

Comprehensive study of the artificial intelligence applied in renewable energy

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ABSTRACT

In the innovative domain of sustainable and renewable energy, artificial intelligence incorporation has appeared as a critical stimulant for improving productivity, cutting costs, and addressing complex difficulties. However, all the reported advancement over the recent years, their experimental implementations, challenges associated have not been covered by single source. Hence, this review aims to give a single data source to get a recent, advanced and a detailed outlook on applications of artificial intelligence in renewable energy technologies and systems along with examples of implementation. More than 150 research reports were retrieved from different data bases and the keywords and selection criteria to maintain relevance. This review specifically explored the applications of diverse artificial intelligence approaches over a wide range of sources of renewable energy innovations spanning solar power, photovoltaics, microgrid integration, energy storage and power management, wind, and geothermal energy comprehensively. The current technological advances, research outcomes, and case studies in the domain of artificial intelligence implications for renewable energy systems are discussed, along with the potential challenges and their possible solutions. The expected advancements and trends in the near future are also discussed which can give a future gateway to researchers, investigators and engineers to look over to advancements and resolve the challenges already associated.

1. Introduction

The advancement of society is inevitable without using energy resources. The demand for energy for daily life usage is exponentially increasing with the growing population worldwide, urbanization, and economy. The non-renewable energy or conventional sources, such as coal, natural gas, oil, etc., have been widely utilized and are still in use in various sectors to overcome the need for energy and power generation [1]. The large-scale depletion of non-renewable energy happened due to the rapid utilization of resources, which also caused adverse effects like climate change and global warming owing to the high emission of greenhouse gases (GHGs) from them [2]. These effects could cause inevitable problems, for example, sea level rising, glacier melting, forest destruction, air pollution, ozone depletion, water and land use, radioactive emissions, acid precipitation, GHGs, wildlife loss, and damaging ecology, which would significantly threaten the economic and social sectors significantly [3]. The International Energy Agency (IEA) has released publications that state that “energy-related GHG emissions could result in considerable environmental deterioration with an

average 6 °C global rise in temperature.” [4]. Less negative effects on the environment and the economy are required when addressing these issues to give humanity a more promising and better energy future.

To combat the previously observed negative consequences of traditional energy supplies, due to fossil fuels, on sustainable development, mankind has now resorted to finding alternative energy. Renewable energy (RE) has gained a lot of interest worldwide in recent years and is regarded as a sustainable alternative approach to avoid the above consequences and be the future of energy development [5]. According to an estimate published by the International Energy Agency (IEA), by 2040, there will be 10,800 GW of renewable energy capacity worldwide [6]. RE-based technologies include solar [7] hydro, biomass, wind, geothermal, etc., which are considered sustainable green technologies owing to their cost effectiveness, very low carbon, and environmental friendliness, and one of the most prominent is their renewability as compared to their non-renewable sources like fossil fuels [8]. The development of innovative technology for the best possible energy generation from the natural resources already in place, improved system management and distribution, and environmental consciousness are the

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primary areas of current and future concern in RE technologies [9]. An important development and research dominion over the previous few decades was the exploitation of sunlight and wind as a significant RE source [10]. It turned attention towards RE technologies based on solar photovoltaic (PV), wind, geothermal, hydropower, tidal, biomass, etc. [11].

This energy revolution using sustainable RE technologies has the key features to be implemented in the power sector, including controlling electricity costs [12], developing the adaptability and stability of energy systems [13], replacing old infrastructure, reducing CO₂ emissions, providing consistent power support to remote areas, and preventing changes in the atmospheric environment [14]. To meet the requirements for emissions reduction and energy savings, the energy storage system (ESS) has been developed successfully in the past few years. This is because enhancing the accuracy of RE forecasts is vital for power systems [15].

Presently, several techniques have been developed to increase RE systems' accuracy. Artificial intelligence (AI) is an all-encompassing high-tech methodology that mostly concentrates on creating intelligent devices and software for certain issues [16]. Before artificial intelligence, there were fundamental renewable energy decision-making systems, such as data collection and monitoring systems [17]. After years of development and evolution, it has started to have a significant impact on our everyday lives and the sectors of sustainable growth and development. Applications for it can be found in a variety of fields [18], including energy, food, education, agriculture, health, and safety [19], as well as business and the arts [20].

AI has greatly influenced the policy and economics surrounding RE technologies [21]. It can model several scenarios, analyze policy effectiveness, and predict the economic impacts of different energy strategies [22]. AI has a range of applications in monitoring eco-systems, measuring the carbon footprint of energy production, and optimizing resource management to address environmental impact and sustainability and minimize damage to the environment [23]. AI also can play an important part in developing solutions that provide access to marginalized communities for clean and affordable energy. The tidal and wave energy can also benefit from data-driven findings and predictive modeling of AI, as these RE technologies are often ignored but can prove highly promising [24]. The researchers have sought to improve the performance of solar energy systems via applying several AI based metaheuristic methods [25]. Multiple AI algorithms integrated with numerical models have recently been developed and utilized to estimate, predict, and forecast wave characteristics and wave energy resources [26]. Advanced biofuels can be further optimized using AI-based processes in biotechnology and chemical engineering, as they tend to lessen carbon emissions in transportation and industry [27].

AI can completely renovate the renewable energy sector and perform a critical role in boosting the use of RE in the energy sector. For example, utilization of a recurrent AI based artificial neural network was recently investigated in the forecasting of solar still performance [28], to predict thermal efficiency and water yield of tubular solar still [29] and developing the low-cost bilayered structure for improving the performance of solar stills [30]. AI approaches being applied to developing RE include the predictive maintenance [31] improvement of safety and reliability [32], approaches to diminish climate and environmental effects, cost-effectiveness, increased efficiency of energy and power systems [33], productivity forecasting of solar distiller [34], water productivity of different designs of solar stills [35], yielding more precise estimates of RE in solar cell performance [36], expanding the incorporation of microgrids (MG) and smart grids, and ideal procedures for RE sources like [37].

To better understand the evolution of AI and RE research, this review paper draws on a broad panorama of the field. Considering the importance of the subject, this review aimed to study the state-of-the-art RE-based technologies using AI tools and techniques in energy conservation, control, and administration of RE. The findings of this review are

supported by various case studies implemented in specific regions that will allow researchers, engineers and investigators to have an overview of the current state of RE technologies based on solar, hydro, wind, and geothermal and the possible use of successful and standard practices in developing AI-driven RE-based arrangements. Also, particular attention was paid to the challenges faced in the successful deployment of an AI-based analytical maintenance set of rules. Data-related problems in RE systems and their possible solutions, along with future trends, were discussed comprehensively.

Overall, this review can provide the comprehensive, advanced, and recent outputs developing in the field of AI applications in RE technologies with experimentally implemented case studies about the AI methods and their deployments in different RE technologies and systems specifically in solar energy, hydro, wind, and geothermal power systems. Along with covering the possible challenges and giving their possible solutions this review also projects some future trends and possible directions in the field. All data variables present at one review will provide assistance to researchers and investigators to have a clearer outlook and grip on the field.

The following is an overview of this review paper's primary contributions:

- This review provides an overview of reviews and the state-of-the-art research outcomes related to applications of AI based on various RE technologies.
- The advancements of the last 10 years are examined for AI-driven RE systems and technologies, mainly discussing solar energy, hydro, wind, and geothermal power systems.
- Four case investigations are presented to show the efficiency and successful integration of AI-based algorithms and approaches in RE-based technologies.
- In addition to the early studies in the field, the most current literature discusses the main challenges to implementing AI-based predictive maintenance for RE systems and offers possible solutions for them.
- Moreover, future research trends/directions are enlisted to have a broad view of upcoming advancements in the domain.

2. Methodology

2.1. Research and data retrieval strategy

To assist the reputable connection between RE and AI applications for RE, an expert-driven theoretical publication search was conducted. Subsequently, the essential features of the articles are explained concerning their research fields and highly cited works. Following data inclusion criteria were looked:

- Peer-reviewed articles published in English.
- Articles published within the last ten years to ensure the relevance and currency of the data.
- Studies that specifically address AI applications in solar, photovoltaics, microgrids, wind and geothermal energy.

Using the retrieval approach shown in Fig. 1, over 150 pertinent papers are retrieved from various databases.

2.2. Data selection criteria

The selection of relevant studies in this domain is guided by several key criteria. Firstly, the relevance of the research to sustainable renewable energy challenges is vital. Research studies that address pressing issues such as the efficiency of solar and wind energy systems, the integration of renewable sources into existing grids, and the development of sustainable energy models are particularly significant. These reports must not only contribute to the academic discourse but also offer practical solutions to real-world problems.

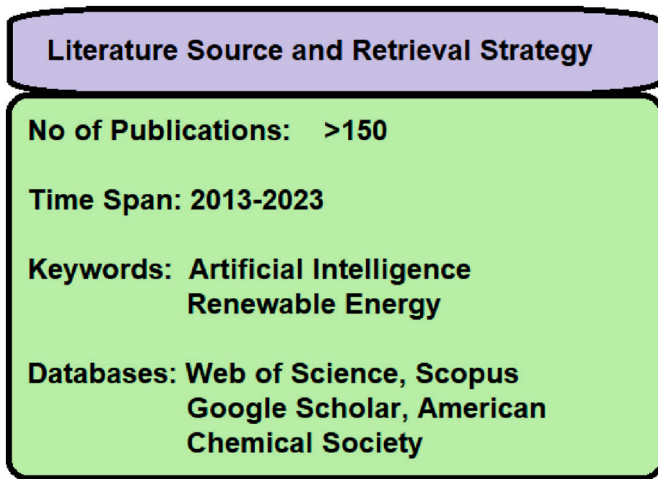


Fig. 1. Literature search sources and retrieval strategy employed in this review.

