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# Renewable energy: Present research and future scope of Artificial Intelligence

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A B S T R A C T

The existence of sunlight, air and other resources on earth must be used in an appropriate way for human welfare while still protecting the environment and its living creatures. The exploitation of sunlight and air as a substantial Renewable Energy (RE) source is an important research and development domain over past few years. The present and future overtaking in RE mainly comprises of (i) the development of novel technology for optimum production from the available natural resources (ii) environmental awareness, and (iii) the better management and distribution system. Like other domains (food, health, accommodation, safety, etc.), Artificial Intelligence (AI) could assist in achieving the future goals of the RE. Statistical and biologically inspired AI methods have been implemented in several studies to achieve common and future aims of the RE. The present study summarizes the review of reviews and the state-of-the-art research outcomes related to wind energy, solar energy, geothermal energy, hydro energy, ocean energy, bioenergy, hydrogen energy, and hybrid energy. Particularly, the role of single and hybrid AI approaches in research and development of the previously mentioned sources of RE will be comprehensively reviewed.

## 1. Introduction

Currently, the world economy is inherently dependent on the effective ways of electrical power generation, appropriate management and distribution [1–3]. The conventional approaches of energy production have a massive side effect on the global climate and climate changes. According to recently published reports by the International Energy Agency (IEA) "*Energy-related greenhouse gas (GHG) emissions would lead to considerable climate degradation with an average 6 °C global warming*" [4]. Consequently, the clean energy is the feasible solution to make the world safer and energy proficient. It is environment-friendly due to minimum $CO_2$ contamination, which is the basic measure of the greenhouse effect responsible for environmental degradation [5–7]. Research and development in the RE domain on both the governmental and public level will achieve better efficiency and guaranteed reimbursement in future demand of energy because of the simple and low cost of maintenance, durability and the unlimited sources [8–10]. The RE sources are also referred as alternative mainly due to their inconsistency to supply the demand uninterruptedly in some specific conditions [11]. Consequently, the performance improvement of alternative energy sources is inevitable to accomplish the future demand of energy in the world [12]. The latter can be achieved by addressing the constraints related to the design, efficiency, performance prediction of the existing RE system, and weather parameter estimation of the region, where the station is installed. The global energy consumption data in different fields, including the crude oil, oil products, natural gas, coal, and renewables, etc. are available in the Global Energy Statistical Yearbook by Enerdata [13]. According to their latest published information on 2015, the total production and consumption of energy in the world is rising year by year as shown in the Fig. 1(a). Fig. 1(b) represents the information of top ten countries in the world, having maximum consumption of energy in the year 2014. China has been the largest energy consuming country from 2009 to 2014, though a reduction of 7 million tons of oil equivalent (Mtoe) in the year 2014 compared to the year 2013 is noticed [13]. China and USA have energy consumption greater than 1000 Mtoe from 2000 to 2014.

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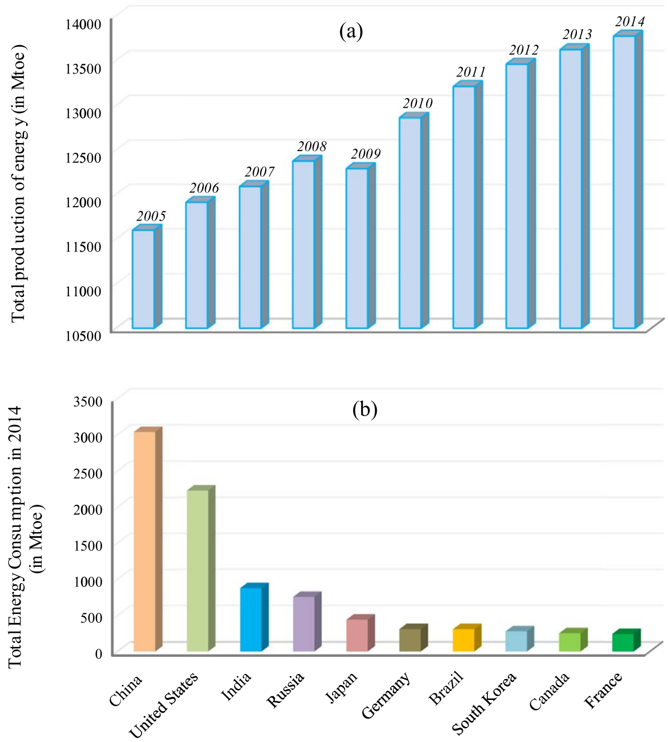



**Fig. 1.** (a) Total consumption of energy in last ten years (2005–2014) in the world, and (b) top ten countries with the maximum consumption of energy in the year 2014 [13].

Most of the countries in the world, including the top ten listed in Fig. 1(b) were trying to include RE as a major constituent of their total energy production. RE sources in China are showing increasing in growth, but their preliminary predictions are not even close to being fully used. Republic of China RE Law and associated conventions have encouraged the additional utilization of RE resources [14]. The similar trend is also followed by many small developing countries like (i) Former Yugoslav Republic of Macedonia (FYROM), where the first wind power plant was completely installed and operating successfully with the total capacity of around 50 MW in 2014, the projected annual production is about 125 GW/h to supply the need of 60,000 people (total population of the country is about 2.1 million) [15]; (ii) Uruguay (population 3.4 million) is producing 94.5% of its energy demands from renewables [16]; (iii) Costa Rica (population 4.8 million) is using maximum renewable and target 100% renewables for the power production by 2021. The European Union (EU) regulations on the RE decided to achieve a target of 20% of RE production in the total energy consumption of EU by 2020 and 27% by 2030 [17]. Fig. 2 exhibits the share of renewables in electricity production by top ten

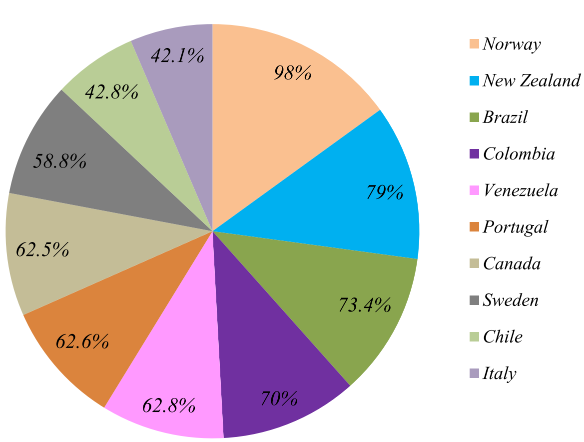



**Fig. 2.** A contribution of renewables in electricity production in the year 2014 [13].

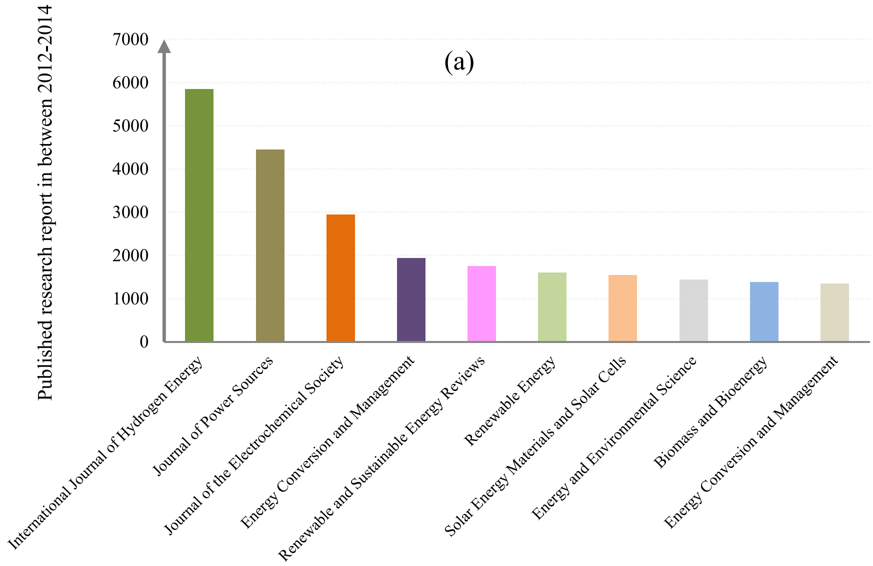
countries in the world for the year 2014, from which it is obvious that the world is focusing additional attention on the alternative ways of energy production [13]. The research and development in the RE have been in full swing within the past few years. A total of 24248 research reports was published in the literature by the numerous research groups worldwide, focusing on the different issues related to the RE domain in between the years 2012–2014 [18]. It results in a total citation count of 144911 [18]. Fig. 3(a) shows the total number of publications related to the RE sustainability and environment in top ten scientific journals in between the years 2012–2014. The citation counts of top ten scientific journals in the similar period of time are represented in the Fig. 3(b). The advancement in the RE domain specifically in the sources, county-wise application, future use, environmental effect, production methods, storage, management, distribution, allied policies and limited technical limitations, etc. are detailed in several review reports [7–12,19–35] available in the literature. The most prioritized research in RE domain includes: life cycle assessment (LCA) [27,36–40], search and analysis of novel sources [41–45], social, economic and environmental effects [46–48], effective storage and relocation system [49–51], planning and design of grid integration and supply systems [52–54], electrification in rural area of developing countries [55–57], data acquisition and monitoring systems [58–61], country and region wise assessment of development and availability [23,35,62–70] and many more. Decision systems have been developed for several aspects of RE such as in the evaluation of prospective, using geographical information system (GIS) database [71], structuring of projects [72], planning for diffusion [73], and selection of project [74].

Optimization in RE is reported in several studies, like in control strategy for hydrogen storage [75], a community-based hybrid system [76], configuration of power generating system [77,78], scheduling of micro-grid [79]. Besides that, simulation and optimization of hybrid RE system, including the solar, wind, and other sources are designed and evaluated [80–82], modeling for high percentage of combined heat and power production (CHF) and wind power [83], solar radiation modeling [84], induction generator [85] are also described.

Adaptability in any field is always mandatory for additional advancement with the passage of time; it is also true for the RE. Since the scope of technology is developing day by day, the application of the previous becomes an essential part of each of the research and development domain currently. Specifically, the use of a machine which acts intelligently to tackle the problems is preferred in most of the research domains. Artificial Intelligence (AI) focuses mainly on developing intelligent machines and software for specific problems [86]. It has countless applications in most of the research domains, including the food, health, safety, education, business, agriculture, art, etc. [87]. AI also plays a substantial role in the advancement of RE. Importance of AI in RE specifically in solar radiation and wind speed prediction, prediction of energy intake of a solar building and heating loads of buildings, modeling of room heater, load and short-term electric power forecasting, sizing photovoltaic systems, wind and solar power modeling and forecasting, electrical load prediction of the city and supermarkets, etc. is summarized in the studies [88–95]. Though most of the previous reports cover the application of artificial neural network (ANN) based approaches in RE, therefore the main focus of the present study is to review the applications of different AI techniques including the ANN, applied in the RE in recent few years. Precisely, the performance of AI methods in the progress of Wind Energy, Solar Energy and other significant sources of RE is detailed. Besides, the impact of hybrid AI approaches in single and hybrid RE system have been thoroughly discussed and summarized.

## 2. Significant renewable energy sources

RE types, according to the source of generation, mainly include wind energy, solar energy, hydro energy, geothermal energy, bioenergy, ocean energy, hydrogen energy, hybrid RE, etc. [1–5]. A schematic diagram



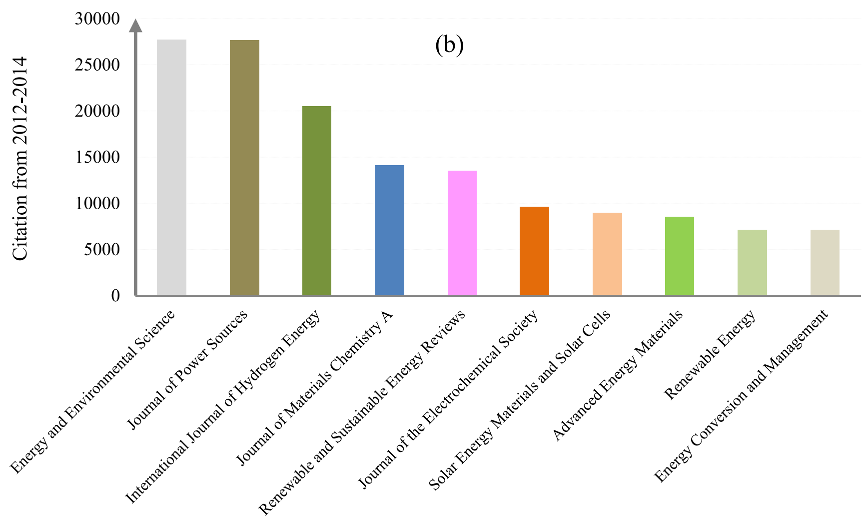




**Fig. 3.** Research reports published (a) from 2012 to 2014 in top ten journals, and (b) citation of reports published from 2012 to 2014 in top ten journals [18].

representing different renewable energy sources is shown in the Fig. 4. A short description of some most significant types of RE is as follows.

