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General overview of artificial neural network applications in renewable energy systems

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ABSTRACT

A country's primary aim is to ensure sustainable development, with clean and accessible energy vital to this goal. Achieving clean and accessible energy requires maximizing the use of renewable energy resources. Significant steps have been taken globally to increase the share of renewable energy in production and consumption to support this objective. This includes establishing national and international policies, setting strategic targets, and implementing necessary measures. Furthermore, the advancement of technology has led to rapid growth in renewable energy-based electricity generation in recent years. This growth has created a need for predictability in electricity generation, distribution, transmission, and financing to balance supply and demand effectively. As a result, integrating artificial intelligence (AI) applications has become essential for digital transformation in the energy sector. This study aims to explore the use of artificial neural networks (ANNs) for predictability in the renewable energy sector by reviewing literature from 2017 to 2024. The focus is primarily on studies published in academic journals indexed in the Science Citation Index (SCI). The research examines the relationship between algorithms, prediction levels, and renewable energy. The study concludes with findings and recommendations intended to contribute to the digital transformation of the renewable energy industry. As a country with significant renewable energy potential such as solar and wind, Türkiye can manage the supply-demand balance more effectively by integrating technologies such as AI and ANNs into the energy sector.

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1. INTRODUCTION

Energy is one of the strategic elements that ensure the continuity and development of countries, increase their welfare, and direct national and international energy policies. Sustainable energy policies must be determined for a sustainable future and development; policies must be reviewed and revised, when necessary, within the framework of predictability, competitiveness, efficiency, financial sustainability, and participation principles. In addition, correctly managing energy markets in parallel with political goals is critical in maximizing the country's energy potential, increasing the diversity of energy resources, and ensuring supply security.

In terms of a sustainable energy and supply security balance, effective and efficient use of renewable energy resources affects more than one parameter of the sustainable development concept, which looks at the economic, social, and environmental dimensions that are interconnected and articulated with each other, evaluates them and establishes a balance between them [1, 2].

For this reason, rational use of renewable energy resources and further integration into the system are among the most critical issues that need to be taken to ensure energy supply security, localize the energy produced, protect the environment, and prevent global warming [1, 2].

For this purpose, international agreements and protocols signed and national legal arrangements have been made. As a result, as can be seen in Figures 1 and 2 and Table 2, the number of power plants for clean energy production and therefore the installed capacity has increased rapidly in our country in recent years, and especially renewable resources have taken a larger share in energy production [1, 2].

Our installed power, which was 99,819.6 MW in 2021, reached 104,134 MW as of February 2023 [1, 2]. However, 54% of our installed power in February 2023, in other words, 56,232.36 MW, was generated by renewable energy power plants, while 33% of electricity production was generated from renewable energy [2].

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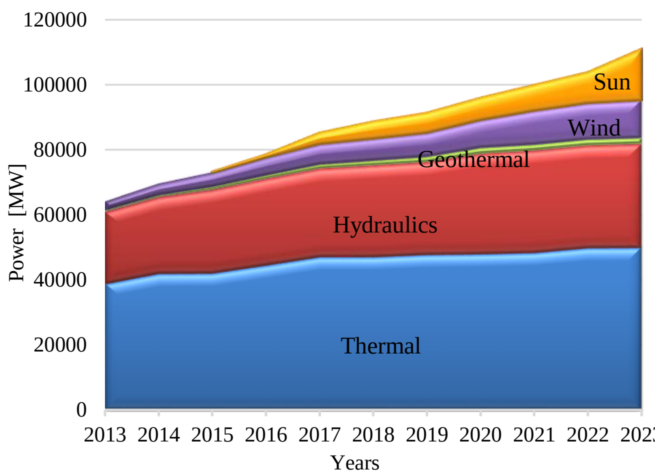

Fig. 1. Development of Türkiye's installed capacity according to primary energy resources (2013-2023) [1].

