universally accepted classification in respect to size of the installed capacity [64]. Because of the missing data for some construction types, especially for the run of river type, and different definitions regarding their range of sizes, the hydropower option is included with no classification in the present study, such as in studies [24, 27, 36] except the dispatchable generation criterion. In the developed four scenarios (A) to (D); coal, natural gas, nuclear, hydropower, wind, and solar-PV technologies are included. These scenarios are presented in Table 7 and in Table 8 according to corresponding electricity generation shares and installed power shares, respectively.

social, technical, economic, and environmental dimensions. Ten different criteria relevant to these dimensions are selected, and the corresponding values of the selected criteria for each power generation technology are collected from the literature. The proportion of the installed capacity of each power generation technology for each scenario is also calculated to perform calculations with the values of criteria whose units are given in term of power. The environmental dimension includes the criteria CO_2-eq and NO_x emissions based on the life cycle assessment. CO_2-eq is a sort of measure to express Global Warming Potential [65] of different greenhouse gases at a common scale [66]. Therefore, this metric shows the effect of each power generation technology on the global warming in terms of CO_2-eq per generated electricity output. The values for the coal, natural gas, hydropower, and wind are taken from [28], which are calculated for Turkey. Average of the values given for small reservoir, large reservoir, and run of river types for the hydropower is used. For the coal, the average value of the coal and

Table 7. Electricity generation shares and amounts by technology according to scenarios

Power generation technology	Scenario-(A)		Scenario-(B)		Scenario-(C)		Scenario-(D)	
	Amount (MWh)	Contribution (%)	Amount (MWh)	Contribution (%)	Amount (MWh)	Contribution (%)	Amount (MWh)	Contribution (%)
Coal	157,554,950	35	180,062,800	40	135,047,100	30	130,545,530	29
Natural gas	135,047,100	30	162,056,520	36	108,037,680	24	90,031,400	20
Nuclear	40,514,130	9	40,514,130	9	121,542,390	27	40,514,130	9
Hydropower	81,028,260	18	45,015,700	10	54,018,840	12	99,034,540	22
Wind	27,009,420	6	18,006,280	4	22,507,850	5	54,018,840	12
Solar-PV	9,003,140	2	4,501,570	1	9,003,140	2	36,012,560	8
Fossil fuels Total	292,602,050	65	342,119,320	76	243,084,780	54	220,576,930	49
Nuclear Total	40,514,130	9	40,514,130	9	121,542,390	27	40,514,130	9
Renewables Total	117,040,820	26	67,523,550	15	85,529,830	19	189,065,940	42
General Total	450,157,000	100	450,157,000	100	450,157,000	100	450,157,000	100

Table 8. Installed power shares and amounts by technology according to scenarios

Power generation technology	Scenario-(A)		Scenario-(B)		Scenario-(C)		Scenario-(D)	
	Amount (MW)	Contribution (%)	Amount (MW)	Contribution (%)	Amount (MW)	Contribution (%)	Amount (MW)	Contribution (%)
Coal	34,561	28	39,499	36	29,624	27	28,637	18
Natural gas	29,624	24	35,549	32	23,699	21	19,749	12
Nuclear	5,744	5	5,744	5	17,231	16	5,744	4
Hydropower	30,751	25	17,084	16	20,500	18	37,584	24
Wind	10,676	9	7,117	6	8,897	8	21,352	14
Solar-PV	10,969	9	5,484	5	10,969	10	43,874	28
Fossil fuels Total	64,185	52	75,048	68	53,323	48	48,386	30
Nuclear Total	5,744	5	5,744	5	17,231	16	5,744	4
Renewables Total	52,396	43	29,685	27	40,366	36	102,810	66
General Total	122,325	100	110,477	100	110,920	100	156,940	100

Scenario-(A) is similar to the recent electricity mix of Turkey in terms of proportions of the power generation technologies in the electricity generation, in addition it includes the NPP option. Considering power generation; fossil fuels, nuclear, and renewables have comparatively higher shares in the electricity mix for the Scenario-(B), Scenario-(C), and Scenario-(D), respectively. Sustainability evaluation is undertaken considering the

lignite is used. The values for the natural gas and wind are directly used. For the nuclear and solar-PV; criteria values are obtained from the review study of Turconi, Boldrin and Astrup [67], and average of the maximum value and minimum value is used for each technology. The NO_x denotes NO_2 and NO that affect environment through several ways such as the acid precipitation and air pollution, and the NO_x might entail detrimental effects on the human health [68]. The NO_x emission values are found by calculating the average of maximum values and minimum values given in [67] for natural gas, nuclear, hydropower, wind, and solar; and in order to find the value for coal, the average of average value of coal and average value of lignite are used.