Another critical criterion is the methodological consistency of the research. In the context of AI applications in RE systems and technologies, this involves a comprehensive examination of the algorithms, models, and statistical and analytical techniques employed. Studies that demonstrate innovative use of AI in the form of machine learning, predictive analytics, statistical data, and other advanced data science methods are highly valued. These methodologies were searched out to be robust, replicable, and capable of handling the complexities inherent in RE systems.

2.3. Information sources

The following information sources were considered suitable evidence for this search:

- Research with real-world worldwide applications, given that the papers under analysis are of sufficient quality.
- Studies that have been published on laboratory or controlled scenarios, provided that the articles that were evaluated met the necessary standards of quality.

- Publicly available information, studies, and proof from accredited and authorized institutions, including the UN and governmental entities.

3. AI in RE

3.1. RE types

The literature findings in the corresponding domain have stressed that advancement and adaptability over time in any field are always vital for making progress, and the same stands true for the RE [38]. A lot of research investigations combine alternative power sources and include cutting-edge technologies to meet power demand. The energy conversion systems reported in the literature are all integrated power sources based on the conservational circumstances, the conditions of the area, and the existence of RE supplies [39].

The RE systems can be constructed from a solo source or an amalgamation of several sources, also termed hybrid sources. According to the source of generation, single-source RE types mainly include solar energy, bioenergy, hydro, geothermal, wind, ocean energy, hydrogen energy, etc. as shown in Fig. 2. In contrast, a hybrid RE system chains the electrical appliances and energy storage with more than two power generation options, i.e., non-renewable and renewable sources. Examples include small gas turbines, diesel-based generators, etc. Various configurations of hybrid RE, such as photovoltaic-based wind-diesel, hydro-wind-based photovoltaic, and fuel cell/hydrogen cell systems, can be employed in a hybrid energy system to produce electricity [40].

3.2. AI tools and techniques

AI was developed using a variety of learning theories [42], including neural, statistical, and evolutionary learning [43], all of which were developed in various literature publications [44]. Neural network (NN) learning algorithms were the most often used learning algorithms in several literary works [45] and Support Vector Machines (SVM) [46]. Additional algorithms include Decision Trees, Random Forests, Logistic Regressions, Linear Regression, Naïve Bayes, Nearest Neighbor, and Hidden Markov [47]. The categorization of algorithms and approaches based on AI is shown in Fig. 3. After implementing smarter systems like AI technologies in nearly all RE systems, from hydro, wind, geothermal, solar, and ocean, to solar photovoltaic systems, RE-based technologies

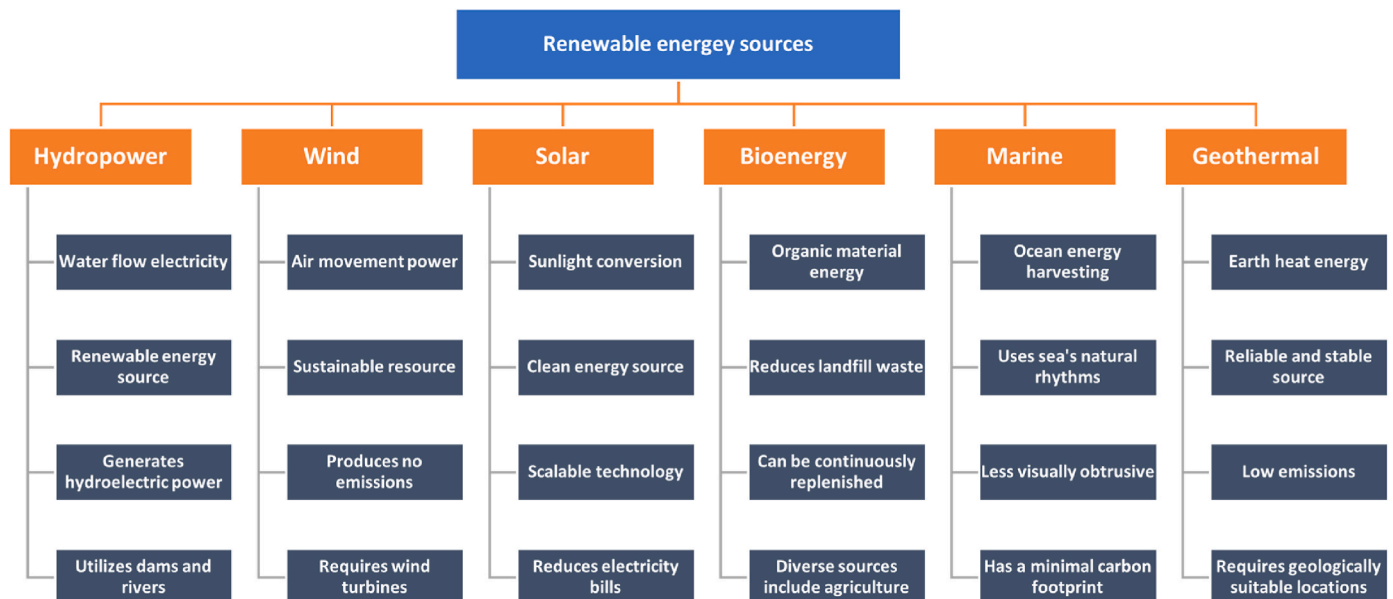


Fig. 2. Type of RE and sources [41].

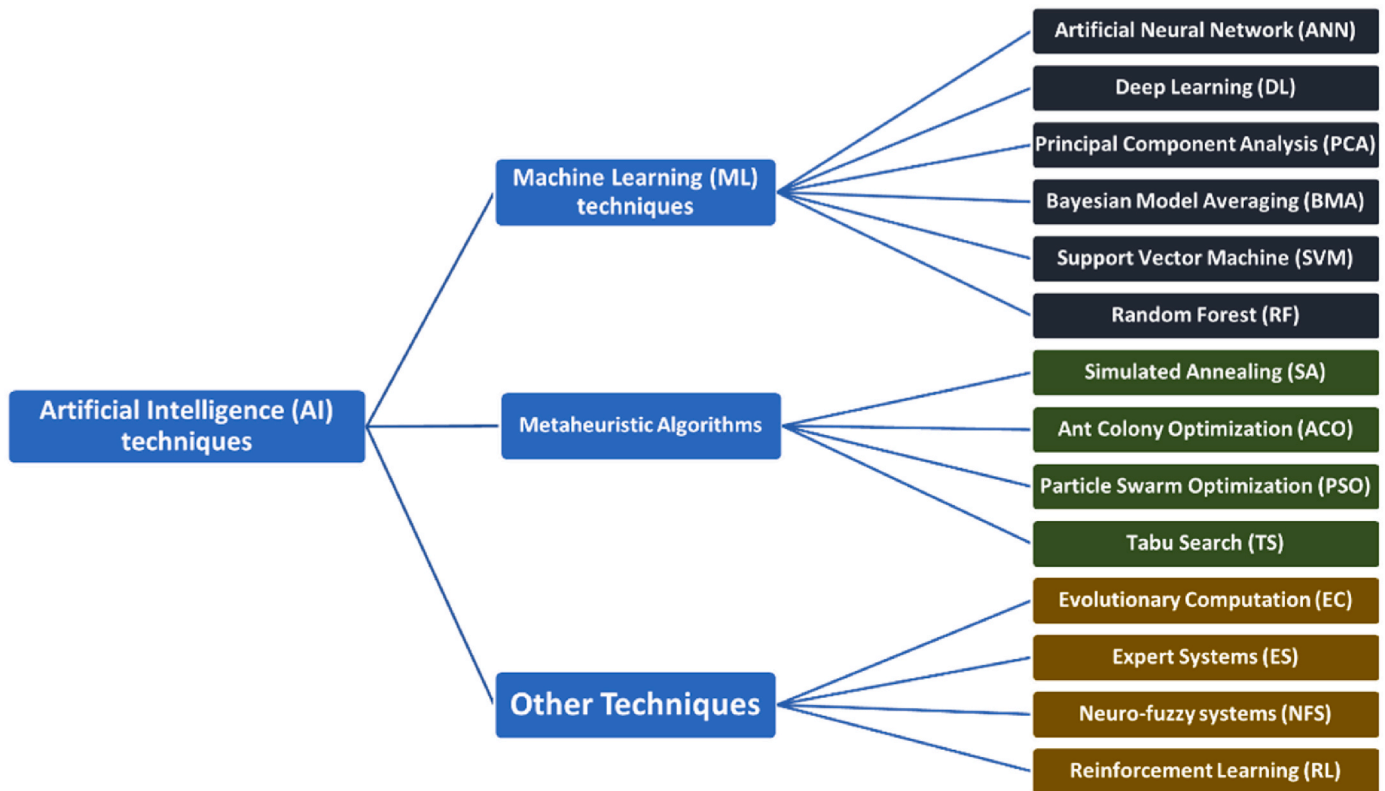


Fig. 3. Classification of AI-Based Techniques and algorithms [48].

are getting more advanced as a result of AI being incorporated to make them stronger and more responsive.