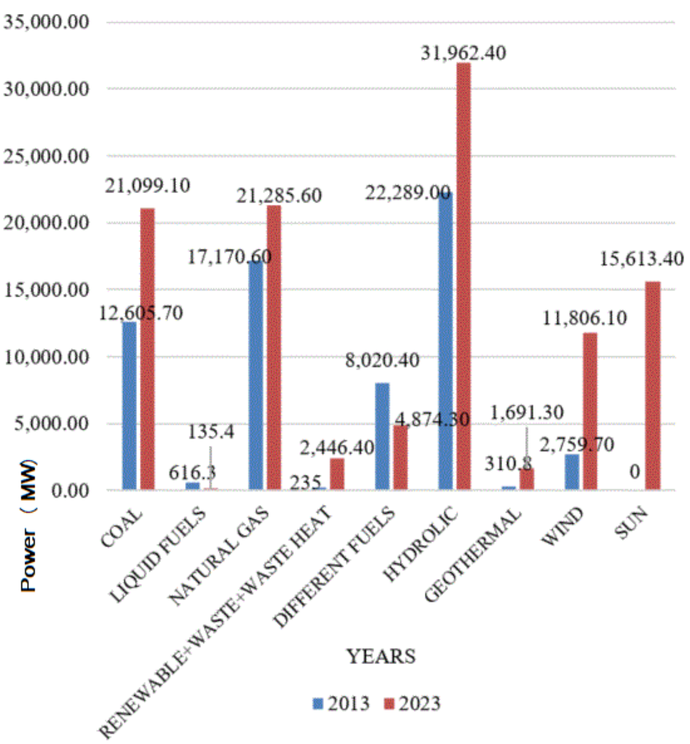

Fig. 2. Türkiye's installed capacity according to primary energy resources in 2013-2023 (MW) [1].

The difficulty and complexity of integrating increasing renewable energy power plants into the existing energy grid have further increased the need for predictability. This requirement has led to the energy sector's evolution and enabled AI to enter this field. AI will make significant contributions in terms of generation estimation, equipment maintenance, energy efficiency, storage analysis, energy management, and grid integration in the field of renewable energy. AI is a multidisciplinary field and consists of methods such as expert systems, genetic algorithms, fuzzy logic, ANNs, and machine learning. ANNs are one of the methods frequently used in the field of renewable energy among AI methodologies, and this study includes research conducted with ANNs in this field regarding predictability.

This study uses artificial intelligence (AI) methods to predict solar power plant generation data based on meteorological data. In particular, multilayer artificial neural networks (MAMN) and adaptive fuzzy artificial neural network inference system (ANFIS) methods are used. The study analyzed the production data of a 200-kW solar power plant located at the Ipekköy campus of Amasya University.

In the study, an output variable was estimated using 12 input variables. The ANFIS model was optimized with different neuron numbers and learning algorithms. The ANFIS application made predictions using a hybrid algorithm and belief membership function. The results show that both models' prediction values converge reasonably well with the measured values.

The results show that the R^2 value of the ESRF is 0.9569, the mean squared error (MSE) value is 0.1434, and the root-MSE (RMSE) value is 0.3786, while the R^2 value for ANFIS is 0.9294, the MSE value is 0.0089, and RMSE value is 0.0946. The study reveals that the models of MFFR and ANFIS effectively predict the output energy of solar power plants and that MFFR performs better than ANFIS. It is also emphasized that similar methods can be applied to power plants in different geological locations [3].

Within the scope of the study, ANN-based forecasting methodology is presented for power generation forecasting using energy indicators such as installed power capacity, gross electricity generation, net electricity consumption, imports, exports, and population of Türkiye between 1985-2019, and electricity generation forecasting from oil, gas, coal and renewable energy sources is performed. The results are evaluated statistically, and the accuracy of the approach is tested. The ANN model in the analysis study is determined as a forward multilayer perceptron network topology. As a result of the paper, it was found that the presented approach meets the high accuracy of power generation prediction [4].

2. RECENT METHODOLOGIES ON THE STATE OF THE ART

ANNs, first developed in the 19th century, are a method of AI that mimics biological nerve cells' structure, learning, recall, and generalization capabilities. ANNs, also known as neural computing, network computing, connected networks, parallel distributed networks, and neuromorphic systems, have been successfully applied in mathematics, engineering, energy, medicine, economics, meteorology, psychology, sociology, biology, environment and many other fields and their use has increased in recent years [5]. Classification, prediction, and modelling are the main application areas of this method since it works in a similar way to the human brain, learns the given data, generalizes, works with an unlimited number of variables, and predicts and classifies with the help of such data [5, 6]. However, there are also many application areas. These areas include pattern recognition, system diagnostics, time series analysis, probability function estimation, data association and pattern matching, intelligent and non-linear control, signal filtering, data compression, interpretation and filtering, non-linear signal processing, non-linear system modelling and optimization, and robotics [6].

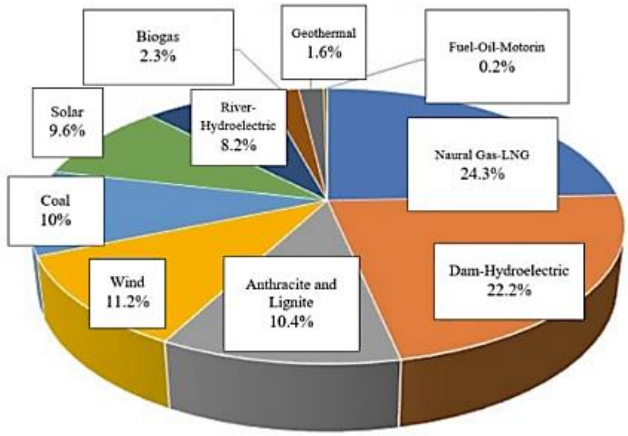

Fig. 3. Distribution of installed electrical power by resources (February 2023) (MW) [2].

