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Review

Analysis of Neural Networks Used by Artificial Intelligence in the Energy Transition with Renewable Energies

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Abstract: Artificial neural networks (ANNs) have become key methods for achieving global climate goals. The aim of this review is to carry out a detailed analysis of the applications of ANNs to the energy transition all over the world. Thus, the applications of ANNs to renewable energies such as solar, wind, and tidal energy or for the prediction of greenhouse gas emissions were studied. This review was conducted through keyword searches and research of publishers and research platforms such as Science Direct, Research Gate, Google Scholar, IEEE Xplore, Taylor and Francis, and MDPI. The dates of the most recent research were 2018 for wind energy, 2022 for solar energy, 2021 for tidal energy, and 2021 for the prediction of greenhouse gas emissions. The results obtained were classified according to the type of structure and the architecture used, the inputs/outputs used, the region studied, the activation function used, and the algorithms used as the main methods for synthesizing the results. To carry out the present review, 96 investigations were used, and among them, the predominant structure was that of the multilayer perceptron, with Purelin and Sigmoid as the most used activation functions.

Highlights:

- The application of different types of RNA is very effective in the energy transition.
- ANNs are a very effective/useful tool in the fight against climate change.
- High capacity of ANNs to make predictions in different meteorological conditions.

Keywords: machine learning; artificial neural network; big data; energy transition

Citation: Iglesias-Sanfeliz Cubero, Í.M.; Meana-Fernández, A.; Ríos-Fernández, J.C.; Ackermann, T.; Gutiérrez-Trashorras, A.J. Analysis of Neural Networks Used by Artificial Intelligence in the Energy Transition with Renewable Energies. *Appl. Sci.* **2024**, *14*, 389. https://doi.org/10.3390/app14010389

Academic Editor: Frede Blaabjerg

Received: 14 November 2023
Revised: 7 December 2023
Accepted: 28 December 2023
Published: 31 December 2023

1. Introduction

Currently, the most accurate, most efficient, and most powerful machine for performing operations is the human brain, which can provide solutions to problems that PCs are not capable of solving. Researchers and scientists have developed artificial intelligence (AI) models to reproduce, to some extent, the processes that take place in the human brain [1]. Currently, AI is divided into different groups: artificial neural networks (ANNs) and different hybrid systems. Among them, ANNs are the best method as they are accurate, fast, and simple and have the ability to model a multivariate system [2].

The neural network (NN) concept has more than half a century of history; however, it is only in the last 20 years that the largest number of applications have been developed in the fields of defense, engineering, mathematics, economics, medicine, meteorology, and many others.

The history of neural networks dates to the 1940s. It was Warren McCulloch and Walter Pitts who first built a very simple neural network using electrical circuits [3]. Later, Donald Hebb proposed that neural pathways strengthen with each use, an important con-

cept in human learning [4]. Then, in the 1950s, Nathaniel Rochester of IBM Research Laboratories first attempted to simulate complex neural networks [5]. In 1959, Bernard Widrow and Marcian Hoff developed models called "ADALINE" and "MADALINE" [6,7]. After the publication of the book "Perceptrons" by Marvin Minsky and Seymour Papert in 1969, there was a period of slowdown in research. This book argued that the concept of a single perception approach to neural networks did not have an effective correlation in multilayer neural networks [8]. In the 1970s, two competing models emerged in the conception of neural networks, called symbolism and connectionism [9]. The controversy ended with the acceptance of the symbolic paradigm as the most viable line of research. In the early 1980s, however, connectionism resurfaced, based on Werbos's 1974 studies. These studies made it possible to rapidly develop the formation of multilayer neural networks using the so-called "backpropagation" algorithm [10,11]. Since then, the field of neural networks has seen significant advances. Some of these advances were the introduction and development of max-pooling in three-dimensional data recognition [12]. On the other hand, advances included the development of deep learning and its application to a wide variety of fields such as renewable energy [12].

However, ANNs are not the only ones that learn by example. There are other methods, such as the following. Supervised learning: this method trains algorithms on the basis of sample input and output data labeled by humans [13]; deep learning: it uses neural networks to learn from the data and to improve performance by increasing the number of samples that are available during the learning process [14]; machine learning paradigms for unsupervised classification such as conceptual clustering [15], which is an unsupervised learning method that focuses on generating concept descriptions for the generated classes. Other machine learning paradigms that learn by example are semi-supervised learning [16], active learning [17], transfer learning [18], and online learning [19].

The data collection needed to train ANNs must be a sufficiently complete and consistent set of information [20]. The development of machine learning models requires historical data from several years, supplemented by information that is more recent. This information amounts to thousands of data points [20]. In the context of different energy transition scenarios and geographical locations, it is essential to ensure that the data collection is as complete, impartial, and representative as possible. This is achieved by managing diverse and reliable sources of information. Some of the most used sources are public repositories, data from official agencies and organizations, research centers, and geographic databases [21,22]. To ensure that the data are impartial, complete, and representative of all the energy transition scenarios analyzed, it is necessary to perform careful data selection and apply measures such as domain adaptation and data augmentation [23]. Model performance can also be improved, and training data can be augmented by using pretrained models in other domains [23]. The authors, based on the objective pursued and the exact geographical location, have analyzed all data obtained in the various studies, with latitude and longitude coordinates provided in many of them. Similarly, much of the data provided are based on measurements made by the authors themselves when using AI.

ANNs have gained momentum to the point where they have become popular and useful models for classification, clustering, recognition, and prediction in a wide variety of applications [24]. ANNs are increasingly being used for different applications due to their ability and effectiveness in solving different problems. They have proven to be very efficient when it is complex to cull through a mass of existing data, for example, in the evaluation of public transportation of people and goods [25], image recognition [26], medical analysis [27], efficiency analysis in nonlinear contexts, or to adjust production functions, among other applications [28,29].

ANN consists, in most cases, of an input layer, at least one hidden layer (in the case of a simplified model), an output layer, the weight, the connection biases, the activation function, and the sum node. The layers in turn are made up of several connected units (called neurons) [30], considered to be the fundamental building blocks for the correct

functioning of a neural network. The link between neurons is achieved by so-called connecting links [2]. The basic diagram of a neuron is shown in Figure 1 [31].

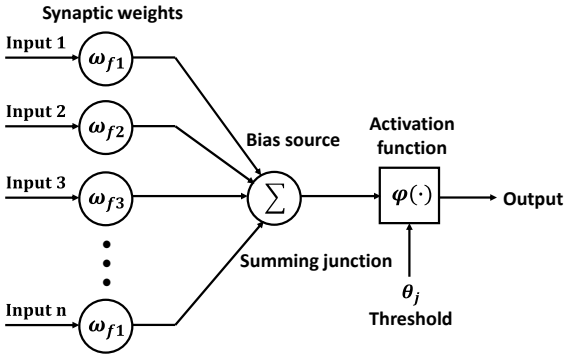

Figure 1. Schematic diagram of a neuron [31].

The main characteristic feature of ANNs compared to other approaches is their ability to learn by example. ANNs can be applied to any situation where there is a relationship between input and output variables [32]. The procedure for the learning process is what is known as a learning algorithm, the purpose of which is to alter the synaptic weights of the networks in order to achieve a previously set goal [33].

ANNs must be trained by feeding the network a set of quantified data to achieve the desired output using a pool of input data [34]. The learning process continues until the NN output matches the expected output [35]. The problem with ANN models lies precisely in overtraining, i.e., when the network capacity for training is too high or too many training iterations are allowed per network [36]. The degree of training accuracy obtained in the different applications where the ANN technique is used is very high, in the order of 10^{-5} to complete the training processes [2]. NNs can be grouped into different categories depending on their structure [37]. This classification is shown in Figure 2. The most commonly used are single-layer feed-forward networks, multilayer feed-forward networks, radial basis networks, and dynamic (differential) or recurrent neural networks. Of these, single-layer power supply networks are the best known and most widely used. Single-layer power supply networks were the first and simplest networks devised. Information travels in only one direction: from input nodes, through hidden nodes, to output nodes. This type of NN can be designed based on different unities, and among them, the perceptron is the most famous and simplest example [38]. Rosenblatt created the perceptron in 1958, thanks to the creation of the training algorithm [39]. The perceptron is composed of a single neuron with adjustable synaptic weights and thresholds [40]. The most frequently used algorithm is the so-called backpropagation (BP) algorithm [41]. The BP algorithm consists of training and correcting the weights until the error function is below the desired tolerance limit [37].

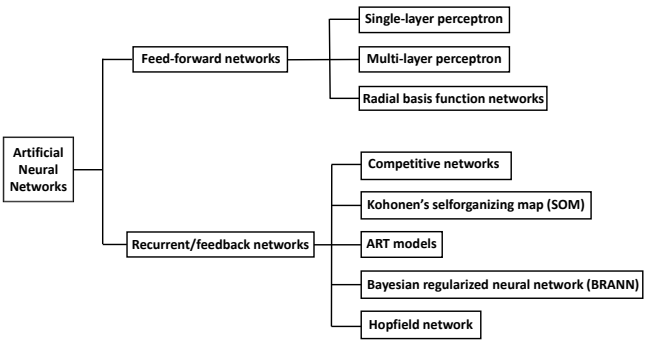

Figure 2. Artificial Neural Networks classification.

ANN models have proven to be a useful tool with great applications in different engineering systems. Unlike mathematical models, ANNs are able to adapt to real-world conditions [42]. Applications of NNs include forecasting [43,44], control [45], modeling [46], and pattern classification [47]. ANNs have been applied to different branches of engineering. In this work, given the wide variety of applications, it has been decided to classify them by energy type.