The following are some AI techniques reported to be employed in RE-based technologies:

- Artificial Neural Network (ANN)
- Support vector-machines (SVM)
- Bootstrap Aggregated Neural Networks (BANN)
- Back-propagation neural network (BPNN)
- Genetic Algorithm (GA)
- Radial basis function-neural-networks (RBFNN),
- Seasonal autoregressive integrated moving average (SARIMA)
- Adaptive Neuro-Fuzzy Inference System (ANFIS)
- Naïve Bayes (NB)
- Historical Similar Mining (HISIMI)
- Transient System Simulation Tool (TRNSYS)
- Group method of data handling neural network (GMDHNN)
- Radial basis function (RBF)
- Autoregressive integrated moving average (ARIMA)

3.3. AI role in RE

The steady expansion of RE technology has made its application a crucial component of every research and development field in recent publications [49]. With the advent of highly intelligent and smart systems [50], especially AI-based approaches to handle the expanding opportunities and problems in RE, such as power management, solar photovoltaic systems, preservation, and control, etc. [51], the use of RE systems has also increased and advanced [52]. Various reports have been published recently depicting AI playing a pivotal role in RE, especially in solar radiation, energy intake prediction of a solar system, prediction of wind speed, wind, and solar energy modeling, heating loads of buildings, long- and short-term electric power prediction, modeling of room heaters, sizing photovoltaic systems, and electrical

load prediction of the area [53]. RE-based systems are becoming more advanced, robust, and responsive after the integration of smarter systems such as AI-based approaches and the Internet of Things (IoT). All RE technologies, including wind, hydro, geothermal, solar, ocean, and solar photovoltaic systems, utilize AI technologies [52]. AI has significant role in sustainable renewable energy and improving productivity, reducing costs, and addressing complex challenges. Research has demonstrated how AI use in RE systems has increased the cost-effectiveness and efficiency of technologies such as PV, wind turbines, and panels, making them more widely used and possibly leading to the elimination of fossil fuel-based power plants [54]. A schematic illustration of AI applications in different RE technologies is depicted in Fig. 4.

3.4. Applications of AI in RE

AI is being applied in almost every sort of sustainable RE, including hydrogen, hydro, solar, geothermal, wind, bio, ocean, and hybrid, as illustrated in Fig. 4. By using machine learning algorithms and statistical analytics like P-values and confidence limits (CIs), AI have the capacity to predict energy production on the basis of weather patterns, hence ensuring that the energy grid remains balanced. Moreover, AI can also aid in the predictive maintenance of energy infrastructure, reducing downtimes and ensuring a consistent energy supply. The main applications of AI in RE are design, optimization, management, estimation, distribution, and policymaking. The focus is on five majorly employed RE technologies namely solar energy, PV technologies, solar microgrids, wind turbine optimization, and geothermal energy, to evaluate the AI applications.

3.4.1. AI applications in solar energy

AI approaches have been extensively employed for the determination of prediction, modeling, and forecasting of solar radiation or estimating solar resources. In the literature, various AI-based models have been

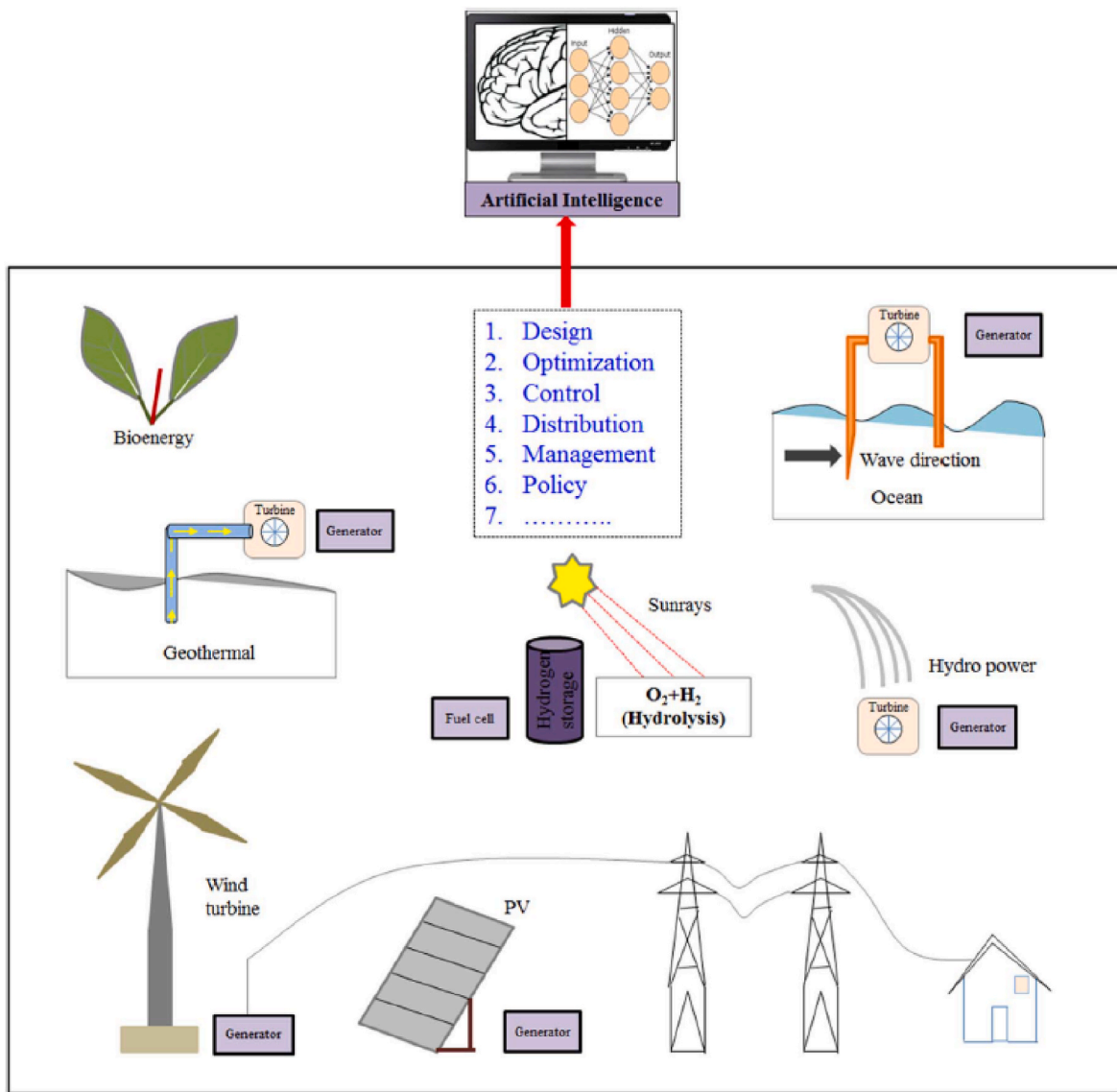


Fig. 4. Schematic representation of AI applications in RE based technologies [40].

reported for modeling, optimization, recreation, and seizing of solar power systems, and successfully modeled the solar radiation, insolation, solving the problem of missing data, and clearness index [55]. Their utilization was mainly reported for assessing data in sites where dimension devices were not accessible for solar energy-related measurements. No data transformations are required for AI approaches, and this property sets them apart from the traditional ones. It was investigated by some researchers that some AI models were location-specific, but they could be easily applied at different locations with some amendments [56]. Numerous compensations of AI-based simulation systems have been documented, one of which is that they provide a potent substitute for traditional physical modeling approaches in the area of solar energy simulation. These simulations can produce a cost effective and solid resolution for multi-variable issues, needless computational work, and don't require knowledge of internal system parameters [23].

Among all other AI-based approaches, ANN was the most commonly employed by researchers around the globe [57]. Many researchers have also been using BPNN and predicted the solar energy, radiation, irradiance, daily surrounding temperature, water heating, daily solar radiation, system, building energy, beam radiation, and maximum power of high-concentration PV modules [58]. ANFIS was reported to be used in

PV power supply modeling, clearness index, prediction of hourly global irradiance, radiation, solar power, and solar chimney power plant (SCPP) performance [59]. In some research, a variety of techniques were combined to provide the best possible predictions, forecasts, and estimations [60]. When comparing the population or sample values projected by a particular model to practical levels, the root-mean-square error (RMSE) and mean absolute percentage error (MAPE) is frequently employed to evaluate the discrepancies. It is employed as a standard statistical metric in fields like air quality and meteorology to measure model performance [61]. Various AI procedures applied to solar energy have been reported in the literature and are enlisted in Table 1 with their potential outcomes in detail.

3.4.2. AI-driven enhancements in PV technology

AI has transformed the solar energy industry and is becoming a disruptive factor in many adjacent industries [76]. Solar cells use the photovoltaic effect to convert sunlight into electric energy is solar cells [77]. In the past, trial-and-error procedures, theoretical models, and empirical approaches were employed in the optimization and design of solar cells. By using AI's capabilities, engineers and researchers have found new approaches to boost PV technology's affordability, functionality, and efficacy [78]. Scientists and engineers, with the

Table 1
Reported AI approaches, results, advantages and limitations for solar energy applications.