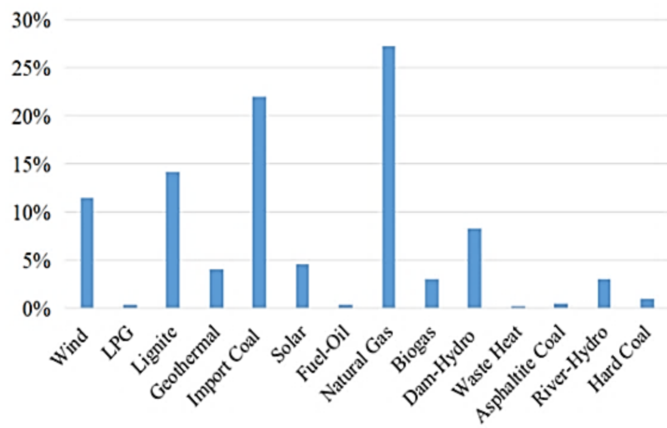

Fig. 4. Distribution of electricity production by resources (February 2023-Cumulative temporary values) (MWh) [2].

The distribution of installed electrical power by resources and the distribution of electricity production with cumulative values can be displayed in Figures 3 and 4. As can be seen in Figure 5, ANNs usually consist of an input layer, one or more hidden and output layers, neurons, and weights in this layer, and information is distributed through the connections in the network and the weights of these connections. ANNs have advantages and weaknesses, which are summarized in Table 1. However, their most significant advantages are their learning capability and the use of different learning algorithms [6]. In addition, a frequently cited drawback is the risk of failure in the learning process due to the inability to analyze the system's operation [5].

The most critical task of ANN is to determine outputs according to its inputs. For this purpose, the network is trained with the relevant sample input set and is given the ability to generalize and make decisions. With these abilities, output information corresponding to similar input information is determined. The cells that make up the ANN, the ability of these cells to use and process information, and how they are connected from different network architectures. In terms of architecture, ANNs are generally divided into feed-forward and feedback networks, and the network classification is given in Figure 6.

Table 1. Advantages and weaknesses of ANN [6-9].

Advantages Features	*Weaknesses Features*
They are capable of learning and can learn with different learning algorithms.	Since there is no specific method for determining the appropriate network structure to solve the problem, the network structure is usually made using trial and error.
They can produce results (knowledge) for unprecedented outputs.	There is no absolute method for determining the end time of network training.
It can work with incomplete or unclear information.	Stability analysis cannot be performed except for some networks.
Make decisions under uncertainty.	If the sample is not available, training is not possible. Although sample data is available, learning is impossible due to the network architecture and learning rule.
They are tolerant of mistakes.	It is hardware-dependent as it requires processors with parallel processing power.
They have distributed memory.	When it finds a solution to a problem, it does not provide any information about why and how it occurred.
It has parallel processing capability and can process real-time information.	Since it can work with numerical data, the problem should be converted into numerical data before introducing it to the networks.

In the feed-forward network structure, neurons are in the form of regular layers from input to output, and there is only one connection between one layer and the following layers [11]. The data coming to the network's input is transmitted to the cells in the hidden layer in the middle without any change, processed in the output layer, and transferred to the external environment. In a feedback network structure, a neuron's output is not only used as input in the following neuron layer. Still, it can also be connected as input to any neuron in the previous layer or its layer. Therefore, it exhibits a non-linear dynamic behaviour. ANNs have two components: the learning algorithm and the activation function [11]. One of the most essential features of ANNs is the ability to learn data from its source. The data is stored at the ends (weights) of the connections of the nerves in the network. For this reason, it is vital to determine the weight values. When a whole network is considered, the weights should take optimal values. The learning process is to find the best and appropriate value of the weights [12].

To reach these weights, the network is trained. Learning strategies are grouped as supervised learning, supportive/reinforcement learning, unsupervised learning, and mixed (hybrid) learning, and these strategies are summarized as follows.

