VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Forecasting of Renewable Energy Generation for Türkiye by Artificial Neural Networks and ARIMA Model: 2023 Generation Targets by Renewable Energy Resources

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ABSTRACT
Purpose: Türkiye attaches particular importance to the energy production with renewable energy sources in order to overcome the negative economic, environmental and social effects which are caused by fossil resources in energy production. The aim of this study is to propose a model for forecasting the amount of energy to be produced for Türkiye using renewable energy resources.
Methdology: In this study, a forecasting model was created by using the generatio amount of energy generation from renewable sources data between 1965 and 2019 and by using Artificial Neural Networks (ANN) and Autoregressive Integrated Moving Average (ARIMA) methods.
Findings: While it was estimated that 127.516 TWh of energy will be produced in 2023 with the ANN method, this amount was estimated as 45,457 TeraWatt Hours (TWh) with the ARIMA (1,1,6) model. Mean Absolute Percent Error (MAPE) was calculated in order to determine the margin of error of the forecasting models. These values were determined as 13.1% for the ANN model and 21.9% for the ARIMA model. These results show that the ANN model gives a more appropriate estimation result.
Originality: In this research, a new model was proposed for the amount of energy to be obtained from RES in Türkiye. It is thought that the results obtained in this study will be useful in energy planning and management.
Keywords: Energy, Renewable Energy Sources, Renewable Energy Generation Forecast, Artificial Neural Networks, ARIMA Model, Time Series Forecast.
JEL Codes: C22, C53, O13.

Yapay Sinir Ağları ve ARIMA Modeli ile Türkiye Için Yenilenebilir Enerji Üretiminin Tahmini: 2023 Yenilenebilir Enerji Kaynaklarına Göre Üretim Hedefleri

ÖZET
Amaç: Türkiye, enerji üretiminde fosil kaynakların neden olduğu olumsuz ekonomik, çevresel ve sosyal etkileri ortadan kaldırmak için yenilenebilir enerji kaynakları ile enerji üretimine ve tahminine çok önem vermektedir. Bu çalışmanın amacı, Yenilenebilir enerji kaynakları kullanılarak Türkiye'de üretecek enerji miktarını tahmin etmek için bir model önermektir.
Yöntem: Bu araştırma 1965-2019 yılları arasında yenilenebilir kaynaklı enerji üretim verileri kullanılarak Yapay Sinir Ağları (YSA) ve Otoregresif Bütünleşik Hareketli Ortalama (ARIMA) yöntemlerinden yararlanılmıştır.
Bulgular: ANN yönteminde, 2023 yılında 127.516 TWh enerji üretileceği tahminedilirken, ARIMA (1.1.6) modeli ile bu miktarın 45.457 TeraWatt Saat (TWh) olacağı tahmin edilmiştir. Tahmin modellerinin hata payını belirlemek için Ortalama Mutlak Yüzde Hatası (MAPE) hesaplanmıştır. Bu değer YSA modeli ile %13,1, ARIMA modeli ile %21,9 olarak belirlenmiştir. YSA modelinin daha doğru bir sonuç verdiğini göstermiştir.
Özgünlük: Türkiye'de YEK'dan elde edilecek enerji miktarı tahmini için model önerisi yapılmıştır. Bu çalışmada ulaşılan sonuçların enerji planlaması ve yönetiminde faydalı olacağı düşünülmektedir.
Anahtar Kelimeler: Enerji, Yenilenebilir Enerji Kaynakları, Yenilenebilir Enerji Üretimi Tahmini, Yapay Sinir Ağları, ARIMA Modeli, Zaman Serisi Tahmini.
JEL Kodları: C22, C53, O13.

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DOI: 10.51551/verimlilik.1031367
Research Article | Submitted Date: 01.12.2021 | Accepted Date: 06.12.2022
Cite: Karadağ Albayrak, Ö. (2023). "Forecasting of Renewable Energy Generation for Türkiye by Artificial Neural Networks and ARIMA Model: 2023 Generation Targets by Renewable Energy Resources", *Verimlilik Dergisi,* 57(1), 121-138.

1. INTRODUCTION

Energy is one of indicators of the development level of thecountries. It is one of the important factors, especially for reducing poverty and increasing life standards (Zolfani and Saparauskas, 2013). In recent years, energy consumption has increased highly due to fundamental changes in the industry and economies in the world. Energy is vital for a country's social, economic and environmental sustainable development (Suganthia and Samuel, 2012). Energy consumption has increased incrementally in the global scale in the last decade. In this regard, accurate demand forecasting is essential for decision-makers to develop an optimal strategy not only for reducing risk but also for improving economy and society as a whole (Oliveira and Oliveira, 2018), and energy supply is one of the most important issues in the global scale (Jahanshah et al. 2019). Accurate forecasting demand for fixed electricity is of paramount importance for protecting material resources (Hu et al., 2019). Accurate estimation of the energy to be obtained from energy sources ensures efficient planning while energy and resource allocation are made.

Forecasting energy demand in the developing markets is one of the most important policy-making tools used by decision-makers around the world. The energy forecasting referring to electrical demand prediction is used in all departments of the public service sector, including transmission, generation, distribution and retail sales. Energy forecasting applications are utilized in distribution and transmission planning, power supply planning, power system maintenance and operations, demand management, rate design, financial plans development (Ahmad et al. 2020). In general, terms of forecast, estimate and prediction are the words used regarding the concept of having an expected value for future demand in markets (Ghalehkhondabi et al. 2016).

In the world, most of energy is provided by fossil resources such as oil, natural gas, coal which are called non-renewable resources. Extinction of fossil resources and increasing concerns about the environmental impact of fossil fuel-related greenhouse gas emissions in the atmosphere cause decision-makers to search for sustainable and renewable energy sources (Jahanshahi et al., 2019; Broadny et al., 2020). Renewable energy covers any permanent energy source which does not have any harmful effect on the environment and which is generated naturally. Today, the concept of sustainable environment is directly identified with renewable energy (Cengiz ve Manga, 2021). As a response to the extinction of supply and demand of fossil resources such as oil, the increase in renewable energy has become the most important issue regarding the energy planning approaches in the world (Ahmad et al. 2019).

Ranked among the developing countries, Türkiye supplies most of its energy by fossil resources. These resources are supplied from foreign countries. For this reason, the use of renewable energy sources is considered as a part of the diversification of energy sources (Alkan and Albayrak, 2020).

The Republic of Türkiye is a country with a strategic location due to having soils in both Asia and Europe. Most of the energy need of Türkiye is supplied by fossil resources. The potential of renewable energy sources, such as wind, solar, hydraulic, geothermal and biomass resources, excluding wave and hydrogen energy, is quite high in Türkiye. The energy amount generated in Türkiye in 2019 through renewable sources and installed power amounts is provided in Table 1. While the ratio of the generation in Renewable Energy Resources Support Mechanism (YEKDEM) to the total electricity generation of the country was 24,07 % in 2020, this rate decreased to 22,37 % in 2021.

