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Research Article

Assessment of future renewable energy use and CO_2 emissions of Türkiye and other countries in terms of climate targets of international agreements: An estimate with anfis

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ABSTRACT

Global climate change is largely driven by increasing fossil fuel use and related emissions. The largest contributors include the United States, China, the European Union, and India, which together account for a significant share of global emissions. International agreements such as the Kyoto Protocol (2009) and the Paris Climate Agreement (2016) aim to reduce emissions and promote renewable energy use; however, they impose similar targets on countries with different energy structures and development levels. this study examines changes in renewable energy shares and co_2 emissions (ce) for selected countries and regions. using three input variables and one output variable commonly adopted in the literature, projections for the 2025–2030 period are obtained with the adaptive network-based fuzzy inference system (ANFIS). The results indicate that Türkiye increases its renewable electricity share from 35% in 2021 to 50% in 2030, while reducing emissions from 12% to 6%. Similar but less pronounced trends are observed in the European Union and the United States. In contrast, India shows an increase in emissions with limited improvement in renewable energy use, whereas China exhibits moderate growth in both indicators. Overall, the findings suggest that while some regions align with international targets, others remain misaligned. Accordingly, defining country-specific targets based on emission levels and renewable energy capacity may lead to more effective and realistic policy outcomes.

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INTRODUCTION

With rapid industrial and technological growth in the early 21st century, global emissions and temperatures have increased significantly. Fossil sources (FS) remain the primary source of these emissions. For this reason, renewable energy sources are increasingly promoted as alternatives due to their lower environmental impact.

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Figure 1 presents the distribution of electricity generation by source across different countries and regions [1]. When nuclear energy is included, the global average renewable share in electricity is approximately 37%, while the direct renewable share is around 31%. In comparison, Türkiye exceeds both averages, with a direct renewable share of about 42%. Over the past decade, this level has been supported by significant investments in hydroelectric (HPP), solar (SPP), and wind (WPP) power plants, which have contributed to the increase in renewable electricity generation [2].

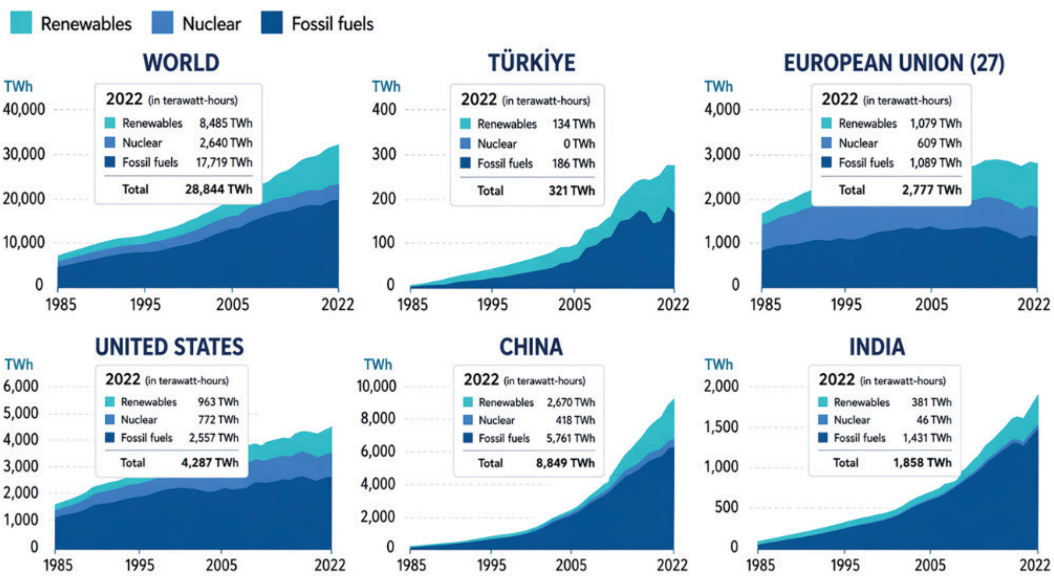
The European Union also remains above the global average, with a combined renewable and nuclear share of approximately 61% and a direct renewable share of 39%. This reflects long-term energy policies that have reduced fossil fuel use while maintaining nuclear energy at a relatively stable level [3]. In the United States, the combined share is about 40%, which is above the global average; however, the direct renewable share remains lower, at around 22%. Although fossil fuel use has slightly declined over the past 15 years, nuclear energy levels have remained stable, and domestic fossil resources such as natural gas and oil continue to limit the expansion of renewable energy. As a result, the expected reduction in CE has not been fully achieved [4].

China also remains below the global average, with a combined share of approximately 35% and a direct renewable share of around 30%. Despite considerable progress in renewable energy development, the strong dependence on coal continues to restrict this transition, leading to increasing emission levels [5]. A similar situation is observed in India, which presents the weakest performance among the countries considered. India has a combined share of approximately 23% and a direct renewable share of about 21%, both below global averages. Although the country aims to generate 30% of its electricity from solar energy by 2040 under the "Hybrid Energy" policy, fossil fuel dependence continues to constrain the growth of renewable energy, similar to the situation in China and the United States [6,7].

International organizations such as the International Energy Agency (IEA) and global agreements, including the Kyoto Protocol (2009) [8] and the Paris Climate Agreement [9], call for increasing renewable energy use and reducing emissions to mitigate temperature rise. However, these frameworks impose similar obligations on countries despite significant differences in fossil fuel use and renewable energy growth rates [10]. Therefore, aligning targets with country-specific energy capacities may lead to more realistic outcomes.

As renewable energy replaces fossil fuels in electricity generation, CO_2 emission levels are expected to decline. To examine this relationship, emission trends for different countries and regions are presented in Figure 2 [7].

In this study, the effects of the above-mentioned protocols on countries and regions and the deficiencies of the protocol texts according to this effect are discussed. For this review, the RES usage rate in electricity generation and the CE increase status of countries and regions are estimated. First of all, inputs and outputs suitable for this study is selected from the literature. Then, data on these parameters are collected for Türkiye, the EU Region, the USA, China and India between 1971-2022. Since renewable electricity production (REP) vary across the specified countries and regions, comparisons are made using REP shares (%) rather than absolute REP amounts (GWh/



*TWh: Terawatt-hours

Figure 1. Electricity generation capacities by sources / countries and regions.