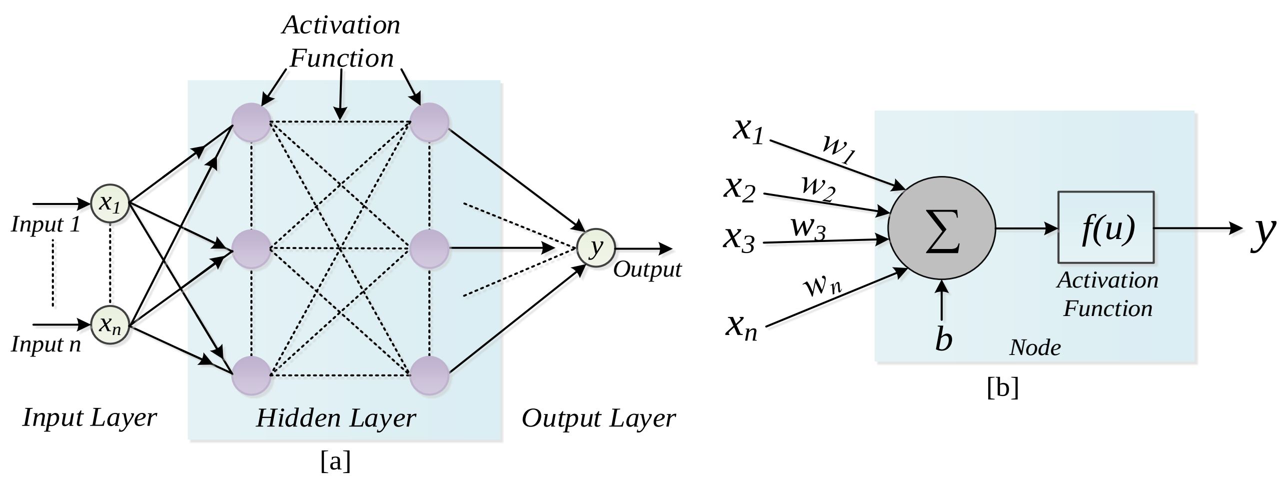

Fig. 5. An ANN structure. Schematic of (a) feedforward neural network and (b) node structure.

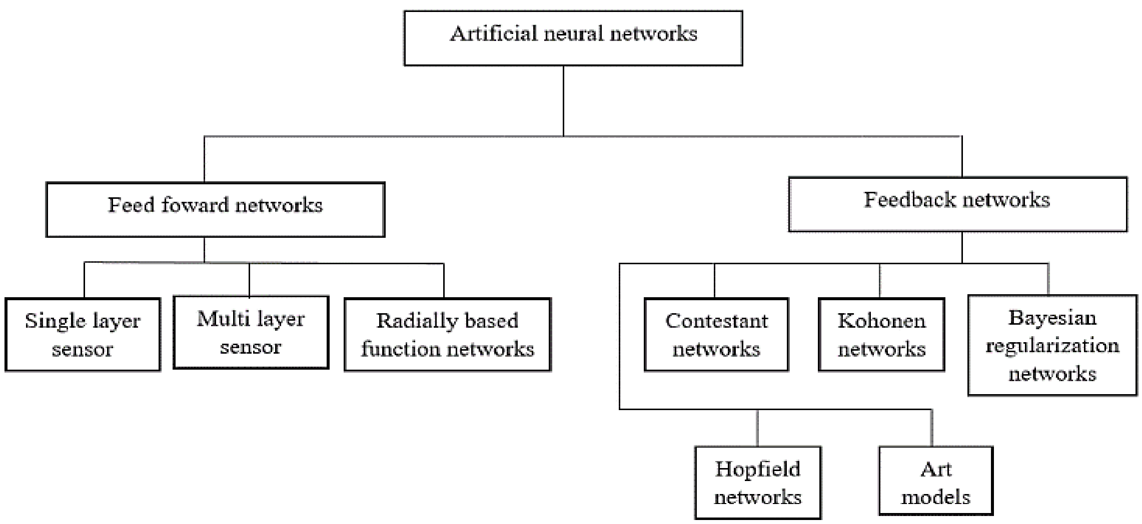

Fig. 6. Different types of ANNs [10].

- **Supervised Learning:**

The input values and the expected output value in response to the input values are given to the neural network system as a training set, and the learning process is performed. The error between the calculated and expected output values is reduced, and the input values are classified.

✓ Single Layer Perceptron (SLP)
✓ Multi-Layer Perceptron (MLP)
✓ Support Vector Machines (SVM)

- **Supportive/Reinforcement Learning:**

The neural network is not given the expected output values in response to the input values. Instead, it is expected to calculate the output value, and the network is informed whether the computed output value is true or false.

- **Unsupervised Learning:**

The neural network is not informed whether the expected output value is the output value calculated on the computer. The network tries to group or cluster the input values. However, the user must label the clustered data after learning.

✓ Adaptive Resonance Theory (ART)
✓ Self-Organizing Map (SOM)

- **Hybrid Learning:**

Both supervised and unsupervised learning are used together.

✓ Radial basis artificial neural networks (ANNs)
✓ Probability-based ANNs

The activation function matches the input and output layers, and the correct choice of the function significantly affects the network performance [12]. This function is usually nonlinear [11]. However, it can be chosen as unipolar (0 to 1), bipolar (-1 to +1) and linear and it is the element that enables the neural network to learn the non-linear structure. Some of the activation functions are listed below:

✓ Stepwise Activation Function
✓ Sigmoid Activation Function
✓ Piecewise Linear Activation Function
✓ Gaussian Activation Function
✓ Linear Activation Function
✓ Hyperbolic Tangent Activation Function

Table 2. Development of the share of renewable resource electric energy production in Türkiye's total output over the years (Unit: MW) (2000-2021) [1].