AI Model	Solar Energy Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
ANFIS	Hourly worldwide radiation prediction	rMBE = -4.08 ± 2.18 % rRMSE = 25.9 ± 0.90 % Standard Deviation (STD) ~ 1.44	The comparisons revealed that the ANFIS replicas outperformed the arithmetical models in terms of performance. Regression models derived from n/N and Kt can be applied to solar energy harvesting applications.	The ANFIS model gave an accurate and feasible prediction compared to the statistical models for global irradiance. However, the performance of ANFIS is heavily dependent on the quality and range of input data, implying a limitation associated with its ability to optimize atmospheric conditions and geographic factors in scenarios.	No	[62]
ANFIS	Solar Chimney Power Plant (SCPP) performance prediction	$R^2 = 0.92$ $P < 0.05$	The investigational statistics and the ANFIS model agreed well, as indicated by the testing's determination coefficient (R^2) error of 0.92 in the ANFIS modeling.	The effectiveness of solar chimney power plants will be precisely measured with less computational cost, as the model was able to predict more than 105 outputs every second. However, it needs to minimize the error of testing performance.	No	[63]
ANFIS	Clarity catalog, radiation prediction	MAPE < 2.2 % $P < 0.05$	The study suggested using the ANISF model to forecast daily global solar radiation (GSR) and underlined the need to choose input parameters carefully. Making precise predictions in this manner makes it lucrative to appropriately build and estimate the solar energy systems' performance, which has positive effects on both the technical and financial fronts.	Such a simple, suitable, and accurate prediction is viable to properly evaluate and design the workings of solar energy systems, which later leads to economic and technical benefits. However, the limitation associated with this is evaluating numerous combinations of input factors for the ANFIS method, which is crucial to optimize.	Yes	[64]
BANN	Hourly solar irradiance prediction,	$R^2 = 0.9680$ RMSE/Wm ⁻² = 62.4856	The solar irradiance received on the plane in Bouzareah (Algeria) over one year, using 8 meteorological and climatological parameters. The experimental and predicted values were compared during the testing phases for BANN, which gave more accurate and robust modeling results.	BANN has the advantage of being used to forecast solar radiation for regions that have no measurement apparatus and when the actual statistics set available is minor. However, limitations are in the instance of a collection of outliers that must be omitted.	No	[65]
BPNN	Diffuse solar radiation prediction	RMSE = 2.823×10^{-4} $P \sim 0.05$	The month of the year, mean temperature, daylight duration, wind speed, relative humidity, rainfall, and daily worldwide solar radiation were the seven characteristics employed in the BPNN technique to obtain the evaluating indices that provided precise measurements.	The advantage associated with this is the accuracy and cost-effective optimization of the BPNN model, which accurately predicted diffused solar radiation. However, a limitation associated with this study is the estimation of error in the input variables.	No	[66]
GA	MPPT Solar tracking	STD ~ 1.55	For tracking and control purposes, a microcontroller was programmed to implement the GA-based tracking technique. A standard power electronic system configuration saw the effective implementation of the whole system, which was built on the suggested GA model.	The advantage of this study was the simulation of a non-conventional approach, which gave successful solar tracking under the same atmospheric changes. The limitation associated with this is the extraction of the maximum power of the PV panel if the PV-generator is partly shaded.	Yes	[67]
GA-BPNN	Prediction of mean temperature	MAPE ≤ 1 %, RMSE = 0.3853 ± 0.4057	The best accurate results were obtained by combining BPNN and GA-BPNN; its MAPE was less than 1 %. The findings may aid in the creation of quick and practical models for predicting outdoor heat environments.	The outcomes of this study are advantageous because they can lead to the prediction of outdoor thermal environments, to accurately forecast mean radiant temperature (MRT) with reduced computational complexity. However, preparing the several training data sets is the major limitation of this study.	No	[68]
BNN, CMLP	Global solar radiation prediction	RMSE 5.67–6.57 % for BPNN	The BNN-based CMLP model performed exceptionally well at all sun energy research locations examined over daily, monthly, and annual timeframes when compared and benchmarked against seven AI-based and seven models based on temperature deterministic.	This hybrid CMLP model is advantageous to discover as a practicable modeling approach for solar energy forecasting and monitoring in actual energy supervision systems. The limitation of the approach is that it may be difficult to integrate and optimize many advanced computational techniques, which may require extensive computational resources.	Yes	[69]
ML, SVR	Global solar radiation prediction	RMSE 0.867 for BPNN	According to RMSE, the experimental results of this study provide a good estimate in every place in Egypt, demonstrating the effectiveness of support vector regression (SVR) models as a greater-accuracy machine learning technique.	Good estimation and accuracy of input variables is the advantage of this modeling approach; however, testing errors in training data sets is the limiting factor that needs to be addressed.	No	[70]
GA+ HISIMI	Forecasting of solar power	RMSE(KW) = 283.89	A high intra-hour fluctuation in its authentic power output has been observed	The advantage associated with this model is its ability to source the spot standards for	Yes	[71]

(continued on next page)

Table 1 (continued)

AI Model	Solar Energy Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
		Prediction rate >98.5 %	in the results of spot forecasting solar power using the HISIMI model for an actual grid-connected power plant.	power predictions, in addition to the uncertainties related to them. The limitation is the complexity and computational resources required for the genetic algorithm to provide accurate forecasting.		
ARMA and Bagged RT	Global solar irradiation forecasting	$P < 0.05$ RMSE ~ 0.13	The forecasting of solar radiation worldwide was examined and contrasted in terms of performance at three locations with various meteorological features. Regression trees (RT) based on bagging mode are the most dependable when cloud occurrences are few. Otherwise, an ARMA model can be used.	The advantage of the ARMA models is the efficiency associated with the selected variability and temporal horizon. The limitation is that the consequences are not fully irrefutable. It seems that the higher the unpredictability, the more intricate the prediction tool, which should be looked into more.	No	[72]
ANN + TRNSYS	Prediction of performance of ICS	$R^2 = 0.94$	TRNSYS-based ANN simulation has the potential to replace tests in their entirety. Even individual components can be simulated. According to a report, the innovative model in its established phase can produce a range of reports.	The advantage of this modeling approach is that a rare-to-rare situation can be created for testing and evaluating the prediction of ICS performance. Initial capital savings is high for obtaining the costly software is the main limitation of this study.	No	[73]
WPD-CNN-LSTM-MLP	Values estimation of solar radiation	MAE ~ 0.19	The new model eliminated the drawbacks of older models and produced forecasting results that were more accurate. Real data, including solar irradiance and climatic factors like temperature, relative humidity, and wind speed, from the United States' Denver, Clark, and Folsom confirmed the model's presentation.	The advantage of this method is the provision of intrinsic features of the multi-layer ideas, overcoming the inadequacies of conventional models; however, its limitation is associated with the prediction precision in other than hourly radiation measurements and prediction.	No	[74]
PSO-BP, GA-BP	Prediction of solar power	MAE ~ 42.96 kW MAPE (0.94797 %)	The study's findings showed that, in distinction to the inventive BP model, the PSO-BP and GA-BP network prediction models have excellent prediction precision and the capacity to successfully lower prediction errors.	The PSO model is advantageous due to its ability to lessen errors related to PV power and energy prediction. PSO-BP showed the highest accuracy with the lowest RMSE (0.015805 MW) and MAPE (0.94797 %). However, investigators constructed a short-term prediction model for the PV output, which is a limiting factor.	Yes	[75]

advancement of AI, now have efficient resources for their removal to enhance the efficiency of solar cells. The recent reports about the practice of AI in PV suggest a standard shift in how RE will be shaped in the future, as listed in Table 2.

The efficiency of solar panels is one of the topmost fields where AI has pointedly contributed to its enhancement. AI algorithms and advanced data analytics made it conceivable to accurately measure and evaluate the different parameters that are affecting the efficiency of solar panels, i.e. temperature, intensity of incident light, and shading effects [90]. With the aim of increasing production, AI algorithms were reported to have the ability to dynamically modify the operating conditions of solar panels by constantly observing and evaluating the operating conditions in real-time. This AI-based optimization of operating conditions increased the overall performance stability and dependability of the energy yield of solar energy systems and solar panels [91].

Reliable solar irradiance forecasts are essential for operative energy management and grid integration, as the generation of solar energy is highly reliant on weather situations [92]. AI has completely transformed the forecasting and resource evaluation of solar energy. Literature investigations revealed that when AI-based algorithms and approaches are mutually compatible with historical and meteorological data on the generation of solar energy, they can yield precise long-term and short-term solar irradiance estimates [93]. This guaranteed system stability, improved energy production, and allowed energy planners and grid operators to improve control and forestall the inconstant nature of solar power.

One of the primary benefits of using AI in the optimization of solar cells is the ability to derive actionable insights and estimate enormous amounts of data [94]. Research in this domain depicts AI systems that are able to process the large number of datasets relating to solar cell

constituents, performance parameters, and device architectures [95]. AI based algorithms were able to spot complicated associations, trends, and patterns by employing large data sets that would be tough to find using conventional techniques. This data-driven AI approach helped the researchers improve the performance of solar panels by figuring out what kinds of variables affect solar cell efficiency and permitting them to progress a thorough grasp of it [96]. These AI algorithms are further modified to combine with machine learning algorithms to figure out the connections and trends among various input factors and the related system of measurement for solar energy cell presentation [97]. Algorithms for machine learning have the potential to predict the performance of original solar energy cell designs. These advancements can lead to new directions for the researchers towards more operative combinations through reviewing historical statistics on solar cell materials, efficiency measurements, and design arrangements.

Leading to these improvements, PV cell modeling is primarily linked to parameter identification accurately. As the importance of parameter identification has gathered increasing interest, and several studies are being investigated and already done to develop achievable and practical approaches to solving this kind of problem. These policies can be classified into two major categories, which are analytical-based strategies and meta-heuristic algorithms. To extract these parameters, analytical methods imply data sets of complex mathematical-based equations. Several meta-heuristic algorithms have gotten the attention of the scientific community for various applications with the advancement of swarm intelligence and computer-based techniques, particularly in complex optimization and extremely non-linear issues [98].

A meta-heuristic algorithm is a search approach that is designed to search for a good solution for optimizing complex problems that are difficult to solve. One of the most important advantages associated with meta-heuristic algorithms is the lower computational cost associated

Table 2
Literature reported AI approaches employed in PV applications.

