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Readiness of artificial intelligence technology for managing energy demands from renewable sources

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ABSTRACT

The use of artificial intelligence (AI) has gained tremendous popularity in recent years, and it has become ubiquitous for use in the energy sector. The newly emerging digitalised tools are reliant on the use of AI which offers seamless possibilities for improved connectivity across the energy supply chains, trade and end-use. In the near course, the integration of energy supply, demand and renewable sources into the power grid will be controlled autonomously and this will aid in swift decision-making processes. This review focuses on studies that highlight the realm of AI to benefit the energy sector as a key enabler to the growth of renewable energy sources from wind, solar, geothermal, ocean as well as hydrogen-based energy storage. The work presented here alludes to an AI based energy management approach in the context of CO_2-neutral hydrogen production and storage landscape. A major intended outcome of this review is that it would allow the readers to compare their AI efforts, ambitions, state-of-the-art applications, challenges, energy efficiency optimization, predictive maintenance control and global roles in policymaking for the renewable energy sector. Finally, observations and ideas for future research, enhancements and investigations through a summary of key discussions are also made.

1. Introduction

The production, distribution and management of sustainable energy are all integral to the global economy (Kishore et al., 2022). Reliance on fossil fuels will continue to adversely impact the climate change (Hu et al., 2019; Rasheed et al., 2021). The International Energy Agency has issued warning stating that the "Energy-related greenhouse gas (GHG) emissions would lead to considerable climate degradation with an average global warming of 6 °C" (Dincer and Acar, 2015).

The world can transform to be a safer place by using clean energy. Safe, sustainable, and environmentally friendly renewable energy sources are essential to the long-term existence of humans (Frankl et al., 2010). It is widely acknowledged that no single energy source has the ability to control and monopolize the global energy market. As a result, the energy-mix model—which makes use of combined resources that are available for use has gained widespread acceptance. The world's main energy sources have historically been fossil fuels such as natural gas, coal and oil (Mehta and Cooper, 2003, Verma and Goel, Verma et al., 2018). As of today, the renewable energy (RE) can be derived from wind, solar, hydro, geothermal, bio, ocean and hydrogen as well as their hybrid variants (Sorensen, 2017; Energy, 2014; Chalk and Miller, 2006). A schematic diagram showing broad category of these different renewable energy sources is shown in Fig. 1.

Knowledge Based Systems (KBS) were among the first AI applications. KBS used human knowledge, primarily in the form of rules, to help with decision-making and its earliest application was in materials selection (Watson and Marir, 1994; Matthews and Swift, 1983). It has since then transformed the use of AI based systems leading to the development of Industry 5.0 ready systems (Popov et al., 2022). Developments in the field of AI have transformed many sectors including healthcare, energy, aerospace, transport and manufacturing to list a few (Ahmad et al., 2021; Bose, 2017). With the use of deep-mind AI technology, Google has reduced its field device management expenses by 40% (Kaplan and Haenlein, 2020). Through the early detection of development prospects associated with the deployment of the Internet of Things (IoT) and the integration of renewables, AI can benefit the energy sector tremendously (Sodhro et al., 2019). Modern infrastructure, including cyber technologies, power electronics, supercomputers, information, and bi-directional control center-equipment connections are

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Abbreviations

AI	Artificial Intelligence
ACO	Ant colony optimization
ANFIS	Adaptive-network-based fuzzy inference system
ANN	Artificial neural network
BMO	Bird mating optimization
BPNN	Backpropagation neural network
CGP	Pola–Ribiere conjugate gradient
COE	Cost of energy
CPV	Concentrator photovoltaics
CS	Cuckoo search
CSP	Concentrated Solar Power
CBR	Case-based reasoning
DL	Deep Learning
FCHV	Fuel cell hybrid vehicles
FFNNs	Feed Forward Neural Networks
GA	Genetic algorithm
GC	Generation cost
GHG	Greenhouse Gas emissions
GSR	Global solar radiation
GRNN	Generalized regression neural network
HI	Human intelligence
HO	Hybrid optimization
HISIMI	HIstorical SImilar Mining
HCPS	Human-cyber-physical system
HCPV	High concentrator photovoltaic
HOMER	Hybrid optimization model for electric renewables
IBM	International Business Machines
IoT	Internet of things
IT	Information technology
KBS	Knowledge Based Systems
KNN	k-nearest neighbor
LEC	Levelized energy cost
LM	Levenberg–Marguardt
ML	Machine Learning
MLP	Multilayer perceptron
NWM	Numerical wave model
NPC	Net present cost
VGCHP	Vertical ground coupled heat pump
PEM	Proton exchange membrane
PSO	Particle swarm optimization
MPPT	Maximum power point tracking
PEMFCs	Proton exchange membrane fuel cell systems
PEMFC	Polymeric electrolyte membrane fuel cell
RMSE	Root mean square error
RE	Renewable energy
RES	Renewable energy sources
RBFNN	Radial basis function neural networks
SCG	Scaled conjugate gradient
SOC	Storage of charge
SFT	Static formation temperature
SVR	Support vector regression
SOFC	Solid oxide fuel cell
VST	Voltage stability index

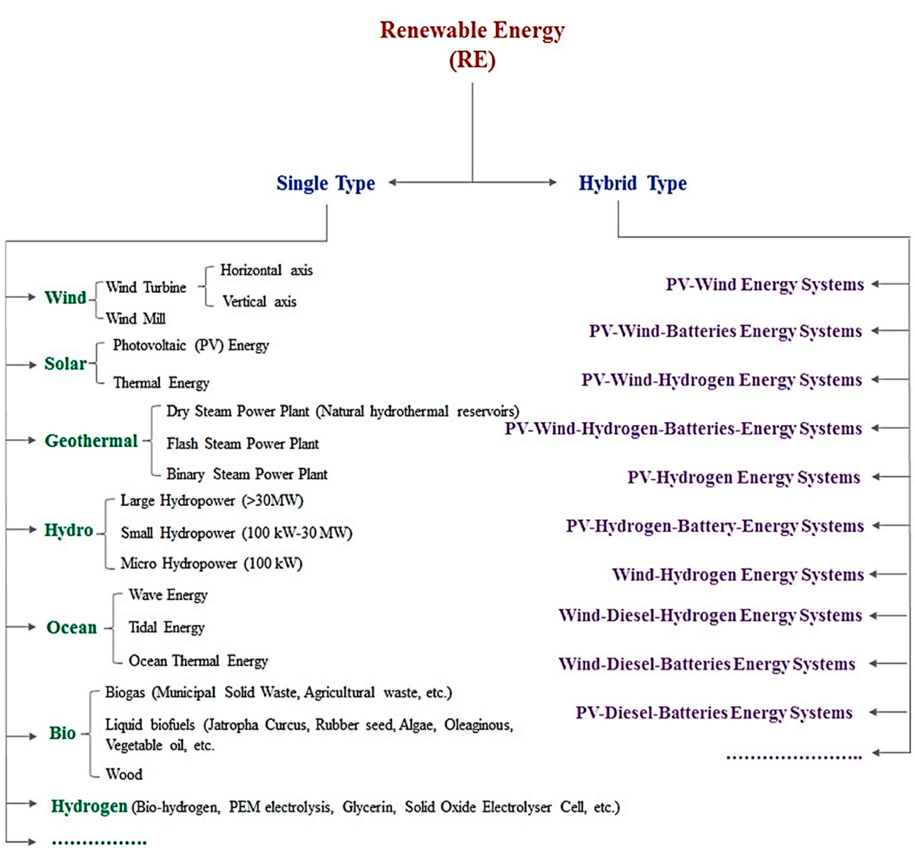


Fig. 1. Categories of renewable energy and their sources (Jha et al., 2017).

now abundantly available in the smart energy sector (Bose, 2017). This is particularly true in cases where the architecture of the current electrical grid is antiquated, ineffective and does not offer enough protection for prompt failure identification. However, the production of energy, the planning of its distribution, and the sustainability of its finances are vital to the world economy (Jha et al., 2017).

Renewable energy resources (RES) were not included in the traditional designs since awareness of their promotion emerged much later than the conventional power networks. Weather dependent variations in the generation of renewable energy made it more difficult to fulfill the needs of the power grid's changing loads. Lately, the energy sector has been undergoing a revolution thanks to AI technologies, such as big data, IoT, deep learning and machine learning. AI technology is now being used in various nations to carry out a variety of activities, including forecasting, controlling and effective power system operations (Kow et al., 2016). The use of AI enables efficient inverter control of photovoltaic (PV) systems (Youssef et al., 2017) and maximizes the ability to track power points (Seyedmahmoudian et al., 2015; Yang et al., 2019). Artificial maximum power point tracking (MPPT) techniques are efficient and can improve performance when compared to conventional MPPT techniques. Particle swarm optimization for MPPT is preferred in swarm intelligence courses because of its simple and fast capabilities (Miyatake et al., 2011). Prediction technologies are frequently used to estimate electricity pricing, load demand and the supply and demand of renewable energy sources (RES) such as wind, hydro, solar, and geothermal energy, as well as fossil fuels such as coal, oil, and natural gas. Probabilistic forecasting, such as predicting future events, or forecasting for distribution plans, different forms of investment programs, fuel purchase management, generation planning, maintenance schedules, and security objectives are examples of forecasting (Ranaweera et al., 1997). The role of AI in planning and forecasting load demand (Kong et al., 2017), solar energy (Rodríguez et al., 2020), wind energy (Ren et al., 2014) and hydro and geothermal energy (Debnath and Mourshed, 2018) is well documented. The forecast seeks to lower uncertainty and provide benchmarking for managing the actual performance of the power networks (Guo et al., 2018). A new generation of artificial intelligence technology has emerged that has the potential to significantly improve forecasting techniques for applications like product demand, labour turnover, cash flow, distribution requirements, personnel forecasts, and inventories, shown in Fig. 2.

Time is of the essence and this is the most opportunistic window where AI technology has risen to its prominence to transform various sectors, in particular the energy section. Considering this scenario, this review aims to enhance our understanding of the applications and implications of AI in the energy sector. Through this review, the readers are expected to gain major learning outcomes concerning the use of AI in the energy sector and how can this potentially be worked on to mitigate the issue of climate change. It is hoped that the funding agencies, research evaluators, academics and policymakers would work collaboratively on this diverse, developing and increasingly growing field to contribute to the development of full scale AI ready trustworthy, responsive and autonomous energy systems with self-decision making capabilities.

2. The history of AI in the smart energy industry

AI's past is built on examples, possibilities, and promises. AI research has been developing experimental devices to carry out various intelligent system functions for the energy sector since the 1950s. The Alan Turing Test was subsequently named after Alan Turing, who devised the "imitation game" idea in 1950. The term artificial intelligence was first used in 1956. In 1964, the List Processing program was introduced as a way to read and solve word problems involving mathematics. Between 1975 and 1980, there was a chilly time for the development of AI technology. This time frame revealed a lack of logic and processing power, as well as a lack of interest in AI and fewer funding prospects for new initiatives. The artificial neural network hypothesis initially gained traction in 1982. From 1990 to 2015, notable advancements in artificial intelligence (AI) gave rise to several well-known campaigns, such as the logistics planning for US military applications (Hoadley and Lucas, 2018), the IBM theory (Feigenbaum, 1963), the application of AI in vertical markets, new web designs, the introduction of the Google browser, image processing and face recognition, free online cutting-edge communication applications, and so forth.