Years	*Dam*	*N. Lake and Run of River*	*Total Hydro*	*Geothermal*	*Wind*	*Solar*	*Renew. +Wastes+ Waste Heat*	*Lignite*	*Hard Coal +Asphaltite*	*Domestic Resources Installed Capacity*	*Total Installed Capacity*	*Domestic Resources Share (%)*
2000	10,501.4	673.8	11,175.2	17.5	18.9	-	23.8	6,508.9	335.0	18,079.3	27,264.1	66.3
2001	10,959.4	713.5	11,672.9	17.5	18.9	-	23.6	6,510.7	335.0	18,578.6	28,332.4	65.6
2002	11,469.4	771.5	12,240.9	17.5	18.9	-	27.6	6,502.9	335.0	19,142.8	31,845.8	60.1
2003	11,752.4	826.3	12,578.7	15.0	18.9	-	27.6	6,438.9	335.0	19,414.1	35,587.0	54.6
2004	11,752.4	893.0	12,645.4	15.0	18.9	-	27.6	6,450.8	335.0	19,492.7	36,824.0	52.9
2005	11,967.4	938.6	12,906.1	15.0	20.1	-	35.3	7,130.8	335.0	20,442.3	38,843.5	52.6
2006	11,966.9	1,095.8	13,062.7	23.0	59.0	-	41.3	8,210.8	335.0	21,731.7	40,564.8	53.6
2007	12,262.0	1,132.9	13,394.9	23.0	147.5	-	42.7	8,211.4	335.0	22,154.5	40,835.7	54.3
2008	12,422.8	1,405.9	13,828.7	29.8	363.7	-	59.7	8,205.0	335.0	22,821.9	41,817.2	54.6
2009	12,681.7	1,871.7	14,553.3	77.2	791.6	-	86.5	8,199.3	470.0	24,177.9	44,761.2	54.0
2010	13,067.1	2,764.2	15,831.2	94.2	1,320.2	-	107.2	8,199.3	470.0	26,022.1	49,524.1	52.5
2011	13,529.3	3,607.7	17,137.1	114.2	1,728.7	-	125.7	8,199.3	470.0	27,775.0	52,911.1	52.5
2012	14,744.6	4,864.8	19,609.4	162.2	2,260.6	-	168.8	8,193.3	470.0	30,864.3	57,059.4	54.1
2013	16,142.5	6,146.6	22,289.0	310.8	2,759.7	-	235.0	8,223.2	470.0	34,287.7	64,007.5	53.6
2014	16,606.9	7,036.3	23,643.2	404.9	3,629.7	40.2	299.1	8,281.3	470.0	36,768.4	69,519.8	52.9
2015	19,077.2	6,790.6	25,867.8	623.9	4,503.2	248.8	370.1	8,663.4	755.0	41,032.2	73,146.7	56.1
2016	19,558.6	7,122.5	26,681.1	820.9	5,751.3	832.5	496.4	9,126.5	755.0	44,463.7	78,497.4	56.6
2017	19,776.0	7,497.1	27,273.1	1,063.7	6,516.2	3,420.7	641.9	9,129.1	782.5	48,827.2	85,200.0	57.3
2018	20,536.1	7,755.3	28,291.4	1,282.5	7,005.4	5,062.8	818.9	9,456.1	782.5	52,699.6	88,550.8	59.5
2019	20,642.5	7,860.5	28,503.0	1,514.7	7,591.2	5,995.2	1,170.5	9,966.0	782.5	55,523.1	91,267.0	60.8
2020	22,925.0	8,058.9	30,983.9	1,613.2	8,832.4	6,667.4	1,502.8	9,988.7	782.5	60,370.9	95,890.6	63.0
2021	23,280.4	8,212.2	31,492.6	1,676.2	10,607.0	7,815.6	1,642.7	9,988.7	812.5	64,035.3	99,819.6	64.2
2022	23,275.2	8,296.3	31,571.5	1,691.3	11,396.2	9,425.4	1,921.3	10,066.3	812.5	66,884.5	103,809.3	64.4

3. GENERAL OVERVIEW OF RELATED METHODOLOGIES

In recent years, the applications of ANNs in the energy sector have been overgrown. ANNs are mainly used for forecasting purposes, especially in renewable energy.

In this study, the documentary search technique, one of the quantitative research types, was used in the literature review on ANN, and Google Scholar and DergiPark databases were utilized. The year range for the studies was determined as 2017-2022. The literature review analyzed 94 (ninety-four) accessible publications [13-102] and [103-106]. The statistics of these publications are given in Table 3.

Table 3. Statistics on the studies reviewed [13-106].