### 2.1. Wind energy

The motion of earth and unbalanced incidence of the sun rays on the surface of the earth (more on equator than the pole) causes wind [96,97]. The application of the wind as a significant source of energy by converting its kinetic energy into the mechanical energy, with the windmills and the wind turbines, is ongoing for many centuries till now. Past evidence was found in Persia and China (200 BCE), Netherlands (1300–1875 CE) to the modern advancement in the USA (1850–1970) [98–100]. The first wind turbine of capacity 12 kW was installed in Ohio, USA in 1887–1888 [100]. Thereafter numerous wind turbines of enhanced capacity were installed in different countries to accomplish the demand of electricity. The installed wind power capacity of top ten countries of the world in between the years 2006–2015 is shown in Fig. 5(a), while the installed capacity of the EU in the similar duration is demonstrated in the Fig. 5(b) [101,102].

China has a maximum number of installed wind power units between the years 2010–2015 (Fig. 5(a)). An obvious improvement in the installed capacity of wind power in USA and Germany is also noticeable in the similar duration. An overall growth rate of 9.96% is obvious in installed wind power capacity in the year 2015 compared with last year capacity in EU [102]. Also, the annual installation is increased from 48 GW in the year 2006–141 GW in the year 2015 with an annual growth rate more than 9% [102]. Vestas *V161* is the largest (height 220 m and diameter 164 m) and most powerful (8 MW) wind turbine in the world was installed at the Danish National Test Centre, Denmark in 2014 [103]. A detailed overview of research and development in different aspects of wind energy [104–111] including the available resources and uses [104], policies worldwide [105], existing technology [106,107], environmental impact [108], influence of climate changes [109], storage schemes [110], and monitoring and error diagnosis [111] were summarized in different review reports. In the past decade (2005–2014), a tremendous amount (80.59%) in a number of scientific reports in the wind energy research is noticed compared to (1995–2004) (Fig. 6).

### 2.2. Solar energy

Sun is a vital source of energy for the entire living creature on the earth. Solar radiation is being used for several purposes by human being since many centuries [112–114]. The first recorded evidence is available from 7th century B.C. when the sun ray was used to make fire after

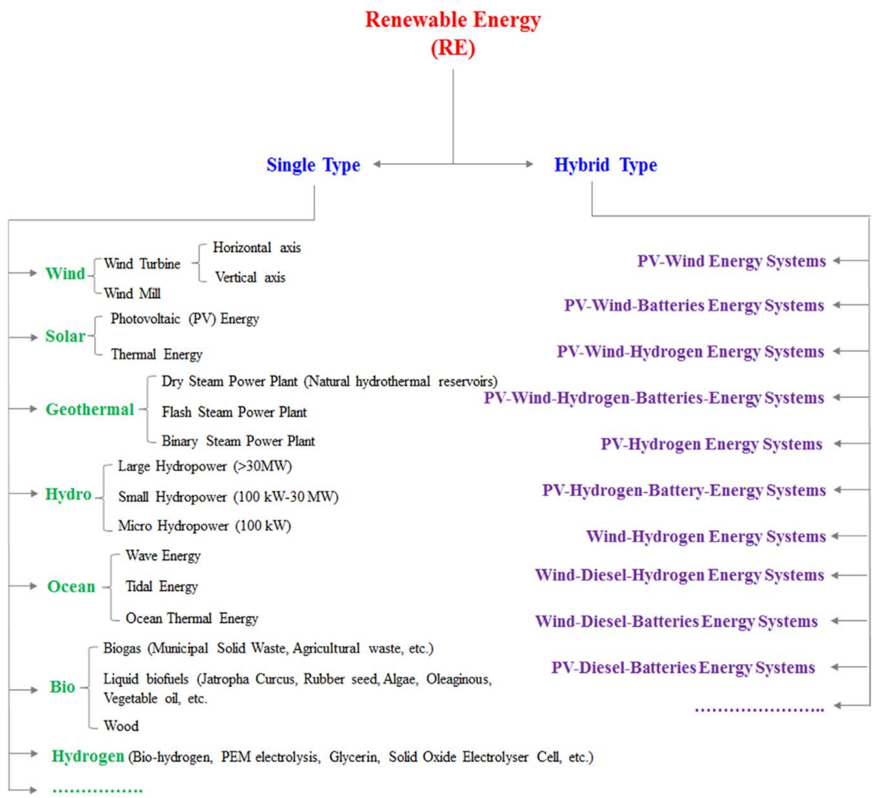



**Fig. 4.** Categories of renewable energy and their sources [96–195].

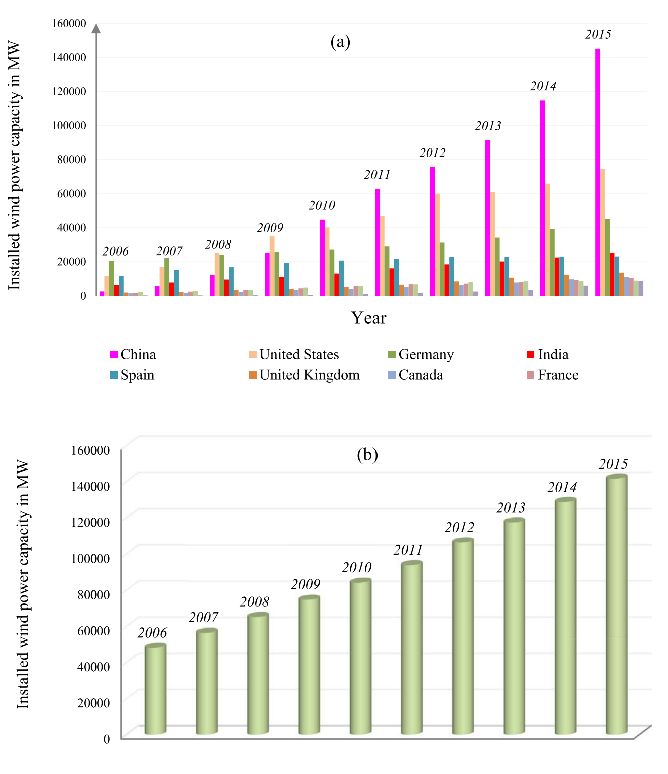



**Fig. 5.** Installed wind power capacity (a) different countries, and (b) EU in between the years 2006–2015 [101,102].

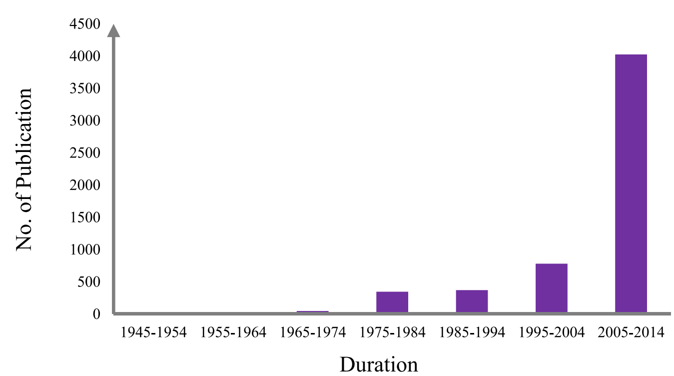



**Fig. 6.** Published scientific reports of wind energy research (web of science).


**Fig. 7.** Published scientific reports of solar energy research (web of science).

concentrating with glass. A detailed record of the historical development of solar energy from ancient time (7th Century BCE – 1200s CE) to the modern era (1767–2001) available in [112]. The major breakthrough was attained in the year of 1839 with the discovery of photovoltaic effects. The solar energy is used mainly with active systems (Photovoltaic, Thermal, etc.) and passive systems. Photovoltaic is the process of transforming the solar energy for electricity production [115], while in the Thermal process first the solar energy is transformed into some mechanical energy thereafter used for the electricity production (Fig. 4) [113–115]. The passive system gathers and distributes the solar energy in building without using any electrical device like in the active systems described before [116]. The development of solar elements in RE for improved efficiency and quality is organized in following areas: novel and efficient materials [117–120], global policies [121], design [122], application [123,124], storage [125], low energy buildings [126]. Mathematical modeling of solar energy systems is also summarized in several reviews [127–130]. Fig. 7 represents the available published reports on the solar energy research available in the web of science. In the past decade (2005–2014), a remarkable increment (73.29%) in a number of scientific reports in the solar energy research is noticed compared to (1995–2004).

### 2.3. Geothermal energy

The gradual decay of radioactive elements in the earth results in the formation of lava. The movement of Tectonic plates breaks the Lava, which generates a geothermal reservoir (a source of geothermal energy) [131–133]. According to the ways of electric power generation from the geothermal reservoir, the geothermal energy is divided into three categories (Fig. 4). The research and development in the field of geothermal energy are summarized in several reviews [134–145] based on determination of available resources [134], current status of technology [135,136], and uses, benefits and application [137–139], characteristics and effect [140], environmental issues [141], and legal status of use [142]. Modeling and simulation of geothermal energy is also described in many studies [143–145]. A variation of the total number of published research reports related to the geothermal energy in between the years 1945–2014 is shown in the Fig. 8.

### 2.4. Hydro energy

Hydro energy is a process to generate electricity by using the natural (waterfall) or controlled motion of water (using an artificial barrage on the river) [146–148]. According to the capacity of power generation hydropower plants were categorized into three main types (Fig. 4). Many reviews summarize the research and development in the field of hydro energy [149–159] specifically, storage plant and their limitations [149,150], reservoir management and operations [151,152], hydrokinetic energy conversion system [153,154], slit erosion techniques in hydro turbines [155], optimal installation of small hydropower systems [156], socio-technical limitation of hydropower plant in developing countries like Nepal [157], environmental protection by minimizing the methylmercury concentration in hydroelectric reservoirs [158], and mathematical modeling [159]. A number of published research reports related to the hydro energy in between the years 1945–2014 is shown in the Fig. 9. It represents maximum research outcomes based on research of hydro energy in the duration of years 2005–2014.

