Using Artificial Intelligence in Renewable Energies

Sepehr Sammak [1,*]
1- Bachelor of Petroleum Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran
* Corresponding Author: s.sammak1993@gmail.com

ABSTRACT

At present, more than half of the world's energy needs are met by coal, natural gas and crude oil. These fossil fuels not only exacerbate the greenhouse effect in the Earth's atmosphere, but also lead to climate change. Awareness of climate change and a critical increase in the cost of traditional energy resources have led many communities to pursue innovative strategies, including renewable energy (RE) systems. For example, solar, wind, and blue energy are renewable energy sources that are environmentally friendly and have the potential to be widely used. Today, artificial intelligence (AI) has taken root in our daily lives and has significantly affected the fields of clean energy storage. The use of artificial intelligence in planning to increase the speed of energy storage from the environment as well as optimizing security and the comfort of the living environment.

Keywords: *renewable energy ,artificial intelligence, Wind energy ,Solar energy , Geothermal energy , Hydro energy*

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 CO2 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.

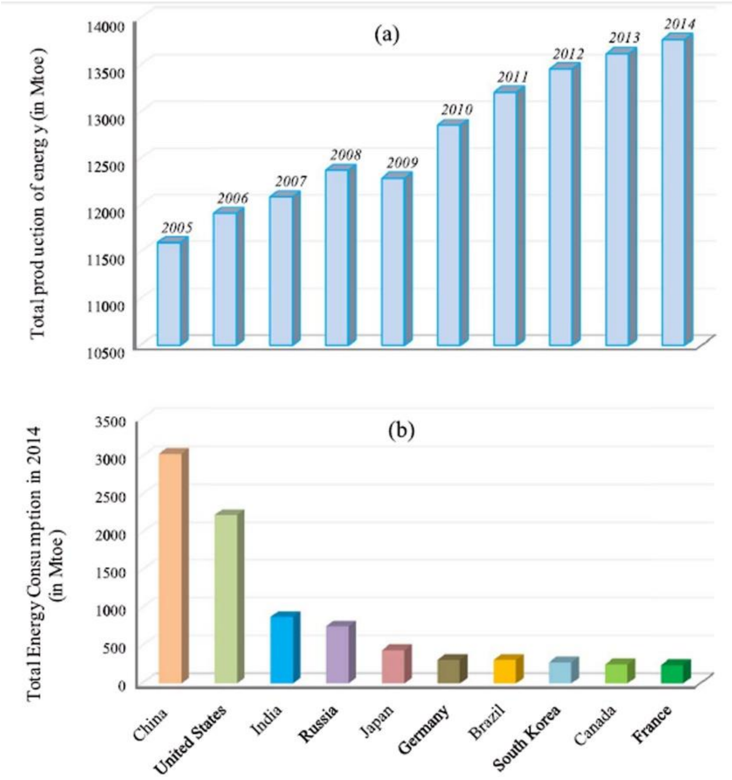

Fig. 1. (a) Total consumption of energy in last ten years (2005–2014) in the world, and (b) top ten countries with the maximum consumption of energy in the year 2014 [13].

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 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].

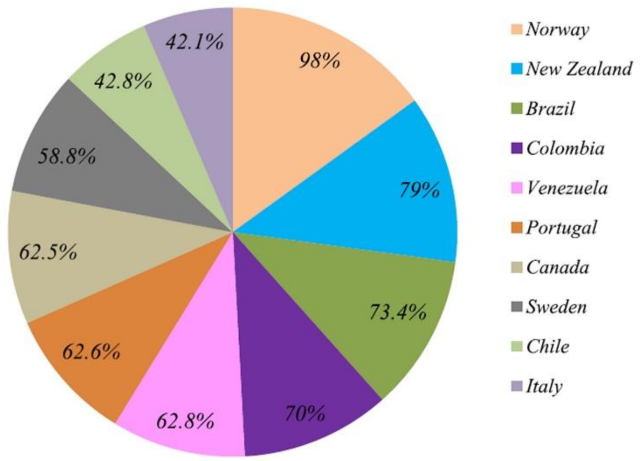

Fig. 2. A contribution of renewables in electricity production in the year 2014 [13].

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.

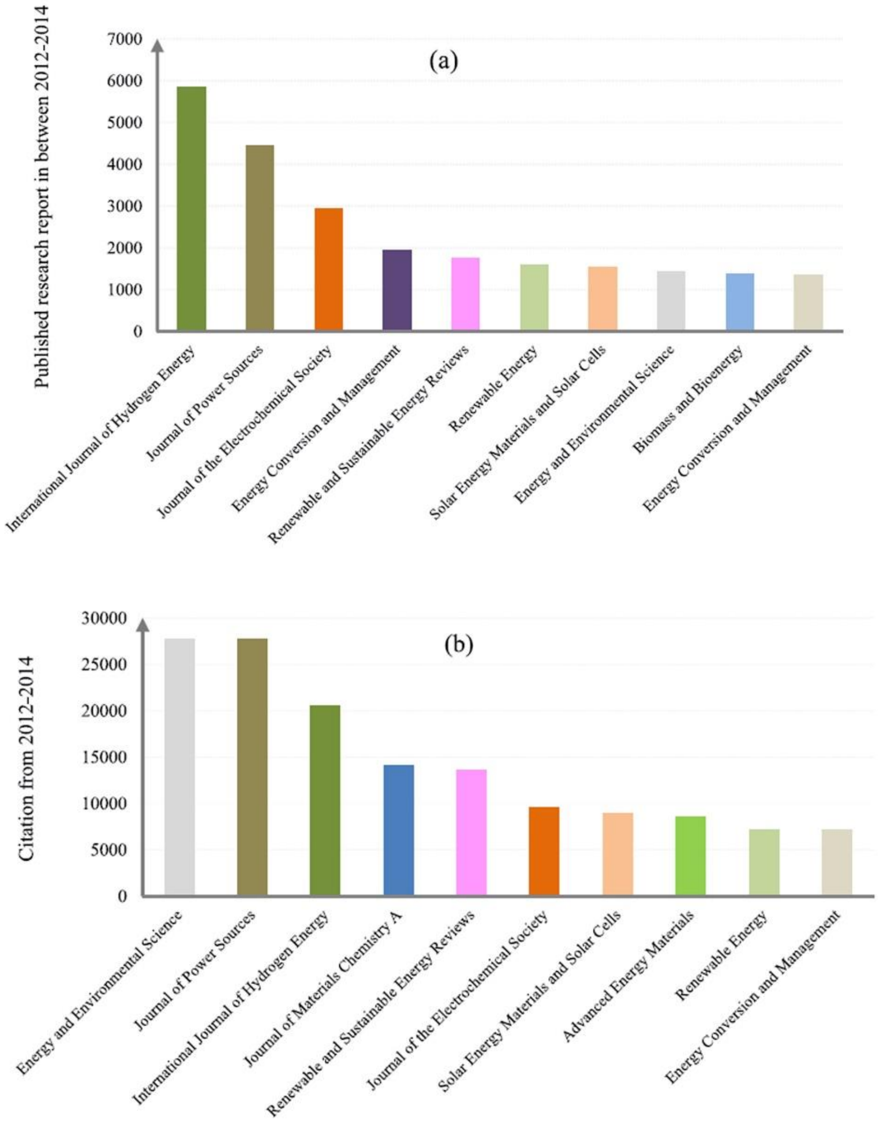

Fig. 3. Research reports published (a) from 2012 to 2014 in top ten journals, and (b) citation of reports published from 2012 to 2014 in top ten journals [18].

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 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).

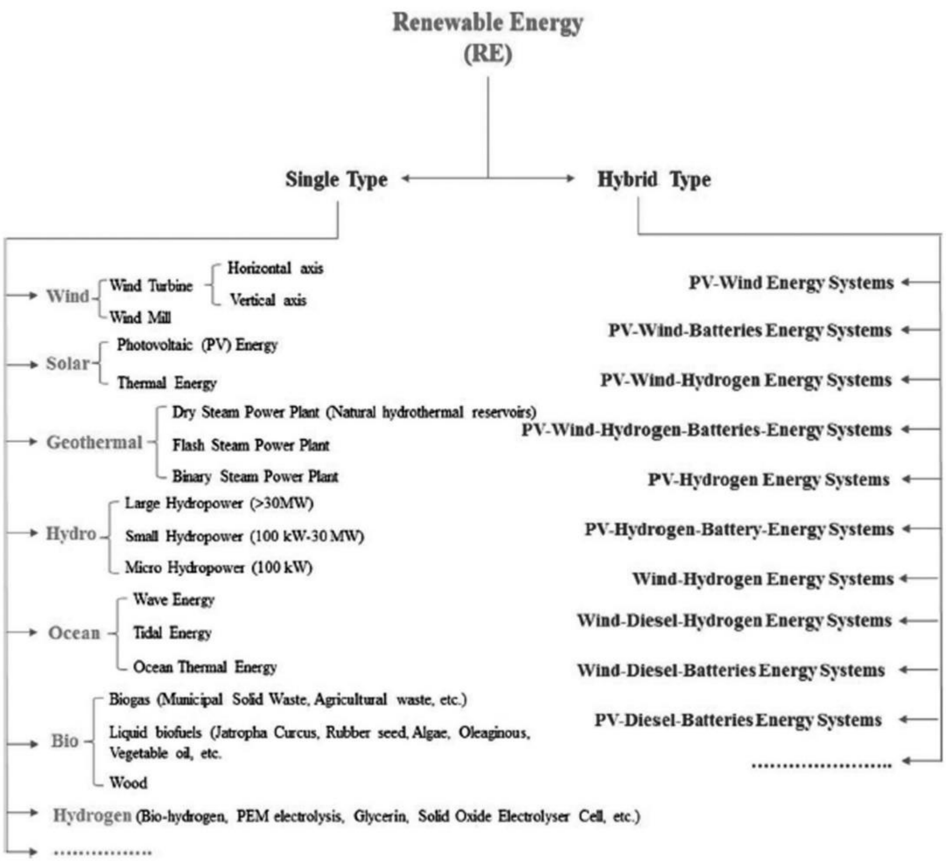

Fig. 4. Categories of renewable energy and their sources [96–195].

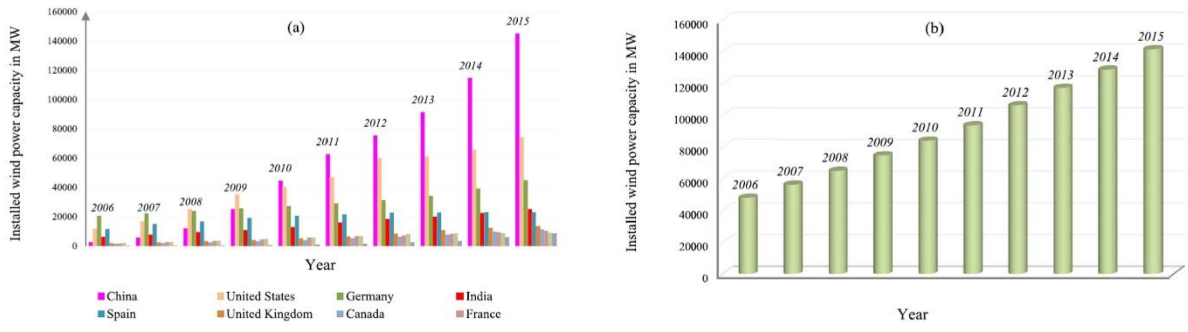

Fig. 5. Installed wind power capacity (a) different countries, and (b) EU in between the years 2006–2015 [101,102].

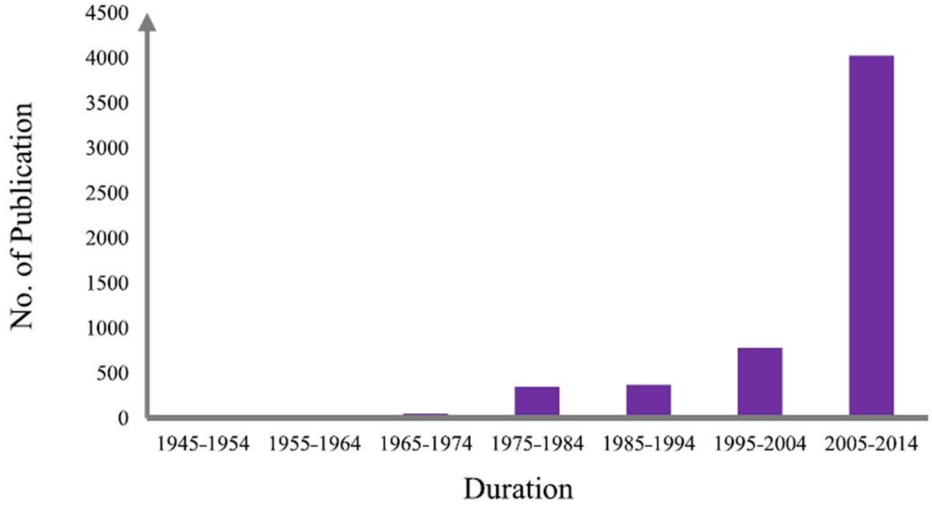

Fig. 6. Published scientific reports of wind energy research (web of science,[416]).

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 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).

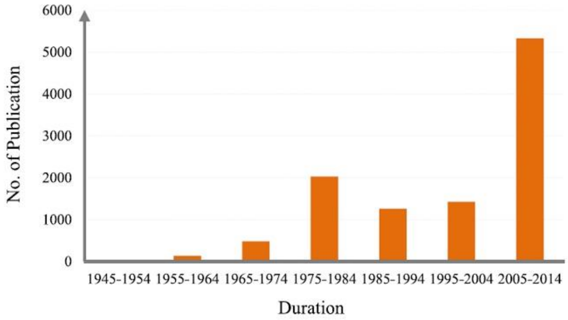

Fig. 7. Published scientific reports of solar energy research (web of science,[416]).

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.