AI Model	PV Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
ANFIS	PV power supply tracking	$R^2 \sim 99\%$ $P < 0.05$	It was discovered that the PV module's maximum power supply was tracked satisfactorily for changes in temperature and irradiance. One notable achievement highlighted is the increase in output power of the PV module by up to 97 % under specific irradiance conditions with the ANFIS-based control scheme.	In comparison to more traditional approaches, the ANFIS model is superior because it can rapidly adjust to variations in irradiance and temperature without producing steady-state oscillations close to the maximum power point. However, the PV system's non-linear structure and the tracker system's complexity pose limitations.	No	[79]
ISOA	Extract the parameters of the PV panel	RMSE SDM mSi = 5.58×10^{-4} RMSE SDM aSi = 4.61×10^{-5}	The papermakers of the monocrystalline silicon photovoltaic cell (mSi), amorphous silicon photovoltaic cell (aSi), and RTC France photovoltaic cell were extracted using ISOA for the single diode model (SDM) and the double diode model (DDM).	When compared to other top algorithms, the ISOA showed an improvement in RMSE of 16 % for the mSi, 5.3 % for the aSi, and 0.002–0.11 % for the RTC France cell. Though ISOA has a small iteration population, it takes a significant 17.6 s for SDM and 20 s for DDM to discover the ideal RMSE, which is thought to be a longer period to acquire the best results.	Yes	[80]
ANN	PV panel power prediction	Power generation $\sim 0\text{--}35$ kW	The optimal topology was determined, and the consequences validated the appropriateness of the planned methodology for the short-range power output prediction challenge.	ANN models proved advantageous due to their simpler architecture, and these algorithms can play a prominent role regarding the remote management of PV. However, their requirement of longer training time is the limiting factor.	Yes	[81]
ISCE	Parameter extraction of solar cell models	RMSE = 9.860219×10^{-4}	The suggested improved shuffled complex evolution algorithm (ISCE) technique shows a lot of promise and is thought to be a precise, dependable, and efficient solution to the factor extraction problem of solar cell models.	The advantage of this model was that it gave a sound solution to the parametric extraction problem, for which the ISCE algorithm obtained the best results in terms of extracting the parameters of the PV cell and panels.	No	[82]
SVR, BPNN	PV panel energy prediction	RMSE 0.133 for SVR and 0.131 for BPNN	The outcomes showed that, compared to the traditional ANN model, the SVR-based BPNN model produced improved prediction accuracy with reduced computing complexity.	Accurate forecasting with simple, less computational modeling in comparison to other models was the main advantage of the study. However, the average forecasting errors are the real limitation, which should be addressed properly to get more accuracy and precision. There was an average of 3.08 percent model prediction error in nRMSE, 34.57 W in MAE, and 11.34 W in MBE.	No	[83]
RFR	PV power generation forecasting	RMSE 7.23 %	This study offers vision into the availability and potentials of XAI in keen grid applications, which might be useful for utility researchers and engineers working on generation of power and forecasting of load by using a random forest regressor.	This model gave the benefits related to computing costs and explained the power generation hourly and globally. Nevertheless, one drawback is the computational difficulty and expense of using these tools, particularly SHAP, which requires a lot of processing power.	Yes	[84]
Hybrid methods MLR, ANNs, MLP, ELM	PV panel power prediction	MAE 0.317 kW/h	This study examined the use of PV panels for solar energy generation in Spain in the Galicia region. It was suggested that a hybrid stepwise method may be used to anticipate the amount of solar energy generated by this pane. When using the hybrid method model-based clustering technique, the results were superior to dealing with the entire dataset accurately.	The advantage associated with this study is that a legal dataset is used for processing rather than eradicating data sets having empty values. The clustering technique also gave accurate results; however, working on large data sets is the limiting factor which needed to be addressed for more advanced applicabilities.	Yes	[85]
Hybrid method (GA-Fuzzy)	Power flow control	Active power = 19.2 W Reactive power = 23.5 Var Harmonics (THD) = 0.6025	In a matrix-related PV framework, GA-fuzzy was used to control actual and receptive force streams effectively. The uncertain foundation regulator produced a switch vector as a result, which was then squeezed with good accuracy and power control flow using a conventional computation. The results from the paper regarding the performance which the static synchronous compensator (STATCOM) compensator exhibited less overshoot in real reactive powers and DC voltage Total Harmonic Distortion (THD) during the simulations	The advantage of this model was the introduction of a real and approachable force stream in a medium related PV framework for effective management, which includes enhanced power flow control and reduced total harmonic distortion (THD), indicating improved power quality. The responsive and real force stream difficulties, are a chief limitation associated with the transfer of a mass measurement of the strength from a PV collection to the power grid.	No	[86]
ANN	Solar PV power production	MAE ~ 0.32	It is possible to view the suggested strategy as a holistic method that will help solar energy plants improve their projections for	This model provided results outperforming the other models, with performance up to 11 %, 12 %, and 9 % for RMSE, MAE, and WMAE. Additionally, it	No	[87]

(continued on next page)

Table 2 (continued)

AI Model	PV Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
			solar power generation while also accounting for potential uncertainties.	achieves a high confidence level of up to 84 % for prediction intervals. However, errors in training data sets are the main limitations associated with this study.		
PSO, MPSO, PSO-CF, PSO-RF, PSO-W	Finding the optimal size of a PV/wind/battery hybrid system	Less computational cost 0.156 for PSO	The encouraging outcomes suggested that hybrid approaches may also be applied in other areas, where it was found that PSO with constriction factor (PSO-CF) showed more promising results in optimizing the total annual cost (TAC).	The advantage of using PSO-CF is its effectiveness in finding the optimal system size with a lower TAC of around 2454.3 \$. However, fine-tuning parameters are needed to achieve optimal results across different scenarios.	Yes	[88]
MPPT, GA, Fuzzy	MPPT of PV array	Line voltage 400 V	The DC/DC boost converter, which was operating to link and successfully extract the extreme solar energy from the PV array, was controlled by means of this hybrid simulation approach. Accurate power transfer from the solar panel to the DC connection.	The main advantage was the controller that is used to sustain the DC-link voltage, which gave accurate results. With ideal parameters like P1 and P2 both set at 0.01, and P3 at 0.647. The drawback associated with this algorithm is the system's functioning point, which oscillates around the MPP in a stable state, resulting in the waste of the available power.	No	[89]

with them, as these algorithms don't require a precise mathematical model. As of late, there has been an increase in the amount of published metaheuristic algorithms designed to identify PV cell parameters. The meta-heuristic methods, with a combination of AI and physical methods, offer more precise PV power prediction for long-term time horizons and mediums and also reduce forecasting errors, for example, RMSE, MAPE, and MAE, in comparison to other approaches and algorithms [99].

The concept, advantages, and disadvantages associated with each algorithm of meta-heuristics methods for PV cell parameter identification have already been reported in detail in the literature, particularly concerning the convergence speed, accuracy, and practicability of applications. The comprehensive detail explaining the variety of every algorithm, the virtual results, and their contrast to each other is already

reported in Ref. [100]. Different metaheuristic algorithms have been reported for PV cell modeling and the identification of cell parameters. They are divided into different categories, like bio-based, physics-based, and mathematical-based algorithms. Bio-based metaheuristic algorithms include flower pollination, bacterial foraging algorithms, grey wolf optimization, etc. Physics-based metaheuristic algorithms include particle swarm, wind-based optimization, water cycle algorithm, lozi-map chaotic optimization algorithm, mutative scale optimization, simulated annealing algorithm, etc. Whereas, the most commonly employed algorithms are mathematical-based metaheuristic algorithms, which include the shuffled complex evolution Jaya algorithm and the pattern search algorithm [90]. Fig. 5 displays the metaheuristic algorithms across various categories.

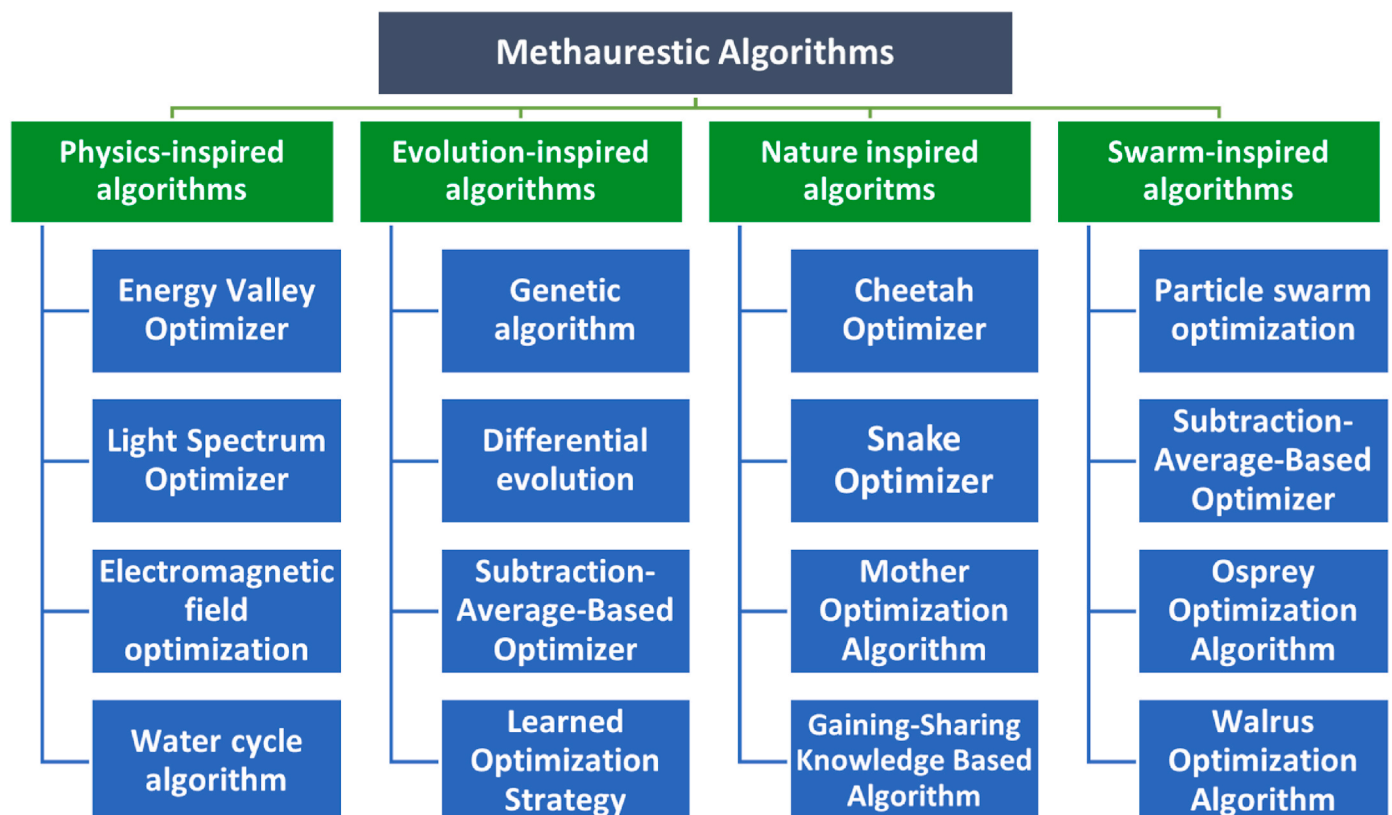


Fig. 5. Categories of the metaheuristic algorithms.