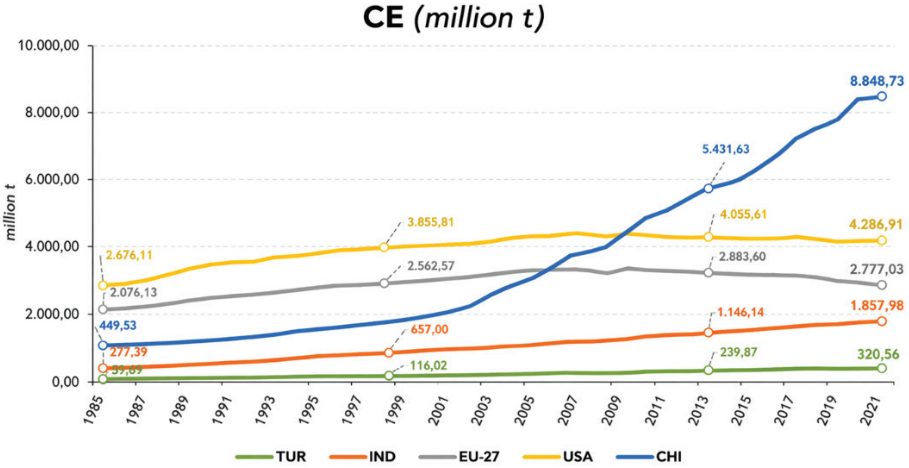


Figure 2. CE by country and region (Mt) / (1971-2022).

TWh). To compute these shares, the total electricity production (TEP) of each country/region must be determined. For forecasting future REP amounts (GWh/TWh), the input variables are Gross Domestic Product (GDP), Population (POP), and Carbon Emissions (CE), and the output variable is the REP amount. Using these three inputs and one output, the values for 2025–2030 are estimated with Adaptive Network-Based Fuzzy Inference System (ANFIS) via MATLAB's Fuzzy Logic Toolbox. For TEP, a simpler ANFIS-based autoregressive approach is used: instead of three inputs, past TEP values, TEP(t), are employed to predict TEP(t+1) using the same fuzzy inference framework implemented in MATLAB's Fuzzy Logic Toolbox. Similar to the REP process, future CE levels were also estimated with ANFIS. The inputs here are GDP, POP, and CE (t). Data between 1971-2022 were processed in MATLAB. CE (t+1) was considered as the output. Similar to the first process, the emissions for 2025-30 were estimated with ANFIS. The important thing in the estimation process is the rate at which the inputs affect the output separately. This effect is understood in the rule base produced at the end of the estimation. If the input data conflict with the output data, then the rule base structure naturally exhibits irregular geometric patterns. On the other hand, a flatter ground will be obtained if there is compatibility. Many studies have been examined while selecting the inputs considered from the literature. The aim is to examine the compliance of countries and regions with the conditions specified in [8,9] and the main target of 1.5^{0}C surface temperature in [9]. As a result, it turns out that some of the countries and regions examined cannot achieve the desired CE reduction or REP increase rate for this target. Energy usage rates vary greatly from country to country. Therefore, it is important that these protocols specify conditions proportional to the usage capacities of the country.

The following section includes the literature review necessary to examine forecasting methods and determine inputs and outputs.

LITERATUR REVIEW

In this section, studies on predicting the energy source level, CE level, and electricity consumption level that will be replaced in the future are examined. Similar estimation methods and input-output parameters are used in these subjects, guiding this study. In addition, one of the main elements sought in the studies examined is that the method is ANFIS or Artificial Neural Network (ANN). Rodrigues et al. [11], in their study published in 2009, used 37 years between 1970 and 2006 as training and test data and made predictions for 2007 with ANFIS. In their studies, POP, GDP, and CE were used as inputs and CE estimates were made for Brazil. Appiah et al. [12] used ANN in their study published in 2018 and made a 2013 CE estimate for China. In the study, the 40 years between 1973 and 2013 for POP, GDP, IE, CE, and EC data were used, and 2014 was estimated. Şekerci and Kara [10], in their study published in 2024, POP, GDP, EC inputs, and CE output were used within ANFIS. Fifty-two years between 1971 and 2022 were used, and 2030 was estimated. In their study published in 2019, Güleryüz [13] made a 2020 industrial EC estimate for Türkiye using data collected between 1990-2019 and GDP, CE, EC and general energy expenditures in industry as inputs. Nassef et al. [14] used the CE data of Saudi Arabia between 1954-2020 as input in their study published in 2023. They estimated the CE data between 2020-30 with ANFIS, FFNN, and LSTM methods. As a result, they found that the CE level decreased by more than 30%. Arevalo et al. [15] in their study published in 2024, estimated the 2050 EC values using Ecuador's POP, TEM, and EC values from previous years. Then, with the EnergyPlan method, they made a plan that meets the electricity completely from RES in 2050. Table 1 and Table 2 show the literature review.

Table 1. Literatur review

Writer(s)	Years	Application*	Method**	Forecasting Year
Rodrigues vd. [11]	2009	Brazil CEE	ANFIS	2007
Özdemir [16]	2011	Türkiye CEE	ANN	2025
Yılmaz and Yılmaz [17]	2013	Türkiye CEE	GP	2020
Baareh [18]	2013	CEE	ANN	2011
Appiah vd. [12]	2018	China CEE	ANN	2014
Güleryüz [13]	2019	Türkiye EC-F	ANFIS & PSO & MLR	2020
Khan and Khan [19]	2019	Pakistan CEE	ANFIS & ANN	2013
Jusoh et al. [20]	2021	Indonesia EC-F	ANFIS	2028
Jena et al. [21]	2021	17 Countries CEE	ANN	2019
Lazım and Pauzi [22]	2021	CEE	ANFIS	2014
Nugraha et al. [23]	2021	Indonesia RES-F	ANFIS	2027
Şekerci [24]	2022	Türkiye CEE	ANFIS	2022
Mutascu [25]	2022	USA CEE	ANN	2022
Ginting et al. [26]	2023	Indonesia RES-F	ANFIS	2023
Nassef et al. [14]	2023	Saudi Arabia CEE	ANFIS & FFNN & LSTM	2030
Behgouy and Uğurenver [27]	2024	USA EC-F	LSTM & NAR	2023
Şekerci and Kara [10]	2024	Türkiye CEE	ANFIS	2030
Arevalo et al. [15]	2024	Ecuador EC-F & RES-F	ANFIS & EnergyPlan	2050

*CEE: CO_2 Emission Estimation, RES-F: RES Level Forecasting, EC-F: Electricity Consumption Forecasting.

**PSO: Partical Swarm Optimization, MLR: Multiple Linear Regression, FFNN: Feed-Forward Neural Network, LSTM: Long Short-Term Memory, GP: Grey Prediction, NAR: Nonlinear Autoregressive.