This article aims to provide a comprehensive review, as there is a lack of research in the literature that unifies in a single article the different ways of applying ANNs to the energy transition. It is of vital importance due to the increasingly frequent and significant environmental impacts and for the achievement of the United Nations (UN) Sustainable Development Goals, thus allowing researchers to know the state of the art so far on the different modalities of applying ANNs in the field of energy transition.

This review will focus on the contribution of renewable energies to the energy transition as the main contributors to mitigating the effects of climate change, as well as the applications of renewable energies to specific sectors such as buildings and transport. Finally, the different ways of using ANNs for the prediction of greenhouse gas emissions will be studied. The review has been carried out through the search and research of keywords in publishers and research platforms such as Science Direct, Research Gate, Google Scholar, IEEE Xplore, Taylor and Francis, and MDPI.

The study models had different applications in terms of scale. Some were designed to illuminate a single household, while others were designed for large-scale networks. The only difference lies in the size of the inputs provided by the authors to the neural networks. The models are highly versatile and have the potential to address energy planning needs and contribute to improvements in the energy transition. To ensure the reliability and robustness of neural networks in predicting or optimizing renewable energy systems, various methods and metrics can be used. Some of these methods are adversarial robustness evaluation [48]; robustness measurement and assessment (RoMA) [49]; extreme value theory approach [50]; and weight alterations [51]. These methods and metrics help evaluate the reliability and robustness of neural networks, especially in the context of adversarial attacks and environmental uncertainty.

The use of AI-powered neural networks in energy transition planning raises several ethical considerations. These considerations include decision making and accountability [52], as AI technology raises ethical questions related to decision making and accountability [53]; fairness and bias [54]; data privacy and security [55]; social responsibility [56], including job displacement and changes in economic structures; and environmental and climate implications [53], as the energy consumption of training large amounts of neural networks can be significant. By taking these ethical considerations into account, it would be possible to ensure that the use of AI-powered neural networks in energy transition planning is responsible, fair, and consistent with social values and environmental sustainability. Human experts are essential in the design, programming, and operation of AI to avoid unpredictable errors and to ensure that decisions made by AI are traceable [57]. In addition, AI development must adhere to principles such as accountability, transparency, verifiability, and predictability to serve society and fulfill human rights [57]. The concept of collaborative intelligence is important, where AI enhances human creativity and capabilities [58]. All of this achieves a responsible and ethical balance between the human experience and the capabilities of AI to serve the needs and preferences of society.

2. Applications of ANNs to Renewable Energies

This section details the different research carried out in the field of renewable energies and more specifically in wind, solar, and tidal energy. These three types of renewable energies have been selected as they are the ones that have the largest contributions to the national energy balances [59] as well as due to the greater abundance of works found.

2.1. Applications of ANNs for Wind Power and Speed Prediction

Within the renewable energy mix, wind energy is currently considered the most economical way to generate electricity. Recently, there has been new research into methods capable of predicting wind speed. This is of great importance due to the continuous growth of wind power generation worldwide [60]. For proper operation of wind farms, a constant stream of data about wind speed and wind direction is required. Artificial neural networks are an excellent method for short-, medium-, and long-term wind speed forecasting.

The following Table 1 summarizes the main research pieces found when performing the review. The studies have been classified according to the ANN structure, journal and region, input and outputs for the network, and the activation function employed.

Table 1. Uses of artificial neural networks for wind power and speed prediction.

	Authors and Year	ANN Type and Structure	Journal	Country/ Region	I/O Setting		Activation Function	Notes
					Input	Output		
1	[61]	Multilayer Perceptron (MLP) 3-4-1	Renewable Energy	Muppandal, India	Wind speed (W_s), relative humidity (RH), generation hours	Energy output of wind farms	logsig (hidden layer) purelin (output layer)	Trained by BP algorithm Input data normalized to [0, 1]
2	[62]	ANN 4-X-2	Renewable Energy	Turkey	Longitude (lon), latitude (lat), altitude (A), measurement height	W_s, related power	logsig (hidden and output layer)	Trained by BP algorithm Input and Output data normalized to [0, 1]
3	[63]	MLP 5-10-5-1	Renewable Energy	Turkey	W_s, month (M)	W_s	logsig (hidden layer) purelin (output layer)	Resilient propagation (RP) algorithm was adopted
4	[64]	Radial Basis Function (RBF) 1-7-2	Renewable and Sustainable Energy Reviews	Iran	W_s	Proportional and integral (PI) gains	-	Use Gaussian function for hidden layer Gravitational search algorithm (GSA) is adopted
5	[65]	MLP 3-(2-100)-24	Renewable Energy	Medina city, Saudi Arabia	Mean daily W_s	W_s prediction of the next day	tansig (hidden layer) purelin (output layer)	Input data normalized to [0, 1] Trained by Levenberg–Marquardt (LM) BP algorithm Compared and outperforms support vector machine (SVM) SVM used Gaussian kernel

								2000 days used for training and 728 days used for testing
6	[66]	MLP 6-7-5-1 MLP 4-7-5-1	Renewable and Sustainable Energy Reviews	Alberta, Canada	Wind power (W_P) W_{P1} (t − 1), W_{P1} (t − 2), W_{P1} (t − 3), W_{P1} (t − 4), W_{P1} (t − 5), W_{P1} (t − 6)	Short-term forecasting of the W_P time series	tansig (hidden layer) purelin (output layer)	Input data normalized to [−1, 1] Imperialist competitive algorithm (ICA), GA, and particle swarm optimization (PSO) are employed for training the neural network 1200 data used for training and 168 data used for testing
7	[67]	ANN 2-(16-32)-(16-32)-1	Renewable Energy	Coquimbo, Chile	W_s, wind direction (W_d)	Turbine power	-	ADAM algorithm is adopted 103,308 data used for training and 52,560 data used for testing
8	[68]	RBF 2-3-1 MLP 2-4-1 ADALINE 2-4-1	Applied Energy	North Dakota, USA	Mean hourly W_s	Forecast value of next hourly average W_s	-	Trained by LM algorithm 5000 data used for training and 120 data used for testing
9	[69]	MLP 5-5-3	Renewable Energy	Guadeloupean archipelago, French West Indies	W_s, 30 min moving average speed	W_p (t + kt)	tansig (hidden layer) purelin (output layer)	Bayesian regularized (BR)
10	[70]	ANN 7-20-1	Renewable Energy	China	Actual W_s, W_p	W_s	-	Trained by BP algorithm
11	[71]	MLP 6-7-1	Renewable Energy	Albacete, Spain	W_{sp1}, W_{sp2}, temperature (T) T_{p2}, solar cicle$_1$, solar cicle$_2$, W_{dp1}	W_s forecast (48 h later)	-	LM algorithm is adopted
12	[72]	ANN 3-3-1 ANN 3-2-X ANN 3-1 ANN	Renewable Energy	Oaxaca, México	Previous values of hourly W_s	Current value of W_s	-	550 data used for training and 194 data used for testing

		2-1						
13	[73]	ANN -	Renewable Energy	Basque Country, Spain	W_s data in the last 3 h	W_s in 1 h	sigmoid (output layer)	Trained by BP algorithm
14	[74]	MLP X-8-X	Renewable Energy	Rostamabad, Iran	Standard deviation, average, slope	W_s (k + l),… W_s (k + 2), W_s (k + 1)	-	Trained by BP algorithm 672 patterns used for training
15	[75]	MLP 5-3-3-1	Communications in Nonlinear Science and Numerical Simulation	Italy	W_s, RH, generation hours, T, maintenance hours	Total wind energy	tansig (first hidden layer) sigmoid (second hidden layer) purelin (output layer)	Trained by BP algorithm
16	[76]	MLP 6-25-1	Renewable Energy	Himachal Pradesh, India	Average temperature (T_{AVG}), maximum temperature (T_{max}), minimum temperature (ax), air pressure (P_{air}), solar irradiance (G), A	Average daily W_s for 11 H.P. locations	-	Trained by LM algorithm Scaled conjugate gradient (SCG) algorithm is adopted Input and target data are normalized to [−1, 1] 60% data used for training, 20% used for testing, and 20% used for validation
17	[77]	MLP 4-15-15-1	Applied Energy	Nigeria	lat, lon, A, M	Mean monthly W_s	tansig (hidden layers) purelin (output layer)	SCG and LM algorithms are adopted Input and target data normalized to [−1, 1]
18	[78]	MLP 14-15-1	WSEAS Transactions on Systems	Portugal	Average hourly values of W_s	Average hourly W_s	-	Trained BP algorithm 87.75% patterns used for training, 9.75% used for validation, and 2.5% used for testing
19	[79]	MLP 5-6-6-6-2	-	Cyprus	M, mean monthly values of W_s at two levels (2 and 7 m)	Mean monthly values of W_s of a third station	tansig (hidden layer) logsig (output layer)	Trained by BP algorithm 90% patterns used for training and 10% patterns used for testing
20	[80]	MLP 9-10-1	Energy	Marmara, Turkey	9 stations W_s	W_s	-	Trained by BP algorithm

			Conversion and Management					
21	[81]	MLP 4-8-1	Theoretical and Applied Climatology	Tabriz, Azerbaijan, Iran	P_{air}, air temperature (T_{air}), RH, precipitation	Monthly W_s	logsig (hidden layer) purelin (output layer)	Trained by LM algorithm Input and output data normalized to [0, 1] 75% of data used for training and 25% used for testing
22	[82]	MLP 31-63-31	Knowledge-Based Systems	Minqin, China	Historical daily average W_s during March previous year	Daily average W_s during March target year	tansig (hidden layer) logsig (output layer)	Trained by BP algorithm
23	[83]	MLP X-25-1	2014 4th IEEE International Conference on Information Science and Technology	Colorado, USA	T, RH, W_d, wind gust, pressure (P), historical W_s	W_s	tansig (hidden layer)	Trained by BP with momentum 1000 input/output pairs used for training and 200 input/output pairs used for testing

The applications have different characteristics in several aspects, such as the ANN structure, the input data, the activation function used, and the training algorithm. As can be seen from the literature, various studies on wind speed prediction have been carried out for more than twenty years in different parts of the world, most of them located in Turkey, India, China, or Iran.