Table 1. Renewable energy sources in Türkiye

	2021 Produce Quantity (MWh)			*2020 installed capacity (MegaWatt-MW)*		
Sources	*Licensed*	*Unlicensed*	*Sum*	*Licensed*	*Unlicensed*	*Sum*
Wind	25200967		25200967	6750		6750
Geotermal	8162845		8162845	1465		1465
Biomass	5169983		5169983	873		873
Solar	1492885	12149419	13642304	305	7083	7388
Hydro	21980145		69	12227		12227

As it can be concluded by this table, the largest share among RES belongs to hydraulic energy sources. However, only the hydraulic energy generation facilities with a river type or reservoir area of less than fifteen square kilometres are considered renewable among all hydraulic resources as reported in YEKDEM (YEKDEM, 2020). Türkiye attaches great importance to renewable energy sources in its future plans, especially its 2023 goals. In accordance with this goal, it is aimed to increase the RES share in the energy generation in 2023 to 30% (The hydraulic source rate in this goal is the generation rate only from hydraulic power plants within the scope of YEKDEM).

Most of Türkiye's national wealth is spent on energy supply. In addition, it is affected by global crises instantly (for example, Iran, Russia crises). This results in the problem of energy supply security. When energy is generated by RES sources, the national wealth spent on fossil resources such as natural gas, oil, coal will be used for the development of the country. In this respect, increasing the share of RES in total energy raw material supply may be considered as a national issue. Naimoğlu and Akal (2022) According to estimation studies conducted with resilient estimators, coal and oil use and energy losses negatively affect energy efficiency, while natural gas, hydro, electricity and renewable resources affect energy efficiency positively.

With this research, a model proposal has been made for the amount of energy to be obtained from RES in Türkiye. It is thought that the results obtained in this study will be useful in energy planning and management.The possible contributions of this study may be listed as follows:

- The most important contribution of this study may be to reveal that RES sources should be used instead of fossil resources with many negative effects for Türkiye related to energy demand security, environment, economy but having 55% of all energy demand.
- To suggest a new model by which RES energy generation forecasting will be made for Türkiye,
- To provide a perspective for 2023 by predicting 2023 RES generation amounts of the Republic of Türkiye by this model,
- Türkiye's sustainable development objectives, one of the most important factors in driving forward research on renewable energy
- To perform a RES generation forecast in Türkiye by ANN and ARIMA methods for the first time,
- To reveal the efficiency of ANN and ARIMA models which are appropriate for prediction.

Within this research, Section 2 briefly reviews the literature for renewable energy sources and energy estimation models derived from renewable energy sources. Section 3 describes the data and empirical estimation methodology. Section 4 reports the empirical findings and Section 5 contains conclusions and policy recommendations.

2. LITERATURE REVIEW

When studies on energy demand and generation forecast are examined, it is seen that in addition to traditional techniques such as econometric and time series models, calculation method applications, utilised with a software, such as ANN, fuzzy logic and other models are also used (Ghalehkhondabi et al., 2016). Most of the first studies conducted in Türkiye on energy forecasting have been based on various modelling types (Ediger and Akar, 2007). In the following studies administered on energy demand, techniques such as ANN, Genetic Algorithms, Grey Prediction Models, Particle Swarm Optimization, ARIMA, Linear Regression, Seasonal Auto-Regressive Integrated Moving-Average (SARIMA) have been utilised (Kankal et al. 2011). The reason for such a frequent use of ANN may be explained with the desire to specify the relationship among the variables such as energy demand, consumption, generation with explanatory variables such as Gross Domestic Product (GDP), population, amount of export, import, electricity generation or consumption. In addition, the ANN model is frequently used when many conditions need to be met. ARIMA models are also used frequently for forecasting but have some limitations. ARIMA models are also often used for forecasting, but they have some limitations. One of them is that they can be applied for stationary time series and the minimum recommended sample size is 50 (Jamil, 2020).

In most of the estimation studies on energy resources in Türkiye and in the world, hydraulic resources have been accepted as renewable energy resources and general energy forecasting models have been created.

Generally, the efficiency of electricity demand forecasting and model results has been checked with cointegration analysis and ARIMA modeling (Erdoğdu, 2007). In order to forecast annual hydraulic source related generation values, a feedback and back-propagation ANN model has been suggested (Cinar and Kayakutlu, 2007). Energy demand forecasting for fossil resources was made by ARIMA and SARIMA models regarding 2005-2020 (Ediger ve Akar, 2007). Sozen and Arcaklioglu (2007), utilised the variables of population, gross generation, installed power, net electricity consumption, import and export as inputs of the ANN model regarding the forecasting of energy sources in Türkiye. Kankal et al. (2011), have used modelling and forecast approaches to analyse the energy consumption in Türkiye by integrating demographic and socioeconomic indicators with regression analysis and ANN technique. A forecast has been performed by ARIMA technique by using annual time series data between 1990-2015 on household energy consumption in the countries of Eurozone (Jahanshahi et al. 2019). The energy consumption for the next year was determined as 186244 tons of petroleum equivalent (TOE) with the ARIMA (0,1,1) estimation model.

There are few studies on energy production, consumption and demand forecasting models for renewable energy sources for Türkiye. For the forecasting of energy generation related to hydraulic sources in Türkiye, Uzlu et al. (2014), utilised ANN and Artificial Bee Colony (ABC) algorithm together by using gross electricity energy demand, population, average annual temperature and energy consumption variables. They have estimated energy generation amount by hydraulic sources to become between 69.1 and 76.5 TWh. Şahin (2020) estimated that Türkiye's total renewable installed power will be 80.3 GW and production amount will be 241.3 TWh in 2030 by applying the fractional non-linear gray estimation method.

When the research for the world is examined, Broadny et al. (2020) developed a model to be used to estimate the consumption amounts of renewable energy resources in Poland as a whole and for different resources using the ANN model. As a result of this forecast, MAPE value of the forecasting model of RES sources has been specified to be 3.07%. Hu et al. (2020), comparing the prediction results of different methods by applying the deep learning framework into the basic echo state network technique, and the effectiveness of the ANN method (according to MAPE) was quite good. Jamil (2020) estimated Pakistan's consumption of energy produced by using hydraulic resources by 2030 using ARIMA models. He has suggested that, according to the ARIMA (9,1,7-19) model, there will be an increase of approximately 24% in consumption by 2030 (MAPE approximately 1.5). Energy demand prediction has been made in France by ANN and ARIMA models (Asensio et al., 2020). In this study, the efficacy of both methods has been specified to be close.

Shireena et al. (2018), have developed a method by MTL-GP-TS algorithm for solar panel PV generation forecasting. Wang et al. (2020), have predicted the monthly energy consumption rate of energy generated by solar in the USA through seasonal Grey Forecast method. Araujo da Silva Junior (2020), has made a biomass energy generation forecast in Brazil. Mason et al. (2018), have developed an ANN model to predict wind energy forecast.

What is more, there are studies in which ANN and ARIMA models have been used together in energy forecasting. Kazemzadeh et al. (2020) and Kheirkhah et al. (2013) employed ANN and ARIMA models together for energy demand prediction. Nair et. al (2017) have utilised ANN and ARIMA models in order to estimate wind speed of certain regions. ANN and ARIMA models have been also used together for the forecast of wind energy generation and it has been provided that more efficient predictions have been performed by ARIMA model.