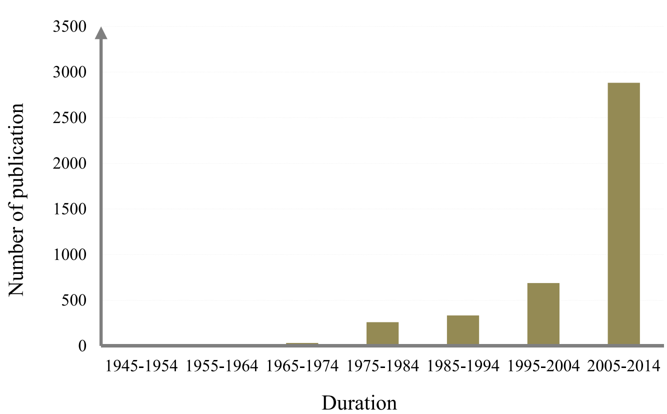



**Fig. 8.** Published scientific reports of geothermal energy research (web of science).

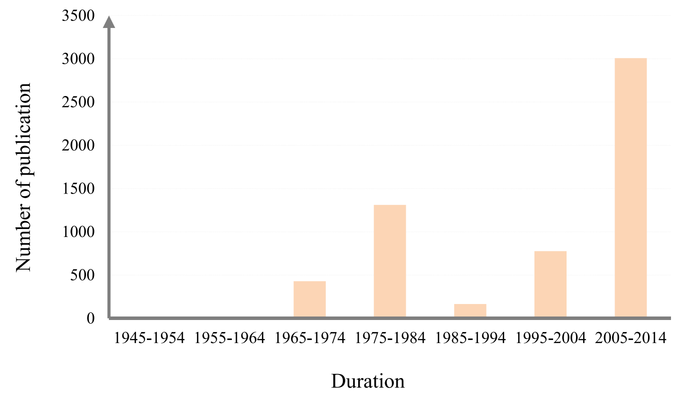



**Fig. 9.** Published scientific reports of hydro energy research (web of science).

### 2.5. Ocean energy

Ocean energy is a part of hydro energy, in which the electricity is generated from the sea in three categories: using the mechanical energy of (i) wave, (ii) tides and (iii) thermal energy of the sea (Fig. 4) [160,161]. Research and development in the field of ocean energy is summarized in several review reports [162–167], especially, wave and tidal energy review [162], development and challenges [163], the financial side [164], wave energy transformation technology [165], future visions [166], modeling [167]. The published report related to the ocean energy research in between 1945 and 2014 is given in Fig. 10. It represents the gradual growth in the research outcomes in the years 1975–2014 and maximum outcomes in the last decade (2005–2014).

### 2.6. Bioenergy

In this category of RE, the electric power is generated using sources like wood, organic wastes, agricultural byproducts and wastes, algae, microorganism, vegetable oils, etc. [168–170]. Several review reports [171–180] compiles the significant research and development in the field of bioenergy, particularly, worldwide production and consumption of bio-ethanol [171], Microalgae in biodiesel production and application [172], microbial fuel cells in bioenergy [173], bio-conversion processes of organic substrate into the bioenergy [174], pyrolysis of bio-mass to bio-oil [175], energy production from biomass [176], logistic issues of bioenergy production [177], Bio-refineries [178], status of bioenergy in EU [179], future of the global bioenergy [180]. Fig. 11 represents the published reports related to the bioenergy research in between the years 1945–2014 obtained from the web of science. More than 10,000 of research reports are published in between the years 2005–2014.

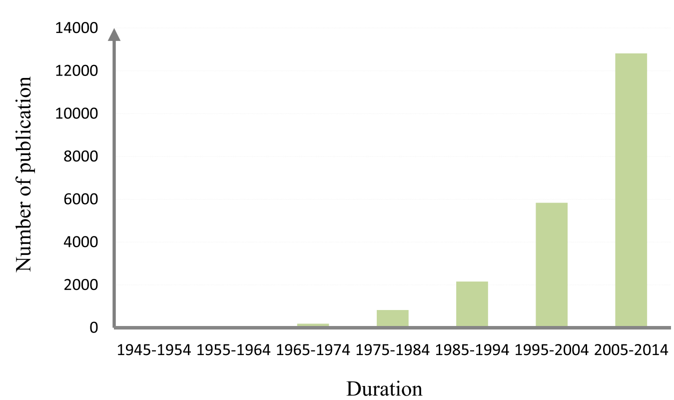



**Fig. 10.** Published scientific reports of ocean energy research (web of science).

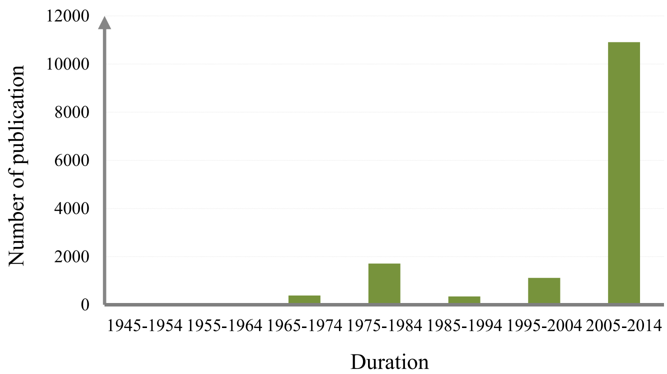



**Fig. 11.** Published scientific reports of bioenergy research (web of science).

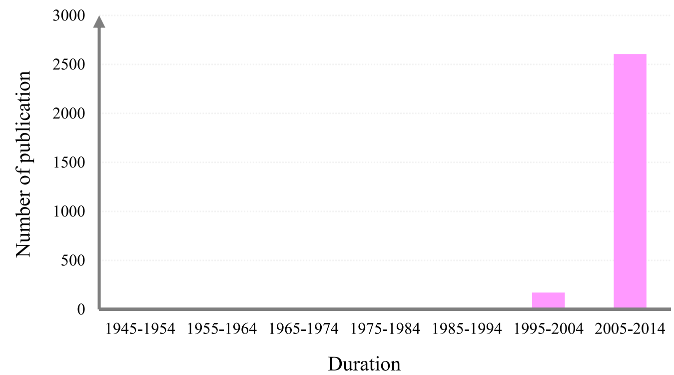



**Fig. 13.** Published scientific report on hybrid RE research (web of science).

### 2.7. Hydrogen energy

Each of the fuel products (hydrocarbon) contains hydrogen as an integral constituent, which is separated from the previous for the independent applications of the latter. Besides that, electrolysis process of water and the biological process of bacteria and algae also discharges hydrogen, which creates high energy after burning and used as a RE source for electric power generation [181,182]. Fuel cells are commonly used for the latter process. Hydrogen energy continuously supplies the demand of electricity, which is a limitation of the wind and solar energy based RE systems [181–183]. The most significant research and development outcomes in the field of hydrogen energy are summarized in several review reports [184–190], mainly, present status [184], photo-production of hydrogen [185], influencing factors in hydrogen production [186], storage process [187], hydrogen fuel cell [188], present and future strategies of hydrogen [189], technical situation and economic part [190]. Published research reports based on the hydrogen energy research in between 1945 and 2014, obtained from the web of science is shown in the Fig. 12. A gradual improvement in the number of published scientific reports is obvious from 1975 to 2014.

### 2.8. Hybrid renewable energy

A hybrid RE system combines multiple RE sources with the objective to improve the efficiency and stability of power sources than what could be achieved using a single RE source. Some of the commonly used hybrid RE sources include PV-diesel, Wind-diesel, PV-hydrogen, Wind–hydrogen, etc. (Fig. 4) [191–193]. Research and development outcomes in the field of hybrid RE are reviewed in several published reports [194–200], especially, applications [194], configuration and control [195], optimal design [196], software tools for integration [197], current status and future potential [198], storage system [199], and mathematical modeling [200]. Fig. 13 represents the number of published research reports based on the hybrid RE research obtained from the web of science in between the years 1945–2014. Maximum research reports are available for the duration of 2005–2014.

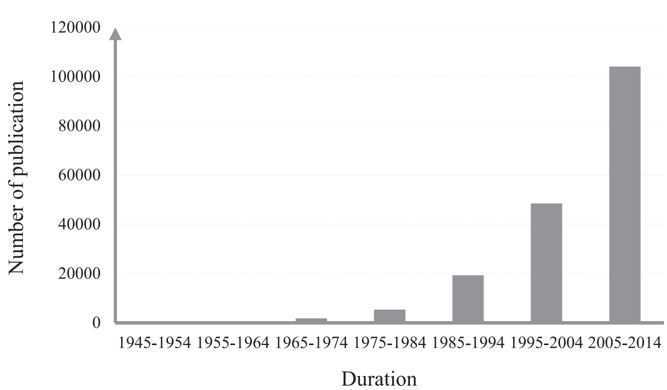



**Fig. 12.** Published scientific reports of hydrogen energy research (web of science).

## 3. Artificial Intelligence (AI)

Artificial Intelligence tries to understand human thinking in order to build smart entities that will perform efficiently for some complicated problems [201–203], even, though the understanding of the complex thinking of a human brain is a tough issue to be resolved. The development in the domain of AI reduced the burden of manual computation [204–206]. Only a few areas outperform the natural brain performance, whilst others have already been surpassed with the development of the technology like computer machines, built to do several thousand calculations per second while this would be impossible for an average human brain [206]. The AI is applied in the several fields, including the database, accounting, information retrieval, product design, production planning and distribution economy and industry, medicine, food quality monitoring, biometric and forensic, etc. [201–204]. AI is based on several learning theories like statistical learning, neural learning, evolutionary learning, etc. [201–205]. Amongst these, neural learning is most commonly used in several applications. ANN is the most fundamental technique of neural learning. The ANN established in 1943 by McCulloch and Pitts with the hypothesis of the mathematical model for a primitive cell of the brain (neuron). The neuron is triggered when the weighted sum of input exceeds a threshold value which results in an output as a response of some activated function. The ANN is able to adjust its values to fix the error from the output, which makes it more powerful learning tool [207]. Fig. 15 shows the schematic representation of a simple ANN model based on the mathematical neuron. Some of the core types of the ANNs are the Feed-forward neural networks, Radial basis function neural networks (RBFNN), Kohonen self-organizing network. Besides, the neural learning, statistical and evolutionary learning based techniques were also used in different practical applications. Some of the statistical learning techniques in AI are Bayesian and naïve Bayes models, clustering, hidden Markov model, nearest neighbor model, etc. [208]. Also, the popular evolutionary learning methods include genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), bees algorithms, etc. [209]. For the past few years, hybrid methods of AI are also being used in many applications with the objective to get the better accuracy than what could be achieved using a single method. Some of the hybrid AI methods are (i) Neuro-fuzzy (combination of ANN and fuzzy inference system); (ii) Neuro-genetic (combination of ANN and genetic algorithm, the latter is used for the connection optimization of previous); (iii) Fuzzy-genetic (combination of fuzzy inference system and genetic algorithm, the latter is used in the optimization of the decision boundary of the previous) and many other kinds will be available in future [210]. In the present study, both the single and hybrid Artificial

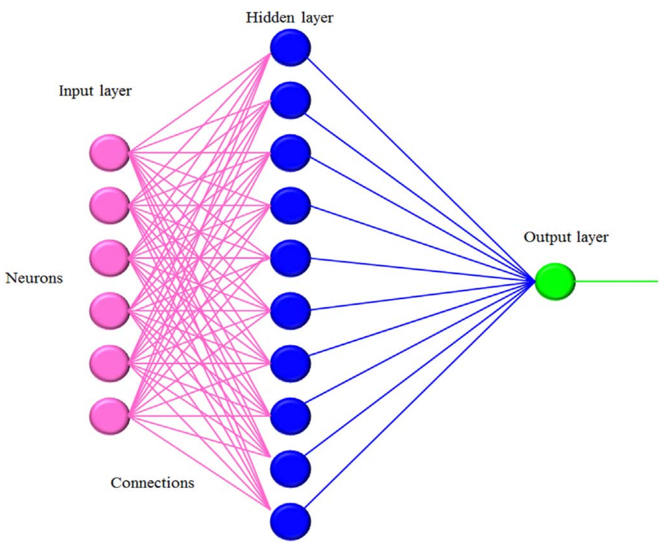



**Fig. 14.** A simple architecture of ANN method.

Intelligence techniques in the RE research mentioned earlier are reviewed in detail in the next section (Fig. 14).

## 4. Artificial intelligence in renewable energy

AI is used in almost each of the type of RE (wind, solar, geothermal, hydro, ocean, bio, hydrogen and hybrid) for the design, optimization, estimation, management, distribution, and policy. A simple demonstration of different types of RE sources and applications of AI is shown in the Fig. 15. The details of AI application for specific RE are as follows.