SCI	*SCI Expanded (SCIE)*	*Emerging Sources Citation Index (ESCI)*	*Others*	*Total*
4	52	4	34	94

The articles published in journals in SCIE and ESCI were analyzed in general, and it was observed that a feed-forward neural network was used in 46 studies, and a feedback neural network was used in 7 studies. In terms of algorithms, the methods mentioned in the studies were compiled and presented in Table 4.

Table 4. The training algorithms used in articles published in SCIE and ESCI journals.

The Training Algorithms Used in Articles Published in SCIE and ESCI Journals	*References*
Levenberg-Marquardt (LM)	[16], [23], [35], [37], [39], [47], [51], [52], [54], [58], [59], [60], [72], [76], [87], [91], [98], [99], [106]
Bayesian regularization	[23], [41], [61], [73], [96], [101]
Resilient propagation	[51],[87]
Scaled conjugate gradient	[23],[54],[87]
Backpropagation	[16], [23], [29], [31], [35], [37], [38], [41], [42], [45], [46], [50], [53], [54], [57], [58], [66], [67], [68], [69], [71], [72], [73], [75], [76], [87], [94], [98]

There are different methods for comparing the performance of ANN models such as MSE, mean absolute error (MAE), normalized root mean square error (NMSE), coefficient of determination/explanation/determination (R^2) and Kappa value in the mentioned studies, MAE, MSE, root mean square error (RMSE), mean absolute deviation (MAD), correlation coefficient (R), mean absolute percentage error (MAPE), nash-sutcliffe efficiency index (NSE), and standard error of prediction (SEP) coefficients were preferred.

When the metric values are analyzed, it is seen that R^2 and R are 0.74 and above, NRMSE is less than 30%, Nash-Sutcliffe efficiency coefficient is 0.96 and 0.97, SEP value is 1.875, and other error metrics have small values and are close to zero. In conclusion, the models proposed in the studies perform well in forecasting.

However, when the studies are analyzed regarding renewable energy source types, thirty-three studies have been conducted on solar energy, fourteen on wind energy, five on biomass energy, five on hydrogen energy, four on hydraulic energy, and one on wave energy, respectively. As a result, most studies were conducted on solar energy, while no study was conducted on geothermal energy. Only four of the studies analyzed were based on the studies in the SCI journals, and only four were examined in detail. Related studies are summarized in detail in Tables 5 and 6. One neuron in the input layer, three neurons in the hidden layer, and one neuron in the output layer [40]; 1 neuron in the input layer, 50 neurons in the 1st hidden layer, 100 neurons in the 2nd hidden layer, and one neuron in the output layer [62]; 4 neurons in the input layer, 12 neurons in the 4th hidden layer, 100 neurons in the 2nd hidden layer and two neurons in the output layer [65]. 70% of the data was used for training, 15% for validation, and 15% for testing [40]; 70% of the data was used for training and 30% for testing [62]; and 50% of the data was used for training and 50% for testing [65].

Table 5. ANN models in articles published in SCIE and ESCI journals.

ANN Models	*Study Reference*	*NB of Study*
Multi-layer perceptron (MLP)	[16], [23], [29], [31], [39], [45], [49], [54], [55], [57], [59], [60], [63], [70], [75], [76],[77], [81], [83], [84], [86], [87], [96], [97], [98], [101], [103]	25
Recurrent neural networks (RNN)	[29], [52], [83], [85], [106]	5
Radial basis function neural network (RBFNN)	[51], [63]	2
Deep neural networks (DNN)	[51], [85]	1
Elman neural network structure (ENN)	[63]	1
Self-organizing feature maps (SOFM)	[75]	1
The wavelet artificial neural network (D-ANN)	[63]	1
Nonlinear autoregressive exogenous model (NARX ANN)	[61], [99], [106]	3
Convolutional neural networks (CNN)	[89], [100]	2
Spiking neural network (SNN)	[100]	1
Multiscale spatial-temporal graph neural network (MST-GNN)	[93]	1

In the mentioned studies, MSE, RMSE, and R^2 are used as error metrics. The RMSE value can vary from 0 to ∞. Predictors with negatively biased values, in other words, predictors with lower values, perform better. The MSE is always positive, and estimators with values close to zero perform better. R^2 is a metric with a value ranging between 0 and 1, with a value closer to 1 indicating better performance. When the values of these metrics are analyzed, it is seen that the models used in the estimations are successful. However, although the metrics frequently used in regression problems were utilized, other metrics could have measured the accuracy of the predictions.

The paper presents a comprehensive review of the history, working principles, and application areas of general ANN models. Deep neural networks (DNNs), as a subset of machine learning, play an important role in understanding complex input-output relationships, especially by working with large data sets.

The main points of the paper are as follows:

1. Fundamentals of Deep Learning: Deep learning builds a hierarchy of higher-level attributes by combining low-level attributes. This enables systems to learn directly from data by reducing the dependence on man-made attributes.

2. Application Areas: Deep learning is used in many areas, such as image processing, voice recognition, object detection, engineering applications, commercial activities, medical applications, and natural language processing.