The main characteristics of the networks studied are detailed below.

- ANN type: from the 23 references analyzed, the MLP network has been used in 17 of them, followed by the RBF in two of them. Five of them did not specify the type of ANN used.
- Structure of the ANN: the predominant type is simple with one hidden layer (70%) and the rest with two hidden layers (26%) with the exception of the investigation of [41], which uses three hidden layers. The number of neurons in the hidden layer is usually around 15, while in other cases more than 63 are selected [44].
- Amount of data: the percentage of research that makes use of data for validation is 8.69%.
- I/O configuration: the inputs to the models usually take in situ measured features such as past wind speeds, temperature, relative humidity, altitude, month, or pressure.
- Activation function: only 13 of the 23 cases detail the activation function used. In the hidden layer, linear functions are used, with tansig and logsig being the most commonly used, while in the output layer, linear functions of the purelin type are adopted.

Figure 3 details the most common inputs and outputs used by ANNs in wind power and wind speed prediction and the operating scheme.

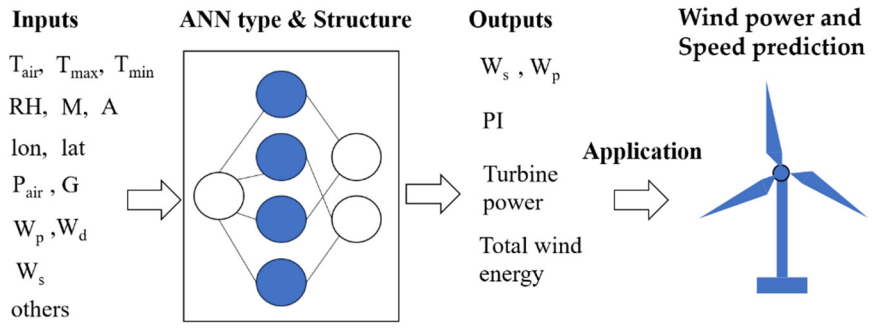

Figure 3. Inputs and outputs in ANNs applied to wind energy and wind speed prediction.

ANNs are highly recommended for predicting wind speed and power generation for several reasons, including self-learning, low error, and high efficiency predictability [84].

2.2. Applications of ANNs for Solar Energy Systems

Within solar energy, the ANN technique has proven to be an alternative to conventional methods, providing great benefits in terms of precision, performance, and modeling. The study indicates that the advantage of ANN techniques over conventional techniques is that they do not require knowledge of internal system parameters, require less computational effort, and offer robust outputs to multivariate problems. NN modeling requires data representing the history, the current performance of the real system, and a correct selection of a NN model. Mellit et al. [85] conducted an overview of the different AI techniques for sizing PV systems. The research shows that one of the advantages of AI in modeling PV systems is that it allows good optimization in isolated areas, where meteorological data are not always available. Mellit and Kalogiriu [86] have applied AI techniques to model, predict, simulate, optimize, and control photovoltaic systems.

The applications of ANNs to solar energy go beyond that, as there is also research such as the one carried out in [42], in which the application of the ANN technique seeks to optimize and predict the performance of the different devices involved in a solar energy system such as solar collectors, heat pumps, or solar air. The research shows how the application of ANNs can save time and reduce the financial costs of the system since it is not necessary to carry out so many experimental tests to determine the relationship between the input and output variables. Another application of ANNs is shown in the research of [87], where the performance of solar collectors is predicted, thus improving the efficiency of the system as a whole. The developed model also showed advantages over conventional computational methods in terms of calculation and prediction time.

Solar radiation data are very important because in most cases they are not available due to the lack of a meteorological station. It is therefore necessary to have techniques to accurately predict solar radiation. ANNs are the solution to the problems of conventional methods [88].

Different ANN models have been applied for solar irradiance prediction, such as the MLP neural network, the RBF neural network, or the general regression neural network (GRNN). The different studies have been classified, taking into account different factors such as network structure and type, input/output configuration, or the activation function and tuning algorithm employed, as is shown in Table 2.

Table 2. Uses of artificial neural networks for solar energy prediction.

	Authors and Year	ANN Type and Structure	Journal	Country/ Region	I/O Setting		Activation Function	Notes
					Input	Output		
1	[89]	RBF 6-11-24 RBF 6-15-24	Solar Energy	Huazhong, China	G (t + 1), W_s(t + 1), T_{air} (t + 1), RH (t + 1), t, power (P_w) (t)	P_{w1}(t+1), P_{w2}(t+1), … P_{w24}(t+1)	-	k-fold (validation) Input and output data normalized to [0, 1]
2	[90]	MLP 2-3-1	Renewable Energy	Jaen, Spain	G, module cell temperature (T_C)	G, ambient temperature (T_a)	-	Trained by LM BP algorithm
3	[91]	MLP 3-3-1 MLP 4-3-1	Energy	Corsica Island, France Bastia Ajaccio	RH, sunshine duration (S), nebulosity (Y) Y, S, P, differential pressure (DGP)	Global radiation (GR)	tansig (hidden layer) purelin (output layer)	Trained by LM algorithm Input data normalized to [−1, 1] 80% data used for training, 10% for validation, and 10% used for testing
4	[92]	MLP 8-3-1	Solar Energy	Ajaccio, Corsica Island, France	Clearness index (K_T) K_{Tt-1}, K_{Tt-2}, K_{Tt-3}, K_{Tt-4}, K_{Tt-5}, K_{Tt-6}, K_{Tt-7}, K_{Tt-8}	Daily global solar radiation (GSR)	purelin (output layer)	Trained by LM algorithm Use Gaussian function for hidden layer Input data normalized to [0, 1] 80% data used for training, 10% for validation, and 10% used for testing
5	[93]	MLP 3-11-17-24	Solar Energy	Trieste, Italia	G, T_{air}, hour or day (t)	G_1 (t + 1), G_2 (t + 1),…,G_{24} (t + 1)	-	Trained by LM BP Algorithm k-fold validation Input and output data normalized to [−1, 1]
6	[94]	RBFN (2-3-4)-(4-5-7)-1 MLP (2-3-4)-(2-3-5)-1	Energy	Al-Medina, Saudi Arabia	T_{air}, S, RH, t	Daily global solar radiation (G_D)	-	1460 data used for training and 365 data used for testing
7	[95]	MLP 6-5-1	Applied Energy	Turkey	lat, lon, A, M, S, T	G	logsig (hidden layer)	Trained by BP algorithm SCG, Pola–Ribiere conjugate gradient (CGP), and LM

								algorithms are adopted Input and output data normalized to [−1, 1]
8	[96]	MLP 3-20-1	Renewable and Sustainable Energy Reviews	Morocco	lon, lat, A	Mean annual and monthly G	-	Trained by BP algorithm Input and output data normalized to [0, 1]
9	[97]	MLP 2-36-1 MLP 3-20-1	Energy Sources, Part A: Recovery, Utilization, and Environmental Effects	Abha, Saudi Arabia	T_{air}, RH, hour or day (t)	Diffuse solar radiation (DSR)	logsig (hidden layer)	Trained by BP algorithm 1462 days used for training and 250 days used for testing
10	[98]	MLP 5-8-1	Expert Systems with Applications	Anatolia, Turkey	lat, lon, A, S, average cloudiness	G	tansig (hidden layer) purelin (output layer)	Trained by BP algorithm
11	[99]	MLP 7-5-1	Applied Energy	Nigeria	lat, lon, A, M, S, T, RH	G	tansig (hidden layer) purelin (output layer)	SCG and LM algorithms are adopted Input data normalized to [−1, 1] 11,700 datasets used for training and 5850 datasets used for validation and testing
12	[100]	MLP 4-X-1	International Journal of Photoenergy	Malaysia	lat, lon, day or hour (t), S	K_T	logsig (hidden layer)	Trained by BP algorithm
13	[101]	MLP 4-4-1	International Journal of Computer Applications	India	lat, lon, S, A	G	tansig (hidden layer) purelin (output layer)	LM algorithm is adopted
14	[102]	MLP 5-40-1	Energy	Egypt	GSR, like long-wave atmospheric emission, T_{air}, RH, P	Diffuse fraction (K_D)	sigmoid (output layer)	Trained by BP algorithm
15	[103]	MLP 7-15-1	Solar Energy	Jaen, Spain	t (day), t (hour), K_T, hourly clearness	Solar radiation maps	-	Trained by BP algorithm (with momentum and random presentations)

					index (k_t) k_{t-1}, k_{t-2}, k_{t-3}, S			Input data normalized to [0, 1]
16	[104]	MLP 6-X-1	Solar Energy	Helwan, Egypt	W_d, W_s, T_a, RH, cloudiness, water vapor	G	sigmoid (output layer)	Trained by LM BP algorithm Input data normalized to [0, 1]
17	[105]	MLP 2-X-1 MLP 3-X-1 MLP 3-X-X-1	Solar Energy	Athalassa, Cyprus	S, theoretical sunshine duration (S_{0d}), M, T_{max}	G_D	tansig (hidden layer)	Trained by BP algorithm 90% data used for training and 10% used for testing
18	[106]	MLP 7-9-1	Renewable Energy	India	lat, lon, A, M, S, rainfall ratio, RH	K_T	tansig (hidden layer) purelin (output layer)	Trained by BP algorithm
19	[107]	MLP 2-5-1	Energy Policy	China	K_t, S (%)	Monthly mean daily K_D	tansig (hidden layer) purelin (output layer)	Trained by BP algorithm TRAINLM algorithm is adopted Input and output data normalized to [0, 1]
20	[108]	MLP 6-15-1	Solar Energy	Uganda	S, T_{max}, Total Cloud Cover (TCC), lat, lon, A	Monthly average daily GSR on a horizontal surface	tansig (hidden layer) purelin (output layer)	Trained by LM BP algorithm Input data normalized to [−1, 1]
21	[109]	MLP 6-6-1	Applied Energy	Turkey	lat, lon, A, M, DSR, mean beam radiation	G	logsig (hidden layer) purelin (output layer)	SCG and RP algorithms are adopted
22	[110]	GRNN 6-1.0-1	Energy	Turkey	lat, lon, A, surface emissivity (ε_4), surface emissivity (ε_5), land surface temperature	G	-	-
23	[111]	MLP 7-4-1	Energy Conversion and Management	Iran	T_{max}, T_{min}, RH, VP, total precipitation, W_s, S	GSR	logsig (hidden layer) purelin (output layer)	Trained by BP algorithm 65 months used for training and 7 months used for testing