The economic dimension comprises three criteria. The first one is the capital cost. This study uses the recent values for the EU region for solar-PV, wind, nuclear, natural gas, and coal gathered from 2018 IEA World Energy Model input data [69]. The values are directly used except wind. The average value of onshore wind value and offshore wind value is used for the wind. As this set doesn't have the hydropower, the average of the mean values of the small and large hydropower is calculated for the capital cost criterion, based on the values obtained from [70], which are basically global cost values. The mentioned approaches are utilized for the second criterion; fuel, and operation and maintenance (O&M) as well. The O&M cost for the hydropower is between 1-4%, and it is assumed to be 2.5% [71] for this study, and the fuel cost is not included for hydropower as in [28]. The values for the third criterion; lifetimes of power generation technologies are obtained from [70].

The criteria chosen for the technical dimension are efficiency, capacity factor, and dispatchable generation. Considering the ranges provided for the efficiencies regarding solar-PV, wind, natural gas, and coal in [72], average values are used for these technologies; the efficiency is given to be greater than 90% for hydropower, and it's assumed to be equal to this value in the present study. The efficiency value for the nuclear is obtained from [73]. The capacity factor values are gathered from [63]; this factor is expressed as gross annual electricity output to the net capacity times 8760 ratio for a power plant. The average values are found using the data for 2005, 2010, 2014, 2015, and 2016 for natural gas, coal, hydro, and wind. Data exists only for three years as 2014, 2015, and 2016 for solar-PV, and the average value is calculated using these values. A common capacity factor category is provided for combustible fuels in the data set. Therefore, the capacity factors of both natural gas and coal are deemed as equal to the values in this category for each corresponding year. The data provided for Turkey is used for the mentioned technologies. The capacity factor for the NPP is found by calculating the average of the values for 2005, 2010, 2014, 2015, and 2016 given for OECD Europe. Dispatchibility refers to the capacity of a power plant to be switched on and off whatever time it's required; coal, natural gas, NPPs, and dam-type hydropower plants can be classified as dispatchable [74]. In line with the approach in [32, 74, 75], the dispatchable generation values are found by calculating the share of mentioned dispatchable power generation technologies in the electricity mix for each scenario in terms of installed capacity. A certain percentage of hydropower share is assumed to be dam-type hydropower technology for each scenario. The value of the certain percentage is found by calculating the recent percentage of total installed capacity of dam-type hydropower plants in total installed capacity of hydropower plants in Turkey [5].

Two different social criteria are chosen in this study; direct employment and land use. The criteria values for the direct employment are obtained from [76] which considers the construction, installation, manufacturing, O&M, decommissioning, and fuel procurement phases for the power plants based on a global analysis. The mean values are used for the natural gas, nuclear, and solar-PV. The average of mean values of coal and lignite, of onshore wind and offshore wind, and of large hydro and mini hydro are used for the coal, wind, and hydropower, respectively. The required land area for a power plant can be classified into the social dimension [77], and the values for all power generation technologies in the present study are gathered from [73] that considers land area as a social criterion. The criteria values are provided in Table 9.