Table 2. Input and output use in literature

Writer(s)	Inputs*						Output**	
	POP	GDP	IE	TEM	CE	EC	CE	EC
Rodrigues vd. [11]	√	√			√		√	
Özdemir [16]		√	√			√	√	
Yılmaz and Yılmaz					√		√	
Baareh [18]					√	√	√	
Appiah vd. [12]	√	√	√			√	√	
Güleryüz [13]		√	√		√		√	
Khan and Khan [19]				√		√	√	
Jusoh et al. [20]	√	√						√
Jena et al. [21]	√	√	√				√	
Lazım and Pauzi [22]	√	√				√	√	
Nugraha et al. [23]	√	√				√		√
Şekerci [24]	√	√		√		√	√	
Mutascu [25]		√	√			√	√	
Ginting et al. [26]	√	√				√		√
Nassef et al. [14]					√		√	
Behgouy and Uğurenver [27]						√		√
Şekerci and Kara [10]	√	√				√	√	
Arevalo et al. [15]	√			√				√
TOPLAM	***10***	***12***	***5***	***3***	***5***	***11***	***13***	***5***

*POP: Population, GDP: Gross Domestic Product, IE: Import-export, TEM: Temperature, **EC: Energy Consumption

As presented from the literature review above, the most frequently used inputs are POP, and GDP. It can be stated that among these outputs, there is a strong positive correlation between CE, the mentioned output, and the two input variables. In countries with a high level of industrial capacity, as the POP and GDP indicators increase, development accelerates, which in turn promotes industrial growth and raises existing emission levels. In addition to this strong correlation, CE(t+1) is selected as the output variable to examine the emission obligations of the specified countries and regions. The third input variable used to predict future CE values is the historical emission data, CE(t).

In this study, the output variable REP is considered instead of the EC output specified in Table 2. The reason for this is to examine the clean energy transition obligations of the selected countries and regions. EC, on the other hand, refers to total electricity generation, including fossil-based sources. The input variables used for this output are POP, GDP, and CE.

Thus, both this inputs and outputs have gained a real basis from the literature. The next section describes the methodology of the study and its application.

METHODOLOGY

In this section, the methodology is examined in two parts. First, the study methodology is explained using a flow chart. Second, the application methodology is explained using mathematical equations.

Methodology of the Study

The study's methodological flow clearly demonstrates how the protocols operate; accordingly, Figure 3 illustrates this framework.

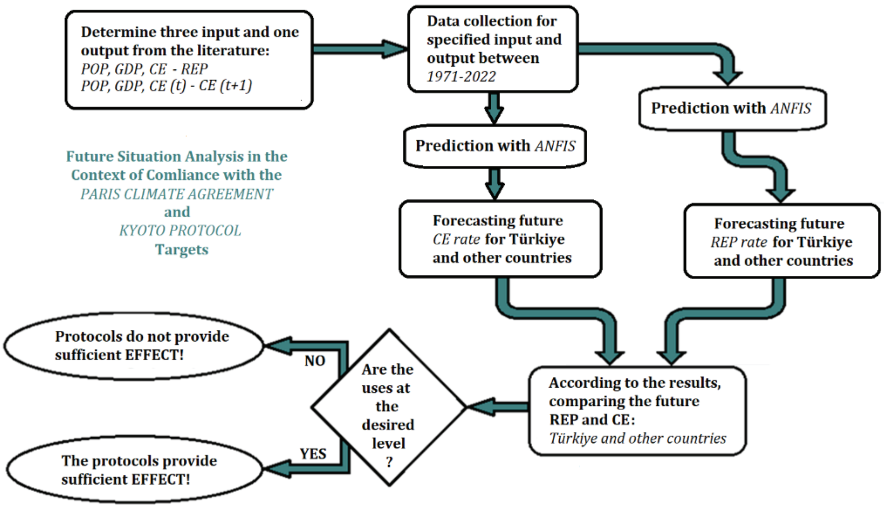


Figure 3. Flow chart of the study.

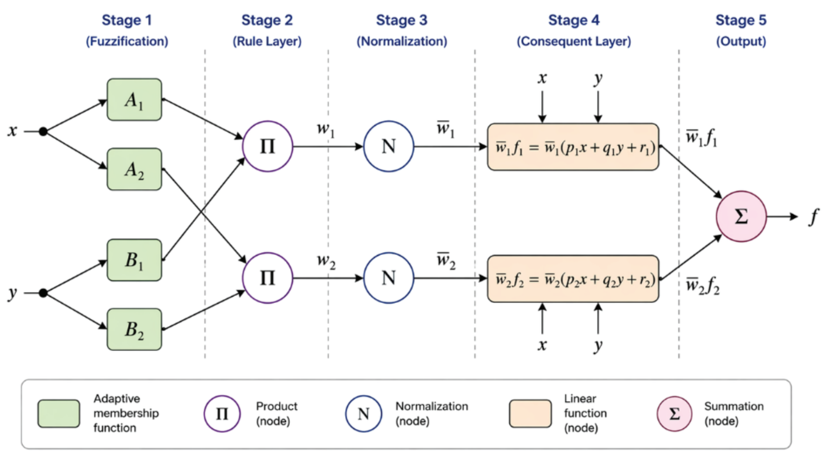


Figure 4. Fuzzy-ANN model of ANFIS method.

The methodological flow of the study is given above. Figure 3 shows how forecast values differ from current values and how countries compare. According to this comparison, the impact of the protocols is examined.

The application methodology used in the study is discussed in the next section.

Application Methodology

The application of this study is the ANFIS method. Therefore, the mathematical methodology of ANFIS is explained in this section [11, 13].

The mathematical model of ANFIS methodology is explained below. [23]:

Layer 1: Degrees of membership of specified inputs are explained [26]:

$$o_i^1 = \mu_{A_i}(x), i = 1, 2, \ldots \tag{1}$$

Membership degrees can be triangular, trapezoidal or Gaussian. Equation-2 shows the graphical bell curve of membership functions (b: number of rules, a: number of inputs, n: number of membership functions):

$$\mu_{A_i}(x) = \frac{1}{1+[(\frac{x-c_i}{a_i})^2]^{b_i}} \tag{2}$$

$$b = n^a \tag{3}$$

Layer 2: The inputs specified in the first layer are blurred and form rules with each other:

$$o_i^2 = \omega_i = \mu_{A_i}(x) * \mu_{B_i}(x), i = 1, 2, \ldots \tag{4}$$

Layer 3: "ω_i" values are normalized.

$$o_i^3 = \overline{\omega}_i = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i}, i = 1, 2, \ldots \tag{5}$$

Layer 4: Rules normalized in the previous layer are subjected to output functions [20].

$$o_i^4 = \overline{\omega}_i f_i = \overline{\omega}_i (p_i x + q_i y + r_i) \tag{6}$$

$\overline{\omega}_i$: Layer 3 output, normalized values

p_i, q_i, r_i : Result parameters - calculated by least squares method

Layer 5: The total contribution of the outputs is calculated [13]:

$$o_i^5 = \sum \overline{\omega}_i f_i \tag{7}$$

The mathematical method of ANFIS is explained with the above equations. The methods used in the forward-feedback feed of the ANFIS structure are shown in Table 3 [10].

METHODOLOGY

This study examines how the requirements of the protocols [8] and [9] affect different countries and regions. These frameworks impose similar obligations on all member states, despite differences in CE levels and renewable electricity production (REP). For this reason, evaluating countries based on proportional indicators, such as the shares of REP and CE, may provide a more meaningful comparison than using absolute values.

To support this approach, changes in REP and CE rates are analyzed for both current and future periods. The application is based on separate estimations of REP and CE using the ANFIS method. The results are then evaluated, and their implications for countries and regions, as well as the effectiveness of the protocols, are discussed in the conclusion section.