24	[112]	ANN 6-6-1	Applied Energy	Turkey	lat, lon, A, M, S, T	G	logsig (hidden layer)	SCG, CGP, and LM algorithms are adopted Trained by BP algorithm Input and output data normalized to [−1, 1]
25	[113]	MLP 3-6-1	Renewable Energy	Khuzestan, Iran	T_{max}, T_{min}, extra-terrestrial radiation (R_a)	GSR	logsig (hidden layer)	Trained by LM BP algorithm Input data normalized to [0, 1] 70% data used for training and 30% patterns used for testing
26	[114]	MLP 5-3-1	Energy Procedia	Bechar, Algeria	M, t (day), t (hour), T, RH	GSR	tansig (hidden layer) purelin (output layer)	Trained by LM BP algorithm 81% data used for training and 19% used for testing
27	[115]	MLP 9-11-1	Renewable and Sustainable Energy Reviews	Republic of Indonesia	T, RH, S, W_s, precipitation, lon, lat, A, M	GSR	-	Trained by BP algorithm
28	[116]	RBF 4-50-2	Energy Sources, Part A: Recovery, Utilization, and Environmental Effects	Saudi Arabia	T_a, RH, GSR, t	DSR, direct normal radiation (DNR)	-	Use Gaussian function for hidden layer 1460 values used for training and 365 values used for testing
29	[117]	MLP 8-15-1	Renewable Energy	Sultanate of Oman	Location (L), M, P, T, VP, RH, W_s, S	GR	-	Trained by BP algorithm

In contrast to the previous case, there is more literature available and the existing research from 1998 to 2012 has been collected. Most of the studies focus on countries that enjoy strong and prolonged hot climates such as the countries bordering the Mediterranean Sea as well as Saudi Arabia and China. As in the previous section and as mentioned at the beginning, the different applications are analyzed. The main characteristics of the networks studied are detailed below.

- ANN type: in most of the investigations, the MLP network has been used (24 out of 29 cases) followed by the RBF.
- Structure of the ANN: most studies use simple structures with a single hidden layer (96%), and the remaining with two hidden layers. The number of neurons in the hidden layer is usually in the order of 10, reaching 50 neurons in the research of [116]. In some cases, the number of neurons in the hidden layer is not specified, as in [105] and [104].

- Amount of data: the percentage of research that make use of data for validation is 6.9%.
- I/O configuration: altitude, latitude, longitude, relative humidity, or month of the year are used as the most common inputs.
- Activation function: only 19 of the 29 investigations detail the activation function used. In the hidden layer, linear functions are used, with tansig and logsig being the most commonly used, while in the output layer, linear functions of the purelin type are adopted.

Figure 4 details the most common inputs and outputs used by ANNs in solar energy prediction and the operating scheme.

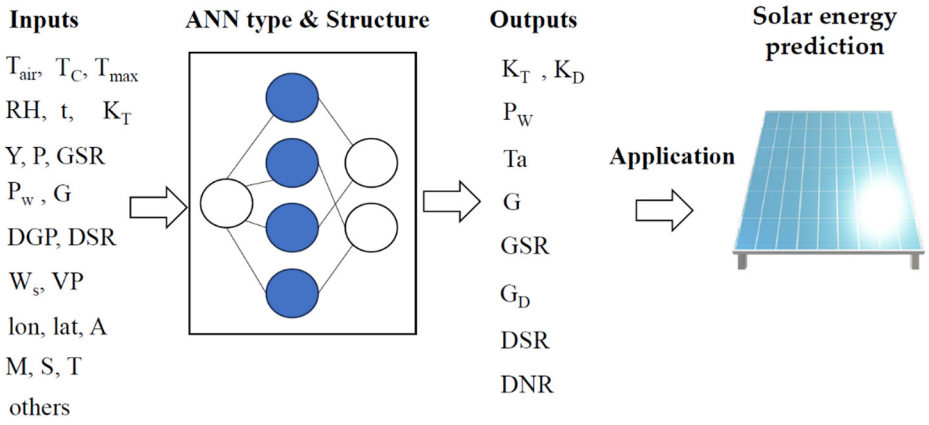

Figure 4. Inputs and outputs in ANNs applied to solar energy systems.

2.3. Applications of ANNs for Wave Prediction

Tidal energy, like other renewable energies, is fundamental to achieving the European climate targets for 2030 and 2050. Recently, the use of NNs for wave height (H) and period prediction has gained importance. ANNs have also been applied in different fields of ocean, coastal, and environmental engineering [118]. The following table summarizes the main research pieces found when performing the review. The studies have been classified according to the ANN structure, journal and region, input and outputs for the network, and the activation function employed. The following Table 3 shows the H predictions.

Table 3. Uses of artificial neural networks for wave height prediction.

	Authors and Year	ANN Type and Structure	Journal	Country/ Region	I/O Setting		Activation Function	Notes
					Input	Output		
1	[119]	ANN 28-15-4 28-9-4 28-4-4 28-7-4	Journal of Atmospheric and Oceanic Technology	Gulf of Maine, Gulf of Alaska, Gulf of Mexico	7 days of significant H	6, 12, 18, 24 h forecast	logsig (hidden and output layer)	Input data normalized to [0, 1] Conjugate gradient algorithm with Fletcher–Reeves is adopted
2	[120]	MLP 3-5-5-2	Ocean Engineering	Bombay, India	Deep water wave height (H_o), wave energy period (T_e)	Breaking wave height (H_b), water depth at the time of	sigmoid (output layer)	Trained by BP algorithm Input and output data normalized to [0, 1]

						breaking (d_b)		
3	[121]	MLP 48-97-24	Ocean Engineering	Ireland	48 h history wave parameters	H and zero-up-crossing peak wave period (T_p) over hourly intervals from 1 h to 24 h	logsig (hidden layer) purelin (output layer)	Trained by resilient BP algorithm
4	[122]	MLP 6-5-1	Proceedings of the Institution of Civil Engineers-Maritime Engineering	Anzali, Iran	H, T_p	Energy flux (F_e) over horizon of 1 to 12 h	sigmoid (output layer)	Conjugate gradient algorithm is adopted 80% data used for training and 20% used for testing
5	[123]	MLP 2-4-3 MLP 4-4-4	Ocean Engineering	Karwar, India	W_s	3-hourly values of H and average cross-period	-	Trained by BP algorithm 80% data used for training and 20% data used for testing
6	[124]	Deep Neural Network (DNN) 6-64-32-32-1	Ocean Engineering	Pacific and Atlantic coasts and the Gulf of Mexico	H, T_e, F_e, weighted average period, T_p, W_s, W_d	F_e, T_e, H	-	SCG BP algorithm is adopted Input data normalized to [0, 1] 75% data used for training and 25% data used for testing
7	[125]	MLP 3-300-300-2	Ocean Engineering	Lake Michigan, United Sates of America	Wind field, d_b, ice coverage	H, T_e	ReLU (hidden layer)	Stochastic gradient-based algorithm is adopted 80% data used for training and 20% data used for testing
8	[126]	MLP 1-x-1	Marine Structures	Goa, India	H	F_e	sigmoid (output layer)	Trained by BP cascade correlation algorithms 80% patterns used for training and 20% patterns used for testing
9	[127]	MLP 6-5-1	Ocean Engineering	Persian Gulf	H_t, H_{t-1}, H_{t-2}, $U_t\cos(\Phi t-\theta)$, $U_{t-1}\cos(\Phi t-1-\theta t)$, $U_{t-2}\cos(\Phi t-2-\theta 2)$	H for the next 3,6,12,24 h	sigmoid (output layer)	Conjugate gradient and LM algorithms are adopted 80% data used for training and 20% data used for testing
10	[128]	MLP 3-4-4-1	Applied Soft	Spain	H, T_e, θ_m	F_e	tansig	Trained by BP algorithm