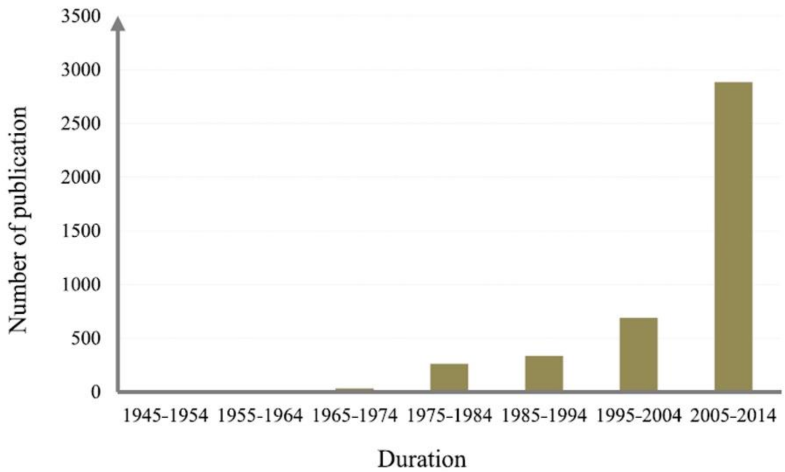

Fig. 8. Published scientific reports of geothermal energy research (web of science, [416]).

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.

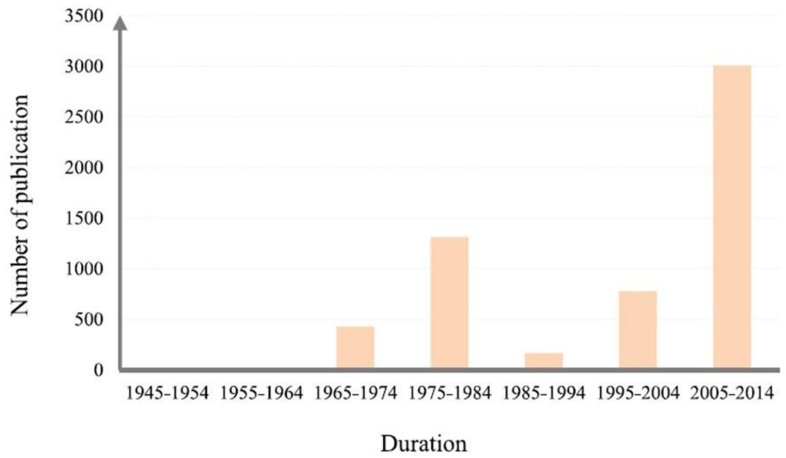

Fig. 9. Published scientific reports of hydro energy research (web of science, [416]).

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).

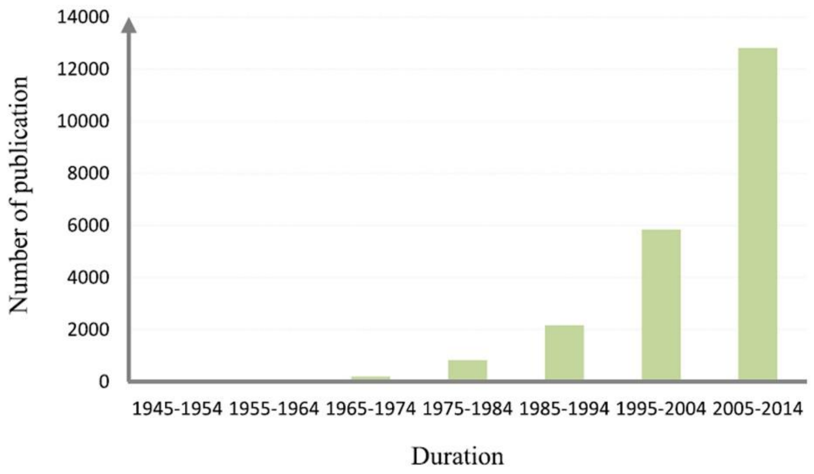

Fig. 10. Published scientific reports of ocean energy research (web of science, [416]).

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.

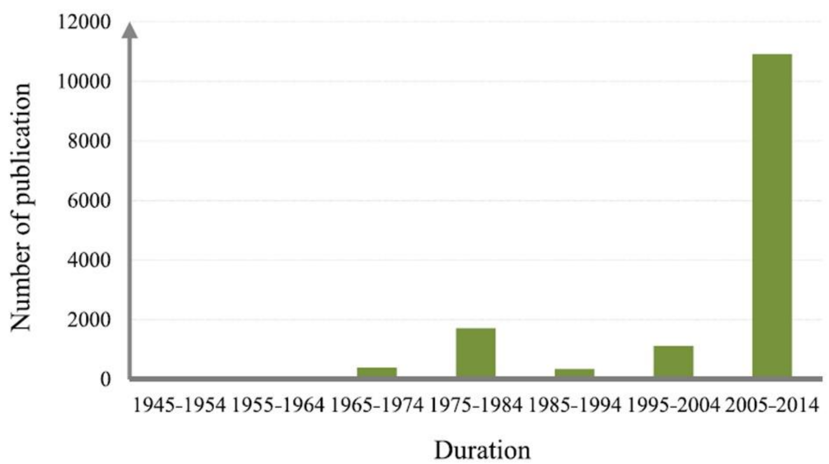

Fig. 11. Published scientific reports of bioenergy research (web of science, [416]).

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.

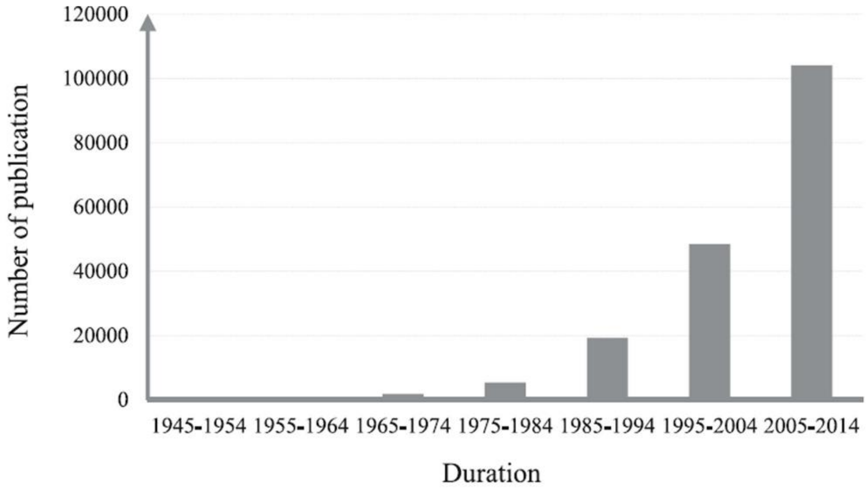

Fig. 12. Published scientific reports of hydrogen energy research (web of science, [416]).

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.

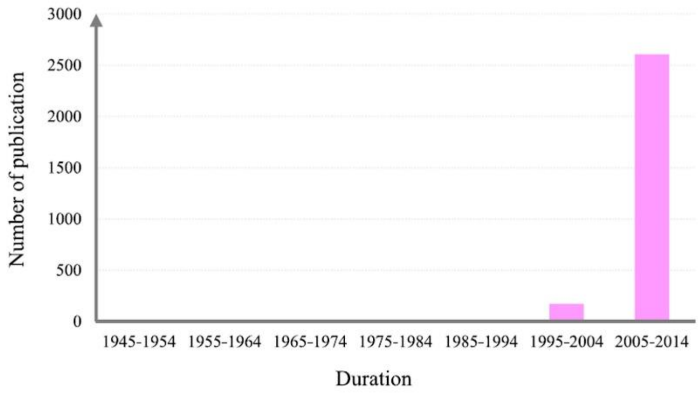

Fig. 13. Published scientific report on hybrid RE research (web of science).

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

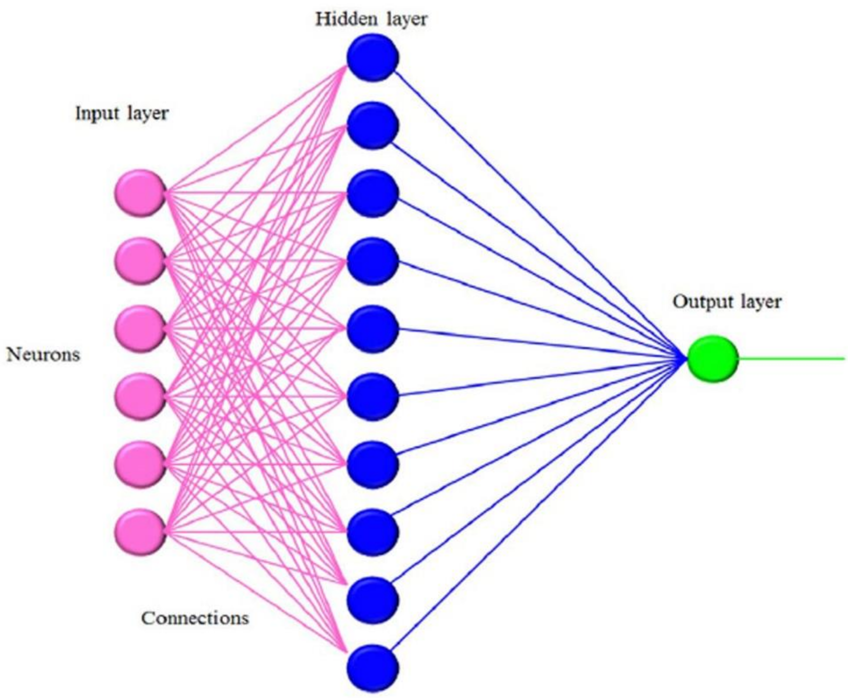

Fig. 14. A simple architecture of ANN method[416]

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.

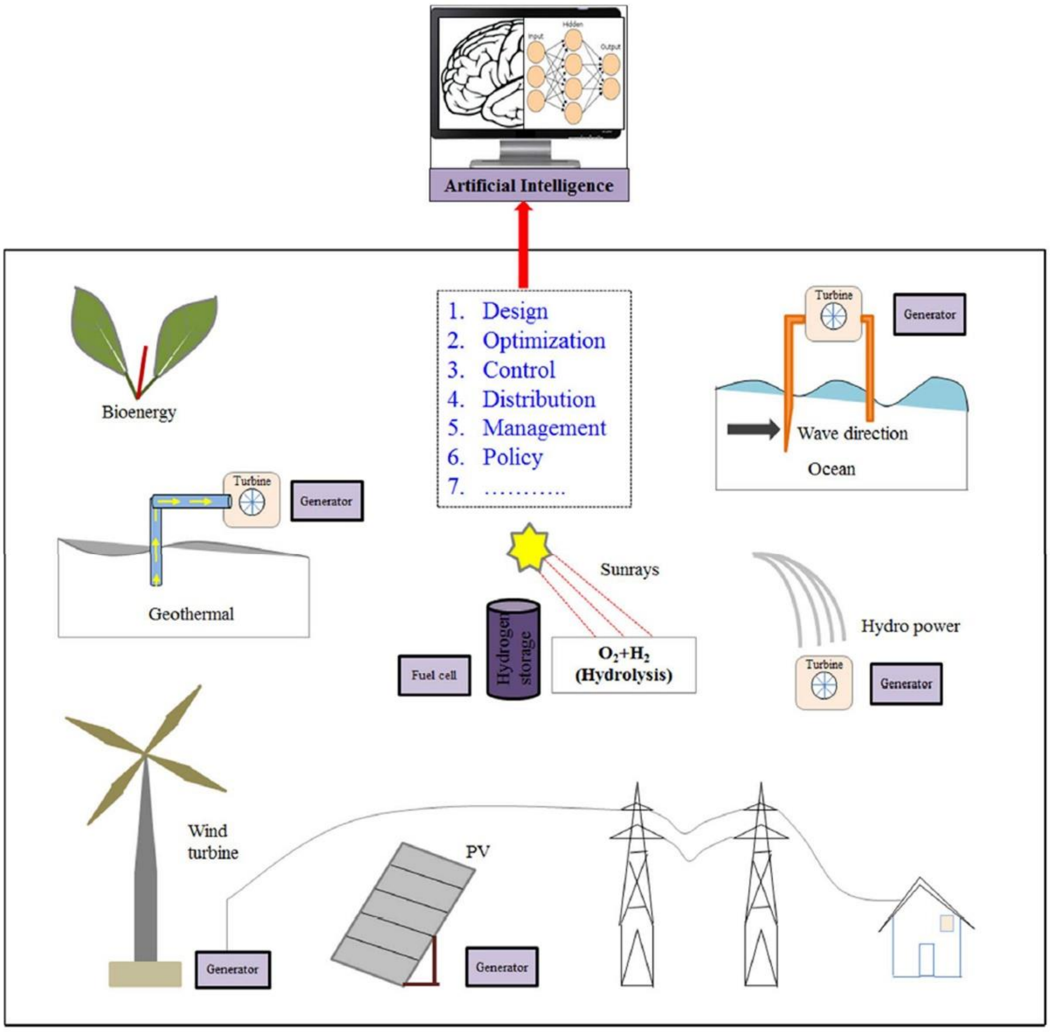

Fig. 15. A schematic representation of application of AI in different sources of RE[416].

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 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-pointtracking (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)-feedforward 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.