Renewable Electricity Production Estimation

As seen in the methodology in Figure 3, three inputs and one output selected from the literature were used in the ANFIS structure. Data from Türkiye, the USA, China, India, and the EU Region were used for inputs and outputs. Applications have been made with ANFIS for all the countries and regions mentioned. However, in this study, only data and application processes for Türkiye are included as a sample study. Within this framework, information about the data is given under subheadings.

It should be noted that, alongside REP, total electricity generation for 2025–2030 was also estimated. Here, a more straightforward method was chosen, electricity generation historical data in ANFIS was considered, and estimation was made with a single input and a single output. Then, REP was estimated with three inputs and one output. Thus, the REP could be determined thanks to the ratio of the two outputs to each other.

Renewable Electricity Production Estimation Data

ANFIS application inputs are considered POP, GDP, and CE, and output is REP. Figure 5 shows POP data from 1971 to 2022 [28].

Table 3. ANFIS methods in feed forward and feedback

	Forward Path	Reverse Path
Antecedent Parameters	Constant	Gradient Descent
Consequent Parameters	Least Squares Estimator	Fixed
Output	Node Outputs	Error Outputs

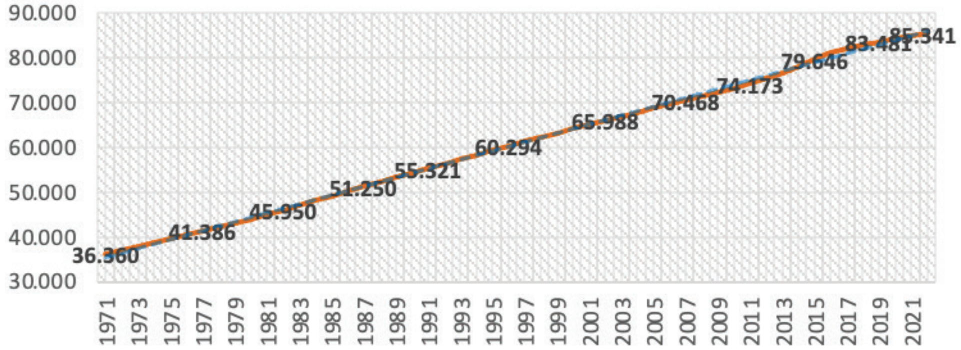


Figure 5. Türkiye POP (1971-2022) (x1000 person).

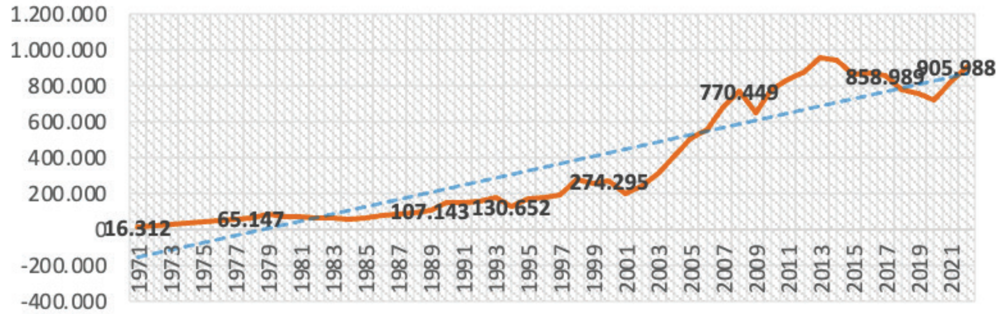


Figure 6. Türkiye / GDP (million $) / (1971-2022).

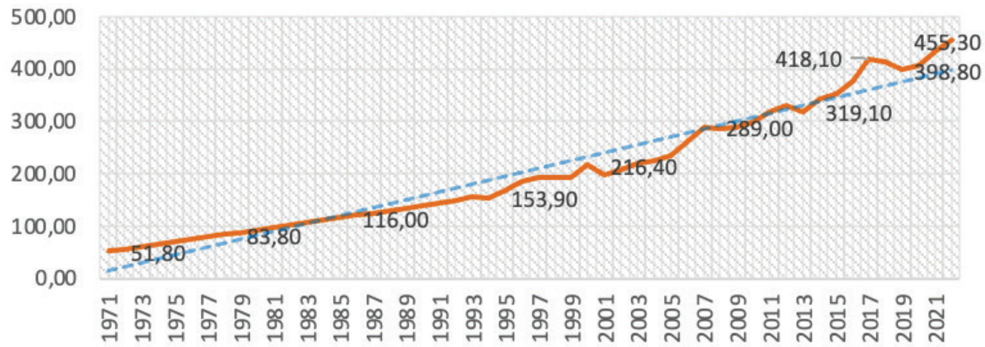


Figure 7. Türkiye / CE (Mt) / (1971-2022).

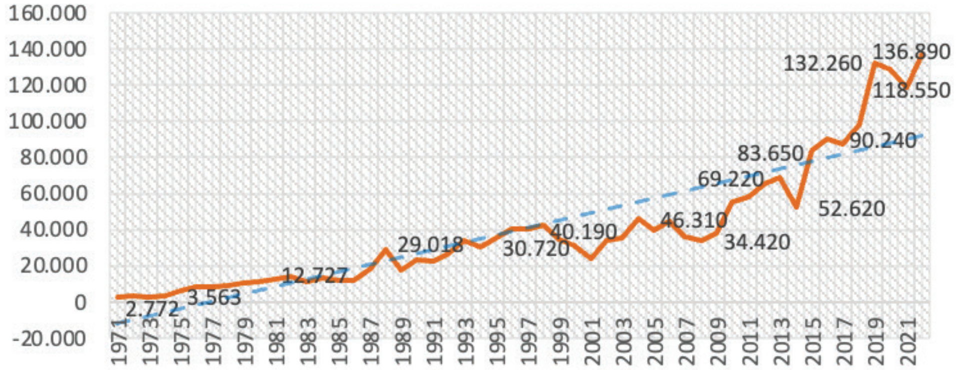


Figure 8. Türkiye / REP (TWh) / (1971-2022).

Figure 6 shows GDP data from 1971-2022 [28] [created by author]

Figure 7 shows CE data from 1971-2022 [28] [created by author]

Figure 8 shows REP between 1971-2022 [1] [created by author]

Using the above input and output data, prediction is made in the next section.

Renewable Electricity Production Estimation Application

Following the approach in previous studies [13], 70% of the dataset was used for training, while the remaining 30% served as test data. Sugeno fuzzy logic base was used in the Fuzzy Logic Toolbox package program of the MATLAB program. In order to obtain a more efficient result from the data, the data was loaded into the interface by mixing it, not according to the increase or decrease rate. As shown in Figure 9, the training and test datasets align well with the output data, indicating consistent performance.

Afterward, the data was epoched 300 times to determine the lowest error in different membership types. Table 4 shows the membership type with the lowest error. The membership type with the lowest error at the end of 300 epochs was determined as "gbellmf" and its membership subset was "4-4-4". Table 4 shows the membership type with the lowest errors.