This study provides production quantity forecast model for energy planning of Türkiye in general and its renewable energy source planning in particular. ANN and ARIMA techniques are used for this model. In this technique, production estimates are made based on Türkiye's 2023 energy perspective. What is more, the efficacy of ANN and ARIMA models for RES generation forecast are investigated. Unlike other studies in the literature, this research aimed to measure the effectiveness of these two prediction models and to propose a usable model.

3. METHODOLOGY

3.1. Artificial Neural Networks

ANN is characterised as a data-based approach. ANN is widely used in practice to solve various classes of tasks such as estimation and approach, pattern recognition and classification, decision making and control (Abdirassilov and Sładkowski, 2018). Data are used by ANN to specify the relationship between input and output variables and to predict output values (Ghalehkhondabi et al., 2016). ANNs are human-controlled initiatives to simulate and understand what is happening in the nervous system by hoping to seize some of the power of biological systems. ANNs are inspired by biological systems with a large number of neurons and that perform tasks which cannot be even matched by the largest computers (Kankal et al., 2011). ANN is a non-linear, easy to apply approach which forms statistical models. Although it is a nonparametric approach, they are parametric models requiring a more comprehensive history of many statistical classifications and statistics (Ahmad et.al, 2020).

Of the different networks, feed-forward neural networks or multilayer perceptron are generally used in the engineering. Multilayer Neural Networks (MLP) networks are normally organized in three neuronal layers; input layer and output layer represent the input and output variables of a model, and there are one or more hidden layers between them containing the network's ability to learn nonlinear relationships (Kheirkhah et al. 2013). The structure of an ANN model formed of these layers is shown in Figure 1.

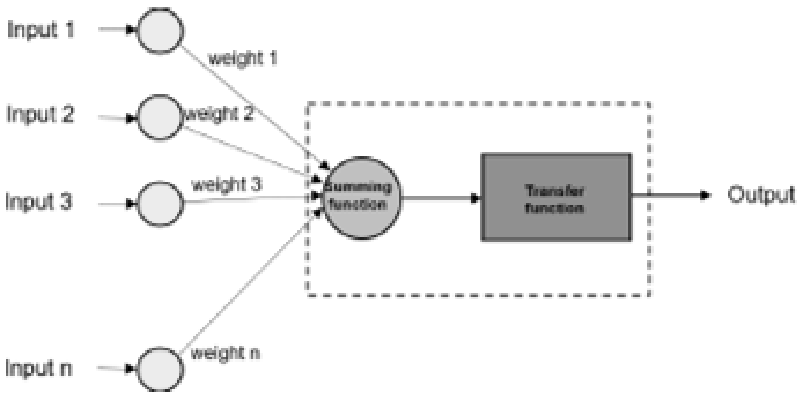


Figure 1. ANN structure (Brodny et al., 2020)

In ANN models, the signals in the input layer (x_i) are transmitted to the neurons in the hidden layer. Input signals have different loads (w_i^x) in each neuron in the hidden layer. Total sign (s_i) is determined by multiplying each input signal with the weight and taking the sum (Jasinski et al. 2016) (Equation 1).

$$s_i = \sum_{i=1}^{n} w_i^x . x_i \quad (1)$$

The activation function, which is called also transfer function, identifies the relationship between the inputs and outputs of a node and network (Wei and Chen, 2012). Some of the important activation functions used in the transformations performed by neurons are as in Equations 2-6 (Jahanshahi et al. 2019):

Logistic function:

$$\varphi(x) = \frac{1}{1-e^{-1}} \quad (2)$$

Hyperbolic tangent function:

$$\varphi(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (3)$$

Exponential function:

$$\varphi(x) = e^x \quad (4)$$

Linear function:

$$\varphi(x) = x \quad (5)$$

The data used were transformed into values in the range of (6) [0,1] by the linear normalization method.

$$x_{normalize} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

3.2. ARIMA Models

Time series forecasting is a significant research field in which previous data are used to estimate future values by developing a statistical model, facilitating to develop a statistical framework to forecast future values of the system with the least predictable error (Bhardwaj et al., 2020). ARIMA method, the most popular forecast method, is used for stationary time series due to its flexibility and simplicity (Kazemzadeh et al., 2020). The ARIMA model, proposed by Box-Jenkins (1970), is a linear combination of historical errors and historical values of a fixed series (Fanoodi et al., 2019).

In fact, the ARIMA model consists of Auto-Regressive (AR) model and Moving Average (MA) model, and these models are called to be ARIMA (p.d.q). ARIMA models are stated as in Equations 7-9 (Han and Li, 2019).

AR(p) p. degree auto-regressive model;

$$Y_t^* = \mu + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2+} \dots \dots \dots . + \varphi_p Y_{t-p+} \varepsilon_t \quad (7)$$

MA(q) q. degree moving average model;

$$Y_t^* = \varepsilon_t - \theta_1 Y_{t-1} + \theta_2 Y_{t-2+} \dots \dots \dots . + \theta_p Y_{t-p} \quad (8)$$

ARMA($p.q$);

$$Y_t^* = \mu + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2+} \dots \dots \dots . + \varphi_p Y_{t-p+} \varepsilon_t + \varepsilon_t - \theta_1 Y_{t-1} + \theta_2 Y_{t-2+} \dots \dots \dots . + \theta_p Y_{t-p} \quad (9)$$

In ARIMA models, d refers the degree to which the series are stationary.

Box-Jenkins methodology is implemented in ARIMA models. An appropriate model is determined in the first step, then appropriate model parameters are predicted and finally, a forecast is made by the obtained model. In the definition stage, stationary of the series is checked by drawing a sample Autocorrelation Function (ACF). If the series are not stationary, the series are made stationary by eliciting a difference.

All reasonable ARIMA models are identified by drawing ACF and Partial Autocorrelation Function (PACF) in the stationary series. These appropriate models have residues similar to good, white noise process and make good out-of-sample predictions (Kheirkhah et al., 2013) number of significant coefficients is the most important criterion to be considered for an appropriate model. A model without a significant coefficient may be eliminated as its coefficients do not contribute to actual data (Jamil, 2020). In addition to these, the best model among appropriate ones may be identified according to the criteria of adjusted R^2, Akaike Criteria (AIC) and Schwartz Bayesci Criteria (SBC).

3.3. Model Efficiencies

If the data used in methods and models are raw material and were previously processed in any other scale, MAPE is appropriate to identify error rates Kankal (2011). Different error measures have been used in the literature to measure the performance of the models offered for forecasting. These are Mean Absolute Error (MAE), MAPE and Root Mean Square Error (RMSE) methods. MAPE was specified in order to compare the efficiency of obtained total renewable energy generation forecasts (Equation 10). The model with the lowest MAPE percent was accepted to be mode efficient.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_o - x_p}{x_o}\right| * 100\% \qquad (10)$$

In this equation, x_o represents observed value, x_p refers to the predicted value.

4. RESULTS and DISCUSSION

4.1. Data Set

In this study, the energy amounts, which were obtained by oil and obtained from the energy-related internet site of British Petroleum company, generated by the renewable sources of solar, wind, geothermal and biomass and hydraulic power plants in TWh in Türkiye between 1965-2019 were used BP (2020). As seen in the general renewable energy generation graph for Türkiye (Figure 2), the generation amount increased in Türkiye over the years. The studies in the literature were benefited when specifying the variables in this study. Generation obtained from renewable energy sources is determined by the total generation from solar, wind, biomass, geothermal and hydraulic sources. The statistical structure of the data set used in the study is provided in Table 2.