### 4.1. AI in wind energy

The role of AI in wind energy is summarized in past few reviews [91,95,211–213]. In detail, a brief review of physical model, statistical model, correlation model and neural network models for wind speed and generated power estimation was presented by Lei et al. [91] and Foley et al. [95]. In another related study by Colak et al. [211], a brief review of data mining methods for wind power estimation in four categories (very short, short, medium, and long terms) have been described. Probabilistic models for wind power estimation in three categories are compiled by Zhang et al. [212]. Tascikaraoglu et al. have

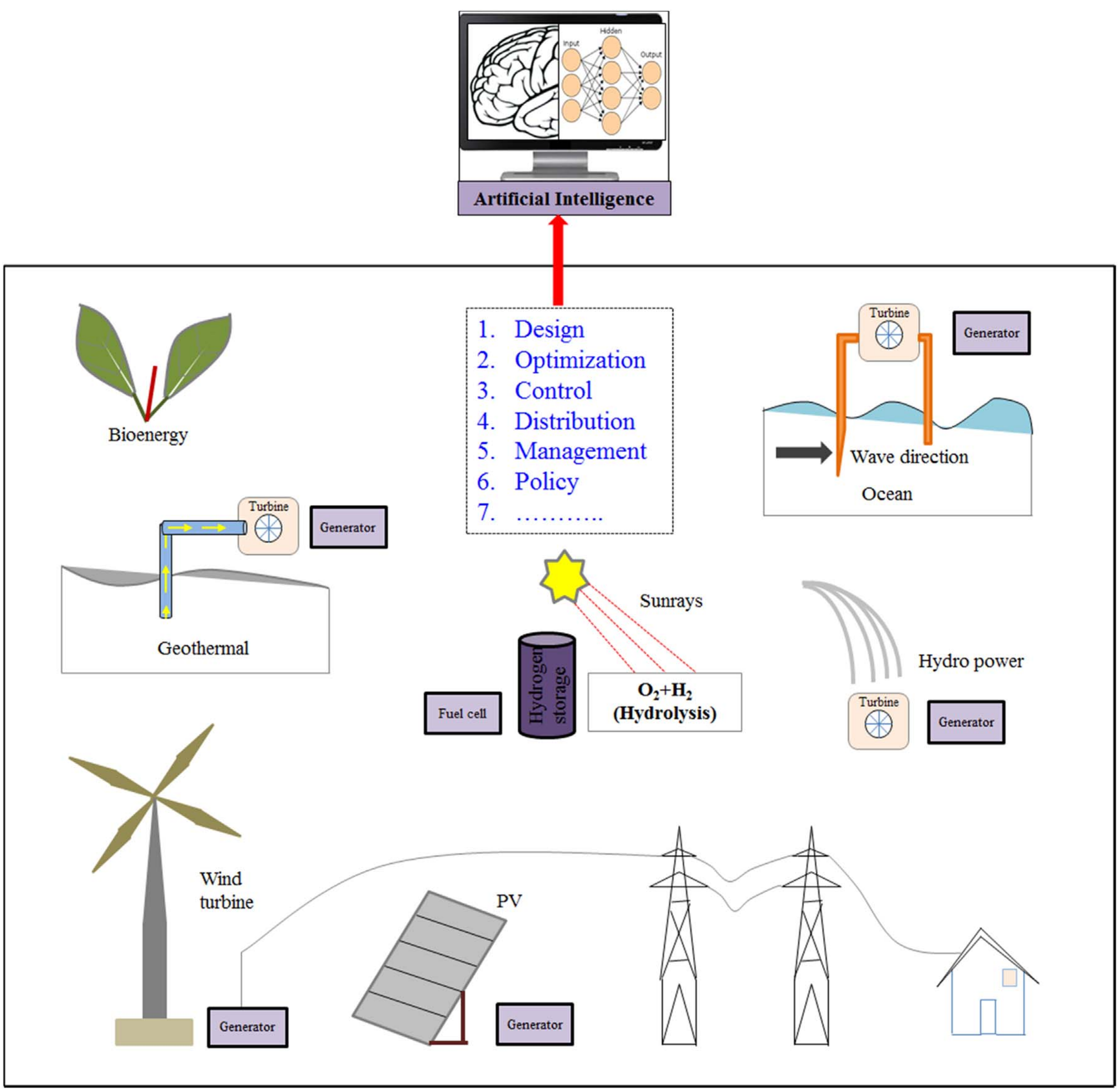



**Fig. 15.** A schematic representation of application of AI in different sources of RE.

briefly reviewed the combined techniques for short term wind speed and power estimation [213].

The prominent research and development in the application of AI in wind energy contain approaches from three main categories: neural, statistical and evolutionary learning and their combination as hybrid AI techniques [214–243]. Most of the research work focus on the prediction of wind speed and wind power using the neural learning approaches of AI [214–216]. Feed-forward backpropagation neural network (BPNN) is used in the estimation of wind power over a period of 3 years from seven wind farms by Mabel et al. [214]. The BPNN has a worthy prediction accuracy (root mean square error (RMSE) 0.0070 for the training data set and 0.0065 for the test data set). Three different types of ANN methods BPNN, RBFNN, and adaptive linear element network (ADALINE)) have been used in wind speed estimation from two different sites; also, the performance of three models is compared [215]. The performance of ANN methods varying according to the location of wind farms, like BPNN results in the best performance for one site (minimum RMSE 1.254) while for another, the best performance is achieved with the RBF method (minimum RMSE 1.444). Mabel et al. [216] have optimized the configuration of BPNN by trial and error in estimation of wind power. Using the wind speed, relative humidity, and generation hours as the inputs, a 3×5×1 ANN model results in the best estimation performance (mean square error (MSE) $7.6\times10^{-3}$).

The performance of ANN methods is not consistent, therefore, some alteration is proposed in ANN with the objective to improve its efficiency [217], as well as other methods were also included for comparison in some studies [218–222]. Kariniotakis et al. [217] implemented an advanced version of ANN (recurrent high order neural networks) for wind power estimation. The performance of ANN model is compared with the naïve Bayes (NB) method. The ANN results in minimum RMSE 4.2 compared to the NB. BPNN method was used in spatial forecasting of wind speed in the Marmara for the years 1993–1997 [218]. The performance of ANN model is compared with the Trigonometric point cumulative semivariogram (TPCSV) method. ANN results in a better correlation coefficient between the actual and predicted wind speed for most of the months and sites, for instance for Canakkale site and in the month of January, the correlation coefficients were 0.95 for ANN and 0.88 for TPCSV. Alexiadis et al. [219] have demonstrated the significant improvement (20–40%) in the estimation accuracy of the wind speed and wind power by using the BPNN method compared to the persistence forecasting model. Li et al. [220] have used Bayesian combination (BC) method, and ADALINE, BPNN and radial basis function neural network (RBFNN) methods in wind speed forecasting from the two wind farms. The BC method results in consistent and better estimation result (RSME 1.5) compared with the ANN methods. A detailed comparison of twelve estimation techniques including the linear (ARMA) methods, neural logic network (NLN) non-linear ANN methods in the analysis of hourly wind speed time series data has been reported [221]. NLN exhibit the best performance (RMSE 4.9%) compared with other methods. Cadenas et al. [222] have used BPNN in the wind speed forecasting of data obtained from wind farm Chetumal, Quintana Roo in Mexico over the duration of two years from 2004 to 2005. The performance of ANN is compared with the single exponential smoothing (SES) method. The earlier method performs better (mean absolute error (MAE) 0.5251) compared with SES method (MAE 0.5617).

In some studies [223–225], fuzzy logic [223], as well as their combination with the ANN methods was also studied in wind power forecasting. Fuzzy logic was used to design a wind generation system (3.5 kW) by Simoes et al. [223]. The developed system performs satisfactorily and has field application capability. Sideratos et al. [224] implemented the combination of ANN, RBFNN, and fuzzy logic techniques for estimation of wind power. The analysis outcomes are effective in the operational planning of wind farm 1–48 h ahead. The BPNN and fuzzy methods have been used in wind speed estimation by Monfared et al. [225]. The proposed methods perform better than the traditional one (RMSE 3.30 and 3.27 for two methods respectively in one of the case).

Some statistical approaches were discussed in [226,227]. Juban et al. [226] proposed a probabilistic method for short-term wind power estimation. The procedure is based on kernel density estimation and results in predictive probability density function for estimation. The reliability of the model lies in between (2–4%), which is comparable to that found in similar research. The support vector machines (SVM) method was used by the Mohandes et al. [227] in wind speed prediction of the wind data from the Madina, Saudi Arabia. Also, the performance of SVM is compared with the multilayer perceptron (MLP) neural networks. SVM achieve less estimation accuracy (MSE 0.009) compared with the ANN method (MSE 0.0078).

The adaptive neuro fuzzy inference system (ANFIS) (a hybrid of neural and fuzzy methods) has been used in some studies [228–231] with the objective to further improve the performance of ANN method. ANFIS is used by Potter et al. [228] to estimate wind power in a very short term basis utilizing wind power data from Tasmania, Australia. MAE is always less than 8 for analysis of wind data in a different session of the year. Mohandes et al. [229] have estimated the wind speed up to a height of 100 m using the wind speed information at heights 10, 20, 30, and 40 m by using ANFIS. The ANFIS predicted wind speed at the height 40 m has 3% mean absolute percentage error (MAPE) compared with the actual wind speed at the same height. ANFIS method is used by Yang et al. [230] in interpolating the missing wind data measured from the twelve wind farms in China. The RMSE in between the ANFIS predicted and actual measured wind speed was 0.230. Meharrar et al. [231] have designed maximum-power-point-tracking (MPPT) based on ANFIS wind generator. The ANFIS is used in the estimation of the rotational speed of wind turbines using wind speed as the input. The ANFIS has effective performance (error 0.005) in training.

Besides ANFIS, the combination of ANN is tried with some other methods for prediction performance improvement [232–235], for instance, BPNN in combination with the wavelet analysis (WT) is used for the fault diagnosis of the wind turbine gearbox by Yang et al. [232], which successfully detected two normal cases, two gentle fault cases, three fault cases and one bad fault case. Evolutionary algorithms (EA) (i) particle swarm optimization (PSO) and (ii) differential evolution (DE) have been implemented by Jursa et al. [233] for the selection of input variables and parameters of ANN and nearest neighbor models used in the short term wind power estimation. The PSO optimized ANN results, 2.8% improvement in prediction accuracy compared with the manually structured ANN. Guo et al. [234] have developed an improved version of the empirical mode decomposition (EMD)-feed-forward neural network (FNN) method for wind speed estimation. Modified EMD-FNN results better performance (MSE 0.1648) than the FNN (MSE 0.1511) and EMD-FMM (MSE 0.1296). An ANN-Markov chain (MC) method has been proposed by Pourmousavi et al. [235] for short term wind speed estimation. The ANN-MC has less error (94.84) compared with the ANN (96.05) for higher margins.

Some other hybrid AI approaches were also described [236–243]. Damousis et al. [236] developed Fuzzy methods using the two GA algorithms (real coded GA and binary coded GA) for wind speed and power estimation. The wind energy data from the remote location were received by using the wireless modems and analyzed with the Fuzzy method which results in 29.7% and 39.8% higher accuracy for the next hour and longtime respectively than the persistent method. A hybrid wind-forecasting technique is developed and examined by Hu et al. [237] by combining ensemble empirical mode decomposition (EEMD) and SVM methods. Average monthly wind speed from three different sites in China was estimated using the proposed hybrid method. EEMD has MAE 0.12 compared with two traditional time series methods: autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA), SVM, and

EMD-SVM. A different hybrid model using ARIMA and BPNN methods was developed and used in wind speed forecasting for three different locations in Mexico by Cadenas et al. [238]. The hybrid method has MSE 0.49 compared with the ANN (MSE 5.65) and ARIMA (MSE 4.1). Salcedo-Sanz et al. [239] have proposed hybridization of the 5th generation mesoscale model (MM5) with the ANN method for short term wind speed forecasts for the thirty-three wind turbine data sets. The output of MM5 is used in the ANN method which results in better estimation accuracy with the MAE in between 1.45 and 2.2 m/s for the different number of neurons (9–15) in the hidden layer and locations of the wind turbine. Liu et al. [240] have developed a hybrid AI method by using deep quantitative analysis, WT, GA and SVM methods. GA is used in tuning the parameters of SVM. The WT-SVM-GA model achieved better performance (MAE 0.6169) compared with the persistent method (MAE 0.8356) and SVM-GA (0.7843). A novel hybrid model for wind speed prediction was developed by Kong et al. [241] by using the improved version of support vector regression (SVR) referred as reduced support vector machine (RSVM), principal component analysis (PCA), and particle swarm optimization (PSO) for parameter optimization of RSVM. The RSVM exhibits effective estimation accuracy. Rahmani et al. [242] developed a hybrid intelligent technique based on the combination of two meta-heuristic techniques: ant colony optimization (ACO) and particle swarm optimization (PSO) for hourly wind power estimation of forty-three wind turbine data sets using wind speed and temperature inputs. The hybrid method performs best MAPE 3.5% compared with ACO (MAPE 5.8%) and PSO (MAPE 10.5%). Pousinho et al. [243] have proposed a hybrid method by using WT, PSO and ANFIS for risk optimization in wind energy trading. This hybrid approach is applied for wind farm data analysis in Portugal. The expected profit was estimated successfully in between 18719 € and 18487€ for different values of risk level in between 0 and 1. A complete summary of describing research work in [214–243] is presented in Table 1.