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

Method/methods	Application	Outcome
BPNN	Wind power prediction	RMSE 0.0065
BPNN, RBFNN, and ADALINE	Wind speed prediction	RMSE 1.254 for BPNN
BPNN	Wind power prediction	MSE 7.6 ×10-3
Recurrent high order ANN, and NB	Wind power prediction	RMSE 4.2
BPNN and TPCSV	Wind speed prediction	Correlation 0.95 for BPNN
BPNN	Wind speed and power prediction	20–40% improved accuracy
BC, ADALINE, BPNN and RBFNN	Wind speed prediction	RSME 1.5 for BC
ARMA, NLN and ANN	Wind speed prediction	RMSE 4.9% for NLN
BPNN, and SES	Wind speed prediction	MAE for BPNN 0.5251
Fuzzy method	Design of wind generation system	3.5 kW
ANN, RBFNN, and fuzzy methods	Wind power prediction	Planning 1–48 h ahead
BPNN and fuzzy methods	Wind speed prediction	RMSE 3.30 for BPNN
Probabilistic method	Wind power prediction	Reliability (2–4%),
SVM, BPNN	Wind speed prediction	MSE 0.0078 for BPNN
ANFIS	Wind power prediction	MAE < 8
ANFIS	Wind speed prediction	MAPE 3% at 40 m
ANFIS	Missing wind data interpolation	RMSE 0.230
ANFIS	Design of wind generation system	Error 0.005
BPNN+WT	Wind turbine fault diagnosis	Detection of 8 conditions
PSO+BPNN	Wind power prediction	2.8% improved accuracy
EMD+FNN	Wind speed prediction	MSE 0.1296
ANN+MC	Wind speed prediction	Error 94.84
Hybrid method (Fuzzy-GA)	Wind speed and power prediction	29.7% improved accuracy
Hybrid method (EEMD-SVM)	Wind speed prediction	MAE 0.12
Hybrid method (ARIMA-BPNN)	Wind speed prediction	MSE 0.49
Hybrid method (MM5-ANN)	Wind speed prediction	MAE (1.45–2.2 m/s)
Hybrid method (WT-SVM-GA)	Wind speed prediction	MAE 0.6169
Hybrid method (SVR-PSO)	Wind speed prediction	Effective accuracy
Hybrid method (ACO-PSO)	Wind power prediction	MAPE 3.5%
Hybrid method (WT-PSO-ANFIS)	Risk optimization in wind energy trading	Profit estimation for risk level (0.0–0.1)

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 2.823×10−4 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 (R2 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 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 R2 0.9978 and 0.9973 respectively [254]. Solar radiation was estimated using the BPNN in Nigeria with R2 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 R2 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/m2) performs better than the RBF (MAE 43 W/m2) and AR (MAE 62 W/m2) 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 m2 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 R2 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 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 points [295].

Table 2

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

Method/methods	Application	Outcome
BPNN	Solar irradiance prediction	Correlation 94–99%
BPNN	Solar radiation prediction	RMSE 2.823×10^{-4}
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
BPNN	Solar beam radiation prediction	RMSE 1.65–2.79%
BPNN	Daily ambient temperature prediction	RMSE 1.96
BPNN	Daily solar irradiation prediction	RMSE 5.0–7.5%
BPNN	Maximum power of HCPV prediction	RMSE 3.29%
BPNN	Global solar irradiation prediction	Correlation 97%
BPNN	Solar energy and hot water quantity prediction	R^2 0.9978 and 0.9973 respectively
BPNN	Solar energy prediction	R^2 0.971
BPNN	Building energy prediction	R^2 0.991
BPNN	Building energy prediction	Prediction rate 94.8–98.5%
BPNN and batch learning ANN	Mean temperature prediction	MPD 2.13-4.17 for BPNN
BPNN and Empirical models	Diffuse solar radiation prediction	RMSE 4.5% for BPNN
BPNN and Ångström linear methods	Global solar radiation prediction	RMSE 5.67-6.57% for BPNN
BPNN and Regression methods	Global solar radiation prediction	RMSE 0.867 for BPNN
SVM, RBFNN, AR	Solar power prediction	MAE 33.7 W/m^2 for SVM
SVR, BPNN	PV energy prediction	RMSE 0.133 for SVR and 0.131 for BPNN in one case.
SVM, PPF, Cloudy	Solar power prediction	RMSE 128 W/m^2 for SVM
GA	Solar tracking	Std. 1.55 in generation gain
GA	Design of solar water heating system	Solar fraction value 98%
GA, PO	MPPT of PV array	Line voltage 400 V
ANN+TRNSYS	Performance prediction of ICS	R^2 0.9392
GA+HISIMI	Solar power prediction	RMSE 283.89
RBF+IIR and BPNN+IIR	Size optimization of PV system	MSE 0.028 for RBF+IIR
WT+BPNN	Solar radiation values estimation	MAPE < 6%
GA+BPNN	Solar power prediction	MAE 42.96 kW
WT+RBFNN	PV energy prediction	MAE 0.19
GA+GMDHNN	Solar system optimization	R^2 0.9986
ANFIS	PV power supply modeling	R^2 98–99%
ANFIS	Hourly global irradiance prediction	RMSE 0.1034
ANFIS	Clearness index, radiation prediction	MAPE < 2.2%
ANFIS	PV power supply modeling	Correlation 98%
ANFIS	Solar power prediction	Correlation 98%
ANFIS	SCPP performance prediction	R^2 0.91
Hybrid method (ANN-GA-PSO)	PV power prediction	Prediction 0–35 kW
Hybrid method (ARMA-TDNN)	Solar radiation prediction	RMSE approx. 25–300
Hybrid method (BPNN-GSO)	PV power prediction	MAE 0.317 kW/h
Hybrid method (SARIMA-SVM)	Solar power prediction	Correlation 99%
Hybrid method (SVM-FFA)	Solar power prediction	RMSE 0.7280

Table 3

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

Method/methods	Application	Outcome
BPNN (LM, CGP, SCG)	VGCHP Performance prediction	R^2 0.9998
BPNN (LM)	SFT prediction of geothermal well	$R^2 > 0.95$
BPNN (LM, CGP, SCG)	Geothermal power prediction	R^2 0.9987
BPNN (LM, CGP, SCG)	Geothermal power prediction	R^2 0.9999
BPNN	Geothermal map generation	Correlation 0.9253
BPNN (LM)	Performance prediction of AGDHS	R^2 0.9999
BPNN (LM)	VF prediction	MPE 0.17
BPNN (QN)	Ammonia-nitrogen prediction	R^2 1.00
BPNN	PID controller efficiency prediction	Correlation 0.9986
BPNN (LM)	Modeling of geothermal plant	R^2 0.99
BPNN (LM, SCG)	Site location modeling	R^2 0.85
BPNN	Conductivity map generation	Correlation 0.9553
BPNN	Pressure prediction in geothermal plant	MAPE < 2.3%
EA	VGSHP optimization	Production cost 0.772$/h for TE
EA (DE, GA, PSO, etc.)	BHEs optimization	18–23% reduced cooling
Fuzzy logic	Design of RAS system	Error zero error
Fuzzy logic	Design of RAS system	Max. RAS production at 2 °C
ANFIS, BPNN (LM, CGP, SCG)	VGSHP performance prediction	R^2 0.9999 for ANFIS
ANFIS, BPNN (LM, CGP, SCG)	AGDHS system evaluation	RMSE 19.6, 3.66 for ANFIS
Hybrid method (GMDH-GA-SVD)	Temperature prediction	R2 0.9899

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-phosphatepho-sphorus 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 GMDHNN 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 knearest 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 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 (R2 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 CO2 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 H2S and NH3 up to 93 ppm (ppm) in biogas using the BPNN (RMSE

416, 5.1 ppm, respectively) [343]; 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].

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

Method/methods	Application	Outcome
BPNN, DDP, KNN	Scheduling of hydropower plant	BPNN 0.011% cost effective
BPNN	Modeling of rainfall-runoff process	RMSE 0.097–0.260
BPNN (LM)	Stream flow prediction	MAPE < 5%
BPNN (GD), AR	River flow prediction	Error 0.2% with BPNN
BPNN	Power discharge estimation	MAPE < 5%
GA, NP	Scheduling of hydropower plant	Less active cost 2.9% by GA
GA	Scheduling of hydropower plant	Population cost 2.05$
CHGA, SGA, NP	Hydrogenation scheduling	190,301$ profit with CHGA
Fuzzy logic	Selection of optimal material	GRP, degree of index 2.07
ANFIS, GA, M-5	Water release prediction	Water shortage 0.0 for ANFIS
ANFIS, ANN, MR	River flow prediction	RMSE 7.1 for ANFIS
Hybrid method (LVQ-ART-MAP)	Acoustic and maintenance prediction	False alarm rate < 10%
Hybrid method (FLC-PSO, FLC-GA)	FLC design for AGC	Scaling factor for hydro area 4.731 with FLC-PSO
Hybrid method (HC-FFT-ANN)	River flow prediction	Std. 26. 48
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].

Method/methods	Application	Outcome
BPNN	Sea level variation prediction	RMSE 10% of tidal range
BPNN	Sea wave height prediction	84% for a lead time of 6 h
BPNN	Wave parameters prediction	RMSE 0.53
BPNN, RBFNN, GRNN	Dispersion coefficient prediction	RMSE 27.9 BPNN
Fuzzy logic	Reducing effect of ocean wave	Stability 0.0 for small amplitudes
GP, BPNN (LM)	Sea level prediction	R^2 0.972–0.973
ANFIS, BPNN, ARMA	Sea level prediction	RMSE 0.055for ANFIS
Hybrid method (NWM-BPNN)	Wave hindcasting	Correlation 0.93
Hybrid method (CVR-SVR)	CO_2 flux prediction	Mean accuracy 96.3%

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

Method/Methods	Application	Outcome
GRNN	CN and density prediction	MAE 1.23, 0.002 respectively
BPNN	Detection of H_2S and NH_3 in biogas	R^2 0.91 and 0.83 respectively
BPNN, RBFNN, GRNN, RNN	CN prediction	Accuracy 3.4%, 5%, 3.8% and 3.6% respectively
BPNN	Methane concentration prediction in biogas	R^2 0.951–0.957
BPNN, MLR, PLS, PCR	Biodiesel properties prediction	RMSE 0.42–51
RBFNN	Performance prediction of biodiesel engine	MSE 0.001985–0.0011
SVM, KNN, RDA, PLS	Biodiesel classification	SVM accuracy 95%
PSO	Biomass supply chain optimization	Decision variable 1–5
GP, BPNN	HHV prediction	Correlation 0.95
ANN, ARIMA ANN-ARIMA	Fuelwood price prediction	RMSE 0.050
Hybrid method (ANN-Fuzzy logic)	Biomass boiler control	3.5% increase of turbine output
Hybrid method (BPNN-GA)	Prediction of methane from waste	R^2 0.8703
Hybrid method (BPNN-GA)	Biogas production optimization	8.64% increase in production

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 ANNARIMA 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 nonmodel 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 CO2 hydrogenation activity [358]; BPNN with eleven training algorithm is used to predict the effect of hydrogen car engine operating conditions on the emission of CO2, CO, NOx, 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 NOx 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 4.89×10^{-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 (H2 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 H2) [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].

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

Method/methods	Application	Outcome
BPNN, SVR, MGGP	MFC output voltage prediction	R^2 0.9872 for the MGGP
BPNN	CO_2 hydrogenation activity	32% conversation rate for Mn-catalyst
BPNN	Prediction of emissions from hydrogen car	RMSE 0.0002 for the CO
BPNN (LM, and Bayesian algorithm)	Error detection in PEM fuel cell	Error 0.0
BPNN (LM)	Voltage and cathode temperature prediction of (PEMFC)	Correlation 0.973–0.983
BPNN (LM)	Hydrogen engine characteristics prediction	RMSE 0.4106 for MAF
BPNN (LM)	Hydrogen engine parameter and emissions prediction	R^2 0.99
BPNN	Tensile strength prediction of graphene	R^2 0.9867
BPNN	Stack voltage prediction of fuel cell	MSE $<$ 0.08
BPNN	Power density prediction	R^2 0.99
Fuzzy logic	Ignition time prediction of hydrogen engine	RMSE $\pm$5%
Fuzzy logic	SOFC current density prediction	RMSE 0.4
Fuzzy logic with GA	Hydrogen consumption management	37.9–43.8% improvement
PSO	FCHV energy management	Optimal path for 50% swarm
BPNN with GA, PCA	Hydrogen production modeling	Maximum production 6897 ml H_2/L
BMO	Modeling of PEMFC system	Std. 3.24×10^{-4}
ANFIS	Stack current and voltage prediction of SOFC	MRE < 0.25% with ANFIS for current
ANFIS, BPNN	Hydrogen safety parameter prediction	RMSE 0.6 for explosion limit
ANFIS, BPNN	Prediction of emission from hydrogen car	RMSE 5.51%, 2.29%, for CO_2 respectively
ANFIS	PEM electrolyzer performance prediction	Error 0.95%, 0.7% for stack and system efficiency
ANFIS, RBFNN, BPNN	Cell voltage prediction of PEMFC	R^2 0.99 for ANFIS
Hybrid method (Fuzzylogic +WT)	HEV energy management	Fuel saving (~8%)
Hybrid method (SVR+PSO)	H_2 reactor temperature prediction	4.89% error
Hybrid method (BPNN+GA)	Biohydrogen yield optimization	MSE of 9.1×10^{-8}
Hybrid method (BPNN+GA)	SOFC cell parameter optimization	RMSE 0.0108
Hybrid method (PSO)	PEMFC parameter prediction	SSE 15.66

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

Method/methods	Application	Outcome
BPNN	Power and generator status prediction	R^2 0.979
BPNN, Fuzzy logic	Power prediction and energy management	Prediction accuracy 2.4–14%
FLC, CS, PSO	Energy management	Excess energy 1.10%
PSO	Size optimization	Cost < 4$
Novel GA	Operation optimization	Better fitness values
Bee algorithm	Performance parameter prediction	Rs. 6.36/kW h
GA	PV/wind system optimization	Optimum sizing ratios of the PV array 1.14
PSO	VSI	0.7866
Markov-GA	Size optimization	Cost < 0.5 M$
PSO, TS, SA, HS	Size optimization	Minimum computational cost 0.156 for PSO
Hybrid method (ANFIS, HOMER, HOGA)	Size optimization	Low excess energy 0.19% for ANFIS
Hybrid method (BPNN-Fuzzy)	Power flow control	SOC 40–80%

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 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].

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.