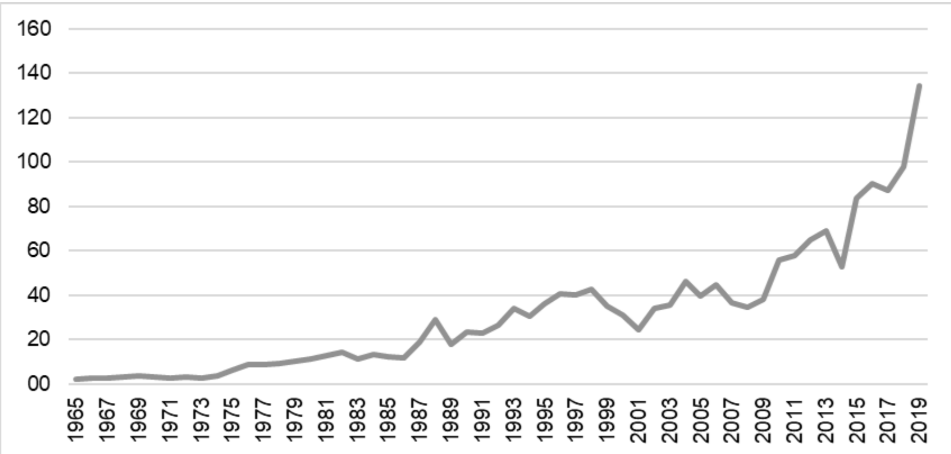


Figure 2. Türkiye 1965-2019 renewable energy production (TWh)

4.2. Artificial Neural Networks Model Result

In this study, nonlinear autoregressive neural networks (NARX) were used in MATLAB program in order to make a forecasting by the ANN method. The data in Annex 1 were used for input and output variables of network. In this study, geothermal and biomass data from renewable energy sources were accepted as a single input variable. Therefore, more data were achieved. There are five input variables in the study: energy amounts generated by solar, wind, geothermal and biomass and hydraulic sources, and the variable (in TWh) consisting of historical values of energy amounts obtained by total renewable sources. On the other hand, the total amount of renewable energy generation is the output variable as a single variable in TWh.

Table 2. Statistical structure of the data set

Variable Name (TWh)	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
Electricity generation from solar energy	0.41	1.82	0.0	10.91958
Electricity generation from wind energy	2.17	5.27	0.0000	21.7040
Electricity generation from Geotermal and Biomass energy	1.07	2.56	0.0000	12.7106
Electricity generation from Hydro energy	27.55	20.97	2.1790	89.1593
Electricity generation from Electricity generation from Hydro energy energy	31.20	28.32	2.2790	134.4934

In this study, three layers of the ANN model was used. These layers are input layer, hidden layer and output layer. While 70% of the data were used for network training in ANN, the remaining 30% was used for confirmation and test. All these data were normalized using Peer 6 so that all inputs could be scaled within a certain range.

Network training should be provided in the first stage of ANN implementation. The neuron number in the hidden layer revealing the features of network should be specified for network training. The layer number in network is determined by trial according to certain rules. Alternatives of 5, 10,12 and 15 were used for appropriate neuron number in the hidden layer and 2-3-4-5-6 network alternatives were tried for lag lengths. Each model was retrained until the reduction in validation error ended. This process continued until minimum performance values that is mean square error (MSE) was achieved. Tried networks and performance results are provided in Table 3. Levenberg-Marquardt Algorithm (TRAINLM), used most in the literature, was utilised for all neuron numbers. As seen in this table, the best ANN algorithm structure has 5 hidden neurons and 5 delayed multi-layer network structures according to the performance value. This network structure is shown in Figure 3.

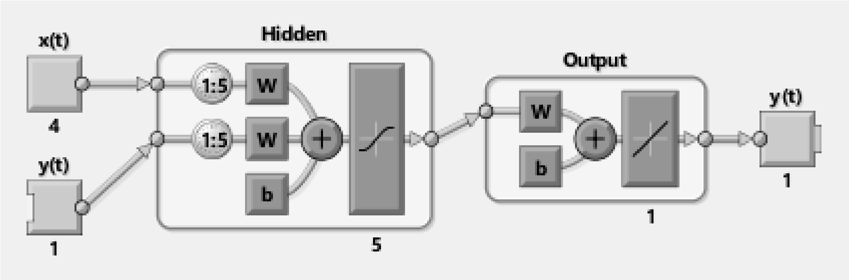


Figure 3. Optimal network structure

Table 3. Comparison of network structures

Network	*Network Structure*	*Delay Number*	*Activation Function*	*Hidden Layers*	*Performans (MSE)*	*Training R*
1	MLP 5-5-1	2	LM	1	0.00200	0.981
2	MLP 5-5-1	3	LM	1	0.00125	0.990
3	MLP 5-5-1	4	LM	1	0.00150	0.977
4	*MLP 5-5-1**	*5*	*LM*	*1*	*0.00033**	*0.996*
5	MLP 5-5-1	6	LM	1	0.00418	0.963
6	MLP 5-10-1	2	LM	1	0.00265	0.972
7	MLP 5-10-1	3	LM	1	0.00080	0.994
8	MLP 5-10-1	4	LM	1	0.00111	0.989
9	MLP 5-10-1	5	LM	1	0.00171	0.984
10	MLP 5-10-1	6	LM	1	0.00135	0.986
11	MLP 5-12-1	2	LM	1	0.00110	0.990
12	MLP 5-12-1	3	LM	1	0.00096	0.989
13	MLP 5-12-1	4	LM	1	0.00726	0.990
14	MLP 5-12-1	5	LM	1	0.00102	0.990
15	MLP 5-12-1	6	LM	1	0.00210	0.977
16	MLP 5-15-1	2	LM	1	0.00789	0.924
17	MLP 5-15-1	3	LM	1	0.00072	0.992
18	MLP 5-15-1	4	LM	1	0.00276	0.986
19	MLP 5-15-1	5	LM	1	0.02690	0.926
20	MLP 5-15-1	6	LM	1	0.00149	0.988

LM:Levenberg-Marquardt

In order to transform data in TWh unit, the output and forecast values of the last decade were first subjected to denormalization process by using the network model forecasted, then the MAPE value of the forecasting was determined (Table 9).