TensorFlow, Caffe-2, and Lite Libraries have replaced cloud devices in AI in recent years, which has made it easier to solve complicated analytical problems. The energy supply is significantly enhanced by the availability of these AI digital technologies, which lead to better operation and maintenance costs, process efficiency, and equipment lifespan in addition to more sophisticated wind farm projections (Ahmad et al., 2021; Cozzi et al., 2020). Fig. 3a provides an exemplary representation of the major advancements in AI during the last many years. Although breakthroughs in AI have been made every ten years, after 2000, there has been a noticeable rise in the rate of progress. AI will run nearly every significant technical system in the coming years, including power systems, cybersecurity, financial markets, payment systems, nuclear power plants, electrical grids, the Internet of Things, logistics, manufacturing, building construction, and so forth.

Fig. 3b shows the impact of AI on energy and business sectors (Gerbert et al., 2017). Energy will keep having a significant impact on the economy in the near future. The influence of AI on energy enterprises across several industries is expected to exceed current expectations. The impact of AI technology on various business kinds over the next five years is covered by the portion of the red line in Fig. 3b. The "Effect of offerings" is represented by the horizontal axis, and the "Effect of processes" by the vertical axis. The "Effect of Processes" refers to a set of activities or procedures done to accomplish a given goal, whereas the "Effect of Offerings" offers enhanced opportunities and influence of AI in many areas (accept or reject as desired). The majority of enterprises

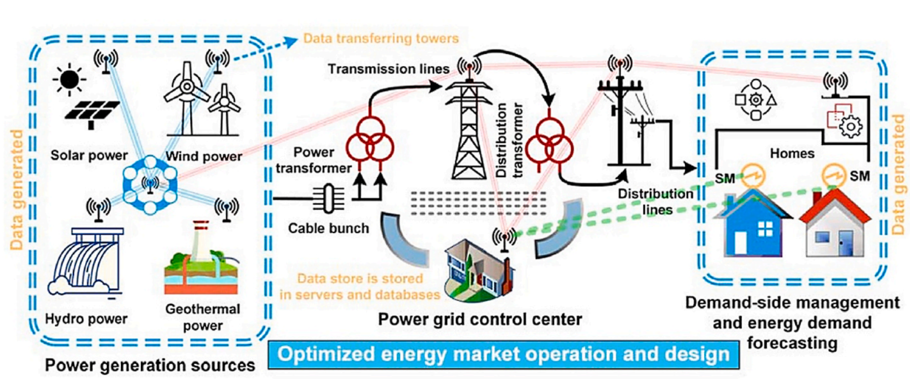
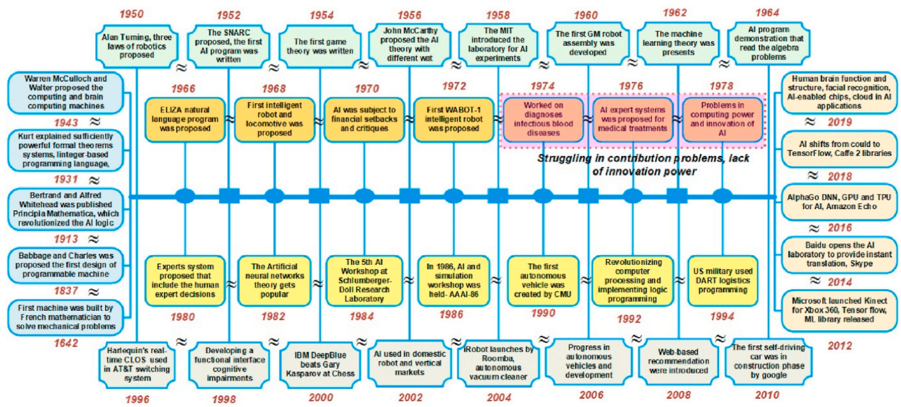
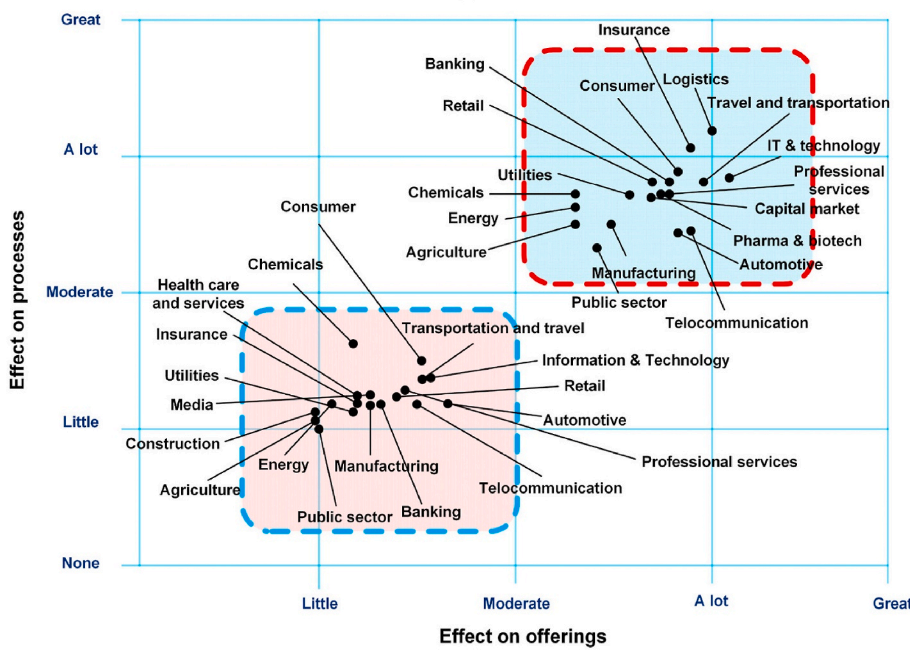


Fig. 2. AI applications in sustainable energy industry (Ahmad et al., 2021).



(a)



(b)

Fig. 3. (a) Evolutionary development in the field of AI (b) Impact of AI on energy and business sectors (Ahmad et al., 2021).

anticipate that AI will have a greater impact on supply chain management, manufacturing and operations, customer-focused activities, and energy information technology (IT). Industrial company executives anticipate a greater influence on the manufacturing, energy, and operations sectors (Ahmad et al., 2021).

Artificial intelligence has been widely used in smart controls of renewable energy systems because of its exceptional learning capability and quick convergence to adjust to changes in parameters and uncertainties in the model. Karabacak and Cetin (Karabacak et al., 2014) systematically reviewed ANN-based power point tracking applications of PV systems, and pitch controllers on wind turbine systems. The use of AI in smart controls for renewable energy systems, such as solar photovoltaic systems, wind turbines, and natural thermal energy systems, is summarized in Table 1. ANNs have been applied to MPPT in a variety of operational and meteorological scenarios (Veerachary and Yadaiah, 2000; Hiyama and Kitabayashi, 1997; Bahgat et al., 2005). According to reports, on a bright, sunny day, the output energy can be increased by roughly 45.2% when ANN is used for MPPT. When the wind speed is high, ANNs can be used in wind turbine systems to adjust the pitch angle through active pitch control. Furthermore, research has been done on the ANN-based MPPT with adjusted power coefficient to produce the greatest mechanical power tracking in both dynamic and steady states (Yilmaz and Özer, 2009). To achieve the greatest energy savings in natural thermal energy storage, smart charging and discharging on PCM storage was accomplished using the reinforcement learning technique (de Gracia et al., 2015; Patel et al., 2022). From the perspectives of control mechanisms, methods, and techniques, this section offers a comprehensive review of the uses of artificial intelligence in smart controls of renewable energy systems. Several significant obstacles are noted to provide insight for further investigation (Kumari and Tanwar, 2021b, Kumari and Tanwar, 2021a).

3. Role of AI in renewable energy sector

To create intelligent systems that can work effectively to tackle challenging issues, AI imitates human thought processes (Jha et al., 2017; Michalski et al., 2013; Hayes-Roth et al., 1983; Jackson, 1986). The advancement of AI lessens the need for human intervention while giving significant importance to past data and system performance (Poole and Mackworth, 2010; Katne et al., 2019; Smolensky, 1987). This can also be alluded to as "responsiveness" of the system. The natural brain is superior to AI in certain domains, but in others, AI has outperformed the human brain. AI is currently influencing several industries and sectors, such as manufacturing (Pan et al., 2021), finance,

Table 1
Application of AI in smart controls in renewable energy systems (Zhou et al., 2010)

Systems	Studies	Approaches/techniques	Control mechanisms	Results
PV	Veerachary and Yadaiah (Veerachary and Yadaiah, 2000)	Maximum power point tracking	Gradient descent algorithm to train the ANN controller and then identify the maximum power point of the solar cell array	The adaptive controller can be applied for different operating conditions with various solar insolation.
	Hiyama and Kitabayashi (Hiyama and Kitabayashi, 1997)		Accurate prediction on weather information	The proposed method can provide more accurate predictions than the conventional multiple regression model.
	Bahgata et al. (Bahgat et al., 2005)		ANN detects the optimal operating point under different operating conditions, to send driving signals to the MPPT	Both power output and operating periods can be increased by the MPPT. The output energy can be improved by about 45.2% for a clear sunny day.
Wind turbine	Ro and Choi (Ro and Choi, 2005)	A neural network (NN) based pitch control (active)	when the wind speed is much high, a blade pitch mechanism will be received and the rotor blade immediately pitches (turns) slightly out of the wind	Compared to a PI controller, the NN pitch controller shows much higher power extraction from wind.
	Mayosky et al. (Mayosky and Cancelo, 1999)	Adaptive controllers based on the combination of Gaussian networks and supervisor controller	Fast convergence to a simple linear dynamic behavior under parameter changes and model uncertainties	The approach is feasible and simple to be synthesized using fixed-point signal processors.
	Li et al. (Li et al., 2005)	ANN-based MPPT with compensated power coefficient	ANN for wind speed estimation and maximum wind power extraction	The controller shows superiority over traditional controllers, in terms of maximum mechanical power tracking in both dynamic and steady states, fast and accurate wind velocity without anemometers, and compensated power coefficient without extra sensors.
	Yilmaz and Özer (Yilmaz and Özer, 2009)	ANN-based pitch angle control	Multi-layer perceptions with back propagation learning algorithm and radial basis function network are adopted for pitch angle controllers	Overloading or outage of the wind turbine can be avoided, when the wind speed is high.
Natural cooling/ heating energy	Gracia et al. (de Gracia et al., 2015)	Reinforcement learning	Smart control on a ventilated façade for charging/discharging on PCM storages	Energy savings from control strategies can be noticed, in different climatic conditions.

accounting, information retrieval, healthcare (Popov et al., 2022), food quality, energy, biometrics, and forensics, among others. Production planning and distribution economics and industry are also affected by AI (Smolensky, 1987). Numerous learning theories, including statistical, neural, and evolutionary learning, are the foundation of AI (Jha et al., 2017). Neural learning is the most widely utilized of them. The most basic method of neural learning is the artificial neural network (ANN). Based on the theory of a mathematical model for a basic brain cell (neuron), the ANN was created in 1943. When the weighted sum of the input values is greater than a threshold, the neuron is activated and produces an output as a result of some active function. Since ANN can modify its values to correct errors in the output, it is an even more potent learning tool (Reed and MarksII, 1999).