REFERENCES

[1] Johansson TB, Kelly H, Reddy AKN, Williams RH. Renewable fuels and electricity for a growing world economy. USA: Island Press; 1993.
[2] Wood AJ, Wollenberg BF. Power generation operation and control. Canada: John Wiley & Sons; 1984.
[3] Sorensen B. Renewable energy: physics engineering environmental impacts economics and planning, 4th ed.. Amsterdam: Elsevier; 2011.
[4] International Energy Agency (IEA). Technology road map solar photovoltaic energy; 2014, p. 1–60.
[5] Chalka SG, Miller JF. Key challenges and recent progress in batteries, fuel cells, and hydrogen storage for clean energy systems. J Power Sources 2006;159:73–80.
[6] Kamat PV. Meeting the clean energy demand: nanostructure architectures for solar energy conversion. J Phys Chem C 2007;111(7):2834–60.
[7] Panwar NL, Kaushik SC, Kothari S. Role of renewable energy sources in environmental protection: a review. Renew Sust Energ Rev 2011;15:1513–24.
[8] Turner JA. A realizable renewable energy future. Science 1999;285:687–9.
[9] Dincer I. Renewable energy and sustainable development: a crucial review. Renew Sust Energ Rev 2000;4:157–75.
[10] Elliott D. Renewable energy and sustainable futures. Futures 2000;32:261–74.
[11] Evans A, Strezov V, Evans TJ. Assessment of sustainability indicators for renewable energy technologies. Renew Sust Energ Rev 2009;13:1082–8.
[12] Berndt ER, Wood DO. Technology prices and derived demand for energy. Rev Econ Stat 1975;57:259–68.
[13] Enerdata. Global Energy Statistical Yearbook; 2015. ⟨https://yearbook.enerdata.net⟩.
[14] Boyu Z. Further discussion on exploitation of renewable energy sources and its legal regulations. Energy Procedia 2011;5:2144, [19].
[15] Kotevski M. Паркот на ветерници во завршна фаз. Енергија 2014;17:1–24 ⟨http://elem.com.mk/images/stories/vesnik_ELEM_br.17.pdf⟩.
[16] The Guardian. Uruguay makes dramatic shift to nearly 95% electricity from clean energy. UK; 2015. (⟨http://www.theguardian.com/environment/2015/dec/03/ uruguay-makes-dramatic-shift-to-nearly-95-clean-energy⟩).
[17] European Commission. Renewable energy moving towards a low carbon economy. (⟨https://ec.europa.eu/energy/en/topics/renewable-energy⟩).
[18] SCImago. SJR — SCImago Journal and Country Rank. Retrieved from 16 March 2016; 2007. ⟨http://www.scimagojr.com⟩.
[19] Mitchell C. The renewables NFFO: a review. Energy Policy 1995;23(12):1077–91.

[20] García-Rodríguez L. Seawater desalination driven by renewable energies: a review. Desalination 2002;143(2):103–13.
[21] Chang J, Leung DYC, Wu CZ, Yuan ZH. A review on the energy production, consumption, and prospect of renewable energy in China. Renew Sust Energy Rev 2003;7(5):453–68.
[22] Mitchell C, Connor P. Renewable energy policy in the UK 1990–2003. Energy Policy 2004;32(17):1935–47.
[23] Bugaje IM. Renewable energy for sustainable development in Africa: a review. Renew Sust Energy Rev 2006;10(6):603–12.
[24] Hepbasli A. A key review on exergetic analysis and assessment of renewable energy resources for a sustainable future. Renew Sust Energy Rev 2008;12(3):593–661.
[25] Menegaki A. Valuation for renewable energy: a comparative review. Renew Sust Energy Rev 2008;12(9):2422–37.
[26] Eltawila MA, Zhengminga Z, Yuana L. A review of renewable energy technologies integrated with desalination systems. Renew Sust Energy Rev 2009;13(9):2245–62.
[27] Varun , Bhat IK, Prakash R. LCA of renewable energy for electricity generation systems—a review. Renew Sust Energy Rev 2009;13(5):1067–73.
[28] Alauddina BZ, Lahijania P, Mohammadib M, Mohamed AR. Gasification of lignocellulosic biomass in fluidized beds for renewable energy development: a review. Renew Sust Energy Rev 2010;14(9):2452–62.
[29] Haas R, Panzer C, Resch G, Ragwitz M, Reece G, Held A. A historical review of promotion strategies for electricity from renewable energy sources in EU countries. Renew Sust Energy Rev 2011;15(2):1003–34.
[30] Bajpai P, Dash V. Hybrid renewable energy systems for power generation in standalone applications: a review. Renew Sust Energy Rev 2012;16(5):2926–39.
[31] Christopher K, Dimitrios R. A review on exergy comparison of hydrogen production methods from renewable energy sources. Energy Environ Sci 2012;5:6640–51.
[32] Lim JS, Manan ZA, Alwi SRW, Hashim H. A review on utilisation of biomass from rice industry as a source of renewable energy. Renew Sust Energy Rev 2012;16(5):3084–94.
[33] Richardson DB. Electric vehicles and the electric grid: a review of modeling approaches, impacts, and renewable energy integration. Renew Sust Energy Rev 2013;13:247–54.
[34] Alotto P, Guarnieri M, Moro F. Redox flow batteries for the storage of renewable energy: a review. Renew Sust Energy Rev 2014;29:325–35.
[35] Alemán-Nava GS, Casiano-Flores VH, Cárdenas-Chávez DL, Díaz-Chavez R, Scarlat N, Mahlknecht J, Dallemand J, Parra R. Renewable energy research progress in Mexico: a review. Renew Sust Energy Rev 2014;32:140–53.
[36] Góralczyk M. Life-cycle assessment in the renewable energy sector. Appl Energy 2003;75(3):205–11.
[37] Ardente F, Beccali G, Cellura M, Brano VL. Life cycle assessment of a solar thermal collector. Renew Energy 2005;30(7):1031–54.
[38] Pehnt M. Dynamic life cycle assessment (LCA) of renewable energy technologies. Renew Energy 2006;31(1):55–71.

[39] Weisser D. A guide to life-cycle greenhouse gas (GHG) emissions from electric supply technologies. Energy 2007;32(9):1543–59.
[40] Stoppato A. Life cycle assessment of photovoltaic electricity generation. Energy 2008;33(2):224–32.
[41] Ginzburg B. Liquid fuel (oil) from halophilic algae: a renewable source of nonpolluting energy. Renew Energy 1993;3:249–52.
[42] Kandpal JB, Madan M. Jatropha curcus: a renewable source of energy for meeting future energy needs. Renew Energy 1995;6(2):159–60.
[43] Gunaseelan VN. Anaerobic digestion of biomass for methane production: a review. Biomass- Bioenergy 1997;13:83–114.
[44] Chynoweth DP, Owens JM, Legrand R. Renewable methane from anaerobic digestion of biomass. Renew Energy 2001;22:1–8.
[45] Koroneos C, Spachos T, Moussiopoulos N. Exergy analysis of renewable energy sources. Renew Energy 2003;28(2):295–310.
[46] Zoulias EI, Lymberopoulos N. Techno-economic analysis of the integration of hydrogen energy technologies in renewable energy-based stand-alone power systems. Renew Energy 2007;32(4):680–96.
[47] Beccali M, Brunone S, Cellura M, Franzitta V. Energy, economic and environmental analysis on RET-hydrogen systems in residential buildings. Renew Energy 2008;33(3):366–82.
[48] Akella AK, Saini RP, Sharma MP. Social, economical and environmental impacts of renewable energy systems. Renew Energy 2009;34(2):390–6.
[49] Kaldellis JK, Zafirakis D. Optimum energy storage techniques for the improvement of renewable energy sources-based electricity generation economic efficiency. Energy 2007;32(12):2295–305.
[50] Blarke MB, Lund H. The effectiveness of storage and relocation options in renewable energy systems. Renew Energy 2008;33(7):1499–507.
[51] Ibrahim H, Ilinca A, Perron J. Energy storage systems—characteristics and comparisons. Renew Sust Energy Rev 2008;12(5):1221–50.
[52] Carrasco JM, Franquelo LG, Bialasiewicz JT, Galvan E, PortilloGuisado RC, Prats MAM, Leon JI, Moreno-Alfonso N. Power electronic systems for the grid integration of renewable energy sources: a survey. IEEE Trans Ind Electron 2006;53(4):1002–16.
[53] Dalton GJ, Lockington DA, Baldock TE. Feasibility analysis of renewable energy supply options for a grid-connected large hotel. Renew Energy 2009;34(4):955–64.
[54] Ustun TS, Ozansoy C, Zayegh A. Recent developments in microgrids and example cases around the world—a review. Renew Sust Energy Rev 2011;15(8):4030–41.
[55] Urmee T, Harries D, Schlapfer A. Issues related to rural electrification using renewable energy in developing countries of Asia and Pacific. Renew Energy 2009;34(2):354–7.
[56] Zahnda A, Kimber HM. Benefits from a renewable energy village electrification system. Renew Energy 2009;34(2):362–8.
[57] Kanase-Patil AB, Saini RP, Sharma MP. Integrated renewable energy systems for off grid rural electrification of remote area. Renew Energy 2010;35(6):1342–9.

[58] Blaesser G. PV system measurements and monitoring the European experience. Sol Energy Mater Sol Cells 1997;47:167–76.
[59] Koutroulis E, Kalaitzakis K. Development of an integrated data-acquisition system for renewable energy sources systems monitoring. Renew Energy 2003;28(1):139–52.
[60] Kalaitzakis K, Koutroulis E, Vlachos V. Development of a data acquisition system for remote monitoring of renewable energy systems. Measurement 2003;34(2):75–83.
[61] Foreroa N, Hernándezb J, Gordillo G. Development of a monitoring system for a PV solar plant. Energy Convers Manag 2006;47:2329–36.
[62] Körbitz W. Biodiesel production in Europe and North America, an encouraging prospect. Renew Energy 1999;16:1078–83.
[63] Kaygusuz K, Kaygusuz A. Renewable energy and sustainable development in Turkey. Renew Energy 2002;25(3):431–53.
[64] Lu L, Yang H, Burnett J. Investigation on wind power potential on Hong Kong islands—an analysis of wind power and wind turbine characteristics. Renew Energy 2002;27(1):1–12.
[65] Nomura N, Akai M. Willingness to pay for green electricity in Japan as estimated through contingent valuation method. Appl Energy 2004;78(4):453–63.
[66] Sadrul-Islama AKM, Islam M, Rahman T. Effective renewable energy activities in Bangladesh. Renew Energy 2006;31(5):677–88.
[67] Ringe M. Fostering the use of renewable energies in the European Union: the race between feed-in tariffs and green certificates. Renew Energy 2006;31(1):1–17.
[68] Lund H, Mathiesen BV. Energy system analysis of 100% renewable energy systems—the case of Denmark in years 2030 and 2050. Energy 2009;34(5):524–31.
[69] Pillai IR, Banerjee R. Renewable energy in India: status and potential. Energy 2009;34(8):970–80.
[70] Ku S, Yoo S. Willingness to pay for renewable energy investment in Korea: a choice experiment study. Renew Sust Energy Rev 2010;14(8):2196–201.
[71] Voivontas D, Assimacopoulos D, Mourelatos A, Corominas J. Evaluation of renewable energy potential using a GIS decision support system. Renew Energy 1998;13(3):333–44.
[72] Haralambopoulos DA, Polatidis H. Renewable energy projects: structuring a multi-criteria group decision-making framework. Renew Energy 2003;6:961–73.
[73] Beccali M, Cellura M, Mistretta M. Decision-making in energy planning. Application of the Electre method at regional level for the diffusion of renewable energy technology. Renew Energy 2003;28(13):2063–87.
[74] Cristóbal JRS. Multi-criteria decision-making in the selection of a renewable energy project in Spain: the Vikor method. Renew Energy 2011;36(2):458–502.
[75] Dufo-Lópeza R, Bernal-Agustína JL, Contreras J. Optimization of control strategies for stand-alone renewable energy systems with hydrogen storage. Renew Energy 2007;32(7):1102–26.
[76] Ashok S. Optimised model for community-based hybrid energy system. Renew Energy 2007;32(7):1155–64.
[77] Senjyu T, Hayashi D, Yona A, Urasaki N, Funabashi T. Optimal configuration of power generating systems in isolated island with renewable energy. Renew Energy 2007;32(11):1917–33.

[78] Haidar AMA, John PN, Shawal M. Optimal configuration assessment of renewable energy in Malaysia. Renew Energy 2011;36(2):881–8.
[79] Morais H, Kádár P, Faria P, Vale ZA, Khodr HM. Optimal scheduling of a renewable micro-grid in an isolated load area using mixed-integer linear programming. Renew Energy 2010;35(1):151–6.
[80] Iqbal MT. Modeling and control of a wind fuel cell hybrid energy system. Renew Energy 2003;28(2):223–37.
[81] Deshmukh MK, Deshmukh SS. Modeling of hybrid renewable energy systems. Renew Sust Energy Rev 2008;12(1):235–49.
[82] Bernal-Agustín JL, Dufo-López R. Simulation and optimization of stand-alone hybrid renewable energy systems. Renew Sust Energy Rev 2009;13(8):2111–8.
[83] Lund H, Münster E. Modelling of energy systems with a high percentage of CHP and wind power. Renew Energy 2003;28(14):2189–93.
[84] Myers DR. Solar radiation modeling and measurements for renewable energy applications: data and model quality. Energy 2005;30(9):1517–31.
[85] Singh GK. Modeling and experimental analysis of a self-excited six-phase induction generator for stand-alone renewable energy generation. Renew Energy 2008;33(7):1605–21.
[86] Russel SJ, Norvig P. Artificial intelligence: a modern approach. New Jersey: Prentice Hall; 1995.
[87] Turban E, Frenzel LE. Expert systems and applied artificial intelligence. New Jersey: Prentice Hall; 1992.
[88] Kalogirou SA. Applications of artificial neural-networks for energy systems. Appl Energy 2000;67:17–35.
[89] Kalogirou SA. Artificial neural networks in renewable energy systems applications: a review. Renew Sust Energy Rev 2001;4(5):373–401.
[90] Mellita A, Kalogirou SA. Artificial intelligence techniques for photovoltaic applications: a review. Prog Energy Combust Sci 2008;34(5):574–632.
[91] Lei M, Shiyan L, Chuanwen J, Hongling L, Yan Z. A review on the forecasting of wind speed and generated power. Renew Sust Energy Rev 2009;13(4):915–20.
[92] Mellita A, Kalogirou SA, Hontoria L, Shaarid S. Artificial intelligence techniques for sizing photovoltaic systems: a review. Renew Sust Energy Rev 2009;13(2):406–19.
[93] Baños R, Manzano-Agugliaro F, Montoya FG, Gil C, Alcayde A, Gómez J. Optimization methods applied to renewable and sustainable energy: a review. Renew Sust Energy Rev 2011;15(4):1753–66.
[94] Zhao H, Magoulès F. A review on the prediction of building energy consumption. Renew Sust Energy Rev 2012;16(6):3586–92.
[95] Foley AM, Leahy PG, Marvuglia A, McKeogh EJ. Current methods and advances in forecasting of wind power generation. Renew Energy 2012;37(1):1–8.
[96] Burton T, Sharpe D, Jenkins N, Bossanyi E. Wind energy handbook. UK: John Wiley & Sons; 2001.
[97] Manwell JF, McGowan JG, Rogers AL. Wind energy explained: theory, design and application. UK: John Wiley & Sons; 2009.