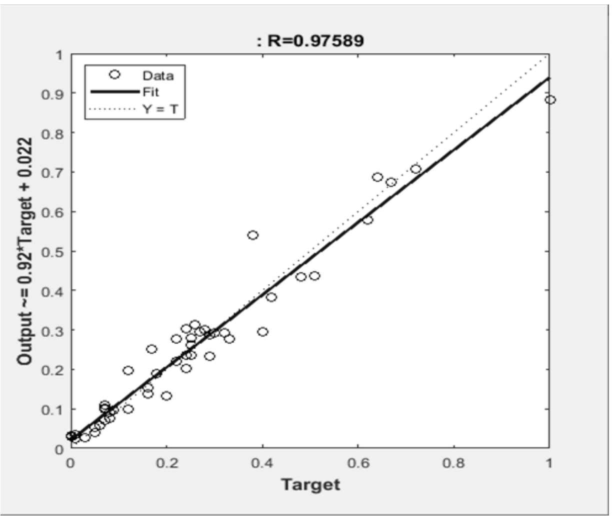
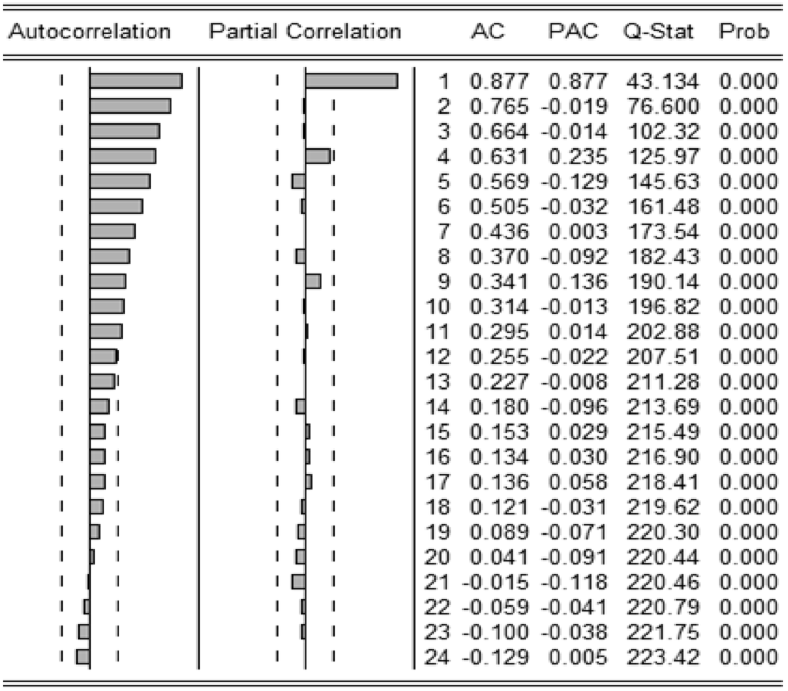


Figure 4. Regression plot between output and target

Reliability level was reviewed to examine the fit between the forecast values obtained in this network structure and real values. This value was determined to be 0.97, which was very high. The predictive power of the model used is clearly seen in the regression graph (Figure 4) between output and target.

4.3. ARIMA Model Result

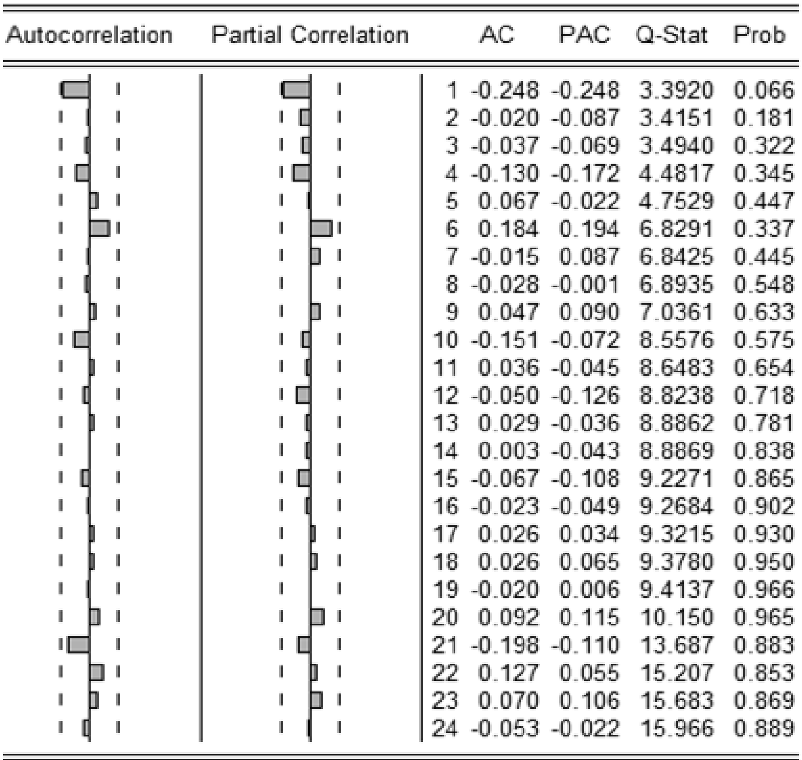
When making a forecast by the ARIMA model, stationaries of series should be first examined. Augmented Dickey-Fuller test (ADF) was administered for renewable source related energy generation amount series (y) by EViews 10 package program. Renewable energy source data are not generally stationary, but series may be rendered stationary with very little difference elicit Bhardwaj et al. (2020). As seen in the cologram in Figure 5, it is not stationary at serial level in 24 delayed stationary test.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.877	0.877	43.134	0.000
		2	0.765	-0.019	76.600	0.000
		3	0.664	-0.014	102.32	0.000
		4	0.631	0.235	125.97	0.000
		5	0.569	-0.129	145.63	0.000
		6	0.505	-0.032	161.48	0.000
		7	0.436	0.003	173.54	0.000
		8	0.370	-0.092	182.43	0.000
		9	0.341	0.136	190.14	0.000
		10	0.314	-0.013	196.82	0.000
		11	0.295	0.014	202.88	0.000
		12	0.255	-0.022	207.51	0.000
		13	0.227	-0.008	211.28	0.000
		14	0.180	-0.096	213.69	0.000
		15	0.153	0.029	215.49	0.000
		16	0.134	0.030	216.90	0.000
		17	0.136	0.058	218.41	0.000
		18	0.121	-0.031	219.62	0.000
		19	0.089	-0.071	220.30	0.000
		20	0.041	-0.091	220.44	0.000
		21	-0.015	-0.118	220.46	0.000
		22	-0.059	-0.041	220.79	0.000
		23	-0.100	-0.038	221.75	0.000
		24	-0.129	0.005	223.42	0.000

Figure 5. Renewable sourced energy generation data collogram (1965-2019)

Series should be rendered stationary as no prediction may be made in non-stationary series, consisting of a unit root. In order to make the series stationary, the 1st difference of the series was elicited and its stationary was rechecked. The series of which cologram is seen in Figure 6 is the first-degree stationary.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.248	-0.248	3.3920	0.066
		2	-0.020	-0.087	3.4151	0.181
		3	-0.037	-0.069	3.4940	0.322
		4	-0.130	-0.172	4.4817	0.345
		5	0.067	-0.022	4.7529	0.447
		6	0.184	0.194	6.8291	0.337
		7	-0.015	0.087	6.8425	0.445
		8	-0.028	-0.001	6.8935	0.548
		9	0.047	0.090	7.0361	0.633
		10	-0.151	-0.072	8.5576	0.575
		11	0.036	-0.045	8.6483	0.654
		12	-0.050	-0.126	8.8238	0.718
		13	0.029	-0.036	8.8862	0.781
		14	0.003	-0.043	8.8869	0.838
		15	-0.067	-0.108	9.2271	0.865
		16	-0.023	-0.049	9.2684	0.902
		17	0.026	0.034	9.3215	0.930
		18	0.026	0.065	9.3780	0.950
		19	-0.020	0.006	9.4137	0.966
		20	0.092	0.115	10.150	0.965
		21	-0.198	-0.110	13.687	0.883
		22	0.127	0.055	15.207	0.853
		23	0.070	0.106	15.683	0.869
		24	-0.053	-0.022	15.966	0.889

Figure 6. The correlogram of the differenced data (1965-2019)

In Figure 5, the ACF coefficients 1,4 and 6 numbered delays (q values) and PACF coefficients 1,4 and 6 delays (p values) are close to the 95% confidence interval limit. Even if they are not accepted completely, these delays will be added to the model and tried to prevent the error. In this regard, 9 models were examined in ARIMA ((p, d, q) form (d shows the degree to which the series is stationary). The ARIMA models which were found to be statistically significant ($\alpha < 0.05$) in these forecast models are provided in Figure 6. of these models, third model forecast was determined to be the most appropriate model in line with the criteria of adjusted R^2, AIC and SIC.