### 4.2. AI in solar energy

Importance of AI in solar energy applications is summarized in reviews [89,90,92,94,244,245]. Particularly, the detail applications of ANN methods in modeling and design, heating load of the building, etc. is summarized in [89]. Mellita et al. [90] have briefed detail research based on the application of AI in modeling of weather data, and sizing, modeling, simulation and control of PV systems. Mellita et al. [92] have also reviewed the uses of AI techniques in the sizing of individual and grid-connected PV systems. Building energy consumption estimation using statistical and AI methods has been compiled in [94]. Dounis et al. [244] summarized the application of agent-based intelligent control systems for energy management of buildings. AI techniques in modeling and forecasting of solar radiation data are discussed in [245].

The research in solar energy contains the application of both the single and hybrid approaches of AI [246–285]. ANN is the most used method in solar energy research [246–258]. ANN is used in solar irradiance prediction for PV connected with the grid [246]. A correlation of 98–99% for sunny days and 94–96% for cloudy days between the actual and predicted solar irradiance is achieved.

Global solar radiation (GSR) is forecasted with the BPNN using temperature and humidity as inputs over the years (1998–2002) [247]. The RMSE value was $2.823\times10^{-4}$ in between the actual and BPNN predicted GSR for the year 2002. BPNN is used in performance estimation of a solar water heating system by Kalogirou et al. [248]. The higher values of coefficient of determination ($R^2$ 0.9914 and 0.9808 for extracted energy and the maximum temperature rise respectively) confirm the better performance of BPNN. Beam solar radiation was estimated using the BPNN by analyzing the data from eleven different stations. The RMSE between the actual and model predicted values of radiation lies in between 1.65 and 2.79% [249]. A BPNN of 3×6×1 is used in daily ambient temperature estimation with RMSE 1.96 [250]. Daily solar irradiation was estimated using the BPNN with RMSE (5.0–7.5%) [251]. The maximum power of high concentrator photovoltaic (HCPV) system was predicted using the

**Table 1**
Summary of reports for application of AI approaches in wind energy [214–243].

| Ref. no. | Method/methods | Application | Outcome |
|---|---|---|---|
| [214] | BPNN | Wind power prediction | RMSE 0.0065 |
| [215] | BPNN, RBFNN, and ADALINE | Wind speed prediction | RMSE 1.254 for BPNN |
| [216] | BPNN | Wind power prediction | MSE 7.6 ×10-3 |
| [217] | Recurrent high order ANN, and NB | Wind power prediction | RMSE 4.2 |
| [218] | BPNN and TPCSV | Wind speed prediction | Correlation 0.95 for BPNN |
| [219] | BPNN | Wind speed and power prediction | 20–40% improved accuracy |
| [220] | BC, ADALINE, BPNN and RBFNN | Wind speed prediction | RSME 1.5 for BC |
| [221] | ARMA, NLN and ANN | Wind speed prediction | RMSE 4.9% for NLN |
| [222] | BPNN, and SES | Wind speed prediction | MAE for BPNN 0.5251 |
| [223] | Fuzzy method | Design of wind generation system | 3.5 kW |
| [224] | ANN, RBFNN, and fuzzy methods | Wind power prediction | Planning 1–48 h ahead |
| [225] | BPNN and fuzzy methods | Wind speed prediction | RMSE 3.30 for BPNN |
| [226] | Probabilistic method | Wind power prediction | Reliability (2–4%), |
| [227] | SVM, BPNN | Wind speed prediction | MSE 0.0078 for BPNN |
| [228] | ANFIS | Wind power prediction | MAE < 8 |
| [229] | ANFIS | Wind speed prediction | MAPE 3% at 40 m |
| [230] | ANFIS | Missing wind data interpolation | RMSE 0.230 |
| [231] | ANFIS | Design of wind generation system | Error 0.005 |
| [232] | BPNN+WT | Wind turbine fault diagnosis | Detection of 8 conditions |
| [233] | PSO+BPNN | Wind power prediction | 2.8% improved accuracy |
| [234] | EMD+FNN | Wind speed prediction | MSE 0.1296 |
| [235] | ANN+MC | Wind speed prediction | Error 94.84 |
| [236] | Hybrid method (Fuzzy-GA) | Wind speed and power prediction | 29.7% improved accuracy |
| [237] | Hybrid method (EEMD-SVM) | Wind speed prediction | MAE 0.12 |
| [238] | Hybrid method (ARIMA-BPNN) | Wind speed prediction | MSE 0.49 |
| [239] | Hybrid method (MM5-ANN) | Wind speed prediction | MAE (1.45–2.2 m/s) |
| [240] | Hybrid method (WT-SVM-GA) | Wind speed prediction | MAE 0.6169 |
| [241] | Hybrid method (SVR-PSO) | Wind speed prediction | Effective accuracy |
| [242] | Hybrid method (ACO-PSO) | Wind power prediction | MAPE 3.5% |
| [243] | Hybrid method (WT-PSO-ANFIS) | Risk optimization in wind energy trading | Profit estimation for risk level (0.0–0.1) |

BPNN with RMSE 3.29% [252]. Monthly average daily global solar irradiation was estimated using the BPNN with the 0.97 correlation between the actual and predicted solar irradiation [253]. Solar energy output, and hot water quantity were estimated using the BPNN with $R^2$ 0.9978 and 0.9973 respectively [254]. Solar radiation was estimated using the BPNN in Nigeria with $R^2$ 0.971 using latitude, longitude, altitude, month, mean temperature, mean sunlight duration, and relative humidity as input variables [255]. BPNN is used to estimate the energy intake of a passive solar building (wall thickness (15–60 cm) with $R^2$ 0.9991) [256]. In another study, BPNN results in 94.8–98.5% prediction rate in the building energy consumption prediction for the insulation thickness of 0–2.5–5–10–15 cm, orientation angles 0–80° and the transparency ratios 15–20–25% [257].

In some studies [258–261], the performance of BPNN model is compared with the other methods. BPNN is used by Tasadduq et al. [258] in the estimation of ambient temperature 24 h ahead and the performance of BPNN is compared with the batch learning ANN. The achieved values of mean percentage deviation (MPD) were 3.16, 4.17 and 2.13 with BPNN for three years. Diffuse solar radiation is predicted by Alam et al. [259] using the BPNN on an hourly and daily basis with RMSE of 4.5% compared to other empirical methods (EKD, Page, etc.) (RMSE 37.4%). Tymvios et al. [260] have used BPNN and Ångström's linear methods in global solar radiation prediction. The performance of BPNN method is comparable (RMSE 5.67–6.57%) to Ångström's linear method. BPNN method is used in global solar radiation estimation of the eight cities of China over the years 1995–2004, and the performance is compared with the empirical regression methods. The BPNN performs better than the empirical regression methods with minimum RMSE 0.867 [261]. Besides ANN, some other techniques were also implemented in solar energy analysis [262–265]. For instance, SVM method is used in the prediction of short-term solar power and its performance is compared with the autoregressive (AR) and RBFNN [262]. SVM method (MAE 33.7 $W/m^2$) performs better than the RBF (MAE 43 $W/m^2$) and AR (MAE 62 $W/m^2$) methods. Li et al. [263] have used SVR for solar PV energy production estimation and compared its performance with the ANN. The RMSE for the two methods were almost similar. The performance of the RBF-SVM method is compared with the existing forecast methods (PPF and Cloudy) in the estimation of solar power generation. SVM exhibits 27% higher estimation accuracy than other two methods [264].

Some evolutionary AI methods were also used in solar energy applications [265–267]. Mashohor et al. [265] suggested, GA in solar tracking for improved performance of PV systems. The GA with initial population size 100, 50 epochs and probability of crossover and mutation 0.7 and 0.001 respectively results in the best GA-Solar system. The low value of standard deviation (1.55) in generation gain also proves the better efficiency of the system. GA is used in the optimal design of a solar water heating system. Specifically, the plate collector area is optimized with the GA to 63 $m^2$ that results in solar fraction value 98% [266]. Kumar et al. [267] have used GA in maximum power point tracking (MPPT) of PV array connected to the battery. The performance of the GA is compared with the traditional perturb and observe (PO) algorithm. The boost converter achieves the line voltage of 400 V.

The combination of AI methods was also reported to improve the prediction efficiency [268–274]. The performance of an integrated collector storage (ICS) solar water heater is predicted using the combination of ANN and TRNSYS with the $R^2$ value 0.9392 [268]. Monteiro et al. [269] have used GA in parameter optimization of HIstorical SImilar Mining (HISIMI) model for power prediction of PV system. The performance of GA+HISIMI model (RMSE 283.89) is compared with the BPNN (RMSE 286.11), and classical persistence (RMSE 445.48) methods. The combination of RBFNN and infinite impulse response (IIR) filter is used for size optimization of PV system in the Algeria [270]. Optimal sizing coefficients were determined using the RBF+IIR method and its performance is compared with the classical models, BPNN, RBFNN and MLP+IIR methods. The sizing coefficients were estimated accurately (correlation 98%) with the RBF +IIR method. A combination of WT and BPNN was used in solar radiation values estimation [271]. The performance of WT+BPNN (accuracy 97%) was observed better than the classical methods (AR, ARMA, MTM), BPNN, recurrent and RBFNN methods. Solar power output is predicted by using GA optimized BPNN without using the exogenous inputs [272]. The performance of GA+BPNN is compared with the persistent model, ARIMA, k-nearest neighbor (KNN) and BPNN methods. The GA+BPNN results in the minimum RMSE 72.86 kW. Mandal et al. [273] have used the combination of WT and RBFNN in the prediction of PV system power and compared its performance with the WT+BPNN, RBF, and BPNN. The WT+RBF have minimum RMSE 0.23. Group method of data handling (GMDH)-NN and GA are used in optimization of the economic benefits of solar energy [274]. The optimal solution results in 3.1–4.9% increment in life cycle savings.

ANFIS method is used in several studies [275–280] like in the modeling of PV power supply system with accuracy 98% [275], prediction of hourly global radiation using the satellite image data [276], clearness index and daily solar radiation prediction with RMSE 0.0215–0.0235 [277], modeling of PS power supply [278], predicting solar radiation using the mean temperature and sunshine duration [279], performance prediction of solar chimney power plant (SCPP) [280].

Several hybrid AI techniques were also used in solar energy systems [281–285], like hybrid evolutionary optimization of ANN using the PSO and GA in the estimation of PV power [281]; Genetic swarm optimization (GSO) of BPNN for PV system energy estimation [282]; solar radiation prediction using the combination of ARMA and time delay neural network (TDNN) [283]; power prediction of PV connected to the grid using the hybrid of seasonal auto-regressive integrated moving average (SARIMA) and SVM methods [284]; hybrid of SVM and Firefly algorithm (FFA) is developed for GSR estimation and performance is compared with the BPNN and genetic programming (GP) methods (RMSE 1.8661 for SVM-FFA). The findings of AI techniques for solar energy systems are summarized in Table 2 [246–285].

### 4.3. AI in geothermal energy

AI approaches have been used in geothermal applications, which are summarized in reviews [286–290]. Particularly, the prospective of AI approaches with sensors and robots in geothermal well drilling design, control, and optimization is briefed in [286]. Computer simulation and modeling of geothermal reservoir and its effect of geothermal energy progress are reviewed in [287]. Similarly, in other reviews by Sanyal et al. [288] numerical simulations for enhanced geothermal systems and for geothermal reservoir by O'Sullivan et al. [289] are reviewed. In another study, a brief history of numerical modeling of geothermal reservoir is also presented [290].