			Computing				(hidden layer) purelin (output layer)	67% data used for training and 33% data used for testing
11	[129]	MLP 3-3-1	Ocean Engineering	Lake Superior, USA	W_s, weather station index (W)	H	sigmoid (hidden and output layer)	Trained by BP algorithm Input and output data normalized to [−1, 1] Compared with SVM, Bayesian networks, and adaptive neuro-fuzzy inference system (ANFIS) 345 patterns used for training and 54 patterns used for testing
12	[130]	MLP 5-2-1	Renewable Energy	Brazil	Wind shear velocity (U) U_1, U_2, U_n, Y (t − 1), Y (t − i)	Wave energy potential	tansig (hidden layer) purelin (output layer)	Trained by LM BP algorithm 90% data used for training and 10% data used for testing
13	[131]	MLP X-15-1	Applied Ocean Research	Canary Islands, Spain	H, T_p	Predict F_e	tansig (hidden layer) purelin (output layer)	Gradient descent with momentum and BP algorithm are adopted 89% data used for training and 11% data used for testing Input and output data normalized to [−1, 1]
14	[132]	MLP 4-4-1	Applied Ocean Research	India	H values of the preceding 3, 6, 12, and 24th hour	H subsequent 3,6,12 and 24th hour	-	Trained by LM BP algorithm 60% data used for training and 40% data used for testing
15	[133]	RBF 21-13-1 MLP 21-9-1	Marine Structures	India	$H_{(1–21)}$	H(SW3)	-	Use Gaussian function for hidden layer BP, SCG, conjugate gradient Powell–Beale (CGB), Broyden–Fletcher–Goldfarb (BFG), and LM algorithms are adopted 80% data used for training and 20% data used for testing
16	[134]	MLP 8-4-1	Ocean Engineering	Taiwan	Significant wave	$H_{1/3}$ (station C)	sigmoid	Trained by BP algorithm

		MLP 2-2-1			height ($H_{1/3}$), highest one-tenth wave height ($H_{1/10}$), highest wave height (H_{max}), mean wave height (H_{mean}) (stations A and B)		(output layer)	Input data normalized to [0, 1]
17	[135]	MLP 2-5-1	Marine Structures	Yanam, India	H_t, H_{t-1}	H_{t+1}	-	Trained by BP algorithm Conjugate gradient and cascade correlation algorithms are adopted 80% data used for training and 20% data used for testing
18	[136]	ANN 9-1-1 ANN 4-1-1 ANN 9-8-1 ANN 9-1-1	Applied Ocean Research	Ratnagiri, Pondicherry, Gopalpur, Kollam, India	t − 24, t − 21, t − 18, t − 15, t − 12, t − 9, t − 6, t − 3	t + 24 (24 h ahead predicted error)	logsig (hidden layer) purelin (output layer)	Trained by LM algorithm Input data normalized to [0, 1] 70% data used for training and 15% used for validation and testing
19	[137]	MLP 4-9-3 MLP 4-7-1 MLP 2-5-1 MLP 4-8-1	Applied Ocean Research	Lake Ontario, Canada/USA	W_s, W_d, fetch length, wind duration	H, T_p, (wave direction) Θ	tansig/ sigmoid (hidden layer) purelin (output layer)	Trained by BP algorithm 10-fold cross-validation used Input data normalized to [0, 1] 611 data used for training and 326 data used for testing
20	[138]	MLP 1-3-1	Ocean Engineering	Lake Superior, Canada/USA	W_s	H	sigmoid (transfer function)	Compared and outperforms with model tree 4045 data used for training and 3259 data used for testing

While it is true that studies appear in the literature since 2001, unlike the two previous cases, there has been an increase in the number of studies carried out in recent years.

Most of the research is concentrated in India, Canada, and the United States and applies to both lakes and the open sea. The main characteristics of the networks studied are detailed below.

- ANN type: as in previous cases, the MLP has been the structure chosen by most researchers (17 out of 20 cases). Research using the DNN [124] and RBF [133] has also been found.
- Structure of the ANN: most of the studies analyzed use simple structures with a single hidden layer. Research has also been found that uses two hidden layers or even the research of [124], which uses three. The number of neurons in the hidden layer is usually in the order of 10, reaching 300 neurons in the research of [125].
- Amount of data: in most research, the volume of data is in the order of hundreds or thousands. Normally, a major part of the data is used for training, with the remainder applied to testing. The percentage of studies that make use of data for validation is 5%.
- I/O configuration: temperature, wind speed, wind direction, and historical wave data are normally used as inputs. Outputs predict wave heights from one hour to 24 hours in advance.
- Activation function: the activation function is specified in 15 out of the 20 research. In the hidden layer, linear functions are used, with tansig and logsig being the most commonly used, while in the output layer, linear functions of the purelin and sigmoid types are adopted.

As a summary of all the previous sections, in the case of renewable energies, the predominant structure chosen is the multilayer perceptron structure with one or two hidden layers, because it may act as a universal function approximator. In addition, together with the backpropagation algorithm, it is able to learn any type of continuous function between a set of input and output variables.

Figure 5 details the most common inputs and outputs used by ANNs in wave height prediction and the operating scheme.

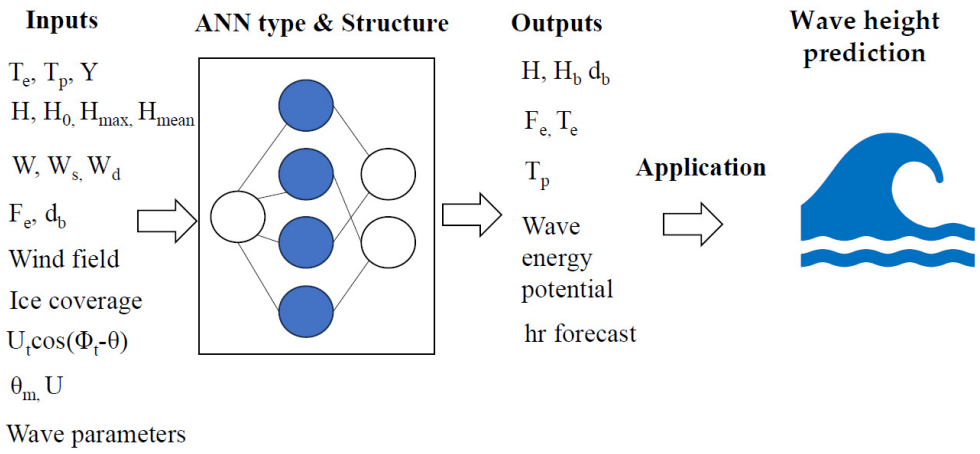

Figure 5. Inputs and outputs in ANNs applied to wave prediction.

3. Applications of ANNs for GHG Prediction

Traditionally, different techniques have been used to estimate greenhouse gas (GHG) emissions, such as the synergies and interactions model of air pollution and greenhouse gases [139]. The technique of ANNs is different from the GAINS (greenhouse gas and air pollution interactions and synergies) model in that ANNs are less complex, require a smaller amount of input data, and the inputs are undetermined [140]. The different research in the literature from 1996 to 2021 is detailed in Table 4.

Table 4. Uses of artificial neural networks for GHG prediction.

	Authors and Year	ANN Type and Structure	Journal	Country/ Region	I/O Setting		Activation Function	Notes
					Input	Output		
1	[141]	MLP 12-8-2	Agricultural Systems	Iran	Machinery, human labor, diesel fuel, pesticide, nitrogen (N), phosphate (P_2O_5), potassium (K_2O), farmyard manure (FYM), water for irrigation, electricity, seed, farm size	Energy, GHG emission	tansig (hidden layer)	Trained by BP algorithm 60% data used for training, 25% data used for cross-validation, and 15% data used for testing
2	[142]	MLP 9-4-1	Environmental Pollution	Texas, USA	Dummy variable, ozone (O_3) level at 9:00 am, carbon dioxide (CO_2), nitric oxide (NO), nitrogen dioxide (NO_2), oxide of nitrogen (NO_X), W_s, W_d, T_{max}	Daily maximum O_3 level	tansig (hidden layer)	Trained by BP algorithm
3	[143]	MLP 6-20-20-2	Atmospheric Environment	London, UK	Low cloud amount (LOW), base of lowest cloud (BASE), UKMO, visibility (VIS), T_d, VP, W_s	NO_x, NO_2	tansig (hidden layer) identify (output layer)	SCG algorithm is adopted Input and output data normalized to [−1, 1]
4	[144]	MLP 3-x-1	Atmospheric Environment	Santiago, Chile	$O_{3,t}$, T_{t+1}, T_t	$O_{3,t+1}$	sigmoid (output layer)	Direct algorithm or series-parallel was used
5	[145]	MLP 10-25-1 MLP 10-11-1	Neural Computing Y Applications	Ravenna, Italy	W_s (t), W_d (t), G (t), G (t − 1), G (t − 2), G (t − 3), SO_2 (t),	Sulphur dioxide (SO_2) (t + 1)	tansig (output layer)	BR SCG algorithm is adopted 20% data used for testing

					SO_2 (t − 1), SO_2 (t − 2), SO_2 (t − 3)		logsig (output layer)	
6	[146]	Elman NN 4-13-3	Environmental Modelling Y Software	Delhi, India	W_s, T, RH, W_d	Predict SO_2 concentration	sigmoid (hidden layer) purelin (output layer)	Trained by LM algorithm
7	[147]	MLP 5-X-1 MLP 9-X-1	Environmental Modelling Y Software	Bilbao, Spain	W_s, W_d, T, RH, P, G, thermal gradient, O_3, NO_2, number of vehicles, occupation percentage, velocity sin (2πt/24), cos (2πt/24), sin (2πt/7), cos (2πt/7), NO_2 (t + k), O_3 (t + k)	O_3 (t + k) NO_2 (t + k) (k = 1,…8)	tansig (hidden layer) purelin (output layer)	SCG algorithm is adopted 85% data used for training and 15% data used for validation and testing
8	[148]	ANN 13-25-1	Advances in Environmental Research	Kuwait	Mon-methane hydrocarbons, carbon monoxide (CO), methane (CH_4), CO_2, SO_2, NO, NO_2, T, RH, suspended dust, solar energy, W_d, W_s	O_3 concentration	logsig (hidden layer)	Trained by BP algorithm with momentum Input data normalized to [0, 1] 90% data used for training and 10% data used for testing
9	[149]	GRNN (7-13)-154-1	Science of The Total Environment	EU-27	Gross domestic product (GDP), gross inland energy consumption (GIEC), incineration of wood…	Annual (particle matter) PM_{10} emission	-	GA was used Input data normalized per capita 84% data used for training and 16% data used for validation
10	[150]	MLP 7-4-1	Atmospheric Environment	Belgium	PM_{10}, boundary layer height (BLH), W_s, T, cloud, W_d, t	Daily average $PM_{10\ day1}$	-	Trained by BP algorithm