The cologram of residues was examined for checking the fit of the third model (Figure 7) . As seen in Table 6, ACF and PACF values are within the confidence interval for all delays, that is all required data and knowledge were included in the model.

Table 4. Comparison of ARIMA models

Model Numbers	*ARIMA Model*	*Significant Number of Parameters*	*Variance*	*Variance for residuals(SIGMASQ)*	*Adjusted R^2*	*AIC*	*SIC*
1	(1.1.1)	2	6.9600	7.4600	0.0210	6.78	6.93
2	(1.1.4)	2	6.8000	6.7800	0.0510	6.75	6.90
3	(1.1.6)*	2	6.4700	6.6300	0.1400	6.68	6.83
4	(4.1.1)	2	6.8200	6.8600	0.0440	6.76	6.91
5	(4.1.4)	0	7.1300	7.0600	-0.0220	6.82	6.97
6	(4.1.6)	1	6.7500	4.8500	0.0600	6.75	6.90
7	(6.1.1)	2	6.6100	6.7000	0.1050	6.70	6.85
8	(6.1.4)	0	6.8300	5.5600	0.0430	6.79	6.92
9	(6.1.6)	0	6.7900	4.9600	0.0550	6.77	6.92

The ARIMA (1,1,1) model presented results close to the ARIMA(1,1,6) model, considering the AIC and SIC values. Since the long lag values (lag value=6) is not preferred for time series analysis, it has been Table 4 and Table 5.

Table 5. Estimation results of ARIMA(1,1,1) and ARIMA(1,1,6) models

	ARIMA (1,1,1) Model				*ARIMA(1,1,6) Model*			
Variable	*Coefficient*	*Std. Error*	*t- Statistic*	*Prob*	*Coefficient*	*Std. Error*	*t- Statistic*	*Prob*
c	1.624540	0.663952	2.446774	0.01810	1.740824	1.059558	1.642972	0.10690
AR	0.258833	0.293291	0.882513	0.38190	-0.303596	0.115531	-2.627819	0.01150
MA	-0.537716	0.299045	-1.798109	0.07785	0.475444	0.148028	3.211854	0.00240
SIGMASQ	44.02547	7.464271	5.898161	0.00000	38.68020	6.626366	5+837316	0.00000
R-squared	0.078985	*Mean dependent var*	1.634310		*R-squared*	0.190808	*Mean dependent var*	1.634310
Adjusted R-squared	0.021421	*S.D. dependent var*	6.981283		*Adjusted R-squared*	0.140234	*S.D. dependent var*	6.981283
S.E. of regression	6.906103	*Akaike info criterion*	6.778624		*S.E. of regression*	6.473295	*Akaike info criterion*	6.678491
Sum squared resid	2289.325	*Schwarz criterion*	6.928720		*Sum squared resid*	2011.370	*Schwarz criterion*	6.828.587
Log likelihood	-172.2442	*Hannan-Quinn criter*	6.836167		*Log likelihood*	- 169.6408	*Hannan-Quinn criter*	6.736.034
F-statistic	1.372137	*Dublin-Watson stat*	2.014227		*F-statistic*	3.772821	*Dublin-Watson stat*	2.045.859
Prob	0.262558				*Prob*	0.016438		

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.032	-0.032	0.0580	
		2	-0.079	-0.080	0.4117	
		3	-0.024	-0.029	0.4443	0.505
		4	-0.114	-0.123	1.2035	0.548
		5	0.085	0.073	1.6334	0.652
		6	0.039	0.024	1.7249	0.786
		7	-0.003	0.006	1.7256	0.886
		8	0.033	0.029	1.7931	0.938
		9	0.065	0.090	2.0687	0.956
		10	-0.105	-0.096	2.8008	0.946
		11	0.002	0.006	2.8012	0.972
		12	-0.031	-0.040	2.8692	0.984
		13	-0.020	-0.016	2.8990	0.992
		14	-0.110	-0.163	3.7867	0.987
		15	-0.000	0.002	3.7867	0.993
		16	-0.030	-0.065	3.8582	0.996
		17	0.003	-0.007	3.8588	0.998
		18	0.040	0.004	3.9891	0.999
		19	0.020	0.070	4.0236	0.999
		20	0.113	0.116	5.1371	0.999
		21	-0.208	-0.188	9.0520	0.973
		22	0.015	0.046	9.0726	0.982
		23	0.114	0.121	10.331	0.974
		24	-0.005	-0.021	10.333	0.983

Figure 7. Collogram of residuals of the optimal ARIMA model

In order to check the validity of the ARIMA(1,1,6) model determined and to examine its performance, a forecast was made between 2008-2018. The graph of forecasts obtained by this ARIMA model is provided in Figure 8. The regression equation of the model used for prediction is as in Equation 11.

$$\Delta y_t = 1{,}74 - 0{,}30 y_{t-1} + 0{,}47 \varepsilon_{t-6} + \delta \qquad (11)$$

In order to check the validity of the ARIMA(1,1,6) model and to examine its performance, an estimate was made between 2008 and 2018.

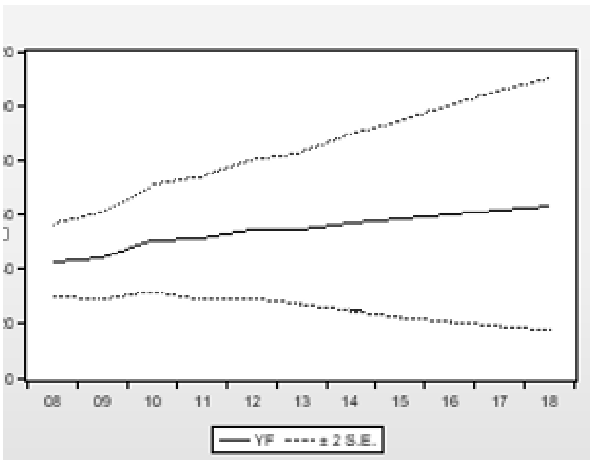


Figure 8. Forecasting with optimal ARIMA model (2008-2018)

In this study, ANN, used to predict the energy to be generated by renewable energy sources and has shown good results in many studies, and ARIMA models, a time series application, were used. MLP 5-5-1 model in ANN networks and ARIMA (1.1.6) models were determined to be appropriate for forecasting. In order to check the validity of the results obtained by the developed model, 11-year data between 2008-2018 were separately predicted by these two models (Table 6).