A schematic illustration of the ANN model based on the mathematical neuron is shown in Fig. 4a. Radial basis function neural networks (RBFNN), feed-forward neural networks, and Kohonen self-organizing networks are some of the types of ANN (Sazli, 2006; McLean et al., 1998). In addition to brain learning, strategies based on statistical and evolutionary learning have also found practical utility. Among the statistical learning methods used in AI, clustering, hidden Markov model, Bayesian and naïve Bayes models are the most popular (Vapnik, 1999). Additionally, ant colony optimization (ACO), particle swarm optimization (PSO), genetic algorithms (GA), and bee algorithms are well-liked evolutionary learning techniques (Fogel, 2006). In recent years, hybrid artificial intelligence systems have also been employed in numerous applications to achieve more accuracy. A variety of hybrid artificial intelligence techniques are on the horizon, including but not limited to (i) Neuro-fuzzy, which combines artificial neural networks and fuzzy inference systems; (ii) Neuro-genetic, which combines ANN and genetic algorithms; and (iii) Fuzzy-genetic, which combines fuzzy inference systems and genetic algorithms (Cord, 2001). This work analyzed artificial intelligence strategies (Fig. 4b) used in renewable energy research, both single and hybrid. Table 2 describes the ANN techniques unique to each type of RE.

3.1. AI in wind energy

The role of AI in wind energy has been reviewed by various researchers (Lei et al., 2009; Foley et al., 2012; Colak et al., 2012; Zhang et al., 2014; Tascikaraoglu and Uzunoglu, 2014). Three primary categories of methodologies used are neural, statistical, and evolutionary learning, as well as their combination to create hybrid AI techniques (Li and Shi, 2010; Cadenas et al., 2010; Monfared et al., 2009). The majority of research focuses on leveraging AI's neural learning techniques to estimate wind power and speed. The Mabel research group used feed-forward backpropagation neural network (BPNN) to estimate the wind generation from seven wind farms over three years (Mabel and Fernandez, 2008). With a root mean square error (RMSE) of 0.0070 for the training data set and 0.0065 for the test data set, BPNN revealed exceptional prediction accuracy. In order to estimate wind speed from two separate locations, three distinct ANN methods—BPNN, RBFNN, and adaptive linear element network (ADALINE) were employed (Li and Shi, 2010). When the effectiveness of ANN approaches was examined in relation to the location of wind farms, it was found that, for one site, BPNN produced the best results (minimum RMSE 1.254), while, for another, the RBF method produced the best results (minimum RMSE 1.444) (Mabel and Fernandez, 2009). used trial and error to optimize the BPNN setup in order to estimate wind power. The optimal estimation (mean square error (MSE) $7.6 \times 10{-}3$) was produced by a $3 \times 5 \times 1$ ANN model with the wind speed, relative humidity, and generation hours as inputs. Additionally, a few statistical techniques were also covered (Juban et al., 2007; Mohandes et al., 2004).

A probabilistic approach was put up by (Juban et al., 2007) for estimating wind power in the short term. The process produced a predictive probability density function for estimate and was based on kernel density estimation. The model's dependability was between 2 and 4%,

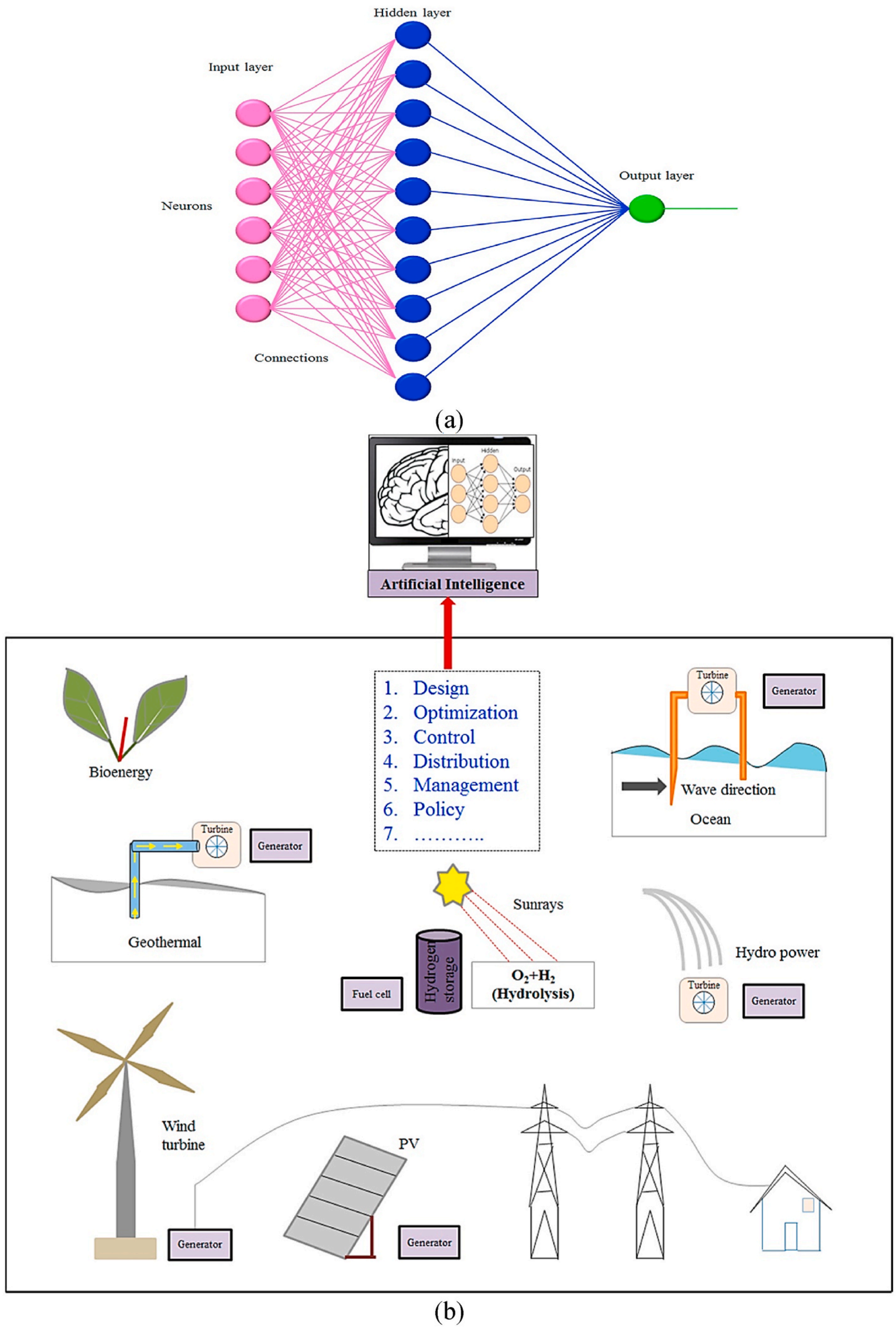


Fig. 4. (a) A simple architecture of ANN method (b) A schematic representation of application of AI in different sources of renewable energy (Jha et al., 2017).

which was consistent with earlier studies. The support vector machines (SVM) method was used (Mohandes et al., 2004) to predict the wind speed from the wind data obtained from Madina in Saudi Arabia. Additionally, a comparison was made between the multilayer perceptron (MLP) neural networks and SVM's performance. In comparison to the ANN approach (MSE 0.0078), SVM demonstrated lower estimation accuracy (MSE 0.009) (Chen et al., 2021). In the framework of Industry 5.0 technologies, a novel notion for an intelligent and semi-autonomous human-cyber-physical system (HCPS) to control wind turbines in the future was proposed. Artificial intelligence (AI) is needed to manage next-generation wind turbines reliably and efficiently due to their exponentially increasing complexity. By using machine learning to effectively train the AI, the digital twin in the proposed system goes beyond the present Industry 4.0 digital twin technology's employment as a purely advisory tool for human decision-making. As demonstrated in Fig. 5, human intelligence (HI) is raised to a supervisory level, where high-level judgments made via a human-machine interface violate autonomy (Chen et al., 2021).

3.2. AI in solar energy

Similar to wind energy research, solar energy research uses both single and hybrid AI techniques (Mellit and Pavan, 2010; Rehman and Mohandes, 2008; Kalogirou et al., 1999; Zhao and Magoulès, 2012). The most popular technique used in solar energy research to date is ANN. ANN is utilized to forecast solar irradiance for grid-connected photovoltaic systems (Jiang, 2009). It has been possible to obtain a correlation between the actual and anticipated solar irradiance of 98–99% on sunny

Table 2
Artificial neural network (ANN) methods of power forecasting (Rahman et al., 2021).

RE Sources	Methods	Prediction Outputs	Inputs
Solar Energy	LSTM based deep learning approach	short-term prediction of solar energy	Time series meteorological data, such as irradiance, temperature, and wind speed
Solar Energy	ANN-based prediction models	the hourly prediction of the PV system's power	Parameters of environment, e.g., Solar irradiance, air humidity, temperature, wind direction/speed, surface temperature of PV
Solar Energy	Feedforward neural network	Predict the monthly solar radiation based on a daily average radiation	solar irradiation on daily basis, Time of sunshine, temperature as well as latitude, and longitude
Solar Energy	Deep Learning and ANN algorithms, such as LSTM, Auto Encoder, and Deep Belief Networks	Forecasting solar power	Daily average solar irradiation, sunshine hours, temperature, location, etc.
Solar Energy	ANN Model	Solar power prediction	Time, direct beam solar irradiance, total solar irradiance, power produced from the solar panel
Solar Energy	Deep convolutional neural networks	Forecasting solar energy generation	Latitude, longitude, altitude and time; temperature, humidity, moisture, wind velocity, etc.
Wind Power	Single-step and multistep RNN	Wind speed prediction from a daily basis to monthly basis	Historical data on wind speed and wind direction for 15 years on an hourly basis
Wind Power	BP neural network	Future prediction of wind speed	1500 daily windspeed patterns
Wind Power	Deep learning approach, Feedforward ANN, Linear regression	Predict of Wind energy From 5 to 30 min ahead	Wind speed
Wind Power	Deep neural network	Wind speed prediction	wind direction, speed of the wind, temperature, air pressure, etc.
Wind Power	BP network, RBF network, and NARX models	Wind speed prediction	Time series historical weather data for 3 years and intervals of 15 min: radiation, wind direction and speed, temperature, humidity, reflected radiation, etc.
Wind Power	multivariable model based on ANN	Prediction of Wind velocity (speed)	Temperature, wind direction and speed, and air pressure
Hydropower	ANN: Feed Forward Neural Networks (FFNNs)	Prediction of power generation	Waters' Flow rate and Net Turbine's head
Hydropower	"multi-layer perceptron" (MLP)	Prediction of the flow rate of the river	the flow rate of the river, rainfall amounts, overall rainfall's volume and duration
Hydropower	multi-layer perceptron (MLP)	Forecasting up to 6 h ahead of the future natural water inflow	Amount of precipitation in the last 15 min, last hour, last 2 or 4 h, current water inflow, natural inflow 8 h ago
Hydropower	the Levenberg–Marquardt algorithm in Neural network and feedforward mode	The annual average's prediction of the hydroelectric energy	series of Inflows, requirements for irrigation water, rates of evaporation, ratio of turbine running time, and the coefficient of C
Hydropower	MLP using the BP algorithm	Forecasting the monthly hydropower generation	Daily rainfall data