The error mentioned in Table 4 is the Root Mean Squared Error (RMSE). The reason is that the above graphic data (except POP) deviates too much from the mean after a certain year and contains large values. Since using standard MSE in this example would artificially inflate the error value [29], ANFIS employs RMSE, which is the square root of MSE. More meaningful error values are reached with the square root operation, and a selection is made among these values according to the degree of closeness to "0". Accordingly, both training and test data were subjected to RMSE examination at 300 cycles. Figure 10 shows this process in ANFIS.

Iterations continue until the RMSE value stabilizes; once it does, the compatibility between the datasets is carefully evaluated. The scale used to examine this compatibility is R^2 and correlation. According to the R^2 scale (ranging from 0 to 1), a higher value reflects greater accuracy [29]; therefore, Figure 11 presents each dataset separately. It should

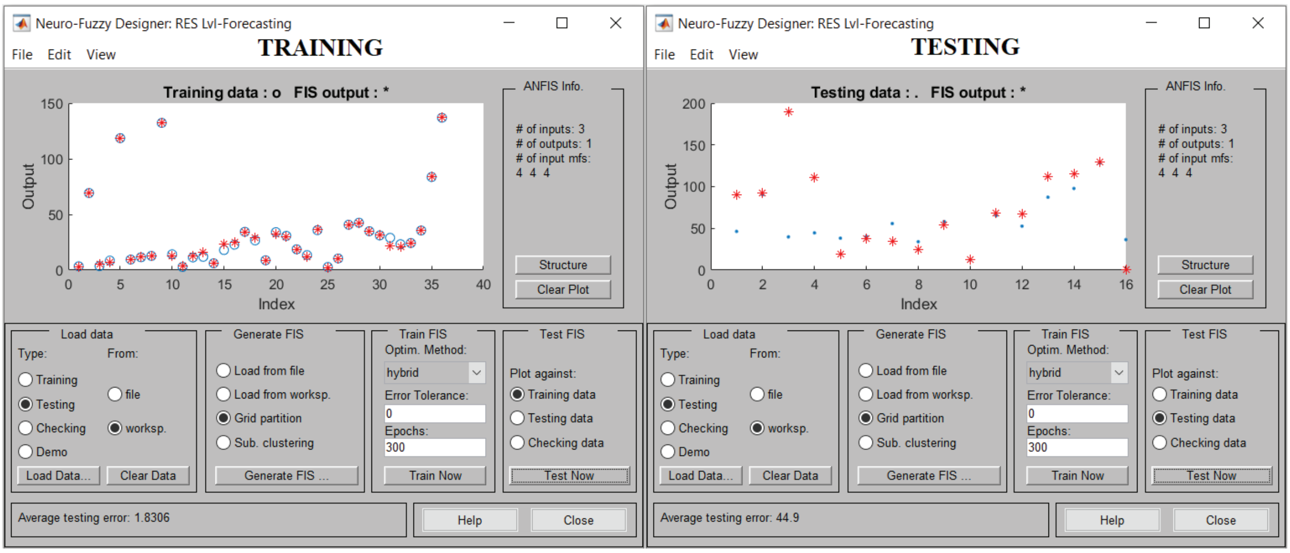


Figure 9. ANFIS / Compatibility of training and testing data with output data.

Table 4. ANFIS / Membership type for lowest error

Membership name	Membership type	Membership subset	RMSE value	RMSE rank
Triangle MF	trimf	3-3-3	2,1838	
Triangle MF	trimf	4-4-4	1,8854	
Trapezoid MF	trapmf	3-3-3	4,0886	
Trapezoid MF	trapmf	4-4-4	3,0863	
Gaussian Bell MF	gbellmf	3-3-3	2,1627	
Gaussian Bell MF	gbellmf	4-4-4	1,8307	min.

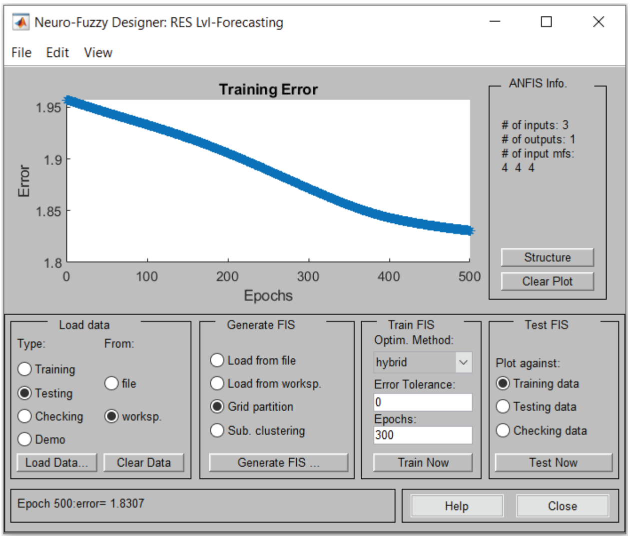
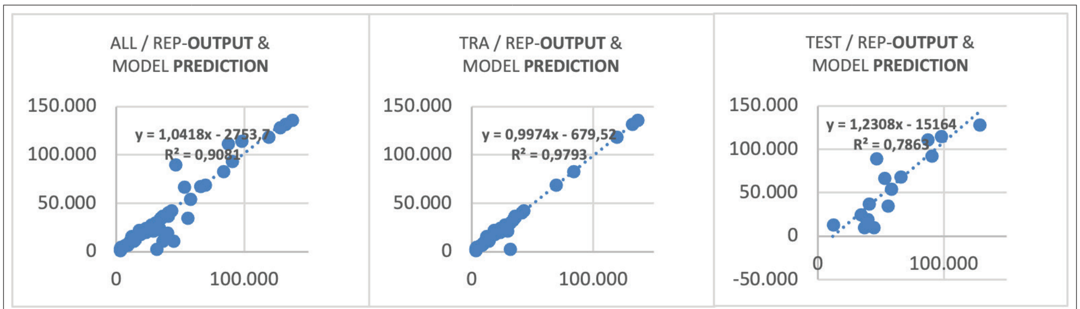


Figure 10. ANFIS / Determining membership type.

be noted that as the correlation coefficient approaches 1, it shows a high relationship between the data.

Figure 11 shows a high correlation for training, testing and all data. Therewithal, the main scale, R^2, is very close to 1 for all data and training data, and this ANFIS declares that the estimation has a high accuracy rate of 90%. Although the test data does not show a very high accuracy rate of 78%, this rate does not pose a significant issue since the main purpose of the test data set is to perform testing in order to measure performance. This rule base and surface is shown in Figure 12.