Table 6. Comparison of prediction models

Years	*Actual*	*ANN Forecasting*	*ANN Differs%*	*ARIMA (1.1.6)*	*ARIMA Differs%*
2008	34.421	42.450	-23.3	42.730	-24.1
2009	38.141	41.157	-7.9	44.490	-16.6
2010	55.715	41.383	25.7	50.800	8.8
2011	58.102	52.759	9.2	51.000	12.2
2012	65.221	59.772	8.4	54.430	16.5
2013	69.227	59.915	13.5	54.340	21.5
2014	52.629	73.822	-40.3	56.640	-7.6
2015	83.658	78.754	5.9	58.210	30.4
2016	90.244	91.290	-1.2	60.000	33.5
2017	87.263	93.122	-6.7	61.730	29.3
2018	97.768	95.686	2.1	96.630	1.2
MAPE%		13.1		21.9	

While MAPE value was specified to be approximately 13.1% in the ANN model, this rate was found to be 21.9% in ARIMA model. This variable refers to the deviation rate in the forecasting model. The predictive power of the model is considered to be *excellent* when MAPE rate is 10%<, *good* when MAPE rate is between 10% and 20%, *reasonable* when MAPE rate is between 20% and 50% and *wrong* when MAPE rate is between above 50% Ghalehkhondab et al. (2016). As it is seen, ANN showed a quite better performance in this study when compared to the ARIMA model. When previous studies were examined, it was observed that ANN mostly provided better results compared to other methods (Ghalehkhondabi et al., 2016). In this study, the results of the model obtained with ANN are more efficient.

The primary goal of this study was to predict the renewable sources related energy generation amount of the Republic of Türkiye until 2023. The renewable sources related energy generation amount of the Republic of Türkiye, forecasted by ANN and ARIMA (1.1.6) models in accordance with 2023 goals, is given in Table 7. Türkiye achieved its 2023 goals regarding the amount of electricity generation from renewable energy in 2019. These results are important for the revision of the 2023 goals.

Table 7. Estimating the amount of energy to be produced (TWh)

Years	*ANN Estimation*	*ARIMA Estimation*
2020	115.599	89.451
2021	116.558	75.631
2022	115.176	58.484
2023	127.516	45.457

5. CONCLUSION and POLICY IMPLICATIONS

In this study, the energy amounts, which were obtained from the BP, generated by the renewable sources of solar, wind, geothermal and biomass and hydraulic power plants between 1965-2019 were used as data. According to a statement made by the EPDK (2020) the share of renewable energy sources (including hydraulic) in total licensed electricity generation was 30.67% in 2018 and 42.10% in 2019 (123789 GWh= 123.789 TWh). Total energy amount generated in 2019 was determined to be 134.49 Twh according to the data provided by BP (2020).

Renewable energy sources will promote development in both economic and social respects for the countries which are dependent on outside energy sources like Türkiye. Spending the sources of country for purchasing energy from other countries will be reduced and new sectors for employment will grow by means of RES. Energy dependence makes countries more sensitive against political conflicts. To provide security of energy transmission lines, for example, pipelines in our country, requires an additional effort. In addition to economic, social and political effects of energy dependence, negative effects of fossil resources on the environment is an issue with a high awareness level around the world. In this regard, Türkiye attempts to reduce greenhouse gas emissions in accordance with the international agreements, such as the Madrid protocol to which Türkiye became a party in 2017.

The Republic of Türkiye is exerting effort to extend the use of RES. To increase the share of RES in total energy generation to 30% is one of the 2023 goals of Türkiye. Türkiye is approaching this goal swiftly, and 5000 MW installed solar energy sources, which is a 2023 goals, was even achieved in 2018.

Although our country has been affected negatively by Covid-19 pandemic in economical respect as it is across the world, the duration in the renewable energy support mechanism was extended for 6 months. Such examples are indicators to what extent the expansion of RES is attached importance in our country. Prediction of generation or consumption amounts is of paramount importance for the interests of the country so that renewable energy sources can be planned in accordance with this goal.

Most of the previous studies revealed that energy consumption will increase in the following years. However, this increasing trend can continue for a while (Ghalehkhondabi et al., 2016). The global economic slowdown, caused by Covid-19 pandemic and which we do not know for now how long its effect will last, will certainly affect the generation of renewable energy sources. The forecasts made in this study revealed that the generation amount would decrease until 2023 when compared to 2019. This may be explained by the fact that the energy generation amounts by RES do not have a regular course in Türkiye and this cannot be only referred to Türkiye. In Türkiye, there was a natural gas problem in 2009 due to the problem between Russia and Ukraine because of transmission price. Moreover, similar problems were also seen in 2006 when Ukraine-Russia ceased natural gas and in 2007 when Iran cut off natural gas. There was a tension with Russia after the plane crisis occurred in November 2016. All these examples have made the strategy of energy generation by renewable sources one of the most significant issues of the energy policy of the country. As seen in the generation amounts in Appendix different energy strategies developed in different circumstances are in a tendency to increase or decrease from time to time by both own investments and incentives of the state.

In this study, ANN, used to predict the energy to be generated by renewable energy sources and has shown good results in many studies, and ARIMA models, a time series application, were used. MLP 5-5-1 model in ANN networks and ARIMA (1.1.6) models were determined to be appropriate for forecasting. In order to check the validity of the results obtained by the developed model, 11-year data between 2008-2018 were separately predicted by these two models. While MAPE value was specified to be approximately 13.1% in the ANN model, this rate was found to be 21.9% in ARIMA model. This variable refers to the deviation rate in the forecasting model. The predictive power of the model is considered to be "excellent" when MAPE rate is 10%<, "good" when MAPE rate is between 10% and 20%, "reasonable" when MAPE rate is between 20% and 50% and "wrong" when MAPE rate is between above 50% Ghalehkhondab et al. (2016). As it is seen, ANN showed a quite better performance in this study when compared to the ARIMA model. When previous studies were examined, it was observed that ANN mostly provided better results compared to other methods (Ghalehkhondabi et al. 2016). In this study, the results of the model obtained with ANN are more efficient.

Another goal of this study was to investigate the efficiency of these two models. In this study, the efficiency of the ANN model was found to be higher than the ARIMA model. Their MAPE values are 13.1 % and 21.9 %, respectively. It was also stated in previous studies that ANN models are more efficient in prediction. Kazemzadeh et al. (2020), made an energy demand by ANN and ARIMA models. While MAPE values were determined to be approximately 16% and 19% for two ARIMA models, it was 1.5% for the ANN model. Nair et al. (2017), found out the MAPE values to be 14% and 18%, respectively for ANN and ARIMA models they used to estimate wind speeds of certain regions. Contrary to these results, Kheırkhah et al. (2013), argued that ARIMA model provided a better result in their energy demand forecasting models due to its dynamic structure (MAPE = 0.103).

The primary goal of this study was to predict the renewable sources related energy generation amount of the Republic of Türkiye until 2023. The renewable sources related energy generation amount of the Republic of Türkiye, forecasted by ANN and ARIMA (1.1.6) models in accordance with 2023 goals. Türkiye achieved its 2023 goals regarding the amount of electricity generation from renewable energy in 2019. These results are important for the revision of the 2023 goals.