days and 94–96% on gloomy days. Using temperature and humidity as inputs, BPNN was used to anticipate global solar radiation (GSR) from 1998–2002 (Atia et al., 2012). For the year 2002, the RMSE value between the actual and BPNN predicted GSR was 2.823×10^{-4} (Kalogirou et al., 1999). investigated a solar water heating system's performance using BPNN. The improved performance of BPNN was confirmed by the higher values of the coefficient of determination (R^2 0.9808 for the maximum temperature rise and 0.9914 for extracted energy, respectively). Using BPNN, beam solar radiation was calculated by examining data from eleven distinct stations. The radiation model's projected values and actual values had an RMSE of 2.69–2.79% (Alam et al., 2006). The daily ambient temperature was estimated with a BPNN of 3 $\times$ 6 $\times$ 1, with an RMSE of 1.96 [250]. The BPNN was used to estimate the daily sun irradiation with an RMSE of 5.5–7.5% (Bosch et al., 2008). The BPNN was used to forecast the maximum power of a high concentration photovoltaic (HCPV) system with an RMSE of 3.29% (Almonacid et al., 2013). The BPNN was used to estimate the monthly average daily global sun irradiation, and the correlation between the projected and real solar irradiation was 0.97 (Mubiru and Banda, 2008). The BPNN was used to estimate the quantity of hot water and solar energy output; the R^2 values were 0.9973 and 0.9978, respectively (Kalogirou, 2000). With an R^2 of 0.971, solar radiation was estimated in Nigeria using the BPNN with the following input variables: latitude, longitude, altitude, month, mean temperature, mean sunshine duration, and relative humidity (Fadare, 2009). BPNN was also used to estimate the energy intake of a passive solar building (wall thickness (15–60 cm) with R^2 0.9991) (Kalogirou and Bojic, 2000). In a different investigation, BPNN predicted building energy consumption with 94.8–98.5% prediction accuracy for insulation thickness values of 0, 2.5, 5, 10 and 15 cm, orientation angles of 0–80°, and transparency rates of 15, 20 and 25%, relative to each other. It was also noted that by combining the AI techniques the forecast accuracy improves (Souliotis et al., 2009; Monteiro et al., 2013; Pedro and Coimbra, 2012). ANN and TRNSYS were combined to forecast the performance of an integrated collector storage (ICS) solar water heater, with an R^2 value of 0.9392. GA was utilized by (Monteiro et al., 2013) to optimize the parameters of the Historical SImilar Mining (HISIMI) model for PV system power prediction. Comparisons were made between the GA + HISIMI model (RMSE 283.89) and the classical persistence (RMSE 445.48) and BPNN (RMSE 286.11) approaches. To optimize the size of PV systems in Algeria, RBFNN and infinite impulse response (IIR) filters were combined

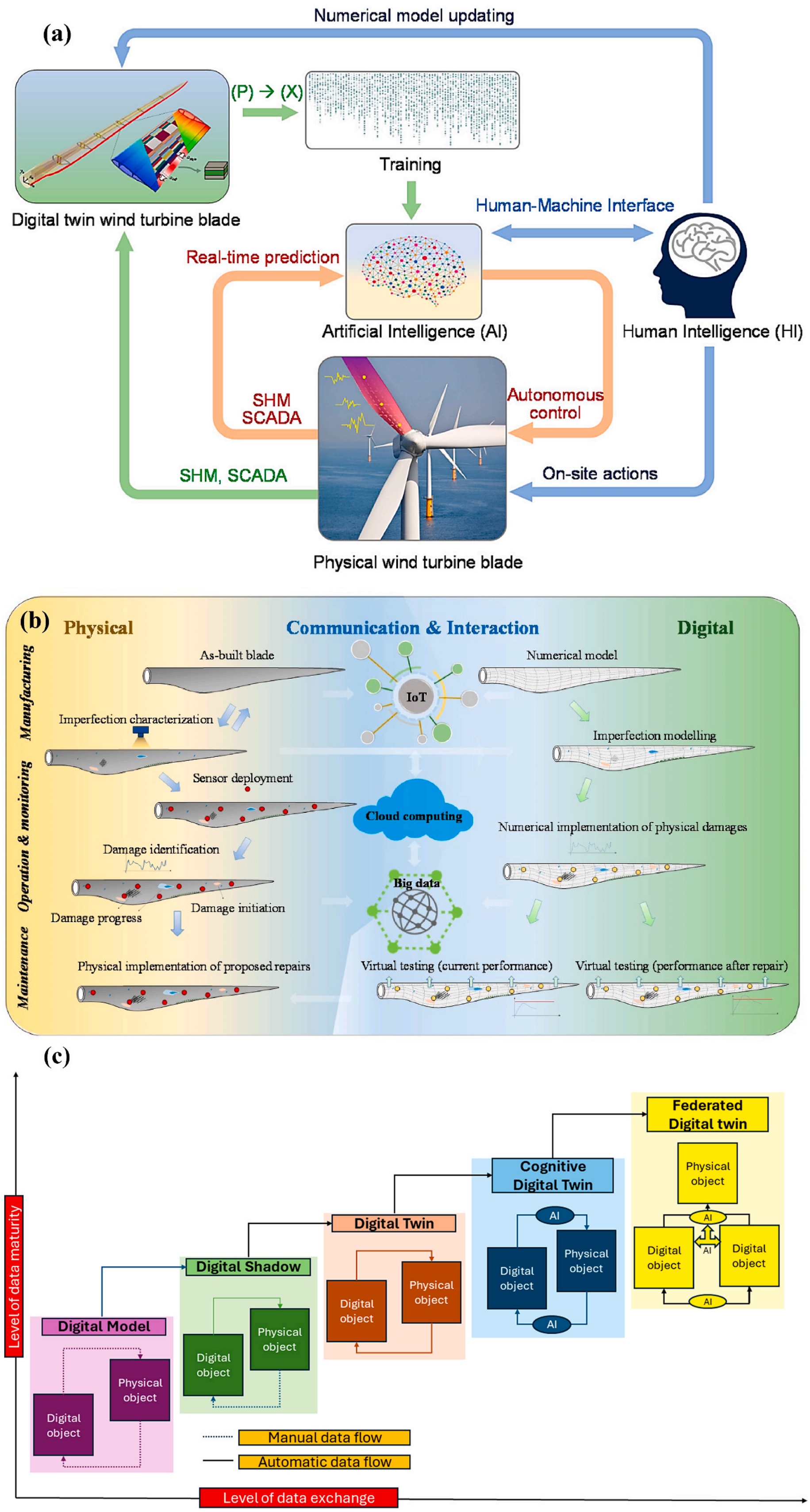


Fig. 5. (a) The human-cyber-physical system (HCPS) concept of future wind turbines in the Industry 5.0 era. The system comprises an AI (red loop) that directly controls the operation of the WT in quasi real time. The AI is trained by a DT that makes predictions to aid the decision-making process (b) A digital twin of a wind turbine blade. The digital twin follows the entire life cycle of a wind turbine blade from manufacturing to operation to maintenance (Chen et al., 2021).

(Mandal et al., 2012). The RBF + IIR approach was used to estimate the optimal sizing coefficients, and its effectiveness was compared to that of the classical models, BPNN, RBFNN, and MLP + IIR methods. Using the RBF + IIR approach, the sizing coefficients were computed with an accuracy of 98%. For the purpose of estimating solar radiation values, WT and BPNN were combined (Amirkhani et al., 2015). WT + BPNN outperformed the traditional approaches (AR, ARMA, MTM), BPNN, recurrent, and RBFNN methods in terms of accuracy (97%) and performance. Without using exogenous inputs, solar power output was forecasted using GA-optimized BPNN. The persistent model, ARIMA, k-nearest neighbor (KNN), and BPNN approaches were contrasted with the GA + BPNN method's performance. The GA + BPNN produced an RMSE of 72.86 kW as the minimum. To estimate the power of a PV system (Mandal et al., 2012), combined WT and RBFNN and evaluated the system's performance against WT + BPNN, RBF and BPNN. The WT + RBF showed an RMSE of 0.23 at minimum. The economic benefits of solar energy were optimized through the application of NN and GA in the group method of data handling (GMDH). The best course of action increased life cycle savings by 3.1–4.9% (Caputo et al., 2010).

Concentrated Solar Power (CSP) is one of the most promising solar technologies that raises the bar for solar energy. Large arrays of mirrors, or heliostats, are key components of CSP systems. Their job is to precisely track the sun's movement and reflect beneficial sunlight onto a central receiver. This receiver, which is often found at the summit of a tower, is filled with heat-transfer fluid, such as molten salt. The fluid warms up when the receiver is exposed to intense sunshine. After being heated, this fluid is utilized to create steam, which powers a conventional steam turbine that is connected to a generator to produce energy. Some cutting-edge CSP technologies can also use thermoelectric or photovoltaic processes to directly turn sunlight into power (Abreu et al., 2020).

A summary of key advances made with the use of AI in the CSP field is made below:

- **Heliostat Alignment and Tracking:** Heliostats, or mirrors used in CSP plants can have their alignment and tracking optimized using AI algorithms. AI determines the most effective angles for the mirrors by analyzing real-time data, such as the sun's location, the weather, and the performance of the plants. By doing this, one can optimize the amount of sunlight reaching the receiver, which raises the total energy production.
- **Predictive Maintenance:** In CSP systems, AI can be used for predictive maintenance. Artificial Intelligence (AI) can forecast probable component failures or anomalies by examining sensor data, performance patterns, and previous maintenance records. It then makes it possible for operators to plan maintenance which cuts downtime and increasing plant efficiency.
- **Energy Dispatch Optimization:** Based on current electricity demand, energy costs, and grid circumstances, artificial intelligence (AI) can optimize the dispatch of energy from CSP facilities. CSP plants can better adapt to changes in energy supply and demand by dynamically varying their power output, which helps in maintaining the grid stability.
- **Thermal Storage Management:** Thermal energy storage devices are frequently used by CSP facilities to store excess heat for use in the production of electricity during low-sun times. AI may be used to evaluate and improve thermal storage behaviors, enhancing charging and discharging plans for optimal energy storage.
- **Solar Irradiance Prediction:** To precisely forecast the irradiance levels of the sun, artificial intelligence (AI) algorithms can use satellite photos, historical meteorological data, and other factors. This data assists CSP operators in forecasting patterns of energy generation and making plans for possible weather-related variations.

AI has many benefits for CSP, including improved performance, cost savings, grid integration, efficiency gains, and efficient thermal storage. Multi-junction solar cells are used in concentrator photovoltaic (CPV) systems, which are designed to convert energy with a high degree of efficiency. Nontracking CPV systems have been created by researchers to minimize the amount of mechanical hardware. Since a building's roof area is constrained, CPV systems ought to be created for the building envelope of multi-story structures. In the same manner, non-tracking tiny concentrators with a high acceptance angle ought to be created for vehicle-based CPV systems. Subsequent advancements will strive towards broadening of the scope of geographical areas where CPV systems can be implemented, encompassing areas with reduced DNI. Improvements in tracking systems, concentrator optics, and system integration with other renewable energy technologies such as energy storage and hybrid systems will aid in achieving this. Future studies should focus on improving the durability and dependability of CPV systems by utilizing high-quality parts, robust construction, and effective heat management techniques (Iqbal et al., 2023).