[98] Fleming PD, Probert SD. The evolution of wind-turbines: an historical review. Appl Energy 1984;18:163–77.
[99] Pasqualetti MJ, Righter R, Gipe P. Wind energy, history of, encyclopedia energy; 2004, p. 419–33.
[100] Kaldellis JK, Zafirakis D. The wind energy (r)evolution: a short review of a long history. Renew Energy 2011;36(7):1887–901.
[101] World Wind Energy Reports 2006–2015. ⟨http://www.wwindea.org⟩.
[102] EWEA. Wind in power european statistics {C}2006–2015{C}. ⟨http://www.ewea.org/statistics⟩.
[103] Wittrup S. Power from vestas giant turbine. ⟨http://ing.dk/artikel/saaproducerer- vestas-gigantmoelle-stroem-165903⟩; 2014.
[104] Sesto E. Wind energy in the world: reality and prospects. Renew Energy 1999;16(7):888–93.
[105] Saidur R, Islam MR, Rahim NA, Solangi KH. A review on global wind energy policy. Renew Sust Energy Rev 2010;14(7):1744–62.
[106] Ackermann T, Söder L. Wind energy technology and current status: a review. Renew Sust Energy Rev 2000;4(4):315–74.
[107] Herbert GMS, Iniyan S, Sreevalsan E, Rajapandian S. A review of wind energy technologies. Renew Sust Energy Rev 2007;11(6):1117–45.
[108] Leung DYC, Yang Y. Wind energy development and its environmental impact: a review. Renew Sust Energy Rev 2012;16(1):1031–9.
[109] Pryor SC, Barthelmie RJ. Climate change impacts on wind energy: a review. Renew Sust Energy Rev 2010;14(1):430–7.
[110] Hasan NS, Hassan MY, Majid MS, Rahman HA. Review of storage schemes for wind energy systems. Renew Sust Energy Rev 2010;14(7):1744–62.
[111] Lu B, Li Y, Wu X, Yang Z. A review of recent advances in wind turbine condition monitoring and fault diagnosis. USA: IEEE PEMWA; 2009.
[112] Kreider JF, Kreith F. Solar energy handbook. NY: McGraw-Hill; 1981.
[113] Green MA. Solar cells: operating principles, technology, and system applications. NJ: Prentice-Hall; 1982.
[114] US Department of Energy, Energy Efficiency and Renewable Energy. ⟨https:// www1.eere.energy.gov/solar/pdfs/solar_timeline.pdf⟩.
[115] Parida B, Iniyan S, Goicc R. A review of solar photovoltaic technologies. Renew Sust Energy Rev 2011;15(3):1625–36.
[116] Balcomb JD. Passive solar building. Cambridge: MIT Press; 1992.
[117] Schaller RD, Klimov VI. High efficiency carrier multiplication in PbSe nanocrystals: implications for solar energy conversion. Phys Rev Lett 2004;92(18):186601.
[118] Mor GK, Varghese OK, Paulose M, Shankar K, Grimes CA. A review on highly ordered vertically oriented TiO2 nanotube arrays: fabrication, material properties, and solar energy applications. Sol Energy Mater Sol Cells 2006;90(14):2011–75.
[119] Granqvist CG. Transparent conductors as solar energy materials: a panoramic review. Sol Energy Mater Sol Cells 2007;17:1529–98.

[120] Mahian O, Kianifar A, Kalogirou SA, Pop I, Wongwises S. A review of the applications of nanofluids in solar energy. Int J Heat Mass Trans
2013;57(2):582–94.
[121] Solangi KH, Islam MR, Saidur R, Rahim NA, Fayaz H. A review on global solar energy policy. Renew Sust Energy Rev 2011;15(4):2149–63.
[122] Ekechukwu OV, Norton B. Review of solar-energy drying systems II: an overview of solar drying technology. Energy Convers Manag 1999;40(6):615–55.
[123] Blanco J, Malato S, Fernández-Ibañez P, Alarcón D, Gernjak W, Maldonado MI. Review of feasible solar energy applications to water processes. Renew Sust Energy Rev 2009;13(6):1437–45.
[124] Mekhilef S, Saidur R, Safari A. A review on solar energy use in industries. Renew Sust Energy Rev 2011;15(4):1777–90.
[125] N'Tsoukpoe KE, Liu H, Le Pierrès N, Luo L. A review on long-term sorption solar energy storage. Renew Sust Energy Rev 2009;13(9):2385–96.
[126] Sartori I, Hestnes AG. Energy use in the life cycle of conventional and low-energy buildings: a review article. Energy Build 2007;39(3):249–57.
[127] Khatib T, Mohamed A, Sopian K. A review of solar energy modeling techniques. Renew Sust Energy Rev 2012;16(5):2864–9.
[128] Fariba B, Dehghan AA, Faghih AR. Empirical models for estimating global solar radiation: a review and case study. Renew Sust Energy Rev 2013;21:798–821.
[129] Yadav AK, Chandel SS. Tilt angle optimization to maximize incident solar radiation: a review. Renew Sust Energy Rev 2013;23:503–13.
[130] Verma P, Singal SK. Review of mathematical modeling on latent heat thermal energy storage systems using phase-change material. Renew Sust Energy Rev 2008;12(4):999–1031.
[131] White DE. Geothermal energy. Bull Volcanol 1966;29(1):481–3.
[132] Armstead HCH. Geothermal energy: its past, present and future contributions to the energy needs of man. NY: Halsted Press; 1978.
[133] Dickson MH, Fanelli M. Geothermal energy: utilization and technology. Paris: UNESCO; 2003.
[134] Muffler LJP. Assessment of geothermal resources of the United States. Geol Surv Circ 1978;790.
[135] Barbier E. Nature and technology of geothermal energy: a review. Renew Sust Energy Rev 1997;1(1):1–69.
[136] Barbier E. Geothermal energy technology and current status: an overview. Renew Sust Energy Rev 2002;6(1):3–65.
[137] Lund JW, Freeston DH. World-wide direct uses of geothermal energy 2000. Geothermics 2001;30(1):29–68.
[138] Fridleifsson IB. Geothermal energy for the benefit of the people. Renew Sust Energy Rev 2001;5(3):299–312.
[139] Lund JW, Freeston DH, Boyd TL. Direct application of geothermal energy: 2005 worldwide review. Geothermics 2005;34(6):691–727.
[140] Menjoz A, Sauty JP. Characteristics and effects of geothermal resources exploitation. J Hydrol 1982;56:49–59.

[141] Rybach L. Geothermal energy: sustainability and the environment. Geothermics 2003;32:463–70.
[142] Haehnlein S, Bayer P, Blum P. International legal status of the use of shallow geothermal energy. Renew Sust Energy Rev 2010;14(9):2611–25.
[143] Hochstein MP. Assessment and modelling of geothermal reservoirs (small utilization schemes). Geothermics 1988;17(1):15–49.
[144] Pruess K. Modeling of geothermal reservoirs: fundamental processes, computer simulation and field applications. Geothermics 1990;19(1):3–15.
[145] O'Sullivan MJ, Pruess K, Lippmann MJ. State of the art of geothermal reservoir simulation. Geothermics 2001;30(4):395–429.
[146] Sherman Josepha. Hydroelectric power. USA: Capstone Press; 2004.
[147] Wagner H, Mathur J. Introduction to hydro energy systems: basics, technology and operation. Berlin: Springer-Verlag; 2011.
[148] Rupert CE. Hydropower: types, development strategies and environmental impacts (energy science, engineering and technology). NY: Nova Science; 2014.
[149] Deane JP, Ó Gallachóir BP, McKeogh EJ. Techno-economic review of existing and new pumped hydro energy storage plant. Renew Sust Energy Rev 2010;14(4):1293–302.
[150] Yanga C, Jackson RB. Opportunities and barriers to pumped-hydro energy storage in the United States. Renew Sust Energy Rev 2011;15(1):839–44.
[151] Yeh W. Reservoir management and operations models: a state-of-the-art review. Water Resour Res 1985;21(12):1797–818.
[152] Labadie J. Optimal operation of multireservoir systems: state-of-the-art review. J Water Resour Plan Manag 2004;130(2):93–111.
[153] Khan MJ, Bhuyan G, Iqbal MT, Quaicoe JE. Hydrokinetic energy conversion systems and assessment of horizontal and vertical axis turbines for river and tidal applications: a technology status review. Appl Energy 2009;86(10):1823–35.
[154] Khan MJ, Iqbal MT, Quaicoe JE. River current energy conversion systems: progress, prospects and challenges. Renew Sust Energy Rev 2008;12(8):2127–93.
[155] Padhy MK, Saini RP. A review on silt erosion in hydro turbines. Renew Sust Energy Rev 2008;12(7):1974–87.
[156] Mishra S, Singal SK, Khatod DK. Optimal installation of small hydropower plant— a review. Renew Sust Energy Rev 2011;15(8):3862–9.
[157] Sovacool BK, Dhakal S, Gippner O, Bambawale MJ. Halting hydro: a review of the socio-technical barriers to hydroelectric power plants in Nepal. Energy 2011;36(5):3468–76.
[158] Mailmana M, Stepnuk L, Cicek N, Bodaly RA. Strategies to lower methyl mercury concentrations in hydroelectric reservoirs and lakes: a review. Sci Total Environ 2006;368(1):224–35.
[159] Verma P, Varuna , Singal SK. Review of mathematical modeling on latent heat thermal energy storage systems using phase-change material. Renew Sust Energy Rev 2008;12(4):999–1031.
[160] Charlier RH, Finkl CW. Ocean energy: tide and tidal power. Berlin: Springer- Verlag; 2009.
[161] McCormick ME. Ocean wave energy conversion. NY: Dover Publication; 2007.

[162] Westwood A. Ocean power: wave and tidal energy review. Refocus 2004;5(5):50–5.
[163] Ferro BD. Wave and tidal energy: its emergence and the challenges it faces. Refocus 2006;7(3):46–8.
[164] Denny E. The economics of tidal energy. Energy Policy 2009;37(5):1914–24.
[165] Drew B, Plummer AR, Sahinkaya MN. A review of wave energy converter technology. J Power Energy 2009;223(8):887–902.
[166] Estebana M, Leary D. Current developments and future prospects of offshore wind and ocean energy. Appl Energy 2012;90(1):128–36.
[167] Large WG, McWilliams JC, Doney SC. Oceanic vertical mixing: a review and a model with a nonlocal boundary layer parameterization. Rev Geophy 1994;32(4):363–403.
[168] Khanal SK, Surampalli RY, Zhang TC, Lamsal BP, Tyagi RD, Kao CM. Bioenergy and biofuel from biowastes and biomass. USA: ASCE Publication; 2010.
[169] Lee S, Shah YT. Biofuels and bioenergy: processes and technologies. Boca Raton FL: CRC Press; 2013.
[170] Dahiya A. Bioenergy: biomass to biofuels. USA: Academic Press; 2015.
[171] Balat M, Balat H. Recent trends in global production and utilization of bio-ethanol fuel. Appl Energy 2009;86(11):2273–82.
[172] Mata TM, Martins AA, Caetano NS. Microalgae for biodiesel production and other applications: a review. Renew Sust Energy Rev 2010;14(1):217–32.
[173] Du Z, Li H, Gu T. A state of the art review on microbial fuel cells: a promising technology for wastewater treatment and bioenergy. Biotechnol Adv 2007;25(5):464–82.
[174] Karthikeyan OP, Visvanathan C. Bio-energy recovery from high-solid organic substrates by dry anaerobic bio-conversion processes: a review. Rev Environ Sci Biotechnol 2013;12:257–84.
[175] Mohan D, Pittman CU, Steele PH. Pyrolysis of wood/biomass for bio-oil: a critical review. Energy Fuel 2006;20(3):848–89.
[176] McKendry P. Energy production from biomass (part 2): conversion technologies. Bioresour Technol 2002;83(1):47–89.
[177] Gold S, Seuring S. Supply chain and logistics issues of bio-energy production. J Clean Prod 2011;19(1):32–42.
[178] Demirbas MF. Biorefineries for biofuel upgrading: a critical review. Appl Energy 2009;86(1):S151–S161.
[179] Faaij APC. Bio-energy in Europe: changing technology choices. Energy Policy 2006;34(3):322–42.
[180] Smeets EMW, Faaij APC, Lewandowski IM, Turkenburg WC. A bottom-up assessment and review of global bio-energy potentials to 2050. Prog Energy Combust 2007;33(1):56–106.
[181] Busby RL. Hydrogen and fuel cells: a comprehensive guide. Oklahoma: Pennwell; 2005.
[182] Drennen TE, Rosthal JE. Pathways to a hydrogen future. UK: Elsevier; 2007.
[183] Sherif SA, Goswami DY, Stefanakos EK, Steinfeld A. Handbook of hydrogen energy. NW: CRC Press; 2014.
[184] Momirlan M, Veziroglu TN. Current status of hydrogen energy. Renew Sust Energy Rev 2002;6(1):141–79.
[185] Bolton JR. Solar photoproduction of hydrogen: a review. Sol Energy 1996;57(1):37–50.