3. The Role of Big Technology Companies: Large companies such as Google, Apple, and Tesla integrate deep learning into their applications and continuously conduct research in this field.

4. Artificial Neural Networks (ANNs): In the article, various models of ANNs and the importance of these models in deep learning processes are emphasized.

In conclusion, the article discusses the current importance and application areas of deep learning in detail and summarizes the developments and research in this field [104]. The article provides a comprehensive comparison of various machine-learning methods used for forecasting solar energy production. It emphasizes the importance of accurate solar power forecasting in optimizing energy management and integrating renewable energy sources into the grid. The study reviews several machine learning algorithms, including ANN, Support Vector Machines (SVM), and Random Forests, highlighting their strengths and weaknesses in predicting solar energy output.

1. Performance of Algorithms: The study shows that different algorithms have varying levels of accuracy depending on the input features and the specific conditions of the solar energy systems being analyzed. For instance, Random Forest and ANN models demonstrated superior performance in many cases.

2. Importance of Input Features: The inclusion of additional input features, such as solar irradiance and temperature, significantly enhances the prediction accuracy of the models.

3. Integration with IoT: The article discusses the role of the Internet of Things (IoT) in improving solar energy forecasting. IoT devices can collect real-time data, facilitating better monitoring and management of solar energy systems. Overall, the article underscores the potential of machine learning to transform solar energy forecasting, making it more efficient and effective in meeting energy demands and supporting sustainable practices [105].

The paper focuses on improving the forecasting and prediction of solar photovoltaic (PV) power output. The authors emphasized the importance of accurately forecasting solar power generation to reduce energy scarcity and improve the reliability of power systems, especially given the variability of solar energy due to weather conditions. The increasing dependence on renewable energy sources, especially solar PV systems, has led to the need for effective forecasting models to manage power generation and grid stability. In this study, three types of ANNs - multilayer feed-forward neural network (MLFFNN), recurrent neural network (RNN), and nonlinear autoregressive exogenous (NARX) model neural network (NARXNN) - are used to predict the output power of solar PV substations in Egypt. The models were trained using real data containing various weather variables. The authors evaluate and validate the performance of these ANN types under different conditions, emphasizing the importance of weather data, timestamps and solar radiation in improving forecast accuracy.

Table 6. Related studies published in high-level journals [40, 56, 62, 65].

Series Number	*Authors*	*Publish Year*	*Prediction*	*Working Area*	*ANN Technique*	*ANN Structure*	*ANN Input*	*ANN Output*	*Performance Evaluation Criteria*	*Renewable Energy Source Type*
1	Baptista et al. [40]	2017	Photovoltaic system power output	Portugal	Multilayer neural network	1-1-1	Solar radiation	Power	MSE: 0.088	Solar energy
2	Jiang et al. [56]	2019	Real-time thrust acting on the rotor of a wind turbine	Scotland	-	-	Wind speed, blade angle, wave motion	Thrust force	MSE:1.193	Wind energy
3	Li et al. [62]	2019	Hybrid renewable energy system power generation (wind + solar)	England	Recurrent Neural Network	1-2-1	Temperature, wind speed, solar radiation	Temperature, wind speed, solar radiation	RMSE (for temperature): 0.948 RMSE (for solar radiation): 188.797 RMSE (for wind speed): 1.607	Wind and solar energy
4	Yogeswari et al. [65]	2019	Hydrogen production	India	Feed-forward back-propagation neural network	1-2-1	Volatile fatty acid (VFA), inlet chemical oxygen demand (COD), pH, time	Residual COD, rate of hydrogen production	R^2 (residual COD) = 0.986, R^2 (hydrogen production) = 0.996	Hydrogen energy

The study reveals that combining different machine-learning techniques can improve the accuracy of solar energy forecasts. Furthermore, the effectiveness of tree-based algorithms for long-term forecasts and the necessity of integrating multiple algorithms to optimize forecasting performance are discussed. The research underlines the critical role of advanced modelling techniques in optimizing solar energy use and ensuring grid reliability in the face of increasing renewable energy integration [106].

4. RECENT USAGE AREAS OF ANN's

While ANNs are used in health, automotive, electronics, energy, space sciences, education, banking and finance, military fields, and production and service sectors, they are primarily used in prediction, classification, data association, interpretation, and filtering processes.

Nowadays, ANNs are used in the field of renewable energy sources (hydro, wind, solar, geothermal, biomass, ocean, hydrogen hybrid) of the energy sector and in intelligent grids that facilitate the integration of renewable energy source facilities into the system.