3.3. AI in geothermal energy

Similar to the previously discussed systems, both single and hybrid approaches of AI are used in geothermal energy applications (Esen and Inalli, 2009; Bassam et al., 2010; Arslan, 2011; Yabanova and Keçebaş, 2013), albeit, the ANN method is used in most studies (Arslan and Yetik, 2014; Yeo and Yee, 2014; Kalogirou et al., 2015).

In order to forecast the performance of a vertical ground coupled heat pump (VGCHP) system (Esen and Inalli, 2009), employed BPNN in conjunction with the Levenberg–Marguardt (LM), Pola–Ribiere conjugate gradient (CGP), and scaled conjugate gradient (SCG) algorithms. Better prediction efficiency was achieved by the LM-based BPNN with eight neurons in the hidden layer (RMS 0.0432). For the geothermal well's static formation temperature (SFT) prediction (Bassam et al., 2010), employed LM-based BPNN. A prediction error of less than 5% was achieved by the BPNN with five neurons in the hidden layer. The ideal geothermal well operating conditions were ascertained by using BPNN (in conjunction with LM, CGP, and SCG). Using the ammonia fraction, temperature and vapor fraction of geothermal water as inputs, the BPNN with seven neurons in the hidden layer produced the best-predicted values of generated and circulation pump power (RMSE 1.5289). ANN was used to optimize the power cycle utilizing BPNN (with LM, CGP, and SCG), much like ORC-Binary. For generating and needed pump circulation power, the LM based BPNN with 14–16 neurons in the hidden layer produced the greatest results (RMSE 0.0001 for s1 and s2 cycles). Although an extra input variable, outlet pressure, was included in the analysis for cycle s2, the input variable of cycle s1 was comparable to that of another study (Bassam et al., 2015). A geothermal map at various depths was created using BPNN, with real values for 96.5% of the data points deviating by less than 5%. The Afyonkarahisar geothermal district heating system (AGDHS) thermal performance and energy destructions were predicted with good accuracy using the LM-based BPNN (RMSE 0.0053) (Keçebaş and Yabanova, 2012).

3.4. AI in ocean energy

The role of some single and hybrid AI approaches in ocean energy was described in several studies (Makarynskyy et al., 2004; Londhe and Panchang, 2006; Chen et al., 2010) and a summary of the performance prediction/analysis showing the use of AI in ocean energy is shown in Fig. 6.

(Londhe and Panchang, 2006) used the BPNN approach (six alternative designs for the number of neurons in the hidden layer) to forecast the conditions of ocean waves for one day. Good accuracy (67% correlation for the projected wave height for lead times of 12 h) was attained. By examining the data gathered from Tasmania between 1985 and 1993, three distinct architects employed the BPNN technique to estimate the wave parameters using the coastal environment factors as input (R2 0.92) (Toprak and Cigizoglu, 2008; Toprak and Cigizoglu, 2008). used

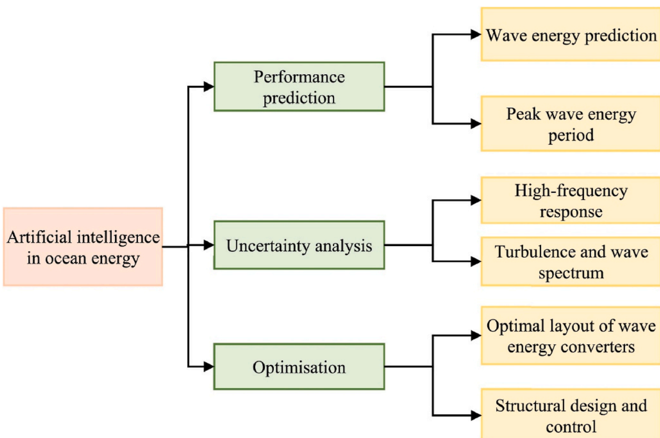


Fig. 6. A summary of artificial intelligence methods used in ocean energy (Y. Zhou, 2022).

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 (Chen et al., 2010) and GP methods have also been used in the study of ocean energy (Chen et al., 2010) developed an 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., 2010). The GP prediction accuracy was better than the BPNN based on the LM algorithm (MSE 230.5–236.2). ANFIS and hybrid AI approaches have been implemented to achieve better prediction accuracy. In order to forecast sea level (Karimi et al., 2013), employed ANFIS (five types with various membership functions) and evaluated its performance against that of BPNN (LM), BPNN (CG), BPNN (GD), and eleven other types of ARMA models. While not quite as good as the ARMA models, the outcomes of the ANFIS and ANN techniques were comparable. For wave hindcasting, a hybrid method combining the numerical wave model (NWM) and BPNN was employed (Malekmohamadi et al., 2008). The hybrid strategy outperformed the NWM and BPNN techniques (De Paz et al., 2012). created a hybrid intelligent system that combines support vector regression (SVR) and case-based reasoning (CVR) to better estimate CO_2 flux and investigate the relationship between the air and ocean.

3.5. AI in hydrogen energy

3.5.1. Hydrogen production

Two important selection criteria for hydrogen generation are affordability and low carbon emissions. The most straightforward way to produce hydrogen is by electrolyzing water, which is also the most cost-effective approach in terms of energy conversion and production costs. Despite this, industrial hydrogen production does not use this process (Holladay et al., 2004; Verma and Goel, 2022; Faisal et al., 2022). Nowadays, the primary energy source for producing hydrogen in industrial hydrogen generation technologies is petrochemical energy. The technology for producing hydrogen from petrochemical energy is quite advanced, and over 95% of the hydrogen generated globally comes from this source. However, the generation of hydrogen from petrochemical energy has a drawback as it produces a large amount of carbon dioxide as a byproduct. We should utilize industrial by-product hydrogen to its full potential from the outset of hydrogen energy development. It should limit the growth of electrolytic water to make hydrogen, develop less oil and natural gas cracking to produce hydrogen and develop coal gasification to produce hydrogen. For long-distance energy transmission (Li et al., 2019), integrated the electrical network into the hydrogen supply chains. The primary benefit of this was lower investment costs and more electrolyze usage. The safety and system economy of the power systems were enhanced by the optimization of the heat, hydrogen (Li et al., 2018), and high-temperature electrolysis system with feed factors and coordinated temperature under varied loading situations (Xing et al., 2018).

3.5.2. Hydrogen storage

High-pressure hydrogen gas storage, cryogenic liquefied hydrogen storage, organic liquid hydrogen storage, porous materials, metal alloys, and other physical solid-state hydrogen storage technologies are some of the hydrogen storage techniques being researched and used. While many technologies and methods have been developed to date for the large-scale storage and transportation of hydrogen energy, only high-pressure gas hydrogen storage technology and cryogenic liquid hydrogen storage technology are most practical for use in industry (Verma and Goel, 2022).

3.5.3. Hydrogen transportation

A long tube trailer is used to carry high-pressure hydrogen, and by raising the operating pressure of the long tube trailer bundle, hydrogen transport efficiency can be increased (Ahmad et al., 2021). The cryogenic liquid hydrogen is transported in an insulated and cold-insulated tank car. Pressurized hydrogen is used by users once they reach their destination. Large-scale hydrogen transportation is appropriate for the long-distance hydrogen transmission line. A certain amount of money must be set aside for hydrogen transportation infrastructure because building long-distance hydrogen transmission pipelines requires significant financial outlays. Long-distance hydrogen transmission pipelines will co-develop with the full development of hydrogen energy in the future to satisfy the demand for long-distance natural gas transmission pipelines (Ahmad et al., 2021).

(Petrone et al., 2013) provided a succinct overview of model-based artificial intelligence (AI) techniques for proton exchange membrane fuel cell (PEMFC) diagnosis. Likewise, three categories of nonmodel-based techniques—AI, statistics, and signal processing methods were described in another study (Zheng et al., 2013). The research application of AI approaches is described in several studies (Liu et al., 2001; Sammak, 2021; Ho and Karri, 2010; Marra et al., 2013). According to (Tardast et al., 2014), the ANN was discovered to be the most widely used technique in the hydrogen energy sector (Fig. 7). Specifically, techniques like BPNN, SVR, and multi-gene genetic programming (MGGP) were utilized to predict the output voltage of microbial fuel cells (MFCs), with MGGP demonstrating the highest accuracy. Additionally, the CO_2 hydrogenation activity was predicted using BPNN (Liu et al., 2001). The effect of hydrogen car engine operating conditions on the emission of CO_2, CO, NO_x, and hydrocarbons was predicted by BPNN with eleven training algorithms (Ho et al., 2008); the prediction of CO emission was 100% accurate; BPNN trained with LM and Bayesian algorithm was used to monitor the stability and error detection in the PEM fuel cell (Hatti and Tioursi, 2009). The voltage and cathode temperature of the polymeric electrolyte membrane fuel cell (PEMFC) were highly accurately predicted using BPNN, which is based on the LM training method (Chávez-Ramírez et al., 2010). Using two inputs, engine speed and throttle position, BPNN with twelve distinct training algorithms was developed for the prediction of hydrogen engine parameters (mass airflow (MAF), air pressure, fuel pulse width, exhaust gas and engine temperature, and NOx emission) (Ho and Karri, 2010). Moreover, BPNN was used in several other studies (Yap et al., 2012; Marra et al., 2013; Tardast et al., 2014) to predict the power density of MFC (RMSE $4.89 \times 10-4$ for one configuration), the stack voltage of the solid oxide fuel cell (SOFC), the hydrogen engine parameter and emissions (RMSE $\pm$ 4%) (Tardast et al., 2014).