[186] Wang J, Wan W. Factors influencing fermentative hydrogen production: a review. Int J Hydrog Energy 2009;34(2):799–811.
[187] Sakintuna B, Lamari-Darkrim F, Hirscher M. Metal hydride materials for solid hydrogen storage: a review. Int J Hydrog Energy 2007;32(9):1121–40.
[188] Cheng X, Shi Z, Glass N, Zhang L, Zhang J, Song D, Liu Z, Wang H, Shen J. A review of PEM hydrogen fuel cell contamination: impacts, mechanisms, and mitigation. J Power Sources 2007;165(2):739–56.
[189] Midilli A, Aya M, Dincer I, Rosen MA. On hydrogen and hydrogen energy strategies: i: current status and needs. Renew Sust Energy Rev 2005;9(3):255–71.
[190] Nicoletti G. The hydrogen option for energy: a review of technical, environmental and economic aspects. Int J Hydrog Energy 1995;20(10):759–65.
[191] Hunter R, Elliot G. Wind-diesel systems: a guide to the technology and its implementation. NY: Cambridge University Press; 1994.
[192] Al-Hallaj S, Kiszynski K. Hybrid hydrogen systems: stationary and transportation applications. London: Springer-Verlag; 2011.
[193] Agrawal A, Wies R, Johnson R. Hybrid electric power systems: modeling, optimization and control. Germany: VDM Publishing; 2007.
[194] Bajpai P, Dash V. Hybrid renewable energy systems for power generation in stand-alone applications: a review. Renew Sust Energy Rev 2012;16(5):2926–39.
[195] Nehrir MH, Wang C, Strunz K, Aki H, Ramakumar R, Bing J, Miao Z, Salameh Z. A review of hybrid renewable/alternative energy systems for electric power generation: configurations, control, and applications. IEEE Trans Sust Energy 2011;2(4):392–403.
[196] Erdinc O, Uzunoglu M. Optimum design of hybrid renewable energy systems: overview of different approaches. Renew Sust Energy Rev 2012;16(3):1412–25.
[197] Nema P, Nema RK, Rangnekar S. A current and future state of art development of hybrid energy system using wind and PV-solar: a review. Renew Sust Energy Rev 2009;13(8):2096–103.
[198] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Appl Energy 2010;87(4):1059–82.
[199] Etxeberria A, Vechiu I, Camblong H, Vinassa JM, Camblong H. Hybrid energy storage systems for renewable energy sources integration in microgrids: a review.
In: Proceedings IPEC; 2010, p. 1947–1262.
[200] Bhandari B, Poudel SR, Lee K, Ahn S. Mathematical modeling of hybrid renewable energy system: a review on small hydro-solar-wind power generation. Int J Precis Eng Manuf Green Technol 2014;1(2):157–73.
[201] Michalski RS, Carbonell JG, Mitchell TM. Machine learning: an artificial intelligence approach. Berlin: Springer-Verlag; 1984.
[202] Hayes-Roth F, Waterman D, Lenat D. Building expert systems. USA: Addison- Wesley; 1984.
[203] Jackson P. Introduction to expert systems. USA: Addison-Wesley; 1986.
[204] Poole D, Mackworth A. Artificial intelligence foundation of computational agents. UK: Cambridge University Press; 2010.

[205] Russsell S, Norvig P. Artificial intelligence, a modern approach, 3rd ed.. UK: Pearson; 2014.
[206] Smolensky P. Connectionist AI, symbolic AI, and the brain. AI Rev 1987;1(2):95–109.
[207] Reed RD, Marks RJ. Neural smithing: supervised learning in feedforward artificial neural networks. USA: MIT Press; 1998.
[208] Vapnik V. The nature of statistical learning theory. NY: Springer-Verlag; 2013.
[209] Fogel DB. Evolutionary computation: toward a new philosophy of machine intelligence. New Jersey: IEEE Press; 2006.
[210] Cordón O. Genetic fuzzy systems: evolutionary tuning and learning of fuzzy knowledge bases. Singapore: World Scientific; 2001.
[211] Colak I, Sagiroglu S, Yesilbudak M. Data mining and wind power prediction: a literature review. Renew Energy 2012;46:241–7.
[212] Zhang Y, Wang J, Wang X. Review on probabilistic forecasting of wind power generation. Renew Sust Energy Rev 2014;32:255–70.
[213] Tascikaraoglu A, Uzunoglu M. A review of combined approaches for prediction of short-term wind speed and power. Renew Sust Energy Rev 2014;34:243–54.
[214] Mabel MC, Fernandez E. Analysis of wind power generation and prediction using ANN: a case study. Renew Energy 2008;33(5):986–92.
[215] Li G, Shi J. On comparing three artificial neural networks for wind speed forecasting. Appl Energy 2010;87(7):2313–20.
[216] Mabel MC, Fernandez E. Estimation of energy yield from wind farms using artificial neural networks. IEEE Trans Energy Convers 2009;24(2):459–64.
[217] Kariniotakis GN, Stavrakakis GS, Nogaret EF. Wind power forecasting using advanced neural networks models. IEEE Trans Energy Convers 2002;11(4):762–7.
[218] Öztopal A. Artificial neural network approach to spatial estimation of wind velocity data. Energy Convers Manag 2006;47(4):395–406.
[219] Alexiadis MC, Dokopoulos PS, Sahsamanoglou HS. Wind speed and power forecasting based on spatial correlation models. IEEE Trans Energy Convers 1999;14(3):836–42.
[220] Li G, Shi J, Zhou J. Bayesian adaptive combination of short-term wind speed forecasts from neural network models. Renew Energy 2011;36(1):352–9.
[221] Sfetsos A. A comparison of various forecasting techniques applied to mean hourly wind speed time series. Renew Energy 2000;21(1):23–35.
[222] Cadenas E, Jaramillo OA, Rivera W. Analysis and forecasting of wind velocity in chetumal, quintana roo, using the single exponential smoothing method. Renew Energy 2010;35(5):925–30.
[223] Simoes MG, Bose BK, Spiegel RJ. Design and performance evaluation of a fuzzylogic-based variable-speed wind generation system. IEEE Trans Ind Appl 1997;33(4):956–65.
[224] Sideratos G, Hatziargyriou ND. An advanced statistical method for wind power forecasting. IEEE Trans Power Syst 2007;22(1):258–65.
[225] Monfared M, Rastegar H, Kojabadi HM. A new strategy for wind speed forecasting using artificial intelligent methods. Renew Energy 2009;34(3):845–8.

[226] Juban J, Siebert N, Kariniotakis GN. Probabilistic short-term wind power forecasting for the optimal management of wind generation. In: Proceedings IEEE Power Tech; 2007, p. 683–5.
[227] Mohandes MA, Halawani TO, Rehman S, Hussain AA. Support vector machines for wind speed prediction. Renew Energy 2004;29(6):939–47.
[228] Potter CW, Negnevitsky M. Very short-term wind forecasting for Tasmanian power generation. IEEE Trans Power Syst 2006;21(2):965–72.
[229] Mohandes M, Rehman S, Rahman SM. Estimation of wind speed profile using adaptive neuro-fuzzy inference system (ANFIS). Appl Energy 2011;88(11):4024–32.
[230] Yang Z, Liu Y, Li C. Interpolation of missing wind data based on ANFIS. Renew Energ 2011;36(3):993–8.
[231] Meharrar A, Tioursi M, Hatti M, Stambouli AB. A variable speed wind generator maximum power tracking based on adaptative neuro-fuzzy inference system. Expert Syst Appl 2011;38(6):7659–64.
[232] Yang S, Li W, Wang C. The intelligent fault diagnosis of wind turbine gearbox based on artificial neural network. In: Proceedings CMD; 2008, p. 1327–1330.
[233] Jursa R, Rohrig K. Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models. Int J Forecast 2008;24(4):694–709.
[234] Guo Z, Zhao W, Lu H, Wang J. Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model. Renew Energy 2012;37(1):241–9.
[235] Pourmousavi-Kani SA, Ardehali MM. Very short-term wind speed prediction: a new artificial neural network–Markov chain model. Energy Convers Manag 2011;52(1):738–45.
[236] Damousis IG, Petros D. A fuzzy expert system for the forecasting of wind speed and power generation in wind farms. In: Proceedings 22nd IEEE PES; 2001, p. 63–69.
[237] Hu J, Wang J, Zeng G. A hybrid forecasting approach applied to wind speed time series. Renew Energy 2013;60(11):185–94.
[238] Cadenas E, Rivera W. Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA–ANN model. Renew Energy 2010;35(12):2732–8.
[239] Salcedo-Sanz S, Pérez-Bellido AM, Ortiz-García EG, Portilla-Figueras A, Prieto L, Paredes D. Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction. Renew Energy 2009;34(6):1451–7.
[240] Liu D, Niu D, Wang H, Fan L. Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm. Renew Energy 2014;62:592–7.
[241] Kong X, Liu X, Shi R, Lee KY. Wind speed prediction using reduced support vector machines with feature selection. Neurocomputing 2015;169(2):449–56.
[242] Rahmani R, Yusof R, Seyedmahmoudian M, Mekhilef S. Hybrid technique of ant colony and particle swarm optimization for short term wind energy forecasting. J Wind Eng Ind Aerodyn 2013;123:163–70.
[243] Pousinho HMI, Mendes VMF, Catalão JPS. A risk-averse optimization model for trading wind energy in a market environment under uncertainty. Energy 2011;36(8):4935–42.

[244] Dounis AI, Caraiscos C. Advanced control systems engineering for energy and comfort management in a building environment—a review. Renew Sust Energy Rev 2009;13(6):1246–61.
[245] Mellit A. Artificial Intelligence technique for modelling and forecasting of solar radiation data: a review. Inter J Artif Intell Soft Comput 2008;1(1):52–76.
[246] Mellit A, Pavan AM. A 24-h forecast of solar irradiance using artificial neural network: application for performance prediction of a grid-connected PV plant at Trieste, Italy. Sol Energy 2010;84(5):807–21.
[247] Rehman S, Mohandes M. Artificial neural network estimation of global solar radiation using air temperature and relative humidity. Energy Policy 2008;36(2):571–6.
[248] Kalogirou SA, Panteliou S, Dentsoras A. Artificial neural networks used for the performance prediction of a thermosiphon solar water heater. Renew Energy 1999;18(1):87–99.
[249] Alam S, Kaushik SC, Garg SN. Computation of beam solar radiation at normal incidence using artificial neural network. Renew Energy 2006;31(10):1483–91.
[250] Dombayci OA, Gölcü M. Daily means ambient temperature prediction using artificial neural network method: a case study of Turkey. Renew Energy 2009;34(4):1158–61.
[251] Bosch JL, López G, Batlles FJ. Daily solar irradiation estimation over a mountainous area using artificial neural networks. Renew Energy 2008;33(7):1622–8.
[252] Almonacid F, Fernández EF, Rodrigo P, Pérez-Higueras PJ, Rus-Casas C. Estimating the maximum power of a high concentrator photovoltaic (HCPV) module using an artificial neural network. Energy 2013;53(1):165–72.
[253] Mubiru J, Banda EJKB. Estimation of monthly average daily global solar irradiation using artificial neural networks. Sol Energy 2008;82(2):181–7.
[254] Kalogirou SA. Long-term performance prediction of forced circulation solar domestic water heating systems using artificial neural networks. Appl Energy 2000;66(1):63–74.
[255] Fadare DA. Modelling of solar energy potential in Nigeria using an artificial neural network model. Appl Energy 2009;86(9):1410–22.
[256] Kalogirou SA, Bojic M. Artificial neural networks for the prediction of the energy consumption of a passive solar building. Energy 2000;25(5):479–91.
[257] Ekici BB, Aksoy UT. Prediction of building energy consumption by using artificial neural networks. Avd Eng Softw 2009;40(5):356–62.
[258] Tasadduq I, Rehman S, Bubshait K. Application of neural networks for the prediction of hourly mean surface temperatures in Saudi Arabia. Renew Energy 2002;25(4):545–54.
[259] Alam S, Kaushik SC, Garg SN. Assessment of diffuse solar energy under general sky condition using artificial neural network. Appl Energy 2009;86(4):554–64.
[260] Tymvios FS, Jacovides CP, Michaelides SC, Scouteli C. Comparative study of Ångström's and artificial neural networks' methodologies in estimating global solar radiation. Sol Energy 2005;78(6):752–62.
[261] Jiang Y. Computation of monthly mean daily global solar radiation in China using artificial neural networks and comparison with other empirical models. Energy 2009;34(9):1276–83.

[262] Zeng J, Qiao W. Short-term solar power prediction using a support vector machine. Renw Energy 2013;52:118–27.
[263] Li Z, Rahman SMM, Vega R, Dong B. A hierarchical approach using machine learning methods in solar photovoltaic energy production forecasting. Energies 2016;9(1):2–12.
[264] Sharma N, Sharma P, Irwin D, Shenoy P. Predicting solar generation from weather forecasts using machine learning. In: Proceedings IEEE Smart Grid Communication; 2011, p. 528–33.
[265] Mashohor S, Samsudin K, Noor AM, Rahman ARA. Evaluation of genetic algorithm based solar tracking system for photovoltaic panels. In: Proceedings IEEE ICSET Singapore; 2008, p. 269–73.
[266] Atia DM, Fahmy FH, Ahmed NM, Dorrah HT. Optimal sizing of a solar water heating system based on a genetic algorithm for an aquaculture system. Math Comput Model 2012;55(3):1436–49.
[267] Kumar P, Jain G, Palwalia DK. Genetic algorithm based maximum power tracking in solar power generation. In: IEEE ICPACE Bangalore; 2015, p. 1–6.
[268] Souliotis M, Kalogirou S, Tripanagnostopoulos Y. Modelling of an ICS solar water heater using artificial neural networks and TRNSYS. Renew Energy 2009;34(5):1333–9.
[269] Monteiro C, Santos T, Fernandez-Jimenez LA, Ramirez-Rosado IJ, Terreros- Olarte MS. Short-term power forecasting model for photovoltaic plants based on historical similarity. Energies 2013;6:2624–43.
[270] Mellit A, Benghanem M, Arab AH, Guessoum A. An adaptive artificial neural network model for sizing stand-alone photovoltaic systems: application for isolated sites in Algeria. Renew Energy 2009;34(5):1333–9.
[271] Mellit A, Benghanem M, Kalogirou SA. An adaptive wavelet-network model for forecasting daily total solar-radiation. Appl Energy 2006;83(7):705–22.
[272] Pedro HTC, Coimbra CFM. Assessment of forecasting techniques for solar power production with no exogenous inputs. Sol Energy 2012;86(7):2017–28.
[273] Mandal P, Madhira STS, Ul-haque A, Meng J, Pineda RL. Forecasting power output of solar photovoltaic system using wavelet transform and artificial intelligence techniques. Procedia Comput Sci 2012;12:332–7.
[274] Kalogirou SA. Optimization of solar systems using artificial neural-networks and genetic algorithms. Appl Energy 2004;77(4):383–405.
[275] Mellit A, Kalogirou SA. ANFIS-based modelling for photovoltaic power supply system: a case study. Renew Energy 2011;36(1):250–8.
[276] Zarzalejo LF, Ramirez L, Polo J. Artificial intelligence techniques applied to hourly global irradiance estimation from satellite-derived cloud index. Energy 2005;30(9):1685–97.
[277] Mellit A, Kalogirou SA, Shaari S, Salhi H, Arab AH. Methodology for predicting sequences of mean monthly clearness index and daily solar radiation data in remote areas: application for sizing a stand-alone PV system. Renew Energy 2008;33(7):1570–90.
[278] Mellit A, Kalogirou SA. Neuro-Fuzzy based modeling for photovoltaic power supply system. In: Proceedings IEEE PES Putra; 2006, p. 1–6.