Table 9. Criteria values for the evaluation with TOPSIS [5, 28, 63, 67, 69, 70, 71, 72, 73, 76]

Power generation technology	Environmental		Economic			Technical			Social	
	CO_2-eq (g/kWh)	NO_x (kg/MWh)	Capital cost ($/kW)	Fuel, and O&M ($/MWh)	Lifetime (year)	Efficiency (%)	Capacity factor (%)	Dispatchable generation (%) (Calculated on the scenario basis)	Direct employment (job-year/GWh)	Land use (km^2/kW)
Coal	1,094	1.525	2,000	45	40	38.5	52.04		0.6985	0.4
Natural gas	499	2	1,000	55	30	49	52.04	Scenario-(A) ≈ 75.52	0.3691	0.04
Nuclear	19	0.025	6,600	35	60	33	80.52	Scenario-(B) ≈ 84.42	0.2693	0.01
Hydropower	5.53	0.032	4,309.5	107.74	80	90	30.08	Scenario-(C) ≈ 77.1	0.5445	0.13
Wind	7.3	0.065	3,040	27.5	25	39	28.88	Scenario-(D) ≈ 51.97	0.611	0.79
Solar-PV	101.5	0.275	1,300	20	25	13	9.37		1.1277	0.12

The Scenario-(C) achieved the highest score among four scenarios according to the evaluation with the TOPSIS. The determined shares of the Scenario-(C) is checked according to the renewable energy resource potential of Turkey. Turkey has a resource potential of 160 TWh/year, 48,000 MW, and 1,500 kWh/m^2-year for hydropower, wind, and solar, respectively [78]. The share of hydropower ≈ 54 TWh/year is below the upper limit. The share of the wind power ≈ 8897 MW is also below the upper limit. Required area for the solar-PV is ≈ 46.17 km^2 with an efficiency value equal to 0.13, and considering the resource potential, it's assumed to be appropriate.

Four different situations are explored in the scope of the sensitivity analysis. In each of them, the weight of a different criteria category; environmental, economic, technical, and social, is adjusted to a value of 0.7, and equivalent weights, a value of 0.1 is assigned to each of the other categories. The main weight set and weight sets used in the sensitivity analysis are given in Table 10. Table 11 provides sustainability evaluation results of the electricity mix scenarios with TOPSIS for each of the weight sets.

In this study, according to the comparison of the selected option Scenario-(C) with the Scenario-(A) given in the Table 7, which is similar to the recent electricity mix of Turkey, the coal and the natural gas shares are 5% and 6% less, respectively. Therefore, considering the rankings of both technologies in the studies in the literature given in Table 12, the decreased values in Scenario-(C) can be assumed as reasonable. The nuclear option is 18% more in the Scenario-(C) compared with the Scenario-(A). The increased proportion of the nuclear in the electricity mix is an appropriate approach as the nuclear option is favourable regarding the studies in the literature given in Table 12. Comparing the Scenario-(C) with the Scenario-(A), the percentages of hydropower and wind are 6% and 1% less, respectively. The percentage of the Solar-PV doesn't change. These values are not similar to the results of the studies in the literature given in Table 12, as the hydropower and wind are the favourable options in them. The solar can't be evaluated as a favourable option regarding the studies in the literature given in Table 12. Though the percentage of the Solar-PV in Scenario-(C) is same with the Scenario-(A), the percentage of it is 2%, which is the lowest value in the electricity mix. In this respect, this value could be assumed as in line with the results of the mentioned studies.

Table 10. Main weight set and weight sets for the sensitivity analysis

Categories	Weight set-(1)	Weight set-(2)	Weight set-(3)	Weight set-(4)	Weight set-(5)
Environmental	0.25	0.7	0.1	0.1	0.1
Economic	0.25	0.1	0.7	0.1	0.1
Technical	0.25	0.1	0.1	0.7	0.1
Social	0.25	0.1	0.1	0.1	0.7

Table 11. Closeness coefficient values and rankings of scenarios according to weight sets

Electricity mix scenarios	Weight set-(1)		Weight set-(2)		Weight set-(3)		Weight set-(4)		Weight set-(5)	
	C_{i*}	Ranking	C_{i*}	Ranking	C_{i*}	Ranking	C_{i*}	Ranking	C_{i*}	Ranking
Scenario-(A)	0.4886	3	0.4241	3	0.4888	3	0.6431	3	0.4796	3
Scenario-(B)	0.3907	4	0.0871	4	0.6027	1	0.7428	1	0.4561	4
Scenario-(C)	0.6793	1	0.8347	2	0.446	4	0.7395	2	0.4909	2
Scenario-(D)	0.614	2	0.9121	1	0.5772	2	0.237	4	0.5475	1