Fuzzy logic methods (Ho and Karri, 2008; Flemming and Adamy, 2008) and EU approaches (Sewsynker-Sukai et al., 2017; Askarzadeh and Rezazadeh, 2013) have also been used for hydrogen energy analysis. For example, the ignition duration of a hydrogen automobile was predicted using the fuzzy logic method and three different membership function types (Ho and Karri, 2008); the current density characteristics

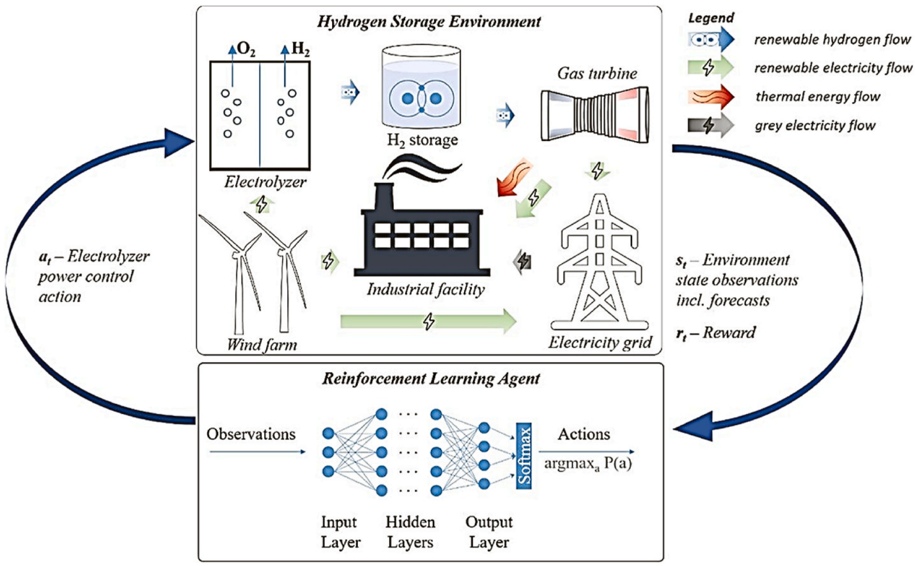


Fig. 7. AI in hydrogen energy storage (Dreher et al., 2022).

of the SOFC were modeled using a recurrent fuzzy system (Caux et al., 2010). Fuel cell hybrid vehicles (FCHV) were equipped with a fuzzy logic controller that was based on parameter optimization using the GA to control hydrogen consumption. In addition to fuzzy logic, GA and PSO were employed in the FCHV energy optimization process (Caux et al., 2010). BPNN, GA and PCA in hydrogen production modeling have been reviewed by (Nath and Das, 2011; Askarzadeh and Rezazadeh, 2013) proposed a bird mating optimization (BMO) approach to model the PEMFC system. Application of ANFIS (Entchev and Yang, 2007; Karri and Ho, 2009) and other hybrid AI approaches (Erdinc et al., 2009; Minqiang et al., 2010) were described in many studies (Zhang et al., 2013; Luna-Rubio et al., 2012). The performance of ANFIS and the ANN technique was examined in the prediction of SOFC parameters, specifically voltage and stack current, with RMSE <2 for ANFIS in current prediction. Using 10 input conditions, ANFIS was utilized to forecast several hydrogen safety parameters (such as explosive limit, hydrogen pressure, and flow rate). Additionally, eleven different forms of BPNN based on various training procedures were tested to see how well ANFIS performed (RMS 1.4 in hydrogen pressure prediction with ANFIS). When it came to predicting emissions (HC, CO, CO_2, and NO_x) from the hydrogen automobile, ANFIS and BPNN (LM) were used, however, the BPNN performed better than the ANFIS (RMSE 1.58% of HC emission with the BPNN). The H_2 flow rate, system, and stack efficiencies of the PEM electrolyzer were studied using ANFIS (1.06% prediction error for hydrogen flow rate). It performed comparably to RBFNN and BPNN and was able to forecast the PEMFC cell voltage with efficiency.

For energy-managing HEVs (fuel consumption of 0.06962 kMol H_2), a hybrid AI strategy based on wavelet and a completely logical method was designed (Amirinejad et al., 2013). The temperature forecasting of a hydrogen reactor was conducted using a hybrid approach based on SVR and PSO, which demonstrated superior accuracy and performance when compared to SVR and BPNN (Minqiang et al., 2010). The biohydrogen yield was optimized using BPNN and GA (54 ml/g improvement with the proposed technique).

Similar techniques have been applied by (Bozorgmehri and Hamedi, 2012) to maximize the SOFC's cell characteristics (standard error of prediction: 1.705%). When the performance of the hybrid ABC algorithm was compared to that of the PSO and GA for the parameter prediction of the PEMFC, it outperformed the other techniques with the lowest sum of squared errors (SSE) (Zhang et al., 2013).

3.6. AI in hybrid renewable energy

Numerous reviews have discussed the use of AI techniques in the hybrid RE, including (Luna-Rubio et al., 2012; Zhou et al., 2010; Fadaee and Radzi, 2012). For a hybrid RE system based on a water power supply, BPNN was utilized to anticipate power consumption and generator state (on/off) with a 97% prediction accuracy (Al-Alawi et al., 2007; Chàvez-Ramirez et al., 2013) used FLC for energy management and the BPNN approach for hybrid RE system power prediction. In a different study (Jha et al., 2017), the hybrid RE system's energy management (levelized energy cost (LEC) 2.01 $ with the CS) employed the FLC and cuckoo search (CS) algorithm along with PSO (Berrazouane and Mohammedi, 2014). PSO was used in the size optimization of the hybrid RE system by (Hakimi and Moghaddas-Tafreshi, 2009) to make it more cost-effective. An improved GA was used in the operation optimization of a hybrid RE system, which performed better than the traditional GA method (Zeng et al., 2010). A Bee algorithm was used in the performance parameters (net present cost (NPC), cost of energy (COE) and generation cost (GC)) optimization of a hybrid RE system (Tudu et al., 2011). In order to optimize the hybrid PV/wind system for the size of the PV array, the wind turbine, and the storage capacity (Khatib et al., 2012), used GA. In order to optimize the size and distribution of a hybrid energy system that combines solar energy, wind power, and fuel cells, a multi-objective (MO)-ABC method was employed (Nasiraghdam and Jadid, 2012). This produced a high voltage stability index (VSI).

The hybrid wind-PV-diesel system's size was optimized using a Markov based GA (Hong and Lian, 2012). ANFIS was utilized in hybrid AI techniques to optimize the hybrid PV-wind-battery system's size to lower production costs. Additionally, a comparison was made between the performance and the hybrid optimization model for electric renewables (HOMER) and hybrid optimization (HO)-GA, with the results showing that ANFIS performed better (Maleki and Askarzadeh, 2014). To control the power flow between the hybrid RE system and the energy storage unit, ANN and fuzzy logic-based controllers were designed as a hybrid AI technique, leading to a high storage of charge (SOC) (Natsheh and Albarbar, 2013) (Fig. 8).

4. AI for demand, planning, and control of energy

An Intelligent energy supply can meet commercial, industrial, and residential needs. Consequently, the energy industry is transforming. Numerous opportunities are presented by AI technologies. Some of them

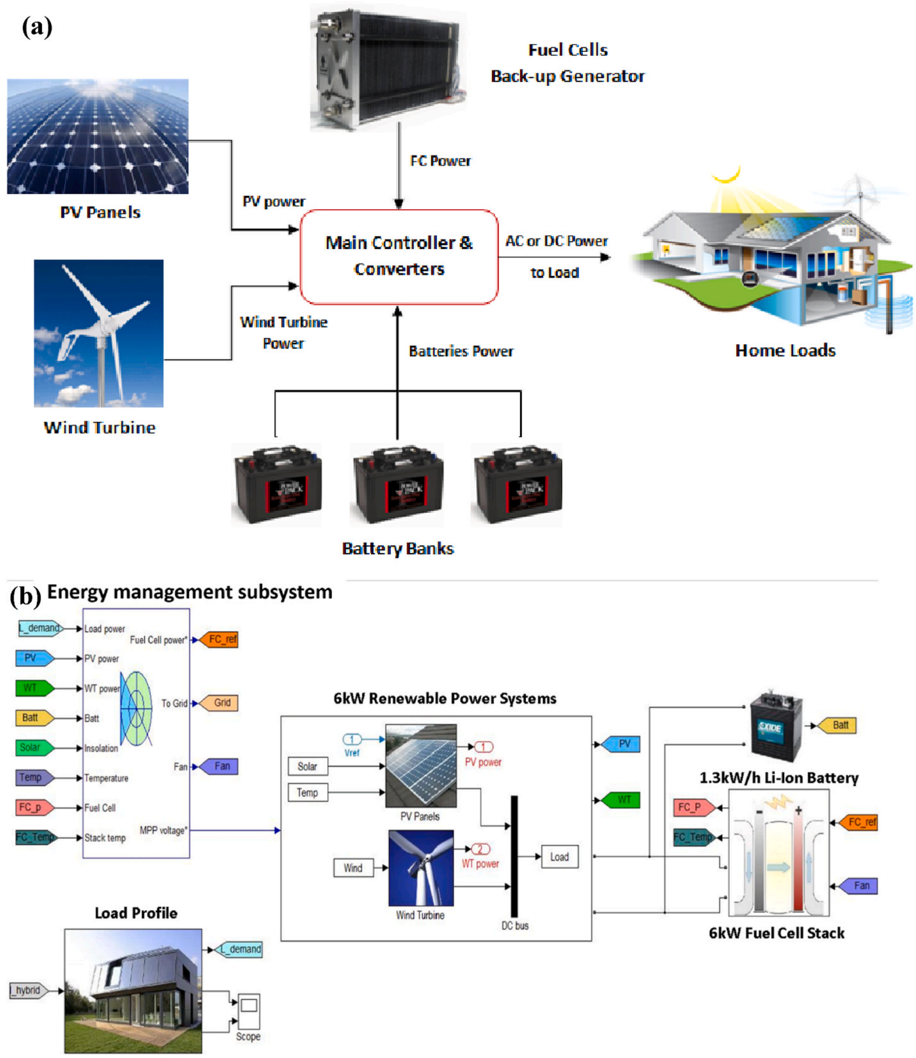


Fig. 8. (a) Block diagram of a hybrid power generation system (b) Hybrid power system simulation model (Natsheh, 2013).

are demand management, energy trading, yield optimization, theft detection, utility energy planning and control, and energy trading.

4.1. *Demand-side management, planning, and control of utilities' energy use*

AI techniques are increasingly being used in utility energy planning and control (Xu et al., 2019). AI may be more advantageous than other technologies when it comes to actively controlling the grid station. Strong utility intelligence systems will be able to negotiate actions, enable self-healing, manage load demand requirements, balance grid stations, and enable a variety of new services and products. AI will help power firms operate more efficiently by assisting in the analysis of unstructured data related to energy supply and consumption. Over the next ten years, distributed energy resources and a broader range of sensor infrastructure will be important AI trends for utilities in energy transactions. To give an example, AI-powered gadgets will automatically determine the net energy demand and consumption, and they will be able to lower and regulate the overall load demand. The majority of utility firms think AI will have a significant impact on their operations, as evidenced by the fact that AI will enable new business models (43%), allow them to offer a competitive edge (33%), and replace particular processes (51%) (Henzelmann et al., 2018). Demand-side management (DSM) involves the use of energy-efficient equipment and reduced energy waste (Foucquier et al., 2013). AI can improve load demand management by increasing its automation and intelligence. AI is being used in the UK to assist power plants in managing power grid components (such as relays and circuit breakers) more flexibly in order to adjust and regulate energy demand in real time. Additionally, without affecting end users, these models are help support and redistribute the peak demand-side load to the network's flexibility during peak hours (Macedo et al., 2015). AI may offer new services including dynamic pricing, direct load control, and specialized charging for electric vehicles (Macedo et al., 2015; Ramanathan and Vittal, 2008). Demand response, energy efficiency, time of use, and auxiliary reserve (production capacity that can temporarily compensate the power system to respond to generation or transmission outages) are some of the aspects of demand management that can be categorized based on the measures taken about consumers and the duration of the process.