[279] Mellit A, Arab AH, Khorissi N, Salhi H. An ANFIS-based forecasting for solar radiation data from sunshine duration and ambient temperature. In Proceedings IEEE PES Tampa; 2007, p. 1–6.
[280] Amirkhani S, Nasirivatan S, Kasaeian AB, Hajinezhad A. ANN and ANFIS models to predict the performance of solar chimney power plants. Renew Energy 2015;83:579–607.
[281] Caputo D, Grimaccia F, Mussetta M, Zich RE. Photovoltaic plants predictive model by means of ANN trained by a hybrid evolutionary algorithm. In: Proceedings IEEE JCNN Barcelona; 2010, p.1–6.
[282] Ji W, Chee KC. Prediction of hourly solar radiation using a novel hybrid model of ARMA and TDNN. Sol Energy 2011;85(5):808–17.
[283] Ogliari E, Grimaccia F, Leva S, Mussetta M. Hybrid predictive models for accurate forecasting in PV systems. Energies 2013;6(4):1918–29.
[284] Bouzerdoum M, Mellit A, Pavan AM. A hybrid model (SARIMA–SVM) for shortterm power forecasting of a small-scale grid-connected photovoltaic plant. Sol Energy 2013;98:226–35.
[285] Olatomiwa L, Mekhilef S, Shamshirband S, Mohammadi K, Petkovic´ D, Sudheer C. A support vector machine–firefly algorithm-based model for global solar radiation prediction. Sol Energy 2015;115(9):632–44.
[286] Satrape JV Potential impacts of artificial intelligence expert systems on geothermal well drilling costs. Technical Report; 87: AC03-86SF16299.
[287] Pruess K. Modeling of geothermal reservoirs: fundamental processes, computer simulation and field applications. Geothermics 1990;19(1):3–15.
[288] Sanyal SK, Butler SJ, Swenson D, Hardeman B. Review of the state-of-the art of numerical simulation of enhanced geothermal systems. In: Proceedings WGC Japan; 2000, p. 3853–8.
[289] O'Sullivan MJ, Pruess K, Lippmann MJ. State of the art of geothermal reservoir simulation. Geothermics 2001;30:395–429.
[290] O'Sullivan MJ, Yeh A, Mannington WI. A history of numerical modelling of the Wairakei geothermal field. Geothermics 2009;38:155–68.
[291] Esen H, Inalli M. Modelling of a vertical ground coupled heat pump system by using artificial neural networks. Expert Syst Appl 2009;36:10229–38.
[292] Bassam A, Santoyo E, Andaverde J, Herna´ndez JA, Espinoza-Ojeda OM. Estimation of static formation temperatures in geothermal wells by using an artificial neural network approach. Comput Geosci 2010;36:11919.
[293] Arslan O. Power generation from medium temperature geothermal resources: ann-based optimization of Kalina cycle system-34. Energy 2011;36:2528–34.
[294] Arslan O, Yetik O. ANN based optimization of supercritical ORC-Binary geothermal power plant: simav case study. Appl Therm Eng 2011;31:3922–8.
[295] Kalogirou SA, Florides GA, Pouloupatis PD, Panayides I, Joseph-Stylianou J, Zomeni Z. Artificial neural networks for the generation of geothermal maps of ground temperature at various depths by considering land configuration. Energy 2012;48:233–40.
[296] Kecebas A, Yabanova I. Thermal monitoring and optimization of geothermal district heating systems using artificial neural network: a case study. Energy Build 2012;50:339–46.

[297] A´ lvarez del Castillo A, Santoyo E, Garcı´a-Valladares O. A new void fraction correlation inferred from artificial neural networks for modeling two-phase flows in geothermal wells. Comput Geosci 2012;41:25–39.
[298] Tota-Maharaj K, Scholz M. Artificial neural network simulation of combined permeable pavement and earth energy systems treating storm water. J Environ Eng 2012;138:499–509.
[299] Yabanova I, Keçebas A. Development of ANN model for geothermal district heating system and a novel PID-based control strategy. Appl Therm Eng 2013;51:908–16.
[300] Arslan O, Yetik O. ANN modeling of an ORC-binary geothermal power plant: Simav case study. Energy Sources Part A 2014;36:418–28.
[301] Yeo I, Yee J. A proposal for a site location planning model of environmentally friendly urban energy supply plants using an environment and energy geographical information system (E-GIS) database (DB) and an artificial neural network (ANN). Appl Energy 2014;119:99–117.
[302] Kalogirou SA, Florides GA, Pouloupatis PD, Christodoulides P, Joseph-Stylianou J. Artificial neural networks for the generation of a conductivity map of the ground. Renew Energy 2015;77:400–7.
[303] Bassam A, Álvarez del Castillo A, García-Valladares O, Santoyo E. Determination of pressure drops in flowing geothermal wells by using artificial neural networks and wellbore simulation tools. Appl Therm Eng 2013;51:908–16.
[304] Sayyaadi H, Amlashi EH, Amidpour M. Multi-objective optimization of a vertical ground source heat pump using evolutionary algorithm. Energy Convers Manag 2009;50:2035–46.
[305] Beck M, de Paly M, Hecht-Méndez J. Evaluation of the performance of evolutionary algorithms for optimization of low-enthalpy geothermal heating plants. In: Proceedings GECCO USA; 2012, p. 1047–54.
[306] Farghally HM, Atia DM, El-madany HT, Fahmy FH. Control methodologies based on geothermal recirculating aquaculture system. Energy 2014;78:826–33.
[307] Farghally HM, Atia DM, El-madany HT, Fahmy FH. Fuzzy logic controller based on geothermal recirculating aquaculture system. Egypt J Aquat Res 2014;40:103–9.
[308] Esen H, Inalli M. ANN and ANFIS models for performance evaluation of a vertical ground source heat pump system. Expert Syst Appl 2010;37:8134–47.
[309] Şahin AS, Yazıcı H. Thermodynamic evaluation of the Afyon geothermal district heating system by using neural network and neuro-fuzzy. J Volcanol Geotherm Res 2012;233–234:65–71.
[310] Porkhial S, Salehpour M, Ashraf H, Jamalic A. Modeling and prediction of geothermal reservoir temperature behavior using evolutionary design of neural networks. Geothermics 2015;53:320–7.
[311] Kishor N, Saini RP, Singh SP. A review on hydropower plant models and control. Renew Sust Energy Rev 2007;11:776–96.
[312] Nourani V, Baghanam AH, Adamowski J, Kisi O. Applications of hybrid wavelet–Artificial Intelligence models in hydrology: a review. J Hydrol 2014;514(6):358–77.
[313] Liang RH, Hsu YY. Scheduling of hydroelectric generations using artificial neural networks. IEE Proc Gener Transm Distrib 1994;141(5):452–8.

[314] Smith J, EIi RN. Neural network models of rainfall-runoff process. J Water Resour Plan Manag 1995;121:499–508.
[315] Dolling OR, Varas EA. Artificial neural networks for streamflow prediction. J Hydraul Res 2002;40(5):547–54.
[316] Kişi Ö. River flow modeling using artificial neural networks. J Hydrol Eng 2004;9(1):60–3.
[317] Estoperez N, Nagasaka K. A month ahead micro-hydro power generation scheduling using artificial neural network. In: Proceedings IEEE PES; 2005, p. 28–34.
[318] Carneiro AAFM, Leite PT, Filho DS, Carvalho ACPLF. Genetic algorithms applied to hydrothermal system scheduling. In: Proceedings IEEE ICPST China; 2005, p. 547–51.
[319] Gil E, Bustos J, Rudnick H. Short-term hydrothermal generation scheduling model using a genetic algorithm. IEEE Trans Power Syst 2003;18(4):1256–64.
[320] Yuan X, Zhang Y, Yuan Y. Improved self-adaptive chaotic genetic algorithm for hydrogeneration scheduling. J Water Resour Plan Manag 2008;134:319–25.
[321] Adhikary P, Roy PK, Mazumdar A. Selection of penstock material for small hydro power project – a fuzzy logic approach. Int J Adv Sci Technol Res 2012;2(6):521–8.
[322] Chang L, Chang F. Intelligent control for modelling of real-time reservoir operation. Hydrol Process 2001;15:1621–34.
[323] Firat M, Gungor M. River flow estimation using adaptive neuro fuzzy inference system. Math Comput Simul 2007;75:87–96.
[324] Molina JM, Isasi P, Berlanga A, Sanchis A. Hydroelectric power plant management relying on neural networks and expert system integration. Eng Appl Artif Intell 2000;13:357–69.
[325] Sinha SK, Patel RN, Prasad R. Application of GA and PSO tuned fuzzy controller for AGC of three area thermal-thermal-hydropower system. Int J Comput Theory Eng 2010;2(2):238–44.
[326] Toro CHF, Meire SG, Gálvez JF, Fdez-Riverola F. A hybrid artificial intelligence model for river flow forecasting. Appl Soft Comput 2013;13:3449–58.
[327] Uzlu E, Akpinar A, Özturk HT, Nacar S, Kankal M. Estimates of hydroelectric generation using neural networks with the artificial bee colony algorithm for Turkey. Energy 2014;69:638–47.
[328] Adam JA. Probing beneath the sea: sending vessels into environments too harsh for humans poses challenges in communications, artificial intelligence, and power-supply technology. IEEE Spectr 1985;22(4):55–64.
[329] Aartrijk ML, Tagliola CP, Adriaans PW. AI on the ocean: the RoboSail project. ECAI; 2002.
[330] Jain P, Deo MC. Neural networks in ocean engineering. Ships Offshore Struct 2006;1:25–35.
[331] Iglesias G, Carballo R. Wave resource in El Hierrodan Island towards energy selfsufficiency. Renew Energy 2011;36:689–98.
[332] Makarynskyy O, Makarynska D, Kuhn M, Featherstone WE. Predicting sea level variations with artificial neural networks at Hillarys Boat Harbour, Western Australia. Estuar Coast Shelf Sci. 2004;61:351–60.

[333] Londhe SN, Panchang V. One-day wave forecasts based on artificial neural networks. J Atmos Ocean Technol 2006;23:1593–603.
[334] Makarynskyy O, Makarynska D. Wave prediction and data supplementation with artificial neural networks. J Costa Res 2007;23(4):951–60.
[335] Toprak ZF, Cigizoglu HK. Predicting longitudinal dispersion coefficient in natural streams by artificial intelligence methods. Hydrol Process 2008;22:4106–29.
[336] Chen C, Lin J, Lee W, Chen C. Fuzzy control for an oceanic structure: a case study in time-delay TLP system. J Vib Control 2010;16(1):147–60.
[337] Ghorbani MA, Makarynskyy O, Shiri J, Makarynska D. Genetic programming for sea level predictions in an island environment. Int J Ocean Clim Syst 2010;1(1):27–36.
[338] Karimi S, Kisi O, Shiri J, Makarynskyy O. Neuro-fuzzy and neural network techniques for forecasting sea level in Darwin Harbor, Australia. Comput Geosci 2013;52:50–9.
[339] Malekmohamadi I, Ghiassi R, Yazdanpanah MJ. Wave hindcasting by coupling numerical model and artificial neural networks. Ocean Eng 2008;35:417–25.
[340] De-Paz JF, Bajo J, González A, Rodríguez S, Corchado JM. Combining case-based reasoning systems and support vector regression to evaluate the atmosphere– ocean interaction. Knowl Inf Syst 2012;30:155–77.
[341] Shabani N, Akhtari S, Sowlati T. Value chain optimization of forest biomass for bioenergy production: a review. Renew Sust Energy Rev 2013;23:2992, [311].
[342] Yang H, Ring Z, Briker Y, McLean N, Friesen W, Fairbridge C. Neural network prediction of cetane number and density of diesel fuel from its chemical composition determined by LC and GC–MS. Fuel 2002;81:65–74.
[343] Strik D, Domnanovich AM, Zani L, Braun R, Holubar P. Prediction of trace compounds in biogas from anaerobic digestion using the MATLAB neural network toolbox. Environ Model Softw 2005;20:803–10.
[344] Ramadhas AS, Jayaraj S, Muraleedharan C, Padmakumari K. Artificial neural networks used for the prediction of the cetane number of biodiesel. Renew Energy 2006;31:2524–33.
[345] Ozkaya B, Demir A, Bilgili MS. Neural network prediction model for the methane fraction in biogas from field-scale landfill bioreactors. Environ Modell Softw 2007;22:518–22.
[346] Balabin RM, Lomakina EI, Safieva RZ. Neural network (ANN) approach to biodiesel analysis: analysis of biodiesel density, kinematic viscosity, methanol and water contents using near infrared (NIR) spectroscopy. Fuel 2011;90:2007–15.
[347] Kumar S, Pai PS, Rao BRS. Radial-basis-function-network-based prediction of performance and emission characteristics in a bio diesel engine run on WCO ester. Adv Artif Intell 2012;2012:1–7.
[348] Balabin RM, Safieva RZ. Biodiesel classification by base stock type (vegetable oil) using near infrared spectroscopy data. Anal Chim Acta 2011;689:190–7.
[349] Izquierdo J, Minciardi R, Montalvo I, Robba M, Tavera M. Particle swarm optimization for the biomass supply chain strategic planning. In: Proceedings IEMSS; 2008, p. 1272–80.
[350] Ghugare SB, Tiwary S, Elangovan V, Tambe SS. Prediction of higher heating value of solid biomass fuels using artificial intelligence formalisms. Bioenergy Res 2014;7(2):681–92.