11	[151]	MLP 4-5-10-1	Energy	Europe	Intake pressure, ṁ, fuel consumption, engine power	Raw emissions NOx	sigmoid (hidden layers) purelin (output layer)	Trained by BP algorithm Input data normalized to [−1, 1] 70% data used for training and 30% data used for testing
12	[152]	MLP 4-13-5	Applied Energy	Tamil Nadu, India	Pre-injection timing (PrlT), main injection timing (MIT), post-injection timing (PIT), test fuels	CO, CO_2, unburned hydrocarbon (UBHC), NO, smoke	sigmoid (hidden layer)	Trained by LM BP algorithm Input data normalized to [−1, 1] 70% data used for training, 15% data used for validation, and 15% data used for testing
13	[153]	MLP 3-(13-7)-1	Applied Energy	-	Injection pressure, engine speed, throttle position (TP)	NO_x, CO_2, SO_2	logsig (hidden layer)	Trained by BP algorithm SCG, CGP, and LM algorithms are adopted Input and output data normalized to [0, 1]
14	[154]	MLP 2-20-9	Applied Energy	Iran	Engine speed, ethanol gasoline blend	Brake power, torque, brake-specific fuel consumption (BSFC), brake thermal efficiency (BTh), volumetric efficiency (η_v) CO, CO_2, hydrocarbons (HC), NO_x	sigmoid (hidden layer) purelin (output layer)	Trained by BP algorithm 70% data used for training and 30% data used for testing
15	[155]	MLP 4-15-5	Applied Thermal Engineering	-	Lower heating value (LHV), engine torque, engine speed, air inlet temperature	BSFC, BTh, CO, HC, exhaust gas temperature (EGT)	sigmoid (hidden layer)	Trained by LM BP algorithm 70% data used for training and 30% data used for testing
16	[156]	MLP 4-22-3	Applied Energy	-	Load, blend %, compression ratio, injection timing	NO_x, smoke, UBHC	sigmoid (hidden layer) purelin (output layer)	Trained by BP algorithm Input data normalized to [−1, 1] 70% data used for

								training, 15% data used for validation, and 15% data used for testing
17	[157]	MLP 4-(7-60)-1	Applied Soft Computing	Iran	Engine speed, intake air temperature, mass fuel, brake power	NO_x	logsig (hidden and output layer)	CGP, CGB, GDM, GD, and LM algorithms are adopted Output data normalized to [0, 1] 90% patterns used for training and 10% patterns used for testing
18	[158]	MLP 6-14-1	Proceedings of the 28th International Symposium on Forecasting	Italy	Oil, solid fuel, electricity, natural gas, population, GDP	CO_2	logsig (output layer)	Trained by BP algorithm Input normalized to [0, 1]
19	[159]	MLP 6-9-1	Journal of Cleaner Production	Turkey	Year, coal, liquid fuels, natural gas, renewable energy and wastes, total electricity production	GHG emissions	-	Compared with SVM 85% data used for training and 15% data used for testing
20	[160]	MLP 4-20-1	AGRIS on-line Papers in Economics and Informatics	Apulia, Italia	CO_2 (t − 1), CO_2 (t − 2), CO_2 (t − 3), ma (CO_2(t−3)), CO_2 (t − 2), CO_2 (t − 1))	CO_2 (t)	sigmoid (output layer)	Trained by LM algorithm Input data normalized to [0, 1]
21	[161]	MLP 5-40-30-1	Water	-	lat, lon, reservoir age, mean depth, surface area	CH_4	tansig (hidden layer) purelin (output layer)	Trained by LM BP algorithm Input data normalized to [−1, 1]
22	[162]	MLP 36-36-1	Science of The Total Environment	Seoul, South Korea	Concentrations at 14:00, meteorological conditions at 14:00, variation velocity between 13:00 and 14:00, 08:00 and 14:00, 11:00 and 14:00, O_3 concentration	O_3 concentration at 15:00	sigmoid (output layer) purelin (output layer)	-

					s at 08:00, 11:00 and 13:00			
23	[163]	MLP 16-8-1	Transportation Research Part D: Transport and Environment	Guangzhou, China	Traffic volume, t (hour), t (day), T, P, W_s, W_d, G, rainfall, RH, concentration 1st hour before, 2nd, 3rd, distance to road center line, street direction, street aspect ratio	CO, NO_2, PM_{10}, O_3	sigmoid (output layer)	Trained by BP algorithm Input data normalized to [0, 1] 495 groups used for training, 24 groups used for evaluation, and 42 groups used for testing
24	[164]	MLP 6-3-1	Applied Sciences	Malaysia	Car numbers, heavy vehicle numbers, S/M, T, Ws, digital surface model (DSM)	Daily traffic CO emissions	tansig (hidden layer)	Correlation-based feature selection (CFS) model algorithm is adopted 70% data used for training and 30% data used for testing

Due to limitations on the length of the article, only 24 investigations have been selected as the most representative. However, other findings, such as those of [165–168], are also in the same direction. The main characteristics of the networks studied are detailed below.

- ANN type: as in all previous sections, the MLP has been the structure chosen by most researchers (21 out of 24 cases). Research has also been found that has made use of the GRNN [149] and Elman NN [146]. The use of GRNN is motivated by the fact that they only require a selection of parameters [169], do not need training, and work well with small data [170].
- Structure of the ANN: most of the studies analyzed use simple structures with a single hidden layer (21 out of 24 cases), with two hidden layers used in all other cases. The number of neurons in the hidden layer is of the order of 10.
- Amount of data: in most research, the volume of data is in the order of hundreds or thousands. Normally, a major part of the data is used for training, with the remainder being applied to testing. The percentage of research that makes use of data for validation is 35.3% (6 out of 17 cases).
- I/O configuration: the networks take different greenhouse gases such as CO_2, CO, CH_4, NO_x, SO_2, O_3, PM_{10}, and F-gases as output, while in most research, the inputs are macroeconomic or meteorological variables.
- Activation function: only 3 of the 24 investigations do not specify the activation function used. In the hidden layer, linear functions are used, with tansig and logsig being the most used, while in the output layer, the purelin and sigmoid types are adopted.

4. Contest Analysis

In this section, the results obtained from the analysis of trends in the use of ANNs in renewable energies and for GHG prediction detailed in the previous sections were compared. As can be seen and already confirmed by Srisamranrungruang and K. Hiyama in

2022, artificial neural networks (ANN) are an essential element of deep learning in artificial intelligence (AI), reaching enormous relevance in applications such as the use of renewable energy.

In addition, Olanrewaju et al. concluded in 2022 that ANNs were very useful when modeling renewable energy systems, such as complex mapping of energy resources, and demonstrated that the errors that could be made with the use of ANNs were within the limits of acceptable tolerances.

4.1. Analysis of the Research Trend Based on the Year of Publication, Country, and Number of Publications by Type of Application

The review of the research articles revealed that the level of publications in relation to the three aspects analyzed was similar. Wind power and speed prediction generated 25 articles, very similar to the 24 articles for GHG prediction, followed by 20 articles on wave prediction and 17 on solar energy prediction. The first research article was published in 1996 and, except for 1997 and 2017, in every year until 2021, research was published on the topics analyzed.

The annual trend for each type of research is shown in Figure 6.

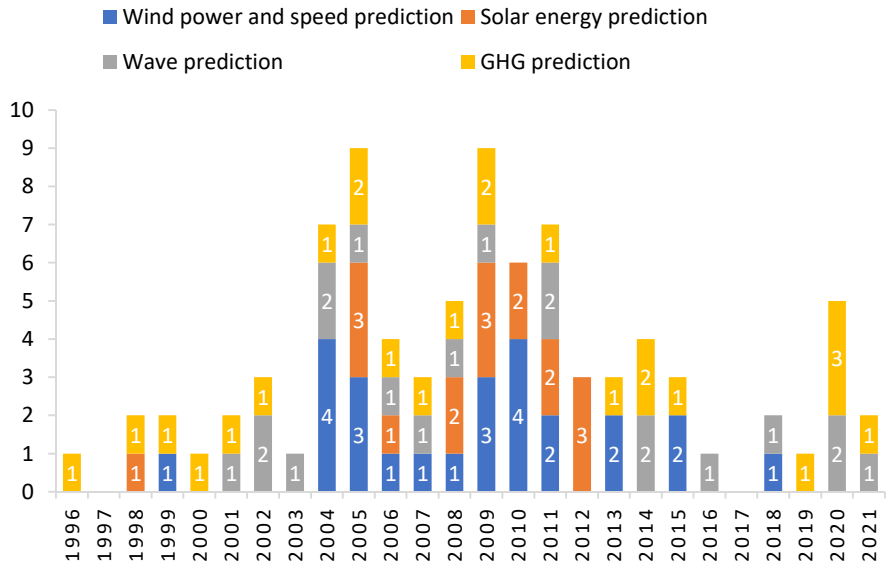

Figure 6. Number of annual publications for each type of research.

4.2. Countries with the Highest Number of Research

Research carried out by 30 countries has been published and interest in the subject extends to all continents. Figure 7 shows that the interest in the different research analyzed maintains a constant distribution. However, a special interest in wave prediction is observed in the USA as well as in India. This last country also stands out for the number of publications on GHG prediction. Turkey's first place as the country with the highest number of publications on solar energy prediction is also particularly relevant.