The prediction of hydraulic related energy generation amount of Türkiye performed by Uzlu et al. (2014), through the ANN model has been between 69.1 and 76.5 TWh for 2021. In addition, Şahin (2020), reported the amount of renewable energy production of Türkiye in 2023 to be 141.0–150.8 (MAPE 7,1) TWh, and 57.3–69.7 TWh (MAPE 9.1) amount of this has been forecasted to be generated by hydraulic energy generation. Şahin (2018), has predicted that 109.1 TWh energy would be generated by hydraulic sources, 5.8 TWh by geothermal sources and 50.63 TWh by wind-related sources in 2023.

In this study, when the data related to renewable energy sources were obtained, hydraulic sources were not included in, and this type of source has the biggest share in energy generation by RES sources. In Türkiye, only the hydraulic energy generation facilities with a river type or reservoir area of less than fifteen square kilometres are considered renewable among all hydraulic resources. However, there is no data regarding the generation amount by hydraulic sources considered within the renewable class between 1965-2019, revealing the separation of generation amounts. The generation amount obtained by hydraulic sources is included in this study as hydraulic sources are domestic and there is no external dependence on main source supply. In further studies, forecasting models can be developed by utilising the variables, such as wind speed, sunshine duration, water temperature of the geothermal resource, which are determinant of generation amount of each renewable energy source. What is more, generation amount of each source is of importance as they may be used as a guide by policymakers, especially regarding energy investment planning.

The study has some limitations. Firstly, There are many different forecasting methods, excluding the ones used in this study. There are many various determinants of energy generation amount by renewable sources, and the technique selected depends on these different determinants. For this reason, predictions may also be carried out by different forecasting methods. In addition, that the dataset cannot be updated until the article is published. Data revision was not preferred as there would be a break between post-corona data and pre- Covid19 data. Analyzes for post-Covid19 period can be renewed and compared.

Çatışma Beyanı /*Conflict of Interest*

Yazar tarafından herhangi bir potansiyel çıkar çatışması beyan edilmemiştir.
No potential conflict of interest was reported by the author.

Fon Desteği / *Funding*

Bu çalışmada herhangi bir resmi, ticari ya da kâr amacı gütmeyen organizasyondan fon desteği alınmamıştır.
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Etik Standartlara Uygunluk / *Compliance with Ethical Standards*

Yazarlar tarafından, çalışmada kullanılan araç ve yöntemlerin Etik Kurul izni gerektirmediği beyan edilmiştir.
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Etik Beyanı / *Ethical Statement*

Yazar tarafından bu çalışmada bilimsel ve etik ilkelere uyulduğu ve yararlanılan tüm çalışmaların kaynakçada belirtildiği beyan edilmiştir.
It was declared by the author that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

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APPENDIX

Table A1. Dataset

	Ç-G5	*G1*	*G2*	*G3*	*G4*
Years	*Produced Amount of Energy from the Renewable and Hydro -TWh*	*Produced Amount of Energy from the Solar - TWh*	*Produced Amount of Energy from the Wind - TWh*	*Produced Amount of Energy from the Geotermal and Biomass- TWh*	*Produced Amount of Energy from the Hydro - TWh*
1965	2.2790	0.0	0.0000	0.1000	2.1790
1966	2.4601	0.0	0.0000	0.1220	2.3381
1967	2.5548	0.0	0.0000	0.1730	2.3818
1968	3.3538	0.0	0.0000	0.1790	3.1748
1969	3.6229	0.0	0.0000	0.1780	3.4449
1970	3.1988	0.0	0.0000	0.1660	3.0328
1971	2.7722	0.0	0.0000	0.1620	2.6102
1972	3.3792	0.0	0.0000	0.1750	3.2042
1973	2.8004	0.0	0.0000	0.1970	2.6034
1974	3.5628	0.0	0.0000	0.2070	3.3558
1975	6.1236	0.0	0.0000	0.2200	5.9036
1976	8.5358	0.0	0.0000	0.1610	8.3748
1977	8.7903	0.0	0.0000	0.2180	8.5723
1978	9.4718	0.0	0.0000	0.1370	9.3348
1979	10.4339	0.0	0.0000	0.1450	10.2889
1980	11.4842	0.0	0.0000	0.1360	11.3482
1981	12.7261	0.0	0.0000	0.1100	12.6161
1982	14.1667	0.0	0.0000	0.0000	14.1667
1983	11.3427	0.0	0.0000	0.0000	11.3427
1984	13.4484	0.0	0.0000	0.0221	13.4263
1985	12.0509	0.0	0.0000	0.0060	12.0449
1986	11.9162	0.0	0.0000	0.0436	11.8726
1987	18.6757	0.0	0.0000	0.0579	18.6178
1988	29.0180	0.0	0.0000	0.0684	28.9496
1989	18.0022	0.0	0.0000	0.0626	17.9396
1990	23.2277	0.0	0.0000	0.0801	23.1476
1991	22.8030	0.0	0.0000	0.1197	22.6833
1992	26.6847	0.0	0.0000	0.1167	26.5680
1993	34.0849	0.0	0.0000	0.1340	33.9509
1994	30.7159	0.0	0.0000	0.1300	30.5859
1995	35.8492	0.0	0.0000	0.3083	35.5409
1996	40.7343	0.0	0.0000	0.2591	40.4752
1997	40.1929	0.0	0.0000	0.3768	39.8161
1998	42.5605	0.0	0.0055	0.3260	42.2290
1999	34.9119	0.0	0.0205	0.2139	34.6775
2000	31.1534	0.0	0.0334	0.2415	30.8785
2001	24.3459	0.0	0.0624	0.2736	24.0099
2002	33.9664	0.0	0.0480	0.2346	33.6838
2003	35.5585	0.0	0.0614	0.1676	35.3295
2004	46.3106	0.0	0.0577	0.1692	46.0837
2005	39.7479	0.0	0.0590	0.1284	39.5605

Table A1. (*Continued*)

Years	*Produced Amount of Energy from the Renewable and Hydro -TWh*	*Produced Amount of Energy from the Solar - TWh*	*Produced Amount of Energy from the Wind - TWh*	*Produced Amount of Energy from the Geotermal and Biomass- TWh*	*Produced Amount of Energy from the Hydro -*
2006	44.5226	0.0	0.1305	0.1479	44.2442
2007	36.4568	0.0	0.3511	0.2549	35.8508
2008	34.4210	0.0	0.8465	0.3047	33.2698
2009	38.1412	0.0	1.4954	0.6874	35.9584
2010	55.7154	0.00240	2.9164	1.0011	51.7955
2011	58.1025	0.00286	4.7239	1.0371	52.3386
2012	65.2213	0.00426	5.8608	1.4913	57.8650
2013	69.2269	0.00678	7.5575	2.2422	59.4205
2014	52.6287	0.01740	8.5201	3.4466	40.6447
2015	83.6580	0.19412	11.6525	4.6655	67.1458
2016	90.2443	1.04310	15.5171	6.4532	67.2309
2017	87.2631	2.88930	17.9038	8.2515	58.2185
2018	97.7680	7.79980	19.9492	10.0805	59.9385
2019	134.4934	10.91958	21.7040	12.7106	89.1593