After these results, there is a surface with an interference pattern formed by the inputs with each other. A steep surface indicates lower accuracy, whereas a flat surface demonstrates higher predictive precision [10]. This "rule surface" is shown on the left in Figure 12. This rule surface is designed on the graph of the prediction values obtained due to the rule formed by the inputs with each other in



	ALL	TRAINING	TEST
Correlation	0,9529	0,9896	0,8868
R^2	0,9081	0,9793	0,7863

Figure 11. Correlation of training-test inputs and output data

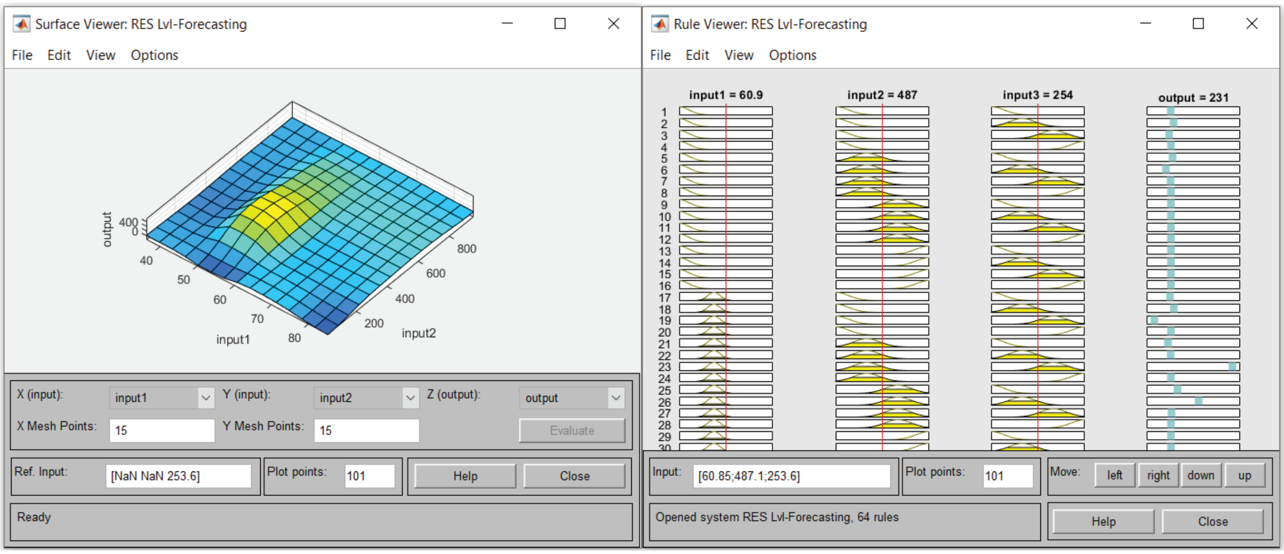


Figure 12. ANFIS / Rule base of the model.

ANFIS. The right representation shows the current inputs and the prediction outputs corresponding to the rules generated by these inputs. This representation is called the "rule base". This rule base is used when making future period forecasts. The estimation results obtained according to this regular structure are given in the "Findings and Discussion" section. However, CE estimations is explained before this section.

CO_2 Emissions Estimation

As shown above, CE estimation was also performed with ANFIS in a similar way to REP estimation. The same three inputs were used. The countries and regions considered for the estimation were also the same. CE data for 1971-2022 and GDP and POP data for this period, shown in Figure 2, were used as inputs. CE (t+1) data were also used as outputs. Again, membership functions with minimum errors were used with ANFIS separately for each country and region.

Estimation results and interpretations are included in the "Findings and Discussion" section.

THE RESEARCH FINDINGS AND DISCUSSION

This section is explained in two parts: "Findings" and "Discussion".

Findings

This study investigates the future REP and CE utilization rates to examine the impact of the protocols on countries and regions. In this regard, these rates are estimated separately for each country and region with ANFIS in the "Application" section, based on the 2025-30 period. The estimation results are shown in Table 5.

As seen in Table 5, the 2023-25-27-30 estimates are given for REP and CE obtained using values between 1971-2022. The left side of the table shows the REP ratio in the electricity produced on a TWh basis. There are three rows for each country and region. The first row shows the REP for the relevant year, and the second row shows the total electricity production for the same year. The third row shows the ratio of the former to the latter, i.e., the proportional REP. According to the future estimate here, Türkiye ranks first with an increase of approximately 15 percent in REP in nine years (2021-30). The closest follower is the EU, which has approximately 12 percent, and China ranks third, with an increase of approximately 11 percent. While the USA did not quite meet the climate protocol expectations with an increase of approximately 2 percent, India could not increase its REP rate in nine years according to the forecast scenario.

On the right side of the table are the CE forecast results for 2021-30. There are two rows for each country and region. The first row shows the CE increase amount by year in million tons, while the second row shows the CE increase rate between years. Accordingly, the EU Region draws the most positive curve with a decrease of approximately 10%. The USA, with a decrease of approximately 8%, and Türkiye, with a decrease of approximately 7%, are the followers. On the other hand, China and India increase their emissions by approximately 4% and 7%, respectively, presenting a negative picture.

In order to understand the increases and decreases in this table more clearly, along with their slopes, a graphical version is presented in Figure 13.

Table 5. Future REP and CE rate forecasting for countries and regions

Regions/Years	REP-rate forecasting					Regions/ Years	CE-rate forecasting				
	21	23	25	27	30		21	23	25	27	30
TÜR-(REP-TWh)	116,5	141,8	172,8	186,9	208,1	TÜR-(Mt)	452,7	446,1	473,8	494,5	520,7
TÜR-(TEP-TWh)	327,9	325,0	351,4	367,9	412,2	*TÜR-(%)*	*12,44*	*-1,46*	*6,20*	*4,37*	*5,30*
TÜR-(REP-%)	*35,53*	*43,63*	*49,18*	*50,81*	*50,48*						
IND-(REP-TWh)	333,0	381,3	427,0	467,9	502,3	IND-(Mt)	2.674,2	2.912,0	3.132,9	3.348,7	3.682,2
IND-(TEP-TWh)	1.714,8	1.896,3	2.127,2	2.302,0	2.590,1	*IND-(%)*	*2,35*	*8,89*	*7,59*	*6,89*	*9,96*
IND-(REP-%)	*19,42*	*20,11*	*20,07*	*20,33*	*19,39*						
EU-27-(REP-TWh)	1.075,3	1.152,3	1.235,0	1.322,8	1.392,9	EU-27-(Mt)	*2.805,8*	*2.700,8*	*2.575,2*	*2.514,1*	*2.410,7*
EU-27-(TEP-TWh)	2.875,0	2.790,5	2.814,9	2.823,1	2.802,7	*EU-27-(%)*	*6,68*	*-3,74*	*-4,65*	*-2,37*	*-4,11*
EU-27-(REP-%)	*37,40*	*41,29*	*43,87*	*46,86*	*49,70*						
USA-(REP-TWh)	862,6	897,4	936,8	1.002,9	1.024,4	USA-(Mt)	5.032,2	5.082,4	4.985,0	4.846,8	4.712,6
USA-(TEP-TWh)	4.153,6	4.284,5	4.346,7	4.503,0	4.555,9	*USA-(%)*	*6,74*	*1,00*	*-1,92*	*-2,77*	*-2,77*
USA-(REP-%)	*20,77*	*20,95*	*21,55*	*22,27*	*22,49*						
CHI-(REP-TWh)	2.449,0	2.876,4	3.384,3	4.002,2	4.792,3	CHI-(Mt)	11.336,2	11.805,0	12.303,4	12.972,9	13.932,2
CHI-(TEP-TWh)	8.534,3	9.285,1	9.911,1	10.871,1	11.987,6	*CHI-(%)*	*3,87*	*4,13*	*4,22*	*5,44*	*7,39*
CHI-(REP-%)	*28,70*	*30,98*	*34,15*	*36,82*	*39,98*						