4.2. *Using AI to identify theft of energy*

The detection of energy theft is a serious issue, particularly in developing nations. Energy theft can take several forms, such as direct connection from electrical distribution lines, physical obstruction, evading the energy meter, tempering of the electronic meter, inserting an external chip into the electricity meter, providing a false reading, corrupt utility staff assisting customers in stealing electricity, political mismanagement, evading the meter, breaching the meter through remote network operation, changing the firmware, obtaining login credentials, manipulating communications, meter malfunction and imprecise reading, failing to pay electricity bills, arranging accounting irregularities within the company, cyberattacks on the billing system, etc. (Jokar et al., 2015). Energy waste in the form of electricity theft is estimated to be around $96 billion per year worldwide (Yip et al., 2018). Numerous methods have been put out to identify energy theft. In research and development, artificial intelligence (AI) and machine learning (ML) techniques are very useful for detecting clients who steal electricity. The AI models help identify potential hotspots for energy theft so that a physical inspection may be conducted (Razavi et al., 2019). The support vector machine is one of the most popular AI methods used to detect suspicious consumer trends (Nagi et al., 2009). It has been witnessed that the theft detection rate of AI-based schemes, e.g., support vector machine and extreme learning machine models (Nizar et al., 2008) is between 60% and 70%. Some other approaches such as set theory (Spirić et al., 2014), decision tree and Naïve Bayesian (Nizar et al., 2008), lower-upper decomposition (Salinas et al., 2013), support vector machine with multiclass (Jokar et al., 2015), linear regression model, linear programming. AI is capable of identifying payment history, energy usage habits, consumer information, and other elements that can result in models of questionable behaviour. It comprises a variety of building types, including commercial centers, business hubs, marketplaces, residences, government buildings, and shopping malls. The local control center and the building smart meters are connected by the neighborhood area. In addition to serving as a link between the main control center and the smart meters, the local control center monitors a limited portion of the network. At the municipal or district level, the main control center keeps an eye on the load behavior of the clients. The main control center can monitor the total discrepancy between the supply supplied to customers and the actual use of energy in real time thanks to the installation of smart meters and the various levels of the local control center. Smart meters are used to detect the dispersion between supply and demand, which allows for the inspection of a particular area or part. It is also possible to start the physical examination to identify faulty customers. Artificial intelligence (AI) facilitates the use of smart energy meters and local control centers to detect and identify problematic customers (Fig. 9) (Yip et al., 2018).

4.3. Supply management and forecasting of load demand

Load forecasting and energy supply management are the primary focus of the utilities and power industry (Saleem and Karmalkar, 2009). In order to optimize a sequence of generators and reduce generation costs, an accurate load forecast is helpful. Building heating and cooling accounts for a significant portion of the demand, making it the primary load driver. The AI models reflect unsettling internal information and building information by utilizing past data on energy use and the environment (Chou and Bui, 2014).

The smart power grid's supply management and load planning network is depicted in Fig. 10. AI models make up the controller. The main goal of the AI controller is to lower demand and raise the cost function of the electricity supply for customers. When compared to the current models in use, AI performs far better (Raza and Khosravi, 2015). Load management and energy forecasting have made extensive use of a variety of population-based multi-objective AI functions, including multiobjective ant bee colony optimization, multiobjective genetic method, and multiobjective particle swarm optimization models. Findings show that these models are capable of producing accurate findings. A single run can forecast the probability of any target coverage, such as solar and wind forecasts, which is another advantage of the multi-objective technique that will yield the best outcomes. Utilities use AI models to assist in decision-making about energy generation, maintenance, and procurement. The amount of electricity required to be generated for its consumers in the short-, medium-, and long-term is predicted using AI-based forecasting models (Debnath and Mourshed, 2018).

The AI-based ANN ratio for monthly, annual, hourly and daily energy consumption forecast is 18%, 24%, 27%, and 31%, respectively (Wei et al., 2019). Accurate resource forecasting for increased renewables is becoming more and more important. Renewable energy sources like

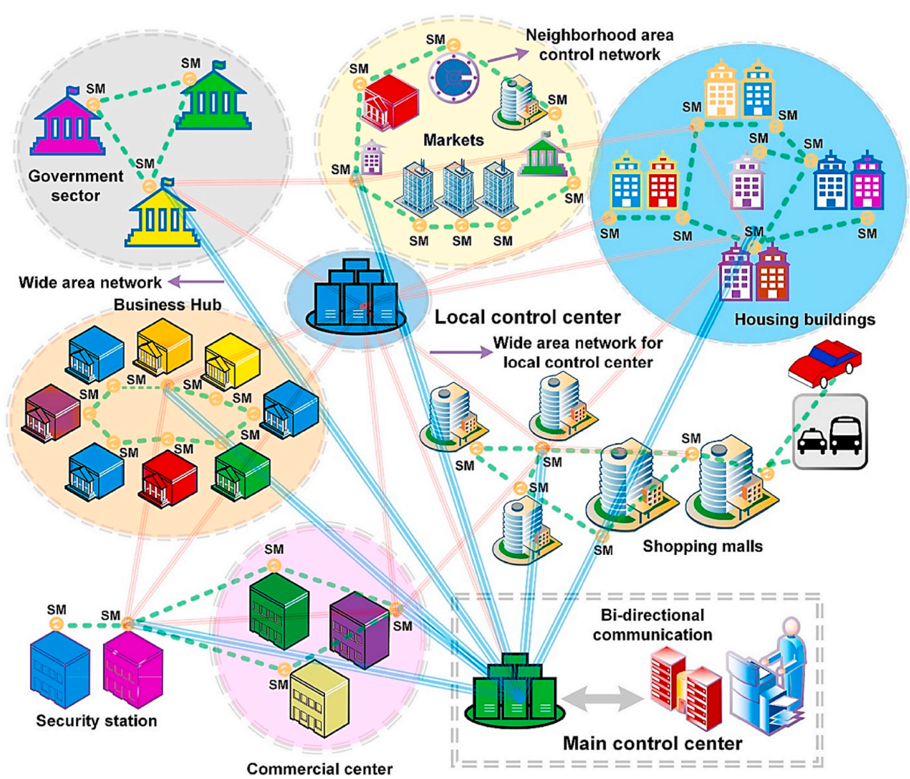


Fig. 9. AI network structure for the detection of energy theft (Ahmad et al., 2021).

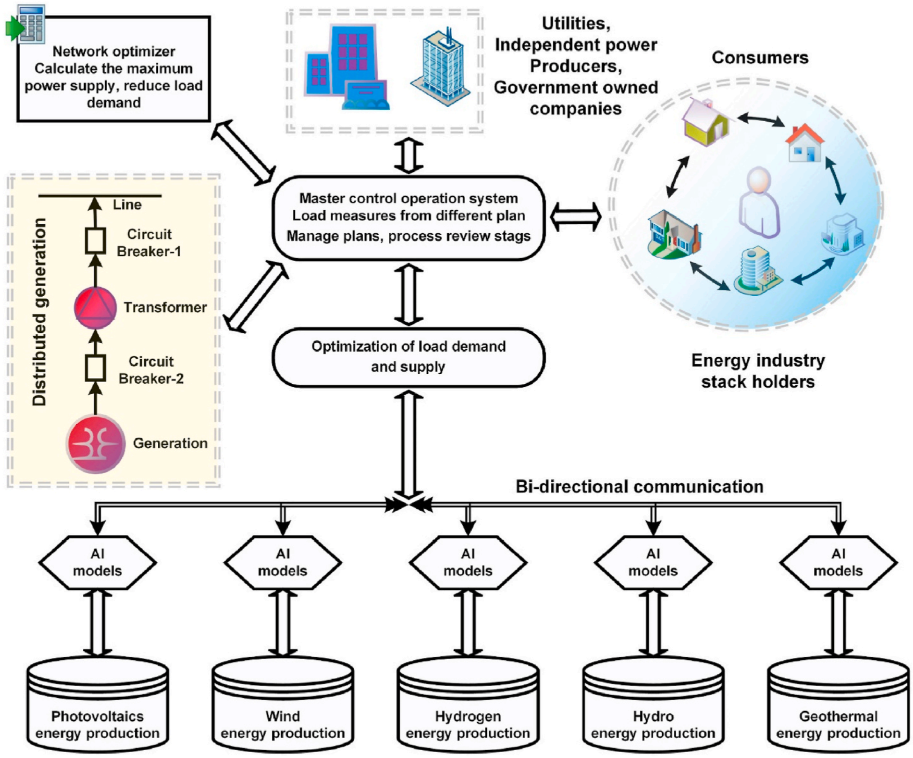


Fig. 10. Smart power network for load planning and supply management (Ahmad et al., 2021).

wind and solar power still struggle with uncertainty. Despite being categorized as renewable, these energy sources vary and are weather-dependent, making long-term energy supply unpredictable. The effects of AI models on statistical optimization should be used for better accuracy and higher forecasting performance in order to suggest an ideal combination of power generation sources to fulfill the anticipated demand and reduce expenses. Numerous models are examined (Yagli et al., 2019). Selecting which of them is the best can be difficult. The production of renewable energy has been successfully predicted by artificial neural networks.

5. Challenges and future research opportunities of AI in the smart energy industry

AI techniques rely heavily on energy data, thus contributing indirectly/directly to the global carbon footprint of information technology (IT) (Nishant et al., 2020). The key energy-related AI challenges include:

- Non-theoretical history: Lack of essential AI skills is one factor contributing to AI's sluggish progress in the energy sector. The majority of businesses lack the technological know-how to comprehend the potential advantages of using AI.
- Lack of practical expertise: Many experts possess extensive technological expertise. Finding competent experts, however, is challenging when it comes to creating trustworthy AI-powered applications with genuine useful advantages. Power companies keep a lot of data under observation and maintenance, but digitizing it with sophisticated management software presents challenges. Risks associated with this include data loss, improper configuration, device malfunction, and illegal access. Due to the enormous cost of error in the energy sector, many businesses are hesitant to even attempt novel approaches.
- Outdated power system infrastructure: The biggest barrier to the energy sector's transformation is its antiquated infrastructure. Utility businesses already generate large amounts of data, but they are unsure about how and when to handle it. Despite having more data than anyone else, the industries' data is also scattered, jumbled, multi-format, and locally stored.
- Economic pressure: Even if it is expensive, integrating cutting-edge advanced energy technologies might be the best course of action. Locating a reputable software supplier, developing and configuring software, and managing, maintaining, and modifying it all take time and money. In addition, the implementation of energy technology will require the development, modification, and management of software, which will require substantial financial and material resources.
- Decentralization and diversification: In all nations around the globe, complicated issues pertaining to energy production, transmission, distribution, and load consumption are brought about by decentralization, diversity, and the emergence of AI technologies and rising demand trends.
- Cellular technologies: The dependency of many developing economies on cellular technology restricts the potential applications of AI, especially in low-income, rural, and other underserved areas. The growing concern and threat of cyberattacks is mostly due to the fact that smart metering and automated control account for nearly 10% of worldwide grid investment, or $30 billion annually, for the installation of digital infrastructure (Fickling, 2019).
  •Black boxes: Customers view AI-based apps as "black boxes," since they are often unaware of their internal workings or development process. This presents a risk. Additionally, the protections will work as long as they are incorporated into the power systems, even though the existing methods are far from ideal.

As it was previously mentioned, artificial intelligence (AI) is widely used in nearly all renewable energy research projects (such as solar, wind, ocean, geothermal, hydro, hydrogen, biofuel, and hybrid) for distribution, design, management, estimation, and optimization. The AI algorithms that have been suggested for research on renewable energy are costly and intricate. These models must be made more affordable and straightforward. In order to optimize energy utilization and save costs, server banks and other energy-consuming devices must be developed without cooling down. In the event of a typhoon, how can artificial intelligence technology regulate and adjust the load demand for wind and solar power farms automatically?