Both the single and hybrid approaches of AI are used in geothermal energy applications [291–310] summarized in Table 3, though the ANN method is used in most of the studies [291–303]. Esen et al. [291] have used BPNN (with Levenberg–Marguardt (LM), Pola–Ribiere conjugate gradient (CGP), and scaled conjugate gradient (SCG) algorithms) in performance prediction of vertical ground coupled heat pump (VGCHP) system. The LM based BPNN with eight neurons in the hidden layer results in better prediction efficiency (RMS 0.0432). Bassam et al. [292] have used LM based BPNN for the static formation temperature (SFT) prediction of the geothermal well. The BPNN with five neurons in the hidden layer results in prediction error $< \pm 5\%$. BPNN (with LM, CGP, and SCG) is used in the determination of an optimum working condition of geothermal well [293]. The BPNN with seven neurons in the hidden layer results in the best predicted values of generated and circulation pump power, using the vapor fraction of

**Table 2**
Summary of reports for application of AI approaches in solar energy [246–285].

| Ref. no. | Method/methods | Application | Outcome |
|---|---|---|---|
| [246] | BPNN | Solar irradiance prediction | Correlation 94–99% |
| [247] | BPNN | Solar radiation prediction | RMSE $2.823\times10^{-4}$ |
| [248] | BPNN | Performance assessment of a solar water heating system | $R^2$ 0.9914 and 0.9808 for $Q_{out}$ and $T_{d\text{-}max}$ respectively |
| [249] | BPNN | Solar beam radiation prediction | RMSE 1.65–2.79% |
| [250] | BPNN | Daily ambient temperature prediction | RMSE 1.96 |
| [251] | BPNN | Daily solar irradiation prediction | RMSE 5.0–7.5% |
| [252] | BPNN | Maximum power of HCPV prediction | RMSE 3.29% |
| [253] | BPNN | Global solar irradiation prediction | Correlation 97% |
| [254] | BPNN | Solar energy and hot water quantity prediction | $R^2$ 0.9978 and 0.9973 respectively |
| [255] | BPNN | Solar energy prediction | $R^2$ 0.971 |
| [256] | BPNN | Building energy prediction | $R^2$ 0.991 |
| [257] | BPNN | Building energy prediction | Prediction rate 94.8–98.5% |
| [258] | BPNN and batch learning ANN | Mean temperature prediction | MPD 2.13-4.17 for BPNN |
| [259] | BPNN and Empirical models | Diffuse solar radiation prediction | RMSE 4.5% for BPNN |
| [260] | BPNN and Ångström linear methods | Global solar radiation prediction | RMSE 5.67-6.57% for BPNN |
| [261] | BPNN and Regression methods | Global solar radiation prediction | RMSE 0.867 for BPNN |
| [262] | SVM, RBFNN, AR | Solar power prediction | MAE 33.7 W/m$^2$ for SVM |
| [263] | SVR, BPNN | PV energy prediction | RMSE 0.133 for SVR and 0.131 for BPNN in one case. |
| [264] | SVM, PPF, Cloudy | Solar power prediction | RMSE 128 W/m$^2$ for SVM |
| [265] | GA | Solar tracking | Std. 1.55 in generation gain |
| [266] | GA | Design of solar water heating system | Solar fraction value 98% |
| [267] | GA, PO | MPPT of PV array | Line voltage 400 V |
| [268] | ANN+TRNSYS | Performance prediction of ICS | $R^2$ 0.9392 |
| [269] | GA+HISIMI | Solar power prediction | RMSE 283.89 |
| [270] | RBF+IIR and BPNN+IIR | Size optimization of PV system | MSE 0.028 for RBF+IIR |
| [271] | WT+BPNN | Solar radiation values estimation | MAPE < 6% |
| [272] | GA+BPNN | Solar power prediction | MAE 42.96 kW |
| [273] | WT+RBFNN | PV energy prediction | MAE 0.19 |
| [274] | GA+GMDHNN | Solar system optimization | $R^2$ 0.9986 |
| [275] | ANFIS | PV power supply modeling | $R^2$ 98–99% |
| [276] | ANFIS | Hourly global irradiance prediction | RMSE 0.1034 |
| [277] | ANFIS | Clearness index, radiation prediction | MAPE < 2.2% |
| [278] | ANFIS | PV power supply modeling | Correlation 98% |
| [279] | ANFIS | Solar power prediction | Correlation 98% |
| [280] | ANFIS | SCPP performance prediction | $R^2$ 0.91 |
| [281] | Hybrid method (ANN-GA-PSO) | PV power prediction | Prediction 0–35 kW |
| [282] | Hybrid method (ARMA-TDNN) | Solar radiation prediction | RMSE approx. 25–300 |
| [283] | Hybrid method (BPNN-GSO) | PV power prediction | MAE 0.317 kW/h |
| [284] | Hybrid method (SARIMA-SVM) | Solar power prediction | Correlation 99% |
| [285] | Hybrid method (SVM-FFA) | Solar power prediction | RMSE 0.7280 |

geothermal water and its temperature, and the ammonia fraction as the input (RMSE 1.5289). ANN is used in the optimization of the power cycle like ORC-Binary using the BPNN (with LM, CGP, and SCG) [294]. The LM based BPNN with 14–16 neurons in the hidden layer result in best accuracy (RMSE 0.0001 for s1 and s2 cycles) for prediction of generating and required pump circulation power. The input variable of the cycle s1 is similar to that described in [293] though for the cycle s2 an additional input variable outlet pressure is included in the analysis. BPNN is used in the generation of geothermal map at different depth with less than 5% deviation with the actual values for the 96.5% data

**Table 3**
Summary of reports for application of AI approaches in geothermal energy [291–310].

| Ref. no. | Method/methods | Application | Outcome |
|---|---|---|---|
| [291] | BPNN (LM, CGP, SCG) | VGCHP Performance prediction | $R^2$ 0.9998 |
| [292] | BPNN (LM) | SFT prediction of geothermal well | $R^2 > 0.95$ |
| [293] | BPNN (LM, CGP, SCG) | Geothermal power prediction | $R^2$ 0.9987 |
| [294] | BPNN (LM, CGP, SCG) | Geothermal power prediction | $R^2$ 0.9999 |
| [295] | BPNN | Geothermal map generation | Correlation 0.9253 |
| [296] | BPNN (LM) | Performance prediction of AGDHS | $R^2$ 0.9999 |
| [297] | BPNN (LM) | VF prediction | MPE 0.17 |
| [298] | BPNN (QN) | Ammonia-nitrogen prediction | $R^2$ 1.00 |
| [299] | BPNN | PID controller efficiency prediction | Correlation 0.9986 |
| [300] | BPNN (LM) | Modeling of geothermal plant | $R^2$ 0.99 |
| [301] | BPNN (LM, SCG) | Site location modeling | $R^2$ 0.85 |
| [302] | BPNN | Conductivity map generation | Correlation 0.9553 |
| [303] | BPNN | Pressure prediction in geothermal plant | MAPE < 2.3% |
| [304] | EA | VGSHP optimization | Production cost 0.772$/h for TE |
| [305] | EA (DE, GA, PSO, etc.) | BHEs optimization | 18–23% reduced cooling |
| [306] | Fuzzy logic | Design of RAS system | Error zero error |
| [307] | Fuzzy logic | Design of RAS system | Max. RAS production at 2 °C |
| [308] | ANFIS, BPNN (LM, CGP, SCG) | VGSHP performance prediction | $R^2$ 0.9999 for ANFIS |
| [309] | ANFIS, BPNN (LM, CGP, SCG) | AGDHS system evaluation | RMSE 19.6, 3.66 for ANFIS |
| [310] | Hybrid method (GMDH-GA-SVD) | Temperature prediction | R2 0.9899 |

points [295]. The LM based BPNN is used in the prediction of thermal performance and exergy destructions of the Afyonkarahisar geothermal district heating system (AGDHS) with good accuracy (RMSE 0.0053) [296]. Void fraction (VF) values of the geothermal well were predicted with the BPNN based on the LM training algorithm using the eight different input parameters. Six neurons in the hidden layer of BPNN result in best prediction accuracy (RMSE 0.0966) [297]. The BPNN (with LM, Quasi-Newton (QN), and Bayesian Regularization (BR) algorithms) is used to predict the biochemical oxygen demand (BOD), ammonia-nitrogen, nitrate-nitrogen, and ortho-phosphatephosphorus of geothermal energy treating storm water. Best accuracy is obtained for Ammonia-nitrogen prediction with the QN based BPNN [298]. BPNN is used to test the effectiveness of PID controller of AGDHS which enhances the energy efficiency by 13% [299]. In modeling of ORC-Binary geothermal plant, BPNN with LM (twenty neurons in the hidden layer) for the o2 and o3 cycles and (twenty-two neurons in the hidden layer) for b3 type cycle results in better accuracy [300]. BPNN based on the LM and SCG algorithms is used for the site location planning model using the geographical information data [301]. BPNN is used in the conductivity map creation of ground with better accuracy (83% of predicted data have deviation less than 10%) [302]. BPNN based on the LM algorithm exhibits better prediction efficiency of pressure drop in the geothermal well by using the wellbore production database [303].

In some studies, EA and fuzzy logic were also used in the geothermal system analysis [304–307] like Sayyaadi et al. [304] have used the single objective-thermodynamic and thermoeconomic (TE) and multi-objective optimizations of vertical ground source heat pump (VGSHP) using the (EA), in another study six EAs (two DE, PSO, GA, Monte-Carlo random search, etc.) were used to locate the optimal position of borehole heat exchangers (BHEs) [305]; a fuzzy logic controller (FLC) system has been designed for geothermal heat in the recirculation aquaculture systems (RAS) [306] and to control the water temperature for the maximum RAS production [307].

ANFIS and hybrid AI approaches were also implemented in a few studies of geothermal energy analysis [308–310] like ANFIS is used for the VGSHP performance evaluation and compared with the BPNN methods (LM, SCG, CGP algorithms), in which ANFIS results in better efficiency than the BPNN methods [308]; ANFIS is used in the evaluation of the AGDHS system (exergy and energy rates prediction) and performance is compared with the BPNN methods (LM, SCG, CGP algorithms) [309]. Again, ANFIS performs better than the BPNN methods; GA and singular value decomposition (SVD) based GMDH-NN is used in geothermal reservoir temperature prediction [310].

### 4.4. AI in hydro energy

Application of AI approaches in hydro energy domain is summarized in reviews [311,312]. Particularly, the design and control of hydropower plants using traditional methods and modern AI approaches like GA, ANN, Fuzzy, ANFIS, etc. has been briefly presented by Kishor et al. [311]. In another review study by Nourani et al. [312] described the significance and application of wavelet pre-processor based hybrid AI approaches in hydro-climatology, specifically in the estimation of significant hydrologic cycle processes.

The application of single and hybrid AI approaches in hydro energy applications [313–327] is summarized in Table 4. BPNN approach is used in optimal scheduling the activities of hydropower plants from ten reservoirs in Taiwan [313]. The BPNN is more cost effective than the k-nearest neighbor (KNN) and differential dynamic programming (DDP). Smith et al. [314] have implemented BPNN method in the modeling of rainfall-runoff process to estimate the discharge peak and time of peak of linear and non-linear reservoirs. Better accuracy of BPNN is achieved for non-linear reservoirs in the prediction of peak discharge and linear reservoir in the prediction of time to peak. BPNN model is used effectively in the steam flow prediction of San Juan River basin in two different seasons for seventeen years [315]. The steam flow is most significant factor in the hydroelectric power production. Kisi O [316] has also studied the river flow modeling using the BPNN with gradient descent (GD) and the performance is compared with the autoregressive (AR) method. BPNN estimates more precisely than the AR method. Estoperez et al. [317] have used BPNN in scheduling of micro-hydro power plant by estimating the power discharge for one month ahead (minimum RMSE 0.061). GA and [318–320] Fuzzy [321] approaches have been also used in the hydro energy study; like Carneiro et al. [318] have used GA in the scheduling of hydrothermal power system in Brazil and compared with the outcomes from traditional non-linear programing (NP) optimization method. The GA has less operating cost (726,742.2 MW) than NP (745,020 MW) for the years 1971–1973. Gil et al. [319] have implemented a new GA (with a set of proficient operators) for a similar application and compared the performance with previously used GA. Yuan et al. [320] have developed a novel version of GA (chaotic hybrid (CH)-GA) to solve the issue of the existence of water delay time as a constraint in the short term hydrogenation scheduling. The CHGA results in a better profit compared with the standard (S)-GA and NP. The application of fuzzy logic based approach in the selection of optimal penstock material from Steel, Asbestos cement and GRP for hydro turbine is addressed by Adhikary et al. [321]. The GRP was declared as the ideal material with a maximum degree of index.