4.3. Comparison of the Proposed Approach with the Existing Studies

The existing studies in the literature mostly focused on ranking the electricity generation technologies individually. The hydropower ranks first in three studies, and second and fifth in the other two studies according to the comparison of studies given in Table 12. The wind ranks first in one study, second in three studies, and fourth in one study. The nuclear exists in three studies, and it ranks first, third, and fourth in these studies. The natural gas is evaluated in four studies, and it ranks second in one study, third in two studies, and fourth in one study. The coal option exists in four studies, and it ranks fourth, fifth, sixth, and again sixth in them. The solar option is evaluated in three studies, and it ranks third, fifth, and ninth in these studies. These results show that the renewable energies, hydropower and then wind are the most favourable energy generation technologies, except solar. The nuclear option follows the hydropower and wind. The fossil fuels; coal, lignite, and the natural gas come after the nuclear option. Though, evaluating the electricity generation technologies individually is useful for discovering the most appropriate technology, this approach is not informative about the share of a specific technology in the electricity mix.

Table 12. Comparison of the proposed approach with the existing studies from literature

Technology	Boran, Boran and Dizdar [23]	Boran [25]	Boran [26]	Atmaca and Basar [27]	Kuleli Pak, Albayrak and Erensal [29]	Proposed approach, Scenario-(C)
Coal	5 (fossil fuels)	4 (fossil fuels)	N/A	6 (coal/lignite)	6 (coal/lignite)	Electricity generation shares (Coal= 30%, Natural gas= 24%, Nuclear= 27%, Hydropower= 12%, Wind= 5%, Solar-PV= 2%)
Natural gas	4	3	N/A	2	3	
Nuclear	3	N/A	N/A	1	4	
Hydropower	1	1	2	5	1	
Wind	2	2	1	4	2	
Solar	5	N/A	3	N/A	9	
Geothermal	N/A	5	4	3	8	
Biomass	N/A	N/A	5	N/A	5	
Oil	N/A	N/A	N/A	N/A	7	

5. CONCLUSIONS

The following conclusions are drawn according to the findings of the study. The performance results of the proposed MLP ANN model, which are given in the Table

2, show that the model could accurately predict the electricity demand of Turkey in the long-term. Nevertheless, prediction set of each of the independent variable is required for the model, and particularly the economic factors have uncertainties in the long-term. According to the prediction performance results of the GPRM model, the MAPE values are less than 10% for population, GDP, and IPI, and the MAPE values are between 10-20% for the imports and exports. The MAPE value could be considered as highly accurate when it's less than 10%, and it could be interpreted as good in the range of 10-20% [79]. It can be concluded that the prediction sets are appropriate for using in the ANN model regarding the overall performance of the GPRM model. Ergo, it's shown that the GPRM is a practical approach to cope with the considerable uncertainty pertaining to the economic factors.

The sustainability evaluation of the electricity mix scenarios with the TOPSIS reveals that the Scenario-(C) is the most sustainable scenario followed by the Scenario-(D) that ranked second, and Scenario-(A) and Scenario-(B) as third and fourth, respectively, as shown in Table 11. Nonetheless, when a weight with relatively high importance is assigned to the environmental, economic, technical, and social categories as given in Table 10; the Scenario-(D), Scenario-(B), Scenario-(B), and Scenario-(D) become the first-ranked scenarios, respectively, as seen in Table 11. This finding indicates that changing the importance of weights may change the ranking of the scenarios dramatically.

More practical electricity generation shares could be set in the development of the electricity mix scenarios owing to the prediction of electricity demand because the comparison of the shares of renewable electricity generation technologies in a scenario with potential limits of the renewable energy sources and consideration of the recent power generation structure of Turkey are ensured.

Future studies could explore different methods, or their combinations for forecasting the electricity demand in the long-term. Besides, appropriateness of various MCDM methods could be explored to evaluate the sustainability of electricity mix in the long-term for a different year.

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Kurtuluş DEĞER: Application of methods, collection of data, analyses of results, writing of manuscript.

M. Galip ÖZKAYA: Review and editing of manuscript.

F. Emre BORAN: Review and editing of manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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