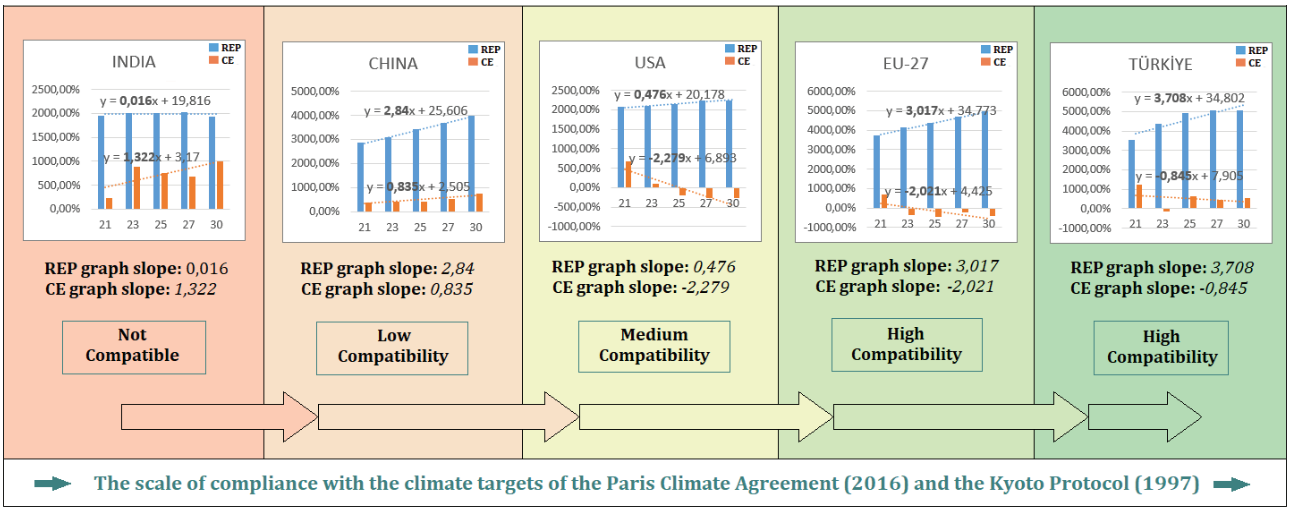


Figure 13. Future projections for REP and CE (2023-2030).

The findings regarding the comparison of REP and CE growth rates of Türkiye and other regions according to their future situations are shown above. It is possible to make some inferences from these findings. These inferences and comments are included in the "Discussion" section.

DISCUSSION

In this study, the conditions that member countries must comply with in order to achieve the climate conditions envisaged by the [8] and [9] protocols are questioned. Countries with different REP and CE levels are subject to the same conditions. However, countries with more emissions should have a higher liability. The first is the status of REP over the years. The second is the status of total CE increase.

First of all, if the current situation is evaluated, as seen in Figure 1 and Figure 2, the most obvious graph belongs to China. In the 1970s, it followed a graph closer to India and Türkiye, and later, by using intensive coal resources in every field from electricity to fuel, it has recently had an emission twice as much as the USA and EU Region. As mentioned above, although the use of RES in electricity has increased in China and even RES policies have gained importance, this increase cannot prevent the increase in CE due to FS. In India, although policies towards RES have gained importance and the RES graph has a good increase slope, the increase in CE due to FS is higher. Similar to China, it cannot prevent this. For these two countries, a high population also plays an active role in the use of resources. The primary objective is to secure the public electricity supply; hence, climate protocols and RES initiatives receive secondary attention. For example, approximately 70% of electricity production in India is provided by coal. When this main source is not sufficient and a deficit occurs, imported coal is used instead of RES [30]. The same applies to China, where the rate is around 61% and increasing [31]. In Türkiye, the CE graph increases with a slight slope. This level can be considered as a typical situation for a developing country. In addition, the RES increase slope is observed to be higher than the CE increase slope. There is an increase slope for coal in electricity, but thanks to the increase in HPP, WPP and SPP installations accompanied by an energy strategy [32], Türkiye suppresses CE in electricity production [31]. Türkiye appears well positioned to meet the requirements of the climate protocols; thus, it aligns with global sustainability goals. The CE level in the EU Region, as seen in Figure 2, is decreasing. This has been triggered by the EU's general need to turn to internal resources due to its decarbonization and energy security policies [33]. In addition, it should be noted that within the EU, it has been decided to reduce even NES, which has been the primary source of electricity for about thirty years, within the scope of these policies [31]. In this way, the FS rate in electricity production has been reduced to 39%. The RES rate is still increasing. This is a positive picture for both the NetZero [34] target and the protocols. Like the EU, the USA actively promotes RES through various incentives; notably, the Inflation Reduction Act plays a key role. According to the IEA estimate, the USA will increase its installed RES capacity from approximately 150 GW to 340 GW between 2023-28. It is predicted that the majority of this installed capacity will be SPPs and HPPs [33]. However, the picture seen until 2022 does not fully reflect this. As stated, there is an increase in all types of RES, and at the same time, the FS ratio in electricity production decreased from approximately 70% in the 2000s to approximately 59% around 2022. However, the subtle nuance here is that there is no decrease in FS resources in this rate decrease. The steady rise in RES share is the primary factor behind the decline in FS use, showing a clear substitution trend. Diminishing coal resources have gradually been replaced by natural gas, as indicated in

Table 6. ANFIS Estimation Performance by Country/Region for REP and CE Processes

	REP Estimation Processes			CE Estimation Processes		
	MF type	MF subset	min. RMSE value	MF type	MF subset	min. RMSE value
Türkiye	gbellmf	3-3-3	2,1838	gbellmf	4-4-4	1,6879
EU-27	trimf	4-4-4	2,0271	gbellmf	4-4-4	2,3627
USA	gbellmf	4-4-4	2,1634	gbellmf	3-3-3	2,8651
China	gbellmf	3-3-3	6,6402	trimf	3-3-3	7,0215
India	trimf	3-3-3	3,3296	trimf	4-4-4	4,4236

reference [31]. The results indicate that the emission reduction in the USA is not sufficient, but it reaches a moderate level in terms of protocol obligations.

After evaluating the current situations of the countries in question, their future projections are assessed. However, before that, information is provided on the ANFIS processes, training-testing phases, and the membership functions selected for minimum error for the countries and regions not specified in the application section. Table 6 presents information regarding the REP and CE level prediction processes for the countries and regions considered in this study.