3.4.3. AI in solar microgrids (MGs)

Localized incorporation of various mechanisms, such as conventional and RE units, loads, and energy loading systems, results in the creation of a microgrid. Because of their qualities of high flexibility, sustainability, and self-sufficiency, MGs can be useful in enhancing power system performance indicators, including dependability and resilience [101]. Scientists and researchers have, however, continuously documented the various obstacles encountered during the design and execution of MGs, in view of the constraints associated with loads and RE materials, energy management of energy resources, abrupt variations in load, etc. [102].

Additionally, the main issue that power systems handle is the massive amounts of data that are produced as a result of the integration and system evolution of many components, such as smart meters, DERs, ESSs, electric vehicles, and communication structures [103]. These problems prompted researchers to employ quick and precise methods, such as artificial intelligence, to solve them and improve the effectiveness, stability, dependability, and security of MGs. Since traditional simulation techniques were unable to produce enough results to manage and process the massive amounts of data effectively, a lot of work has recently been published using AI techniques in power systems to resolve the issues [104].

The AI approaches in power systems can be primarily characterized as expert systems (ES) [105] and machine learning based ensemble methods [106]. A synopsis of the AI practices applied in the MGs by different research reports is given in Table 3. AI-based models and algorithms can be broadly applied in RE systems, MGs, and smart grids, and some of these general applications are enlisted below:

- Wind and PV power generation forecasting
- Neural network-based modeling of elements of static and dynamic system and immediate simulation by DSPs/FPGAs chips
- High performance effective control of system elements
- Online fault-tolerant control and diagnostics, protection schemes
- Energy management systems
- Consumer load prediction on the grid
- Efficient scheduling of power generation and storage
- Sensor-less robust estimation of feedback signals
- Cyber-attack detection
- Real time electricity predictions pricing with demand management
- Delay less and noise filtering of signals

3.4.4. AI in wind turbine optimization (WTO)

Current years have seen a significant expansion in the use of wind turbine systems worldwide, and they are now a standard feature of contemporary power grid systems [118]. The wind that flows through a wind turbine directly affects the amount of power it can produce. A careful analysis of wind patterns using potential site locations is imperative for wind turbines to determine the optimal tower placement for efficient wind power extraction [119]. Researchers stressed the need to improve each wind turbine's control, which is done by taking into account the intricacy and magnitude of the electrical topology of the wind turbines, to attain maximum proficiency as well as the highest profits for power providers.

When it comes to creating effective control systems for wind power generation, researchers have faced numerous obstacles [120]. Another crucial element to take into account when analyzing the wind currents originating from a wind turbine is the wake turbulence, which has been documented in many studies. Because of their interaction with the wind turbine blades, wind current oscillations produce wake turbulence (WTB). A certain wind turbine may have a detrimental consequence on the wind currents [121]. Wind power is an additional consideration while developing controllers for systems used in wind farms.

In light of these considerations, the researchers concluded that remote control and monitoring of energy wind turbines are crucial for achieving their full power generation potential. Along with this, it is also

important to limit the time interval a wind farm is down in case of any sudden damage due to mechanical failure, electrical faults, or extreme weather conditions. An efficient control system for wind turbines must be able to adjust to nonlinear and time-varying wind currents and concentrations [122].

To avoid the above-mentioned limitations and to assist in predicting, controlling, and monitoring wind turbine systems, scientists and engineers have successfully employed AI and machine learning algorithms and models [123]. The most commonly employed AI-based approaches in wind turbine systems by researchers and engineers are ANN, SVM, and SOA.

The ANNs, when utilized for prediction, are quite adaptive, highly accurate, fault-tolerant, self-organizing, and easy to implement; therefore, they have been implemented in several cases by researchers to predict wind speed, power, and density [124]. Similarly, SVMs have also proved very accurate and have mainly been employed for the revealing of faults and classification [125]. These have also been projected for the sake of prediction, but they require more in-depth investigations and analysis as their efficiency is not outperforming the ANNs in the domain. The SOAs are bionic algorithms and population-based models that mimic the swarm features in nature [126]. Engineers across the globe hence preferred the AI algorithms and nonlinear controllers to assist in wind turbine optimization, as depicted in Fig. 6. To reduce the error rate of wind-based weather forecasts, the National Center for Atmospheric Research (NCAR) has lately released an updated version of their weather prediction model that incorporates AI [127]. Table 4 displays latest insights into AI methods and their use in enhancing wind turbine efficiency.

3.4.5. AI in geothermal energy

In many nations across the world, geothermal energy has been a consistent source of space heat and natural heat for bathing, cooking, and washing, since ancient times. Geothermal energy developed over the 20th century into one of the most dependable and renewable sources of electricity, and it was also widely supported for the development of clean energy [135]. However, many of the older and larger geothermal plants were started during the height of the energy boom, which led to its ongoing extraction, and problems have since surfaced [136]. Due to uncertainties in geology, economics, and technology, geothermal technology has not been developed and adopted at the same rate as RE technologies. Thus, to lower the cost and risk of geothermal projects, experts have always emphasized the necessity of identifying strategies for minimizing the uncertainties related to the investigation of geothermal resources.

Recent collaborative developments in AI and RE have provided opportunities for investments in the utilization of geothermal energy [137]. The current research using these approaches primarily considers big areas and does not effectively investigate the incorporation of machine learning and AI models and algorithms. AI approaches and models are reported to have promising applications in handling the challenges of geothermal exploration [138]. Using both surface and subsurface data, artificial intelligence was initially applied to a fairway investigation for the regional assessment of geothermal-potential [139]. It has incorporated machine knowledge to copy the results of the human assessment of the fairway. A lot of research reports are available for remote sensing applications for the exploration of geothermal energy [140] and a summary of recent reports on the domain are enlisted in Table 5. One example is thermal infrared which was used in airborne SAR (Synthetic Aperture Radar), and the satellite data was used to map potential geothermal resources [141]. Another investigation has used a spectrometer to recognize and evaluate the geothermal mineral indicator, whereas a portable spectrometer was employed in drill cores by some researchers [142]. AI-based Fuzzy logic was also used by researchers to evaluate the geothermal potential through regional evaluation [143].

Table 3
Recent Reports on AI Techniques and their Application in MGs.

AI Model	Solar MGs Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
BFO	Parameter Extraction control in microgrid	Prediction accuracy 2.5–14 %	The BFO, was applied to propose a new extraction method to evaluate parameters. After analyzing both the experimental and simulation consequences obtained after using BFO, it was found that the module factors proved more precise than conventional approaches.	Results show that the BFO-based method yields lesser fitness function percentages, indicating higher accuracy in parameter extraction. Variable weather circumstances like temperatures and solar radiation levels are the limitations that need attention.	No	[107]
BPSO	Solar microgrid power generation	Optimal path for 50 % swarm	This study successfully proposed a new optimal plan controller to manage RE resources in a virtual power plant (VPP) using the BPSO model. A comparative analysis of the PSO algorithms with conventional ones justified the integration use of solar MGs and validated the developed PSO model for emissions reduction and energy management.	Study achieves approximately 47 % power savings from the national grid and reduces CO ₂ emissions by 8.46 % compared to random scheduling methods; however, errors and precision in data sets are the limiting factors.	Yes	[108]
ARIMA time series algorithm	Electric consumption prediction	MSE <0.08	A ARIMA forecast model based on available power utilization patterns was successfully built to forecast future electricity consumption in the town of Karnataka State, India. The prediction model was efficient enough to forecast consumption and can be applied to other regions.	The advantage of the model is that it gives the actual data power consumption of previous years to scrutinize and forecast the consumption pattern for the future; however, regional geographic and error determination are the critical factors that need attention.	No	[109]
Icos ϕ control algorithm	Sharing power and improving the quality of power	Prediction accuracy 2.1–11 %	By forecasting the output energy of the microgrids with RESs, this research advances the aptitude of the proposed AI-based IIC and achieves power flow supervision with charge control without compromising the worth of power.	The study shows notable improvements in total harmonic distortion (THD), which is reduced from 30.66 % in the uncompensated system to 3.64 % under equal tariff conditions.	No	[110]
MGWO	Management system for SPV-based microgrid	R ² ~ 98 %	The suggested method can be applied to EV charging stations with different rates in accordance with the ToU in cases where the topology is automobile to grid and grid to automobile. It shows significant operating cost reductions and improves grid performance under a range of weather scenarios.	Under both clear and foggy situations, the modified grey wolf optimizer (MGWO) strategy produced reductions in operating expenses of 23.34 % and 45.55 %, respectively. It also successfully lowers the energy consumption on the grid, but the error estimation was the main limitation.	No	[111]
ML techniques	PV solar irradiation and temperature forecasting	MAE ~ 0.3	RF plus SVM can greatly improve prediction performance for short-term temperature and sun irradiance forecasts. It performs noticeably better than the outcomes of the common approaches, KNN and LR. However, because of its built-in features and settings, the SVM outperformed RF by a small margin.	Accuracy and precision were the main benchmarks for this model, but the limitations associated with this study were good performance in short-term forecasting and uncertainties in long term solar irradiation and temperature measurements.	Yes	[112]
ML, ANN-SVM	Distribution automation in MGs	38–44.8 % improvement	The effectiveness of the ML-based ANN-SVM model was implemented on the MG model in Aalborg, Denmark. Such adaptive configurations can be employed with enhanced policymaking to change the analysis situation and guarantee the intelligent operation's reliability.	The main advantage of this model was its capacity to build a microgrid model with enhanced decision-making and constructive reconfiguration. The limitation was the uncertain elements in a microgrid.	No	[113]
BFOA	Development of stand-alone microgrid system	R ² ~ 0.99	The system demonstrates how carbon emissions can be decreased, self-sufficiency can be increased, and dependency on non-RE sources can be diminished. The simulation of the system was developed using MATLAB.	The strength and merging analysis of the anticipated MG system with an intellectual controller were successfully attained, but the variability of the data sets was a limitation.	No	[114]
ML algorithm, regression tree model	Solar panel microgrid power prediction	77 % and 85 % power prediction accuracy	This study presented a ML-based algorithm that used a deterioration tree model with humidity and time of day as key parameters. The regression tree model presented a promising precision. This work showed that the solar panel estimate in Houston was heavily dependent on the dampness of the region.	Regarding solar power estimates, the model's accuracy was 85 % in the morning and 77 % in the afternoon. It took only 3 s for the model to calculate, but varying regional weather conditions make unfeasible to apply the same model across various regions which was a limiting factor.	No	[115]
ANN	output prediction of solar energy generation	R ² ~ 0.99 RMSE = 3.38 W/m ²	The anticipated and actual output energy differences were between 0.5 and 9 %. The ANN-based tool's prediction accuracy was good enough to be deployed in systems with integrated solar generators.	The advantage was the accuracy of the tool to be introduced in systems that have integrated solar generators. With a regression value of 0.98981 at the 9th iteration. Actually, the produced and	Yes	[116]