How can we use the IoT and AI technology to increase the efficiency of geothermal plants? How can we use AI technology to automate circuit breakers and relays so they operate longer and at the lowest cost under fault conditions? How might AI and IoT technologies be used to avoid and detect lighting-related effects on transmission and distribution lines? How can smart meters be integrated with consumer appliances in the home to help consumers control and manage their energy use more easily and conveniently? These problems still need to be resolved (Hatani, 2020).

Fig. 11 illustrates the projected demand for AI techniques across several sectors, together with organizational aspirations. In general, 61% of firms believe that developing AI strategies is essential while 39% say they agree with AI advancements to some extent but not strongly. AI technology is already being used by 50% of enterprises. The distinction between data algorithms and AI is demonstrated by four maturity clusters, which include pioneers, investigators, experiments, and passives for varying degrees of AI understanding technologies. Organizational respondents anticipate a significant impact from AI on industrial activities, including media, telecommunications, energy, and technology. 15% organizations report on the significant impact of AI on current technological advancement and 59% expect to predict major impacts over the next five years (Yang et al., 2020). The major participants in the energy sector should make sure that regulators, legislators, major suppliers, and supervised network monopolies are all aware of AI technology, especially in the areas of machine learning, data analysis, and digital automation of electrical networks. Above all, the disadvantages of these advances are becoming increasingly significant, and proper planning can help guarantee that they are taken into account when making decisions for the organization. Guidelines on best practices for coordinating data storage, usage, and access with privacy, security, and customer confidence should be provided by stakeholders. AI is a very potent tool that, when used well, has the potential to drastically change the energy sector. However, the caliber of the training and data sources determines how useful these technologies are. Furthermore, a lot of the strategies, especially the ones that are essential to safeguarding the energy industry, can include a black box component (Gerbert et al., 2017; Tang et al., 2018).

After a thorough analysis of the available evidence, it is possible to conclude that improving energy efficiency can greatly lessen the effects of climate change. Smart manufacturing has the potential to cut carbon

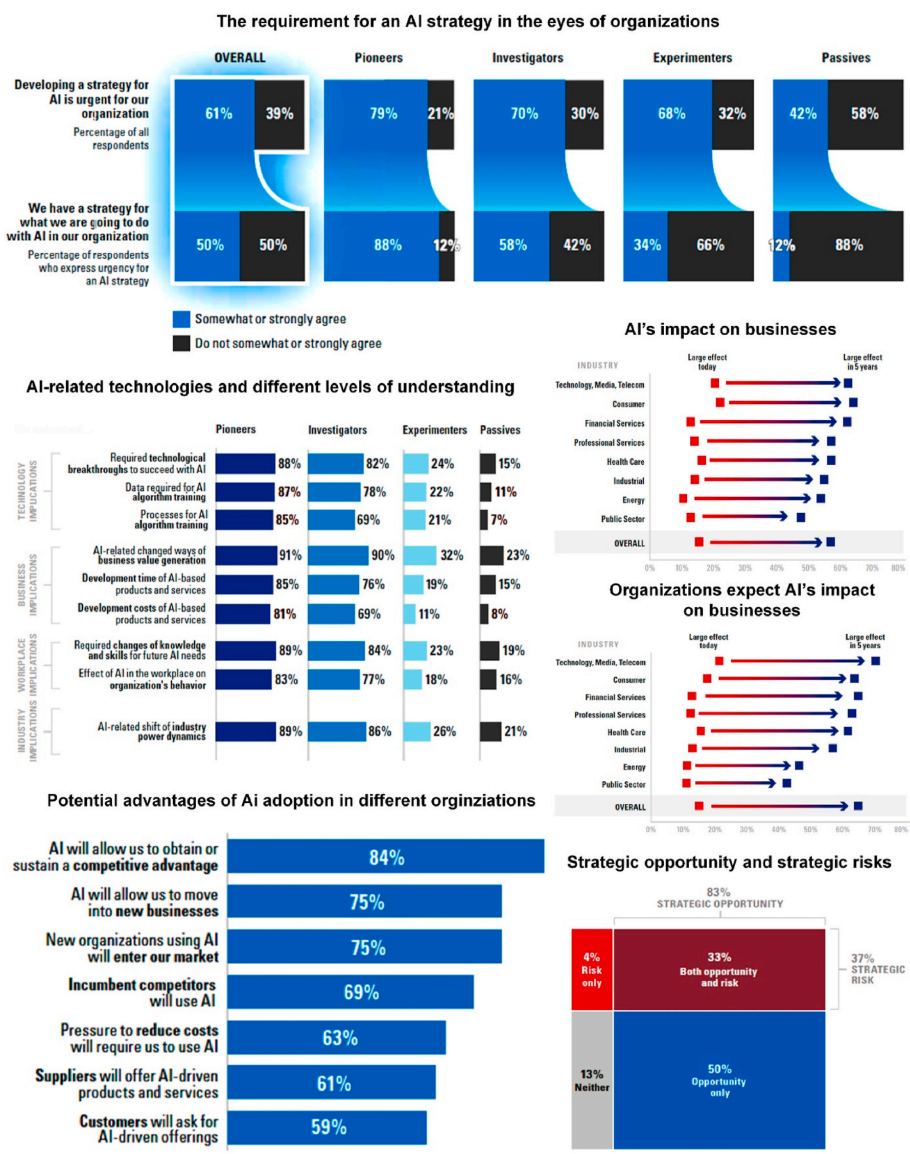


Fig. 11. Organization expectations and future forecasting of AI techniques in various sectors (Ahmad et al., 2021).

emissions, waste, and energy use by 30–50%. It can also cut energy use in buildings by the same amount. Artificial intelligence technologies are employed by around 70% of the worldwide natural gas business to improve the precision and dependability of weather forecasts. Artificial intelligence and smart grids together can maximize power system efficiency and cut electricity costs by 10%–20%. Transportation systems with intelligence can cut carbon dioxide emissions by over 60%. Furthermore, artificial intelligence may be used to manage natural resources and create resilient city designs, which will further advance sustainability (Fig. 12) (Chen et al., 2023).

6. Conclusion and future directions

This paper surveys and charts the most recent significant trends in the use of AI algorithms in the renewable energy sector. This includes the likes of wind energy, solar energy, geothermal energy, ocean energy and hydrogen energy. Both singular and hybrid AI approaches have been used and applied to efficiently manage energy demands. In addition to neural learning, statistical and evolutionary learning-based methods are also effectively employed in AI. Examples of these methods include clustering, hidden Markov models, closest neighbor models, Bayesian and naïve Bayes models, and so on. Additionally, well-known evolutionary learning techniques such as bee algorithms, ant colony optimization (ACO), particle swarm optimization (PSO), and genetic algorithms (GA) are also successfully applied. The analysis made it clear that by applying AI, the energy sector can well achieve its full potential. Some impediments may need to be overcome which include, for instance, properly utilizing fresh sources of RE, particularly in the hybrid RE system. The performance of RE sources will be enhanced by the application of innovative and hybrid AI techniques.

Artificial intelligence developments could help the energy sector in optimizing the power system and successfully maintaining resilience and reliability. Although AI is widely used, it may be broadly categorized into three areas: response (such as taking action and making decisions), assessment (such as receiving and recognizing), inferring (such as learning and processing from this knowledge), and evaluation. Big data explosions, machine learning advances, smart robotics for infrastructure production and power grid monitoring, enhanced integration of renewable energy, a significant rise in IoT in the energy sector, security privileges and prevention of cyberattacks, and increased computational power are just a few examples of the broad role that the AI is playing in solving several global issues in the energy sector. AI and related modelling and simulation techniques will be able to use previously unimagined capabilities due to the spark developments in the field of quantum computing. While the AI relies on learning from the data sets, data analysis requires high-quality precision data sets. The data about the energy business can be broadly classified intocategories such as data collected from network systems; data on measurement and use; data on consumers; and data on real-time energy consumption by suppliers and customers. To improve interactions between people and assets and infrastructure, which support regular operations, asset management, and field service operations, power system operators and utilities should depend more and more on artificial intelligence (AI) technologies. AI-based technologies for the integration and optimization of renewable energy sources with the power grid can improve the efficiency, load management, resilience, stability, and reliability of the power system. In conclusion, artificial intelligence (AI) is not only urgently needed, but also a vital instrument for bolstering and enhancing the energy sector's digitalization initiatives. AI can revolutionize several energy industries and spur growth in the years to come.

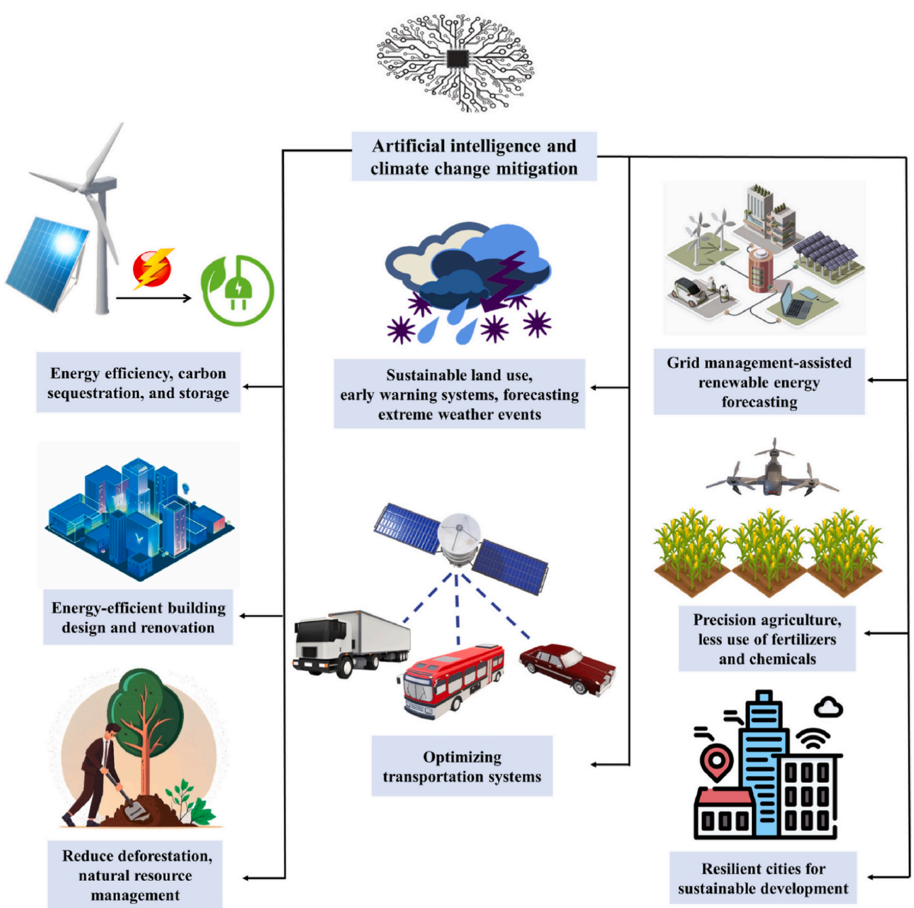


Fig. 12. Utilization of artificial intelligence in reducing the impact of climate change(Chen et al., 2023).

CRediT authorship contribution statement

Jaya Verma: Conceptualization, Data curation, Investigation, Methodology, Validation, Writing – original draft. **Laura Sandys:** Writing – review & editing. **Allan Matthews:** Writing – review & editing. **Saurav Goel:** Funding acquisition, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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