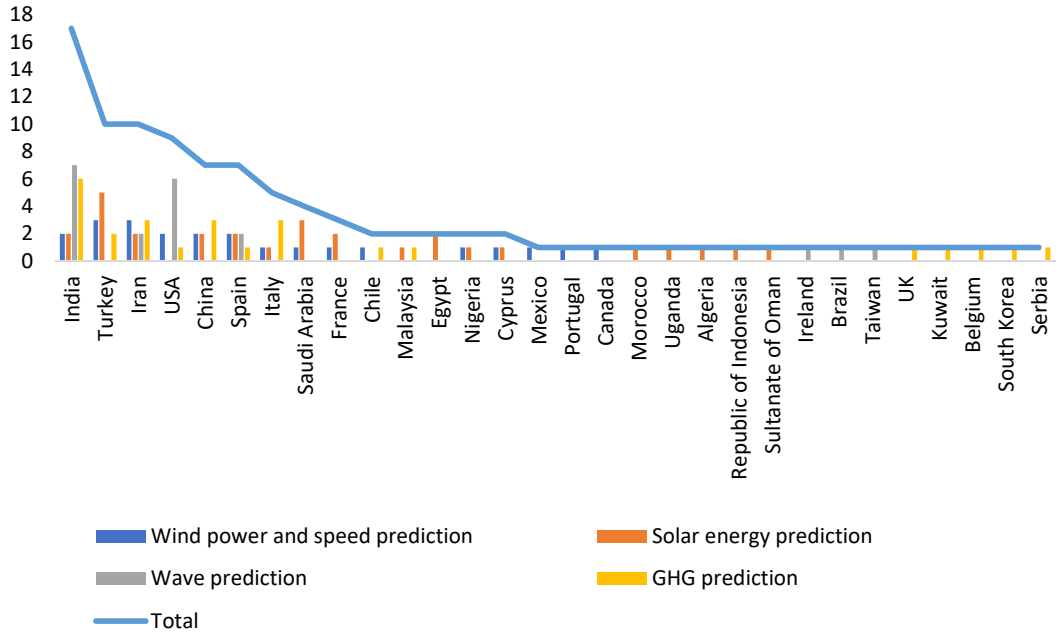

Figure 7. Number of research published by country.

4.3. Methodological Preferences in Research Carried out with ANNs and Types for the Different Applications

Figure 8 presents the different network structures used. Most of the investigations opted for MLP as the ANN type. The use of MLP is especially predominant in GHG prediction and solar energy prediction.

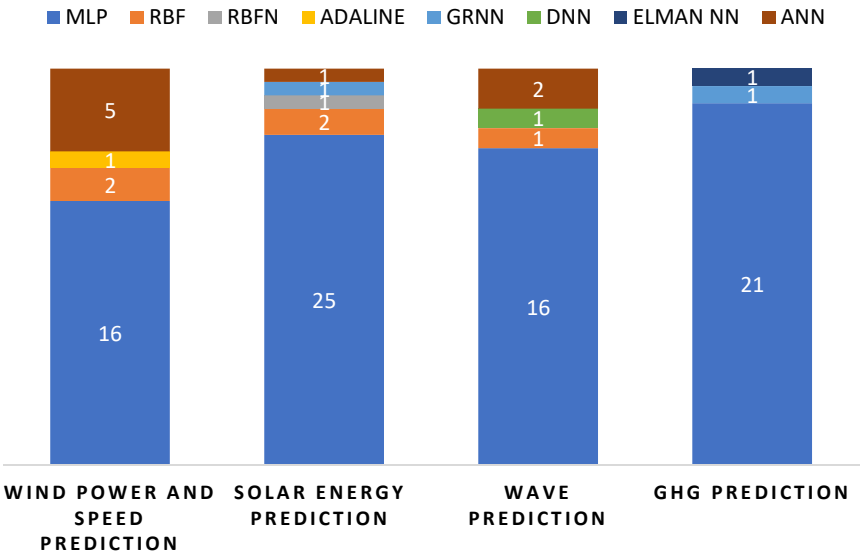

Figure 8. Network structures used with each research.

4.4. Trends in Publishing on Applications of Artificial Neural Networks to Energy Transition and Journals with Higher Productivity

The interest in the subject matter is evident from the large number of prestigious journals that have published research articles, as can be seen in Figures 9–11. Although some journals are repeated in the three investigations, each one of them presents a type of journal influenced by its area of research.

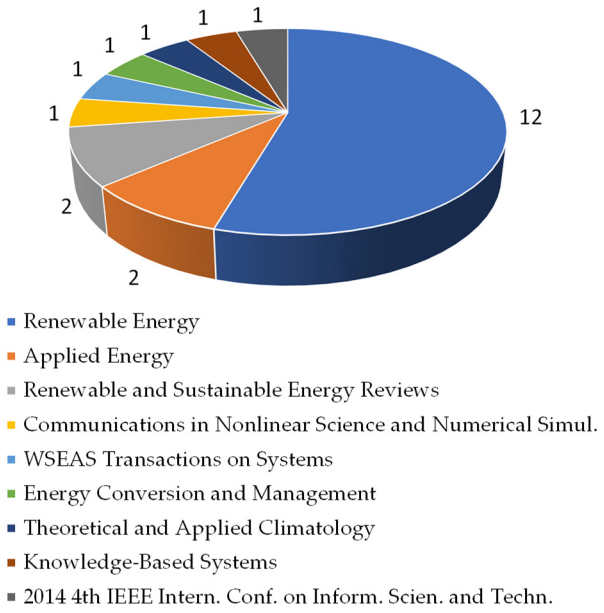

Figure 9. Journals with higher productivity in ANNs for wind power and speed prediction.

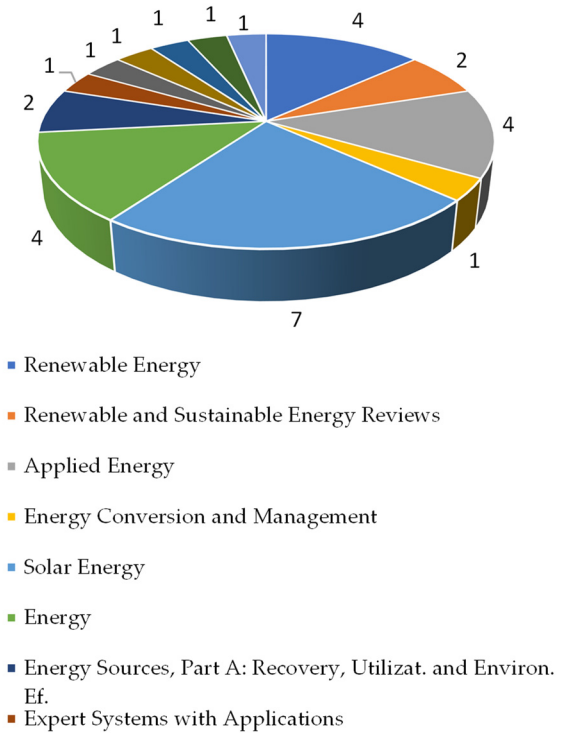

Figure 10. Journals with higher productivity in ANNs for solar energy prediction.

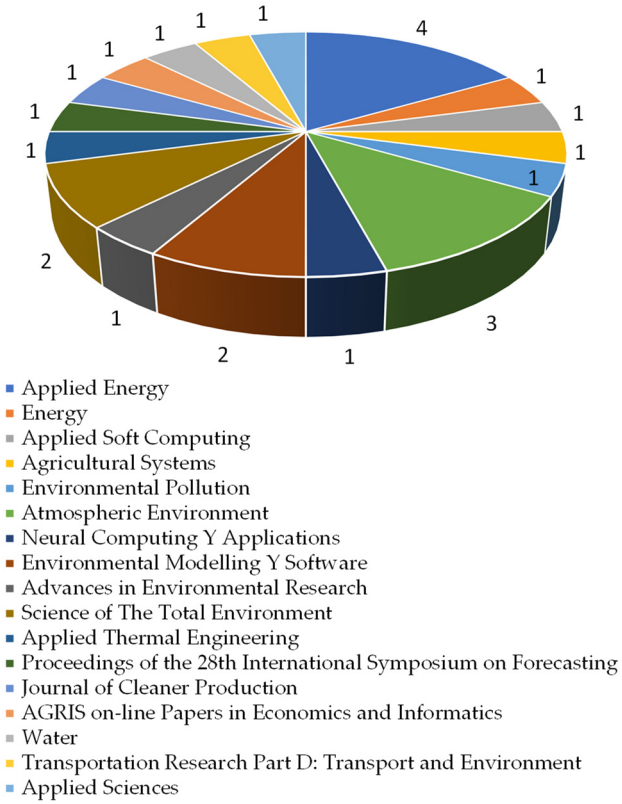

Figure 11. Journals with higher productivity in ANNs for GHD prediction.

4.5. Most Used Activation Functions

Figure 12 shows the trend regarding the use of the 37 types of activation functions used in the different investigations. purelin (output layer) and tansig (hidden layer) turned out to be the most used for wind power and speed prediction. For wave prediction, purelin (output layer) and sigmoid (output layer) stood out, while for solar energy prediction, the most used were purelin (output layer), tansig (hidden layer), and logsig (hidden layer). For GHG prediction, the most used were purelin (output layer), tansig (hidden layer), and sigmoid (hidden layer).