The data in Table 6 represent the scaled training–testing datasets of the countries and regions (the numerical values were reduced to comparable magnitudes to avoid outlier errors). These results were obtained from ANFIS after 300 epochs. The models with the minimum MF values serve as the rule bases for both the REP and CE estimation processes, thus providing the foundation for forecasting future values of the countries and regions.

As can be seen, China's minimum error value remains the highest among all. This can be attributed to the steeply increasing trend observed in Figures 1 and 2. Similarly, although the EU-27 REP values are higher than those of Türkiye, the smaller variation and higher consistency among its data lead to a lower minimum error value in Table 6. The same situation applies to the USA, whereas the India case resembles China. The same interpretation pattern can also be applied to the CE process results.

The estimation results obtained based on the rule bases formed by the models with the minimum errors specified in Table 6 are presented in detail in Table 5 and Figure 13. As can be seen in, three graphs are on a positive trend towards 2030. These graphs belong to Türkiye, the EU region, and the USA. Türkiye presents the most optimistic picture with an increase slope of 3,7 in REP. It can be stated at this point that there is an important driving force for Türkiye in this table. The force in question is the energy expenses, which constitute the most oversized item in its current deficit and are mostly imported. To overcome this situation, Türkiye has turned to domestic use, and while continuing its natural gas exploration activities [35], it has also significantly increased its REP. REP reached 42% by the end of 2023 [36]. As a result of the orientation towards emission-free energy, the increase rate in CE level is decreasing with a slope of -0,84. This situation shows its compliance with the protocols.

Apart from Türkiye, two other regions are trying to comply with the protocols. The EU Region is increasing its REP with a slope of 3,0 towards 2030. This increase rate is quite good for the EU Region, which realizes 15% of the world's electricity REP [1]. In addition, the CE increase rate is decreasing with a slope of -2. According to the graphs in Figures 1 and 2, RES strategies have gained significant importance in European countries in the last 15 years [37] and many measures are being taken to reduce emissions. For example, the EU has expanded the "Emissions Trading" agreement to include buildings and roads. It has also established a carbon border adjustment system [33]. Although more than this positive situation is needed for the 2050-net zero [34] target, it will provide a future close to this target. The protocols appear to be effective in the EU region. Similarly, the USA is also offers practices such as tax breaks and incentives for the use of RES technologies [33]. Nevertheless, the increase slope of REP towards 2030 has not exceeded 0,45. Although the increase in REP was not at the desired level, a CE reduction slope of -2.82 was achieved by reducing the use of FS. This is the most positive emission graph in all countries and regions examined. In this context, it can also be said that the effect of the protocols is evident in the USA. On the other hand, China cannot display a net positive outlook since it shows a rapid trend towards both FS and RES towards 2030. The reason for not giving up fossil fuels while moving towards RES is its intensive coal resources. Here, it has both high FS resources and a good REP increase slope [33,38]. Comparatively, China is projected to have approximately five times more REP than the USA in 2030. The slope increase of REP in China is 2.84 which is six times higher than the USA and an increase almost on a par with the EU Region. On the other hand, the CE increase slope is also increasing and is 0,84. Therefore, although REP is growing in China, it can be said that the protocols are not effective due to the positive emission rate.

India, one of the countries examined, is decreasing the REP growth rate and increasing the CE growth rate towards

2030, according to the forecast projection. However, India's energy policies include the target of meeting half of its power generation capacity from RES by 2030. In addition, there is a net-zero target by 2070 [34]. The estimates show that these policies are not fully implemented, and the effect of the protocols is insufficient.

When this study is compared with earlier works in the literature, such as Yılmaz and Yılmaz [17], who employed a fuzzy logic model for a single-country analysis of Türkiye, this study expands the scope to a multi-regional comparative framework that integrates both renewable energy forecasting and international policy evaluation. Similar studies in the literature (such as Kumar et al. [39] for India, Li et al. [40] for China, and Rahman et al. [41] for the EU region) primarily focused on energy–emission trends using separate machine learning or statistical models, yet their forward-looking projections under the same global protocols produced findings consistent with this study. As stated above, these studies also show that Türkiye and the EU-27 appear more compliant with international protocols, while China and India show weaker alignment. In addition, the RMSE values in those studies are higher for China and India, whereas they are lower—and thus more consistent—for Türkiye and the EU-27 countries. However, there are also studies that produce findings not fully consistent with the results. For instance, Şahin [38] obtained similar findings to this study regarding the increase in renewable energy production (REP) in future projections; however, as a consequence of this increase, contrary to the results indicate that the rate of emission growth would slow down.

The present study fills this gap by linking quantitative forecasting (ANFIS) with policy-based interpretation, providing a cross-country perspective on protocol effectiveness.

The 2030 forecast of the countries and regions examined along with the impacts of the protocols and the resulting positive and negative trends, were presented and discussed. The overall results are evaluated in the next section.

CONCLUCION

Today, in the pursuit of sustainability, there is an increasing shift toward next-generation energy sources that aim to achieve both resource abundance and emission reduction. Energy diversification and emission mitigation also vary according to the specific goals of each country and region. This study aims to estimate the future renewable energy use and emission levels of countries and regions in order to examine the impact of international climate protocols on them. Among these agreements, the United States of America, China, and the Europa Union-27 signed the Kyoto Protocol in 1998, while India ratified it in 2002 and Türkiye became a party in 2009. Similarly, all five countries/regions signed the Paris Climate Agreement in 2016. At this point, Türkiye is the main country considered for comparison with other countries and regions. The criteria are the renewable electricity production and the CO_2 emission level. The 2025-27-30 estimate is made with ANFIS, and their future situations are examined. In this context, despite being a developing economy, there is a positive picture in which Türkiye is reducing its fossil sources use and turning to renewable energy sources. The region with the most optimistic picture after Türkiye is the Europe Union, which both reduces its emission slope and increases its renewable electricity production. The United States of America follows these two; although the decrease in the emission slope is good, the renewable electricity production increase remains low. The country that follows is China. Although the renewable energy soruces increase is higher than all other regions, since the fossil sources use is also high at a similar rate, the emission rate remains far from the warning of the protocols. India cannot increase its renewable electricity production, and its emission rate increases considerably with fossil sources use. The findings are consistent with earlier literature in identifying the general link between renewable energy expansion and emission reduction, but the multi-country comparison here reveals a broader perspective: countries with high industrial growth diverge from protocol expectations, while Türkiye and the EU-27 show more balanced adaptation.

According to these results, it should be noted that it would be more effective to transform the standard and common language texts of the protocols into country and region-based texts. High-emitting countries should be subject to more conditions. The renewable energy soruces orientation should be encouraged much more in the text prepared for these countries. In this way, texts should be created separately for countries and regions and specific to their own situations.

At this point, the core idea proposed by this study is that the standards established by international protocols should be able to define adaptable provisions in response to changing conditions. Although the methods and datasets may vary, the fundamental rationale of this study can serve as a foundation for future works.

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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