The contribution of ANFIS and hybrid AI approaches in hydro energy generation has also been discussed in some studies [322–327]. The ANFIS method is used in control of Shihmen reservoir in Taiwan (in the prediction of water release); also the performance is compared with the M-5 rule curves [322]. The ANFIS exhibits better performance (less water shortage) than the M-5 rule curves. The ANFIS model is used efficiently in flow estimation of the Menderes River in Turkey by Firat et al. [323]. The performance of ANFIS is compared with the ANN and multiple regressions (MR) (minimum relative error 0.073 for ANFIS). The integration of ANN with the expert system is used in acoustic prediction (AP) and predictive maintenance (PM) of hydropower plant by using the Learning Vector Quantization (LVQ) and ART-MAP respectively [324]. More accurate predictions are obtained by the AP and PM. Sinha et al. [325] have developed GA and PSO tuned FLC for the automatic generation control (AGC) in hydropower system. The GA-FLC and PSO-FLC perform better (less peak overshoot, and settling time) than the FLC.

A hybrid AI approach (referred as case-based reasoning (CBR)) using the hierarchical clustering (HC), Fourier frequency transform (FFT), Elman ANN and Modular ANN have been developed for the river flow estimation [326]. The performance of CBR is compared with the BPNN, Elman ANN, RBFNN, etc. (minimum MAE 17. 11 for CRB). BPNN in combination with the artificial bee colony (ABC) algorithm (particularly the BPNN is trained with ABC) is used to predict the hydraulic energy production in Turkey (relative error (RE) 0.23 [327].

### 4.5. AI in ocean energy

The use of AI approaches in ocean energy is summarized in the reviews [328–331]. Mainly, the role of AI in investigating the sea for the development of power supply system is discussed in [328]; the impact on AI in the ocean is briefed by Aartrijk et al. [329]. Several applications of ANN in the ocean engineering are presented by the Jain et al. [330]. Iglesias et al. [331] have discussed in detail about the availability of the renewable energy resources, especially the potential of ocean energy wave farm in Canary Islands (which will be a first Island in the future having 100% renewable energy).

The role of some single and hybrid AI approaches in ocean energy were described in the studies [332–341] and main outcomes are summarized in Table 5. A three layer BPNN method is used in the estimation of sea level variation on the coast of Western Australia (correlation coefficient 0.7–0.9) [332]. One day forecast of ocean wave

**Table 4**
Summary of reports for application of AI approaches in hydro energy [313–327].

| Ref. no. | Method/methods | Application | Outcome |
|---|---|---|---|
| [313] | BPNN, DDP, KNN | Scheduling of hydropower plant | BPNN 0.011% cost effective |
| [314] | BPNN | Modeling of rainfall-runoff process | RMSE 0.097–0.260 |
| [315] | BPNN (LM) | Stream flow prediction | MAPE < 5% |
| [316] | BPNN (GD), AR | River flow prediction | Error 0.2% with BPNN |
| [317] | BPNN | Power discharge estimation | MAPE < 5% |
| [318] | GA, NP | Scheduling of hydropower plant | Less active cost 2.9% by GA |
| [319] | GA | Scheduling of hydropower plant | Population cost 2.05$ |
| [320] | CHGA, SGA, NP | Hydrogenation scheduling | 190,301$ profit with CHGA |
| [321] | Fuzzy logic | Selection of optimal material | GRP, degree of index 2.07 |
| [322] | ANFIS, GA, M-5 | Water release prediction | Water shortage 0.0 for ANFIS |
| [323] | ANFIS, ANN, MR | River flow prediction | RMSE 7.1 for ANFIS |
| [324] | Hybrid method (LVQ-ART-MAP) | Acoustic and maintenance prediction | False alarm rate < 10% |
| [325] | Hybrid method (FLC-PSO, FLC-GA) | FLC design for AGC | Scaling factor for hydro area 4.731 with FLC-PSO |
| [326] | Hybrid method (HC-FFT-ANN) | River flow prediction | Std. 26. 48 |
| [327] | Hybrid method (ANN-ABC) | Hydraulic energy prediction | MAPE 4.6% |

**Table 5**
Summary of reports for application of AI approaches in ocean energy [332–340].

| Ref. no. | Method/methods | Application | Outcome |
|---|---|---|---|
| [332] | BPNN | Sea level variation prediction | RMSE 10% of tidal range |
| [333] | BPNN | Sea wave height prediction | 84% for a lead time of 6 h |
| [334] | BPNN | Wave parameters prediction | RMSE 0.53 |
| [335] | BPNN, RBFNN, GRNN | Dispersion coefficient prediction | RMSE 27.9 BPNN |
| [336] | Fuzzy logic | Reducing effect of ocean wave | Stability 0.0 for small amplitudes |
| [337] | GP, BPNN (LM) | Sea level prediction | $R^2$ 0.972–0.973 |
| [338] | ANFIS, BPNN, ARMA | Sea level prediction | RMSE 0.055for ANFIS |
| [339] | Hybrid method (NWM-BPNN) | Wave hindcasting | Correlation 0.93 |
| [340] | Hybrid method (CVR-SVR) | $CO_2$ flux prediction | Mean accuracy 96.3% |

condition was done by the Londhe et al. [333] using the BPNN method (six different architectures for the number of neurons in the hidden layer) with good accuracy (67% correlation for the predicted wave height for lead times of 12 h). Three different architects used the BPNN method in the prediction of wave parameters using the coastal environment variables as input by analyzing the data collected from Tasmania during 1985–1993 ($R^2$ 0.92) [334]. Toprak et al. [335] have used BPNN, RBFNN and generalized regression neural network (GRNN) to forecast the longitudinal dispersion coefficient in streams for 65 data sets from 30 rivers in the USA (MSE 13275 for BPNN). Fuzzy [336] and GP [337] methods have also been used in the study of ocean energy. Chen et al. [336] have developed a FLC to reduce the effect of the external ocean wave force. The FLC exhibits good stability. Sea level is predicted using the GP and ANN by Ghorbani et al. [337]. The GP prediction accuracy was better than the BPNN based on LM algorithm (MSE 230.5–236.2).

ANFIS [338] and hybrid AI approaches [339,340] have been implemented to achieve better prediction accuracy. Karimi et al. [338] have used ANFIS (five types with different membership functions) in sea level forecasting and compared the performance with the BPNN (LM), BPNN (CG), BPNN (GD) and eleven types of ARMA models. ANFIS and ANN methods result, almost similar but better than the ARMA models. A hybrid approach using the combination numerical wave model (NWM) and BPNN is used for wave hindcasting [339]. The hybrid approach performs better than the BPNN and NWM method. De-Paz et al. [340] have developed a hybrid intelligent system based on case-based reasoning (CVR) and support vector regression (SVR) for improved prediction of $CO_2$ flux to explore the understanding of interaction between the air and ocean.

### 4.6. AI in bioenergy

A brief review of deterministic and stochastic mathematical modeling for optimization of forest biomass (specifically the optimum design of the supply chain) in RE generation is presented by Shabani et al. [341]. The use of single and hybrid AI approaches for bioenergy analysis is described in several research reports [342–354] and summarized in Table 6. ANN is applied in several studies [342–347] related with the bioenergy: like forecasting the cetane number (CN) and density of diesel fuel using the GRNN by Yang et al. [342]; detection of trace compounds like $H_2S$ and $NH_3$ up to 93 ppm (ppm) in biogas using the BPNN (RMSE 416, 5.1 ppm, respectively) [343];

**Table 6**
Summary of reports for application of AI approaches in bioenergy [342–354].

| Ref. no. | Method/Methods | Application | Outcome |
|---|---|---|---|
| [342] | GRNN | CN and density prediction | MAE 1.23, 0.002 respectively |
| [343] | BPNN | Detection of $H_2S$ and $NH_3$ in biogas | $R^2$ 0.91 and 0.83 respectively |
| [344] | BPNN, RBFNN, GRNN, RNN | CN prediction | Accuracy 3.4%, 5%, 3.8% and 3.6% respectively |
| [345] | BPNN | Methane concentration prediction in biogas | $R^2$ 0.951–0.957 |
| [346] | BPNN, MLR, PLS, PCR | Biodiesel properties prediction | RMSE 0.42–51 |
| [347] | RBFNN | Performance prediction of biodiesel engine | MSE 0.001985–0.0011 |
| [348] | SVM, KNN, RDA, PLS | Biodiesel classification | SVM accuracy 95% |
| [349] | PSO | Biomass supply chain optimization | Decision variable 1–5 |
| [350] | GP, BPNN | HHV prediction | Correlation 0.95 |
| [351] | ANN, ARIMA ANN-ARIMA | Fuelwood price prediction | RMSE 0.050 |
| [352] | Hybrid method (ANN-Fuzzy logic) | Biomass boiler control | 3.5% increase of turbine output |
| [353] | Hybrid method (BPNN-GA) | Prediction of methane from waste | $R^2$ 0.8703 |
| [354] | Hybrid method (BPNN-GA) | Biogas production optimization | 8.64% increase in production |

detection of CN in biodiesel using the BPNN, RBFNN, GRNN and recurrent neural network (RNN) using the fatty acid composition (the best performance is achieved with BPNN) [344]; estimation of methane concentration in the biomass from bioreactors using alkalinity, BOD, chloride, conductivity, pH, sulfate, and temperature as input parameter for ten types of BPNN (according to different training algorithms) (RMSE 0.00263-0.00250) [345]; estimation of biodiesel properties (density, viscosity and water and methanol content) using the multiple linear regression (MLR), principal component regression (PCR), polynomial and Spline partial least squares regression (PLS), BPNN methods and their performance comparison (the best performance is achieved with the BPNN compared with the rest methods) [346]; performance estimation of biodiesel engine (thermal efficiency and energy consumption of break, exhaust temperature, and engine emissions) using the load, compression ratio, blend, injection timing, pressure as inputs of RBFNN (accuracy 69–96%) [347].

Besides ANN, some other methods, including SVM and KNN [348], PSO [349] and GP [350] methods have been also implemented in bioenergy analysis. Balabin et al. [348] have implemented regularized discriminant analysis (RDA), PLS, KNN and SVM methods to classify the biodiesel into ten different classes (according to their origin) using the near-infrared (NIR) data. SM results in better classification accuracy than the rest three methods. A modified version of PSO is implemented in the optimization of biomass supply chain (flows from sources of production) [349]. GP and BPNN have used the higher heating value (HHV) estimation of biomass fuels and performance is compared with the existing HHV models [350]. GP and BPNN exhibit better prediction accuracy than the conventional models (RMSE 0.942-0.987).

Some research reports the application of hybrid AI approaches in the bioenergy analysis [351–354]. Koutroumanidis et al. [351] have used ARIMA, ANN and hybrid of ANN-ARIMA for estimation of fuelwood prices in Greece for the years 1964–2006. The ANN-ARIMA model predicts better estimation than the ANN and ARIMA methods independently (MAPE 14%). A hybrid system based on the combination of Fuzzy logic and ANN is used for improving the biomass boiler cleaning and maximizing heat transfer which saves 12 GW h/year [352]. BPNN and GA based hybrid AI method is developed for the methane production from the waste digester [353]. The hybrid method with optimized parameters results in 6.9% increment in methane production. In another study, a similar hybrid method is used for the optimization of biogas production (from the banana stem, cow dung, paper waste, rice bran, saw dust) [354] which result in the biogas production of 10.280L.