(continued on next page)

Table 3 (continued)

AI Model	Solar MGs Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
Q-learning algorithm	Energy management	RMSE ± 4 %	The study presents two primary scenarios: the first scenario examines how the microgrid's system reacts to an increase in load, while the second scenario focuses on a microgrid fault state, particularly a line fault.	predicted energy difference was the limitation. The microgrid's operating costs increase by 0.4 % in scenario 2 compared to scenario 1, but environmental costs are significantly reduced by 7.7 %. As a result, compared to scenario 1, the total expenses in scenario 2 are 3.1 % lower.	No	[117]

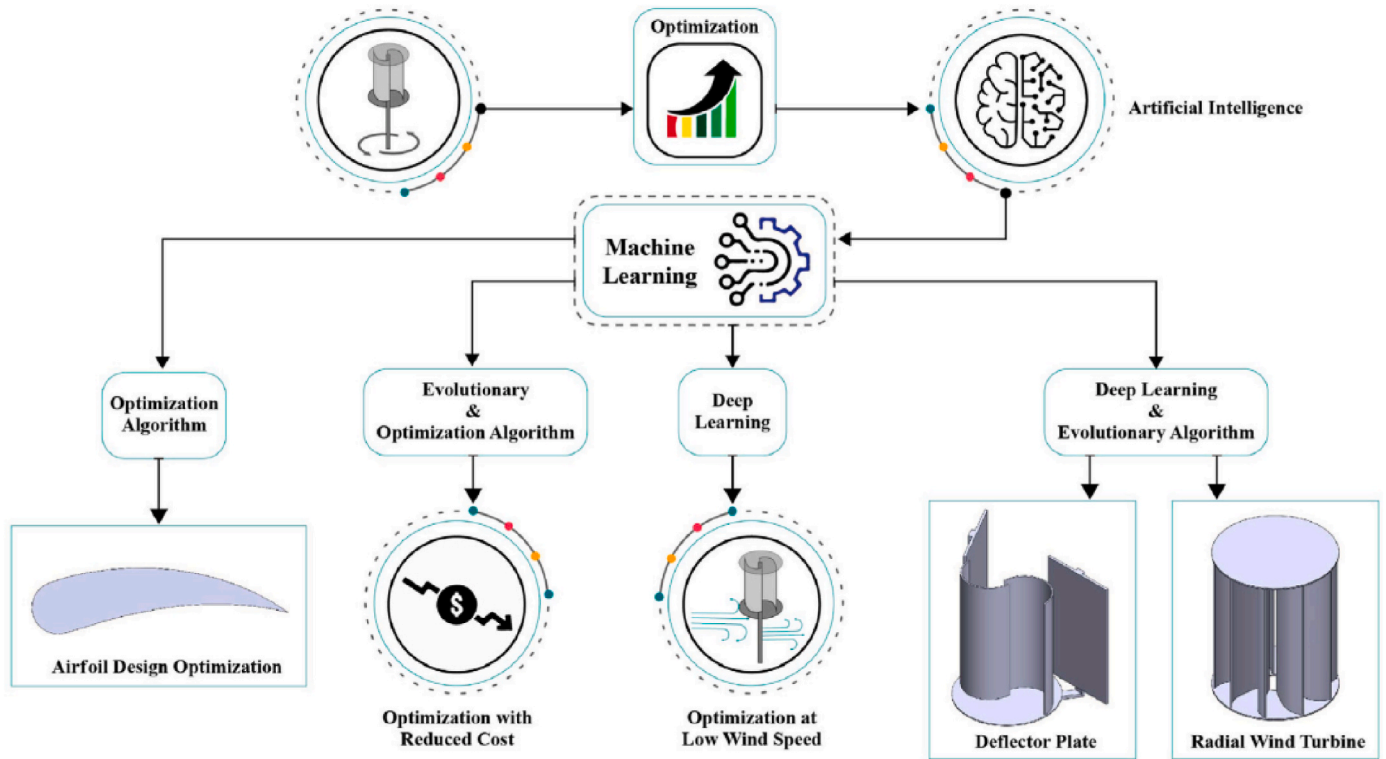


Fig. 6. Ai based algorithms for modern optimization for wind turbines [40].

3.5. Case studies

3.5.1. Case study 1: wind power generation and prediction via ANN in India

Background: Many emerging countries, including India, have begun wind energy projects in areas with year-round high average wind speeds. One Indian state that is vigorously following wind-power generation projects is Tamil Nadu. Muppandal, one of the state-designated locations for generating electricity, has a high concentration of wind farms. The researchers assessed the wind energy output of wind farms at the above-mentioned location, using the ANN technique [154]. This site was used to collect field data from seven wind farms over 3 years, from April 2002 to 03/2005, for study and wind farm power generation forecasting. The objective of this study was to measure the output of wind farms, for which AI techniques were successfully improved. Wind energy engineers may find this study to be rather interesting.

Potential Results: The AI-based model was developed by modifying and using ANN methods. It considered 3 input variables: relative humidity, speed of the wind, and generation hours, in addition to 1 output variable, or the energy output of the wind farms. The activity index for ANN training was given in terms of MSE, while MAE and RMSE were calculated and matched. Ultimately, modeling was done using the MATLAB toolbox. The model's accuracy was estimated to be

outstanding and in good agreement with the expected results of the actual values that were measured at the wind farms. Fig. 7 shows the ANN-based model's forecast for producing wind power in seven wind farms, while Eq. (1) was used to model the air density.

$$\text{Air density} = D \times \frac{273.15}{T} \times \frac{B - 0.3783e}{760} \tag{1}$$

Discussion: The ANN model yields a consistent prediction of the output in the form of wind power from wind farms through the input constraints, such as relative humidity, average wind speed, and generation hours. Power generation is typically impacted by wind speed. However, high generation hours and speeds of wind greater than the turbine's rated wind speed are found to be important for high power generation [155]. On the other hand, the natural world controls the fluctuations in wind speed that occur throughout the year. Maximum generating hours should be attained through the seasonal time by reducing the wind turbine's downtime in any practical way. Nonetheless, wind turbine stoppage hours for grid maintenance, turbine repair, etc., should be carried out during the off-season when power generation is erratic due to considerable changes in wind speed within the wind turbine's cut-in range.

Advantages and Limitations: For each of the seven wind farms, the anticipated wind energy output from the ANN model matches well with

Table 4
Recent Reports on AI Techniques and their Application in Wind Turbine Optimization.