- Design,
- Optimization (Biomass production optimization, biohydrogen efficiency optimization, energy consumption optimizations),
- Estimation (wind power, wind speed, parameters affecting the rotation of the wind turbine, the amount of solar radiation, the power of the PV system, PV module performance, surface temperature and efficiency estimation, flow estimation, wind power plant, solar power plant and hydroelectric power plant energy production, ocean water level, wave height, wave parameters, distribution coefficient estimation, two flux estimation, specific number and density in bioenergy, fuel wood price, methane estimation in waste, safety parameter estimation in hydrogen energy, power and generator status and performance parameter estimation in hybrid energy),
- Control and monitoring (peak power monitoring in hydroelectric power plants, photovoltaic systems, biomass boiler control, power flow control in hybrid energy, monitoring of changing parameters in intelligent grids),
- Detection and fault diagnosis (Fault diagnosis in wind and solar energy, H_2S and NH_3 detection in biogas, preventive measures for turbine scales, which are one of the parameters that reduce the capacity factor in geothermal energy),
- It is used in various specific calculations and modelling (peak discharge and time calculation in hydraulic energy, water flow modelling, modelling of solar energy potential).

5. DISCUSSIONS

To meet the increasing energy consumption due to industrialization, population growth, development and spread of technology, economic growth, and increase in welfare level and to reduce the adverse effects such as global warming and climate change caused by fossil-based energy sources, countries have turned to alternative energy sources and focused on sustainable energy technologies for sustainable development. In this context, they have developed international and national policies to develop and spread the technology and use renewable energy effectively and efficiently. They have implemented incentive and support mechanisms within this scope.

However, while increasing renewable energy-based electricity production ensures energy supply security, difficulties have been experienced in production, distribution, and transmission due to renewable energy's dependence on meteorological conditions. Therefore, higher predictability and better planning have been needed to meet this need. To meet this need, AI techniques have started to be used within the scope of digitalization in renewable energy technologies.

In a multi-disciplinary field, AI technologies comprise many predictive models, such as expert systems, fuzzy logic ANNs, machine learning, and genetic algorithms. Since ANNs are used more in the renewable energy field and smart grids, the studies on the methodology mentioned in the article are focused on. ANNs, which can also be expressed as connected networks, parallel distributed networks, and neuromorphic networks, have features such as non-linearity, parallel operation, learning, generalization, error tolerance, and flexibility, working with incomplete data, using a large number of variables, adaptability, and parameters.

6. CONCLUSION

This study examines the approach's estimation role in the renewable energy field. For this purpose, studies on ANN between the years 2017 and 2022 were investigated within the scope of the study, and 89 studies were reached.

When a general evaluation was made in the light of the results obtained, it was concluded that the relevant studies mostly made estimations with similar ANN-based training algorithms and activation functions and error metrics such as R^2, MAPE, MSE, MAE, RMSE, which are frequently used to measure the accuracy of the estimations in regression models, were used. When the metric values are taken into account, it can be said that neural networks have achieved significant success in estimating renewable energy production, which is not a linear problem.

Since training algorithms and activation functions are effective parameters in ANNs, it is recommended that in future studies, more diverse training algorithms and different activation functions be used in the network's training process. This will increase estimation performance with the proposed new models. In addition, although the literature contains a few studies on the applicability of hybrid AI approaches, including ANN, in renewable energy systems (RESs), more studies are needed.

In addition, when examining renewable energy sources specifically, it is seen that the use of ANNs in the estimation modelling of geothermal, hydraulic, hydrogen, and biomass energy production is very limited. Since more and better modelling of these systems can increase their economic benefits, it is recommended that more studies be conducted in this area.

As a result, considering the studies and applications carried out, AI technologies, which include many models together with ANNs, will play an active role in every field of renewable energy production with renewable energy production estimation, equipment maintenance, efficiency, storage, and management of renewable energy with smart grids in the near future, when risks such as security and privacy are eliminated, and thus renewable energy can become the main source of electricity generation in the world. In addition, with the digitalization in the energy sector, new solutions will be produced that can instantly respond to sectoral needs; global networks can transform into more flexible, independent but connected, smart, efficient, reliable, and sustainable systems.

7. FUTURE DIRECTIONS

Adapted to Türkiye's renewable energy sector, the study results show that increasing the use of renewable energy sources is critical for the country to achieve its sustainable development goals. As a country with significant renewable energy potential such as solar and wind, Türkiye can manage the supply-demand balance more effectively by integrating technologies such as AI and ANNs into the energy sector. This digital transformation can provide significant gains in terms of energy efficiency and cost-effectiveness, especially by increasing predictability in renewable energy production. The study is an important guide for the development of strategic planning and policies that will support Türkiye's renewable energy goals.

Since renewable energy accounts for a relatively small share of total energy production, it is crucial to utilize existing resources efficiently. In this direction, integrating high-penetration artificial intelligence applications into RESs increases predictability in production and consumption processes and optimizes the energy supply-demand balance. As a result, the rapid adoption of artificial intelligence-based solutions will be a critical step in maximizing the potential of renewable energy sources and achieving sustainable energy goals.

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