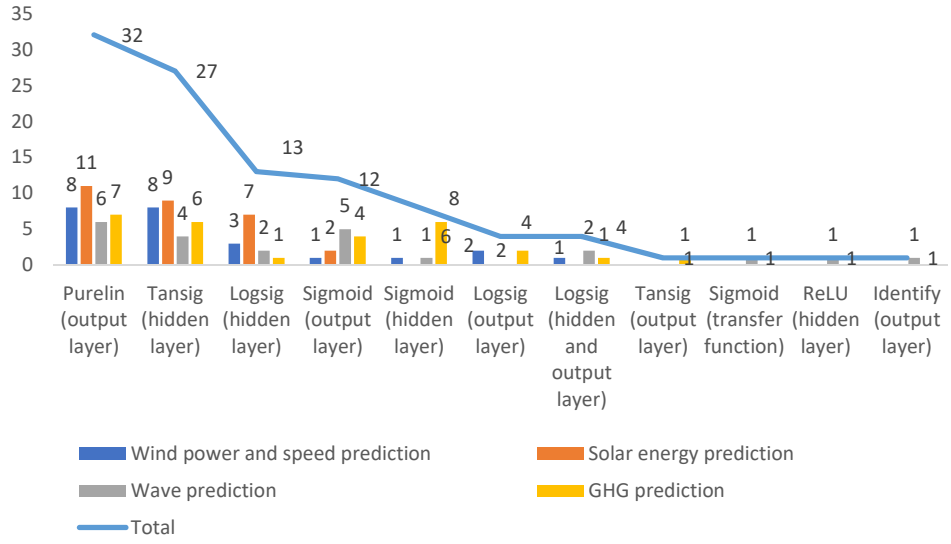

Figure 12. Trend in the use of activation functions.

5. Conclusions

The ANNs turned out to be a reliable and mature model for forecasting energy resources and the level of associated pollutant emissions.

The great interest in the subject has led to the publication of research in a wide variety of prestigious scientific journals. In particular, the level of productivity of two magazines stands out: *Renewable Energy* and *Applied Energy*, with 18% and 10%, respectively, of the total published. These two journals belong to the Elsevier publishing house. Their areas of knowledge are energy and fuel and green and sustainable science and technology and energy and fuel and chemical engineering, presenting JCR indexes and Q1 quartiles.

The descriptive analysis of the journal articles together with the analysis of their content allowed for the finding of similarities regarding the use of ANN type. Both in the applications of ANN to renewable energies and in the applications of ANNs for GHG prediction, the most used ANN type was the MLP, used in 80% of the research.

This article aims to provide a detailed description of the existing literature on the different applications of ANNs to the energy transition. It includes relevant aspects such as the use of renewable energies and the reduction in GHG. Additionally, the analysis of results will provide future research with data on current trends in the management of ANN and existing limitations.

Although the research results have been published throughout the world and in 30 different countries, 80% of the research is concentrated in India, Turkey, Iran, USA, China, Spain, Italy, and Saudi Arabia. Especially relevant is the contribution of India with almost 20% of the total.

The analyzed research began in 1996, focusing on GHG prediction and extended until 2022. The years with the highest number of publications were 2005 and 2009. In addition, the rate of publications remained constant over the years, with a significant resurgence of publications in 2020, confirming the interest in the topic. In this way, the use of ANNs presents a sufficient temporal development to demonstrate its usefulness and compete with the use of other algorithms. Some variables were difficult to model with ANN, for example, environmental variables due to the large number of associated uncertainties. However, the ANN turned out to be a valid prediction aid. Thus, ANNs occupy a central place in the transition due to their ability to learn and decide and are increasingly present in intelligent systems. As it has been shown, ANNs are very useful in the field of renewable energies for predicting wind speed, solar radiation, or wave height. This is of great importance for the design of efficient energy systems, capable of anticipating and adapting to future phenomena. Therefore, it is considered necessary that further research should reinforce efforts to develop networks capable of a wider range of predictions with a smaller number of variables.

Likewise, there is also abundant literature for predicting energy consumption in buildings and traffic as well as forecasting the pollutant emissions of a given activity. Although a large number of contributions have been found in the aforementioned sectors, it would be necessary to extend the use of ANNs to all sectors that make up a country's energy scenario, such as manufacturing, construction, agriculture, and mining, among others. This is really useful as it opens the way to the development of new applications capable of predicting the energy of a complete national energy system, thus making our energy systems more competitive, safe, and sustainable. As a result, world energy systems will be in a position to meet current global environmental commitments.

On the other hand, the type of architecture most chosen by the researchers was the multilayer perceptron, while the algorithms most used for training were backpropagation and Levenberg–Marquardt. The choice of MLP as the most used network is based on the fact that it is the most suitable ANN for classification and prediction. Moreover, the most used activation functions were purelin (output layer) and tansig (hidden layer). They stood out in the four investigations carried out. In addition, logsig (hidden layer) was also widely used in the case of solar energy prediction, as was sigmoid (output layer) for wave

prediction and sigmoid (hidden layer) for GHG prediction. It is also noteworthy that research in which the greatest variety of activation functions was observed was the wave prediction with nine different activation functions, compared to the solar energy prediction with only four types.

The results and analysis performed with ANNs in this study can serve as a guide for the parties involved in the energy transition, in decision making, and in planning concrete actions to achieve the goals of increasing the contribution of renewable energy sources to the energy system, reducing GHG, and improving energy efficiency. Several methods can be used to communicate ANN results and recommendations to stakeholders. These can range from detailed technical reports for technical stakeholders to user manuals or graphs and diagrams for less technical or business-oriented end users. Data and information can also be reflected in technical equipment, through control panels of generation and distribution units, feedback loops, or other types of technical and informational channels.

As it has been seen, the largest number of contributions of ANR to the energy transition are focused on both renewable energy and greenhouse gas emissions. While these are the pillars of EU and international energy policy, it would be desirable to further develop new applications with a view to achieving fully efficient, secure, and sustainable energy systems.

Future research work could analyze research trends with ANNs in other aspects related to the energy transition, such as the generation and use of energy-recoverable biomass. In addition, the study of these techniques in the use of both residual biomass and specific crops could be useful to properly value the use of this resource and avoid increases in food prices. Another line of work could be the analysis of the application of the ANN in new sustainable mobility. Thus, the efficient control of freight traffic and private travel would be of great importance in reducing the level of polluting emissions associated with transport. Other future lines of research could be to try to find sufficient data to measure the diagnostic performance of ANNs using the receiver operating characteristic (ROC) method.

Author Contributions: Conceptualization, Í.M.I.-S.C. and A.M.-F.; methodology, Í.M.I.-S.C., A.J.G.-T., J.C.R.-F. and A.M.-F.; software, Í.M.I.-S.C.; validation, A.J.G.-T.; formal analysis, Í.M.I.-S.C., A.J.G.-T., J.C.R.-F. and A.M.-F.; investigation, Í.M.I.-S.C., A.J.G.-T., J.C.R.-F. and A.M.-F.; resources, Í.M.I.-S.C.; data curation, Í.M.I.-S.C., A.J.G.-T., J.C.R.-F. and A.M.-F.; writing—original draft preparation, Í.M.I.-S.C., A.J.G.-T., J.C.R.-F. and A.M.-F.; writing—review and editing, A.J.G.-T. and J.C.R.-F.; supervision, A.J.G.-T.; project administration, A.J.G.-T. and J.C.R.-F. All authors have read and agreed to the published version of the manuscript.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interests.

Abbreviations

ANNs	artificial neural networks
MDPI	Multidisciplinary Digital Publishing Institute
AI	artificial intelligence
GA	genetic algorithms
FL	fuzzy logic
BP	backpropagation
UN	United Nations
MLP	multilayer perceptron
W_s	wind speed
Lon	longitude

Lat	latitude
A	altitude
RBF	radial basis function
W_d	wind direction
W_p	wind power
M	month
RP	resilient propagation
LM	Levenberg–Marquardt
ICA	imperialist competitive algorithm
PSO	particle swarm optimization
BR	Bayesian regularized
T	temperature
T_{AVG}	average temperature
T_{max}	maximum temperature
T_{min}	minimum temperature
P_{air}	air pressure
G	solar irradiance
T_{air}	air temperature
SCG	scaled conjugate gradient
IEEE	International Conference on Information Science and Technology
P	pressure
I/O	input/output
GRNN	general regression neural network
P_w	power
S	sunshine duration
Y	nebulosity
DGP	differential pressure
K_T	clearness index
t	hour or day
G_D	daily global solar radiation
k_t	hourly clearness index
S_{0d}	theoretical sunshine duration
TCC	total cloud cover
K_D	diffuse fraction
ε_4	surface emissivity
ε_5	surface emissivity
R_a	terrestrial radiation
L	location
H	height
DNN	deep neural network
H_o	deep-water wave height
T_e	wave energy period
H_b	breaking wave height
d_b	water depth at the time of breaking
T_p	H and zero-up-crossing peak wave period
F_e	energy flux
W	weather station index
U	wind shear velocity
ANFIS	adaptive neuro-fuzzy inference system
$H_{1/3}$	significant wave height
$H_{1/10}$	highest one-tenth wave height
H_{max}	highest wave height
H_{mean}	mean wave height
CGB	conjugate gradient Powell–Beale
BFG	Broyden–Fletcher–Goldfarb
T_p	wave direction
GHG	greenhouse gases

GAINS	greenhouse gas and air pollution interactions and synergies
N	nitrogen
P_2O_5	phosphate
K_2O	potassium
FYM	farmyard manure
O_3	ozone
CO_2	carbon dioxide
NO	nitric oxide
NO_2	nitrogen dioxide
NO_X	oxide of nitrogen
LOW	low cloud amount
BASE	base of lowest cloud
VIS	visibility
CO	carbon monoxide
CH_4	methane
GDP	gross domestic product
GIEC	gross inland energy consumption
BLH	boundary layer height
PrlT	pre-injection timing
MIT	main injection timing
PIT	post-injection timing
UBHC	unburned hydrocarbon
TP	throttle position
LHV	lower heating value
BSFC	brake-specific fuel consumption
BTh	brake thermal efficiency
η_v	volumetric efficiency
EGT	exhaust gas temperature
CFS	correlation-based feature selection
AI	artificial intelligence

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