[351] Koutroumanidis T, Ioannou K, Arabatzis G. Predicting fuelwood prices in Greece with the use of ARIMA models artificial neural networks and a hybrid ARIMA ANN model. Energy Policy 2009;37:3627–34.
[352] Romeo LM, Gareta R. Fouling control in biomass boilers. Biomass- Bioenergy 2009;33:854–61.
[353] Qdais HA, Hani KB, Shatnawi N. Modeling and optimization of biogas production from a waste digester using artificial neural network and genetic algorithm. Resour Conserv Recycl 2010;54:359–63.
[354] Kana EBG, Oloke JK, Lateef A, Adesiyan MO. Modeling and optimization of biogas production on saw dust and other co-substrates using artificial neural network and genetic algorithm. Renew Energy 2012;46:27681.
[355] Petrone R, Zheng Z, Hissel D, Pera MC, Pianese C, Sorrentino M, Becherif M, Yousfi-Steiner N. A review on model-based diagnosis methodologies for PEMFCs. Int J Hydrog Energy 2013;38:7077–91.
[356] Zheng Z, Petrone R, Pera MC, Hissel D, Becherif M, Pianese C, Steiner NS, Sorrentino M. A review on non-model based diagnosis. Int J Hydrog Energy 2013;38:8914–26.
[357] Garg A, Vijayaraghavan A, Mahapatra SS, Tai K, Wonga CH. Performance evaluation of microbial fuel cell by artificial intelligence methods. Expert Syst Appl 2014;41:1389–99.
[358] Liu Y, Liu Y, Liu D, Cao T, Han S, Xu G. Design of CO2 hydrogenation catalyst by an artificial neural network. Comput Chem Eng 2001;25:1711–4.
[359] Ho T, Karri V, Lim D, Barret D. An investigation of engine performance parameters and artificial intelligent emission prediction of hydrogen powered car. Int J Hydrog Energy 2008;33:3837–46.
[360] Hatti M, Tioursi M. Dynamic neural network controller model of PEM fuel cell system. Int J Hydrog Energy 2009;34:5015–21.
[361] Chavez-Ramirez AU, Munoz-Guerrero R, Duron-Torres SM, Ferraro M, Brunaccini G, Sergi F, Antonucci V, Arriaga LB. High power fuel cell simulator based on artificial neural network. Int J Hydrog Energy 2010;35:12125–33.
[362] Ho T, Karri V. Basic tuning of hydrogen powered car and artificial intelligent prediction of hydrogen engine characteristics. Int J Hydrog Energy 2010;35:10004–12.
[363] Yap WK, Ho T, Karri V. Exhaust emissions control and engine parameters optimization using artificial neural network virtual sensors for a hydrogenpowered vehicle. Int J Hydrog Energy 2012;37:8704–15.
[364] Vijayaraghavan V, Garg A, Wong CH, Tai K, Bhalerao Y. Predicting the mechanical characteristics of hydrogen functionalized graphene sheets using artificial neural network approach. J Nanostruct Chem 2013;3:15.
[365] Marra D, Sorrentino M, Pianese C, Iwanschitz B. A neural network estimator of solid oxide fuel cell performance for on-field diagnostics and prognostics applications. J Power Sources 2013;241(1):320–9.
[366] Tardast A, Rahimnejad M, Najafpour G, Ghoreyshi A, Premier GC, Bakeri G, Oh S. Use of artificial neural network for the prediction of bioelectricity production in a membrane less microbial fuel cell. Fuel 2014;117:697–703.

[367] Ho T, Karri V. Fuzzy expert system to estimate ignition timing for hydrogen car. LNCS 2008;5264:5709.
[368] Flemming A, Adamy J. Modeling solid oxide fuel cells using continuous-time recurrent fuzzy systems. Eng Appl Artif Intell 2008;21:1289–300.
[369] Caux S, Hankache W, Fadel M, Hissel D. On-line fuzzy energy management for hybrid fuel cell systems. Int J Hydrog Energy 2010;35:2134–43.
[370] Caux S, Wanderley-Honda D, Hissel D, Fadel M. On-line energy management for HEV based on particle swarm optimization. In: Proceedings IEEE VPP FR; 2010, p. 1–7.
[371] Nath K, Das D. Modeling and optimization of fermentative hydrogen production. Bioresour Technol 2011;102:8569–81.
[372] Askarzadeh A, Rezazadeh A. A new heuristic optimization algorithm for modeling of proton exchange membrane fuel cell: bird mating optimizer. Int J Energy Res 2013;37(10):1196–204.
[373] Entchev E, Yang L. Application of adaptive neuro-fuzzy inference system techniques and artificial neural networks to predict solid oxide fuel cell performance in residential microgeneration installation. J Power Sources 2007;170:122–9.
[374] Ho T, Karri V, Madsen O. Artificial neural networks and neuro-fuzzy inference systems as virtual sensors for hydrogen safety prediction. Int J Hydrog Energy 2008;33:2857–67.
[375] Karri V, Ho TN. Predictive models for emission of hydrogen powered car using various artificial intelligent tools. Neural Comput Appl 2009;18:469–76.
[376] Becker S, Karri V. Predictive models for PEM-electrolyzer performance using adaptive neuro-fuzzy inference systems. Int J Hydrog Energy 2010;35:9963–72.
[377] Amirinejad M, Tavajohi-Hasankiadeh N, Madaeni SS, Navarra MA, Rafiee E, Scrosati B. Adaptive neuro-fuzzy inference system and artificial neural network modeling of proton exchange membrane fuel cells based on nanocomposite and recast Nafion membranes. Int J Energy Res 2013;37(4):347–57.
[378] Erdinc O, Vural B, Uzunoglu M. A wavelet-fuzzy logic based energy management strategy for a fuel cell/battery/ultra-capacitor hybrid vehicular power system. J Power Sources 2009;194:369–80.
[379] Minqiang P, Dehuai Z, Gang X. Temperature prediction of hydrogen producing reactor using SVM regression with PSO. J Comput 2010;5(3):388–93.
[380] Prakasham RS, Sathish T, Brahmaiah P. Imperative role of neural networks coupled genetic algorithm on optimization of biohydrogen yield. Int J Hydrog Energy 2011;36:4332–9.
[381] Bozorgmehri S, Hamedi M. Modeling and optimization of anode-supported solid oxide fuel cells on cell parameters via artificial neural network and genetic algorithm. Fuel Cells 2012;12(1):11–23.
[382] Zhang W, Wang N, Yang S. Hybrid artificial bee colony algorithm for parameter estimation of proton exchange membrane fuel cell. Int J Hydrog Energy 2013;38:5796–806.
[383] Luna-Rubio R, Trejo-Perea M, Vargas-Vazquez D, Rios-Moreno GJ. Optimal sizing of renewable hybrids energy systems: a review of methodologies. Sol Energy 2012;86:1077–88.

[384] Zhou W, Lou C, Li Z, Lu L, Yang H. Current status of research on optimum sizing of stand-alone hybrid solar–wind power generation systems. Appl Energy 2010;87:380–9.
[385] Fadaee M, Radzi MAM. Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: a review. Renew Sust Energy Rev 2012;16:3364–9.
[386] Al-Alawi A, Al-Alawi SM, Islam SM. Predictive control of an integrated PV-diesel water and power supply system using an artificial neural network. Renew Energy 2007;32:1426–39.
[387] Chavez-Ramirez AU, Vallejo-Becerra V, Cruz JC, Ornelas R, Orozco G, Munoz-Guerrero R, Arriaga LG. A hybrid power plant (solar-wind-hydrogen) model based in artificial intelligence for a remote-housing application in Mexico. Int J Hydrog Energy 2013;38:2641–55.
[388] Berrazouane S, Mohammedi K. Parameter optimization via cuckoo optimization algorithm of fuzzy controller for energy management of a hybrid power system. Energ Convers Manag 2014;78:652–60.
[389] Hakimi SM, Moghaddas-Tafreshi SM. Optimal sizing of a stand-alone hybrid power system via particle swarm optimization for Kahnouj area in south-east of Iran. Renew Energy 2009;34:1855–62.
[390] Zeng J, Li M, Liu JF, Wu J, Ngan HW. Operational optimization of a stand-alone hybrid renewable energy generation system based on an improved genetic algorithm. In: Proceedings IEEE PES MN; 2010, p. 16.
[391] Tudu B, Majumder S, Mandal KK, Chakraborty N. Optimal unit sizing of standalone renewable hybrid energy system using bees algorithm. In: Proceedings IEEE ICEAS Odisha; 2011, p. 1–6.
[392] Khatib T, Mohamed A, Sopian K. Optimization of a PV/wind micro-grid for rural housing electrification using a hybrid iterative/genetic algorithm: case study of Kuala Terengganu, Malaysia. Energy Build 2012;47:321–31.
[393] Nasiraghdam H, Jadid S. Optimal hybrid PV/WT/FC sizing and distribution system reconfiguration using multi-objective artificial bee colony (MOABC)
algorithm. Sol Energy 2012;86:3057–71.
[394] Hong Y, Lian R. Optimal sizing of hybrid wind/PV/diesel generation in a standalone power system using Markov-based genetic algorithm. IEEE Trans Power Del 2012;27(2):640–7.
[395] Maleki A, Askarzadeh A. Comparative study of artificial intelligence techniques for sizing of a hydrogen-based stand-alone photovoltaic/wind hybrid system. Int J Hydrog Energy 2014;39:9973–84.
[396] Rajkumar RK, Ramachandaramurthy VK, Yong BL, Chia DB. Techno-economical optimization of hybrid pv/wind/battery system using Neuro-Fuzzy. Energy 2011;36:5148–53.
[397] Natsheh EM, Albarbar A. Hybrid power systems energy controller based on neural network and fuzzy logic. Smart Grid Renew Energy 2013;4:187–97.
[398] Liu J, Wang X, Lu Y. A novel hybrid methodology for short-term wind power forecasting based on adaptive neuro-fuzzy inference system. Renew Energy 2017;103:620–9.

[399] Naderloo L, Javadikia H, Mostafaei M. Modeling the energy ratio and productivity of biodiesel with different reactor dimensions and ultrasonic power using ANFIS. Renew Sust Energy Rev 2017;70:56–64.
[400] Zou L, Wang L, Xia L, Lin A, Hu B, Zhu H. Prediction and comparison of solar radiation using improved empirical models and adaptive neuro-fuzzy inference systems. Renew Energy 2017;106:343–53.
[401] Dong Q, Sun Y, Li P. A novel forecasting model based on a hybrid processing strategy and an optimized local linear fuzzy neural network to make wind power forecasting: a case study of wind farms in China. Renew Energy 2017;102:241–57.
[402] Kavousi-Fard A. A hybrid accurate model for tidal current prediction. IEEE Trans Geosci Remote Sens 2017;55(1):112–8.
[403] Monjoly S, André M, Calif R, Soubdhan T. Hourly forecasting of global solar radiation based on multiscale decomposition methods: a hybrid approach. Energy 2017;119:288–98.
[404] Sepasi S, Reihani E, Howlader AM, Roose LR, Matsuura MM. Very short term load forecasting of a distribution system with high PV penetration. Renew Energy 2017;106:142–8.
[405] Chang GW, Lu HJ, Chang YR, Lee YD. An improved neural network-based approach for short-term wind speed and power forecast. Renew Energy 2017;105:301–11.
[406] Parvizimosaed M, Farmani F, Monsef H, Rahimi-Kian A. A multi-stage smart energy management system under multiple uncertainties: a data mining approach. Renew Energy 2017;102:178–89.
[407] Kermadi M, Berkouk EM. Artificial intelligence-based maximum power point tracking controllers for Photovoltaic systems: comparative study. Renew Sust Energy Rev 2017;69:369–86.
[408] Voyant C, Notton G, Kalogirou S, Nivet ML, Paoli C, Motte F, Fouilloy A. Machine learning methods for solar radiation forecasting: a review. Renew Energy 2017;105:569–82.
[409] Wasilewski J, Baczynski D. Short-term electric energy production forecasting at wind power plants in pareto-optimality context. Renew Sust Energy Rev 2017;69:177–87.
[410] Kumar A, Sah B, Singh AR, Deng Y, He X, Kumar P, Bansal RC. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. Renew Sust Energy Rev 2017;69:596–609.
[411] Messalti S, Harrag A, Loukriz A. A new variable step size neural networks MPPT controller: review, simulation and hardware implementation. Renew Sust Energy Rev 2017;68:221–33.
[412] Ramli MA, Twaha S, Ishaque K, Al-Turki YA. A review on maximum power point tracking for photovoltaic systems with and without shading conditions. Renew Sust Energy Rev 2017;67:144–59.
[413] Dileep G, Singh SN. Application of soft computing techniques for maximum power point tracking of SPV system. Sol Energy 2017;141:182–202. [414] Molina-Solana M, Ros M, Ruiz MD, Gómez-Romero J, Martin-Bautista MJ. Data science for building energy management: a review. Renew Sust Energy Rev 2017;70:598 609.
[415] Zhang J, Zhao L, Deng S, Xu W, Zhang Y. A critical review of the models used to estimate solar radiation. Renew Sust Energy Rev 2017;2017(70):314–29..

[416] Jha S, Bilalovic J, Jha A, Patel N, Zhang H,. "Renewable energy: Present research and future scope of Artificial Intelligence" Renewable and Sustainable Energy Reviews 77 (2017) 297–317 .