### 4.7. AI in hydrogen energy

Petrone et al. [355] have presented briefly, a review of model based AI approaches for the diagnosis of proton exchange membrane fuel cell systems (PEMFCs). Similarly, in another study, three categories of non-model based approaches, including AI, statistical, and signal processing methods for a similar problem is detailed in [356].

The research application of AI approaches is described in several studies [357–382], summarized in Table 7. The ANN is the widely implemented method in the hydrogen energy [357–366] like three AI approaches, including the BPNN, SVR and multi-gene genetic programming (MGGP) is used in the prediction of output voltage of microbial fuel cell (MFC) in which MGGP results in the best accuracy [357]; BPNN is used to predict $CO_2$ hydrogenation activity [358]; BPNN with eleven training algorithm is used to predict the effect of hydrogen car engine operating conditions on the emission of $CO_2$, CO, $NO_x$, and hydrocarbons [359] (CO emission is predicted with 100% accuracy); BPNN trained with LM and Bayesian algorithm is used for monitoring the stability and detection of error in the PEM fuel cell [360]; BPNN based on LM training algorithm is used to predict the voltage and cathode temperature of the polymeric electrolyte membrane fuel cell (PEMFC) with high accuracy [361]; BPNN with the twelve different training algorithms were implemented for the prediction of hydrogen engine characteristics (mass air flow (MAF), air pressure, fuel pulse width, exhaust gas and engine temperature, and $NO_x$ emission) using two inputs engine speed and throttle position [362]. BPNN is also implemented in another studies [363–366] to predict the hydrogen engine parameter and emissions [363] (RMSE ± 4%); for the tensile strength prediction of hydrogen-functionalized graphene [364]; to predict the stack voltage of the solid oxide fuel cell (SOFC) [365]; and in the power density prediction of MFC (RMSE $4.89\times10^{-4}$ for one configuration) [366].

Fuzzy logic methods [367–369] and EU approaches [370–372] have also been used in hydrogen energy analysis: like Fuzzy logic method is used in prediction of ignition time of hydrogen car using three different types of membership functions [367]; recurrent fuzzy system is used to model the current density characteristics of SOFC [368]; Fuzzy logic controller based on parameter optimization with the GA is used to manage the hydrogen consumption in fuel cell hybrid vehicles (FCHV) [369]. Besides the fuzzy logic and GA, PSO is also used in the energy optimization of FCHV [370]. BPNN, GA and PCA in hydrogen production modeling is reviewed by Nath et al. [371]. Askarzadeh et al. have proposed the bird mating optimization (BMO) approach to model the PEMFC system [372].

Application of ANFIS [373–377] and other hybrid AI approaches [378–382] were described in many studies [378–382]: ANFIS is used to predict the SOFC parameters (stack current and voltage) and the performance is compared with the ANN method (RMSE < 2 for ANFIS in current prediction) [373]; ANFIS is used in prediction of several hydrogen safety parameters (like explosive limit, hydrogen pressure, and flow rate) using the ten input conditions [374], performance of ANFIS is compared with the eleven types of BPNN based on different training algorithms (RMS 1.4 in hydrogen pressure prediction with ANFIS); ANFIS and BPNN (LM) were implemented for emissions (HC, CO, CO2, NOx) prediction from the hydrogen car, BPNN shows better prediction than the ANFIS (RMSE 1.58% of HC emission with the BPNN) [375]; ANFIS is used in the performance ($H_2$ flow rate, system and stack efficiencies) prediction of PEM electrolyzer (1.06% prediction error for hydrogen flow rate) [376]; ANFIS used in prediction of cell voltage of PEMFC efficiently [377], and performance is compared with RBFNN, and BPNN; a hybrid AI approach based on wavelet and fully logic method is implemented for energy controlling of HEV (fuel consumption of 0.06962 kMol $H_2$) [378]; SVR and PSO based hybrid approach is used in temperature forecasting oh hydrogen reactor with high accuracy and performance is compared with the SVR and BPNN [379]; BPNN in combination with the GA is used in the biohydrogen yield optimization (54 ml/g improvement with proposed approach) [380]; in another study [381] similar combination of methods is used to optimize the cell parameters of SOFC (standard error of prediction 1.705%); a hybrid ABC algorithm is used in the parameter prediction of PEMFC and performance is compared with the PSO and GA, hybrid ABC performs better than the other methods with the minimum sum of squared error (SSE) [382].

### 4.8. AI in hybrid renewable energy

Applications of AI approaches in the hybrid RE were briefly described in the reviews [383–385]. The development of approaches for the optimal sizing is briefly presented by Luna-Rubio et al. [383]. Specifically, the design methodologies of solar-wind hybrid RE system are presented by Zhau et al. [384]; application of different EA approaches in optimization is summarized in [385].

Few single and hybrid AI approaches in hybrid RE applications [386–397] are summarized in Table 8. BPNN is used in the power use and generator status (on/off) prediction for a water power supply based hybrid RE system (prediction accuracy 97%) [386]. Chavez-Ramirez et al. [387] implemented BPNN method for power prediction of hybrid

**Table 7**
Summary of reports for application of AI approaches in geothermal energy [357–382].

| Ref. no. | Method/methods | Application | Outcome |
|---|---|---|---|
| [357] | BPNN, SVR, MGGP | MFC output voltage prediction | $R^2$ 0.9872 for the MGGP |
| [358] | BPNN | $CO_2$ hydrogenation activity | 32% conversation rate for Mn-catalyst |
| [359] | BPNN | Prediction of emissions from hydrogen car | RMSE 0.0002 for the CO |
| [360] | BPNN (LM, and Bayesian algorithm) | Error detection in PEM fuel cell | Error 0.0 |
| [361] | BPNN (LM) | Voltage and cathode temperature prediction of (PEMFC) | Correlation 0.973–0.983 |
| [362] | BPNN (LM) | Hydrogen engine characteristics prediction | RMSE 0.4106 for MAF |
| [363] | BPNN (LM) | Hydrogen engine parameter and emissions prediction | $R^2$ 0.99 |
| [364] | BPNN | Tensile strength prediction of graphene | $R^2$ 0.9867 |
| [365] | BPNN | Stack voltage prediction of fuel cell | MSE < 0.08 |
| [366] | BPNN | Power density prediction | $R^2$ 0.99 |
| [367] | Fuzzy logic | Ignition time prediction of hydrogen engine | RMSE ±5% |
| [368] | Fuzzy logic | SOFC current density prediction | RMSE 0.4 |
| [369] | Fuzzy logic with GA | Hydrogen consumption management | 37.9–43.8% improvement |
| [370] | PSO | FCHV energy management | Optimal path for 50% swarm |
| [371] | BPNN with GA, PCA | Hydrogen production modeling | Maximum production 6897 ml $H_2$/L |
| [372] | BMO | Modeling of PEMFC system | Std. $3.24\times10^{-4}$ |
| [373] | ANFIS | Stack current and voltage prediction of SOFC | MRE < 0.25% with ANFIS for current |
| [374] | ANFIS, BPNN | Hydrogen safety parameter prediction | RMSE 0.6 for explosion limit |
| [375] | ANFIS, BPNN | Prediction of emission from hydrogen car | RMSE 5.51%, 2.29%, for $CO_2$ respectively |
| [376] | ANFIS | PEM electrolyzer performance prediction | Error 0.95%, 0.7% for stack and system efficiency |
| [377] | ANFIS, RBFNN, BPNN | Cell voltage prediction of PEMFC | $R^2$ 0.99 for ANFIS |
| [378] | Hybrid method (Fuzzylogic +WT) | HEV energy management | Fuel saving (~8%) |
| [379] | Hybrid method (SVR+PSO) | $H_2$ reactor temperature prediction | 4.89% error |
| [380] | Hybrid method (BPNN+GA) | Biohydrogen yield optimization | MSE of $9.1\times10^{-8}$ |
| [381] | Hybrid method (BPNN+GA) | SOFC cell parameter optimization | RMSE 0.0108 |
| [382] | Hybrid method (PSO) | PEMFC parameter prediction | SSE 15.66 |

RE systems and FLC for energy management. In another study, FLC and cuckoo search (CS) algorithm and PSO were used in energy management of hybrid RE system (levelized energy cost (LEC) 2.01 $ with the CS) [388]. PSO is used in size optimization of hybrid RE system by Hakimi et al. [389] with the objective to make it more cost effective. An improved GA is used in operation optimization of hybrid RE system, which performs better than the traditional GA method [390]. Bee algorithm is used in performance parameters (net present cost (NPC), cost of energy (COE) and generation cost (GC)) optimization of hybrid RE system [391]. Khatib et al. [392] have implemented GA in the optimization of the hybrid PV/wind system for size of PV array and wind turbine and storage capacity. A multi-objective (MO)-ABC algorithm is used in hybrid (photo voltaic/wind turbine/fuel cell) energy system in size and distribution optimization [393], which results in a high voltage stability index (VSI). Markov based GA is used in size optimization of hybrid wind-PV-diesel system [394].

The performance of four techniques (PSO, tabu search (TS), simulated annealing (SA), and harmony search (HS)) for the size optimization of PV/wind/battery and PV/wind/FC systems is described in [395]. PSO results in better performance than rest three methods.

In hybrid AI approaches, ANFIS is used for size optimization of the hybrid PV-wind-battery system with the objective to reduce the production cost; also, the performance is compared with the hybrid optimization model for electric renewables (HOMER) and hybrid optimization (HO)-GA (ANFIS achieve better performance) [396]. ANN and fuzzy logic based controller is developed as a hybrid AI approach to control the flow of power between the hybrid RE system and the energy storage unit, resulting, a high storage of charge (SOC) [397].

Some recent studies, [398–406] proposed the implementation of hybrid and improved AI methods for different RE systems, like ANFIS in wind power estimation [398,401], modeling of biodiesel [399], and solar radiation [400]; SVR+ARIMA for tidal current estimation [402]; empirical decomposition, wavelet decomposition, ANN and autoregressive methods in solar radiation estimation [403]; improved and hybrid ANN in load estimation of PV system [404], and in wind speed and power prediction [405]; and data mining method based efficient energy management system [406]. The detailed applications of AI methods have been also discussed in some latest review studies [407–415], specifically, for power tracking of PV system [407,412,413], solar energy and wind energy estimation [408,409,414], decision system in RE [410], controllers for PV systems [411], and energy management [415].

**Table 8**
Summary of reports for application of AI approaches in hybrid energy [386–397].

| Ref. no. | Method/methods | Application | Outcome |
|---|---|---|---|
| [386] | BPNN | Power and generator status prediction | $R^2$ 0.979 |
| [387] | BPNN, Fuzzy logic | Power prediction and energy management | Prediction accuracy 2.4–14% |
| [388] | FLC, CS, PSO | Energy management | Excess energy 1.10% |
| [389] | PSO | Size optimization | Cost < 4$ |
| [390] | Novel GA | Operation optimization | Better fitness values |
| [391] | Bee algorithm | Performance parameter prediction | Rs. 6.36/kW h |
| [392] | GA | PV/wind system optimization | Optimum sizing ratios of the PV array 1.14 |
| [393] | PSO | VSI | 0.7866 |
| [394] | Markov-GA | Size optimization | Cost < 0.5 M$ |
| [395] | PSO, TS, SA, HS | Size optimization | Minimum computational cost 0.156 for PSO |
| [396] | Hybrid method (ANFIS, HOMER, HOGA) | Size optimization | Low excess energy 0.19% for ANFIS |
| [397] | Hybrid method (BPNN-Fuzzy) | Power flow control | SOC 40–80% |

## 5. Conclusion

The present review briefly presented the current status of research and development in single and hybrid RE systems. Moreover, the role of AI approaches in the control, decision, simulation, and optimization of RE systems is summarized. From the current state-of-art, it is obvious that in most of the research reports, the effective application of AI approaches in wind and solar energy based system is discussed. Though there are few research reports based on the implementation of AI approaches in other and hybrid RE sources. AI approaches possess great potential. There is a need for their proper utilization in future research for the novel sources of RE and especially in the hybrid RE system. The implementation of novel and hybrid AI approaches will add additional performance improvement of RE sources for world prosperity.

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