AI Model	Wind Turbine Optimization Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
Swarm intelligence optimization algorithm	Wind energy potential analysis	MAE~0.108 RMSE~0.163	The numerical findings demonstrate that the wind energy verdict system can both satisfactorily approximate real-time wind speed predictions and give an effective wind energy assessment. As a result, it can be a useful tool for managing and making decisions on wind farms.	The method's strength was in its ability to remove noise from the source wind speed time series; yet, the key limitation was preserving the characteristics of the wind speed data.	Yes	[128]
ANN-wake-power model	Power generation of wind turbines	$R^2 \sim 98\%$	It has been demonstrated that the ANN wake-power model works well for calculating power generation. It strikes a decent balance between accuracy and computational expense. The model is used with a genetic algorithm to optimize the yaw angles.	The model produced a total power ratio of up to 0.96. The limitation was the adoption of sufficient input data during the training process. The accuracy and effectiveness of the model are drastically impacted by the quality of the input data.	No	[129]
ANN	Wind speed distribution	$R^2 \sim 99\%$	Compared to atmospheric models like weather research and forecasting (WRF), artificial neural networks (ANN) have shown themselves to be a flexible solution in terms of accuracy and computer time utilization. The study is to predict wind speeds for energy applications in Saudi Arabia.	The ability to predict wind speeds was the main highlight of this study, with an RMSE of 0.8078 it compares ANN with other machine learning methods to demonstrate its competitive performance. One drawback noted is that the models' training process depends heavily on precise and copious amounts of data.	No	[130]
RL Q-Learning algorithm	Variable pitch variable speed wind turbine	RMSE $\pm 3\%$	The validation outcomes from this paper's simulation using the Matlab/Simulink environment are encouraging and demonstrate that the control technique devised is appropriate for controlling the yaw angle in wind turbines subjected to various wind situations.	A number of wind speed realizations accessed using the software were the main advantage of this model; however, uncertainties were not accurately directed, which is the major limitation that needs attention.	No	[131]
CNN-based model	Short-term wind speed forecasting	RMSE ~ 0.99 MAE = 0.8002	According to experimental findings, Wind Net produces the most effective outcomes in terms of both RMSE and MAE. The suggested Wind Net model's viability and efficacy have been fully confirmed during this trial.	The main highlight was the accuracy and precision of the modeling, with a MAE of 0.800227 and an RMSE of 0.999978, but the limitation was the application to long-term forecasting of wind speed.	Yes	[132]
ANN	Simulating and sizing of clean energy community	MAE ~ 0.32 $P < 0.05$	It is anticipated that the framework created for this study will assist academics in creating forecasting instruments for various energy-related applications. Additionally, the suggested ANNs are approachable instruments with the benefits of requiring less input data and without requiring a high level of knowledge to use transient simulation software.	A very high prediction accuracy was attained in this study, which proved advantageous in predicting the yearly CEC energy performance and reliability. However, maintaining the output indicators was a limitation that needs to be improved to get more advancement.	Yes	[133]
ANN	WTO system generation	$R^2 \sim 99\%$	The study looks into how the power forecast accuracy is affected by the 4-layer FFBP ANN hyper-parameters. When the FFBP ANN model was compared to conventional power curve correction methods, the density correction resulted in a 40% increase in MAE.	The advantage was the good prediction with diverse atmospheric stability rules, for which it achieved an average energy production error of only 0.4% over nine months. The limitation was the strongly steady rule of the atmospheric border layer prediction.	No	[134]

the measured data. This model can assist energy planners and wind farm owners with future planning and implementation. A good ANN prediction was obtained using the AI model for high-generation hours and power. The ANN model achieved an RMSE of 0.0806, an MSE of 0.0070 for training and 0.0065 for testing, and with MAEs of 0.0588 and 0.0586, respectively. However, the limitation associated with this case study was the stoppage hours of wind turbines for grid and turbine maintenance in seasonal periods that must be carried out when the seasonal period is off and power generation is recurrent because of maximum fluctuation in the wind speed and that requires work.

3.5.2. Case study 2: AI-based optimization of PV/wind MGs for house electrification in Malaysia

Background: Since PV-based systems are a safe, sustainable energy source, installing them has been essential to the growth of RE sources. However, the main limitation of PV systems is their high initial and operating costs when compared to alternative sources of energy [156].

To determine the ideal values for PV array tilt angle, the capacity of a wind turbine, the size of battery storage and inverter, and several PV modules, a variety of research is now being carried out to improve hybrid PV/wind systems [157]. Because the metrological variables have a considerable influence on the size and performance of hybrid PV/wind systems, extensive research on them is required to optimize these systems. AI techniques have been functional to optimize hybrid PV/wind systems. Using GA, stand-alone PV/wind systems are sized optimally [158].

Potential Results: The Solar Energy Research Institute (SERI), University Kebangsaan Malaysia, carried out the study in Kuala Terengganu, Malaysia. This study sought to show the optimal dimensions for a PV-wind hybrid system at different loss-of-load probabilities based on the amount of wind speed and solar energy that are available in the area [159]. The optimal structures for a PV-wind hybrid system for the above-mentioned location were supplied in this study using an LLP technique. The available meteorological records including wind speed

Table 5
Some recent reports on AI techniques bring used in geothermal energy.

AI Model	Geothermal Energy Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
ANN and SVM precision models	Geothermal heat pump prediction	$R^2 > 0.99$	This study demonstrated how the employed function, algorithm, and architecture all had an impact on the accuracy of geothermal heat pumps. Furthermore, it was found that increasing the estimation accuracy of these models' hyper-parameters by the use of optimization procedures.	While the precision models were able to reliably forecast the soil layers' temperatures and thermal conductivity, the key constraints to overcome were the uncertainties linked to the input variables.	Yes	[144]
SLFNN, BPNN	Geothermal subsurface temperature prediction	$R^2 = 0.97$ RMSE ~ 1.41	This work created a single-hidden-layer constructive backpropagation code. The data collected from magnetotelluric measurements and borehole thermograms was effectively used to estimate subsurface temperature using a feed-forward neural network (SLFNN) based on BPNN.	The structurally flexible network for the prediction of subsurface temperature that was attained in this study was the main highlight of the work, with an absolute average deviation (AAD) of 4.09. The limitation was the small data set used for testing the network system, which makes its applicability very limited in large data sets.	No	[145]
ANFIS-PSO and MLP-PSO	Modeling of geothermal organic Rankin cycle	RMSE for power generation = 12.023 kW	Compared to MLP-PSO, ANFIS-PSO performs better when modeling the geothermal organic rankine cycle (GORC) using the solar system. The advantages of using the ANFIS-PSO model such as a more accurate prediction of future net power generation, efficient energy, exercise efficiency, and leveled energy cost.	The accuracy of the hybrid models was the main highlight. The RMSE for power generation, energy efficiency, energy efficiency, and LCOE are 12.023 kW, 3.587×10^{-4} , 3.278×10^{-4} , and 1.332×10^{-4} . In comparison, errors in the input variables caused the uncertain predictions.	No	[146]
Distributed computational intelligent (CI) algorithm	Control in smart distribution grids	RMSE ~ 0.82	They suggested distributed CI method can provide a near-optimal solution in fewer algorithm iterations than current consensus-based dispersed methods for smart grid optimization.	Despite the benefits of centralized and benchmark algorithms in terms of convergence and flexibility, distribution grid optimization was the key disadvantage of these results.	No	[147]
ML	Operational efficiency of geothermal plants	$R^2 > 0.97$	A framework for geothermal operational optimization with machine learning (GOOML), is presented in this research. Geothermal developers can use GOOML worldwide to create digital twins that will help them optimize procedures, increase outputs, and manage their operations sustainably.	The approach successfully implied for the real-world performance characteristics, where the MAE for total system mass take and separated steam had values of 783 (8.1 %) and 133 (5.2 %). However, the applicability of the complex interaction of components in larger systems was unclear in the findings of the study.	Yes	[148]
BPNN, Gaussian Regression	Prediction of multiaxial fatigue life	16Mo3 = 0.03 6082-T6 = 0.04 SM45C = 0.03 Cu-ETP = 0.02 7075-T651 = 0.01 304 L = 0.06	The multiaxial fatigue life prediction capabilities of the BPNN-GPR technique are satisfactory, which used to test a set of six materials known as 16Mo3 steel, 6082-T6 aluminum alloy, SM45C, Cu-ETP copper, 7075-T651, 304 L stainless Steel. Furthermore, the findings demonstrate the BPNN-GPR method's predictive capacity for multiaxial, non-proportional loading routes that are unknown.	The advantage was the ability to predict the capability of the modeling approach for un-known multiaxial non-proportional loading paths, with results falling within a life factor of ± 3 . The result is close to 0 which indicates that the prediction result is close to the experimental result. However, errors in precision and input variables were the main limitation.	Yes	[149]
Fuzzy logic and binary index overlay	Optimization of system	production at 2 °C	The case study's findings for possible geothermal zonation in Iran showed that the region is in a very high-risk classes. Five effective geothermal potential factors-land surface temperature (L.S.T.), lithology, surface evidence, geomagnetic, and fault-are employed in this study.	The logic accurately predicted the potential geothermal zones. But the results are region-specific. It needs to be implemented in wide-ranging environmental regions to check and evaluate the efficacy of the prediction model.	No	[150]
ANFIS, ANN	Ground source heat pump performance	$R^2 > 0.99$ for ANFIS	The ANISF and ANN findings demonstrated that the models offer good accuracy and dependability when estimating ground-source heat-pump system performance indexes using fewer parameters.	This hybrid approach was advantageous for measuring the heat pump's COP. For COP prediction, for instance, the ANFIS model produced RMS values of 0.09601 and R^2 of 0.99934. Reliability of training data sets was the limitation.	No	[151]
ANFIS, PSO, GA	Hybrid thermal power plant	R^2 for ANFIS is 0.9991, ANFIS-PSO is 0.9994, and ANFIS-GA 0.9997.	A reliable tool for evaluating the performance of hybrid thermal power plants was made available to designers, energy managers, and decision-makers using the hybrid models utilized in this work.	The advantage was the exceptional accuracy in assessing and predicting plant performance. This model's notable benefit is its high overall correlation coefficient but the tripping of system parameters was the limiting factor associated.	Yes	[152]

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Table 5 (continued)

AI Model	Geothermal Energy Applications	Major Results	Discussion on Results	Advantages and Limitations	Dataset Included?	[Ref.]
(GMDH/GA/SVD)	Prediction of temperature, Thermal energy management	$R^2 > 0.98$	In this work, hybrid models that were employed to categorize various cold and hot water levels showed exceptionally good performance. The outcomes demonstrated how AI hybrid models might be successfully integrated to use thermal energy wasted and sustainably produce electricity.	The main advantage was the successful hyper-parameter optimization of the hybrid models. where the LightGBM algorithm, exhibited a remarkable prediction accuracy of 98.7 %. However, dividing various hot and cold-water levels with very good classification performance was the real limitation.	No	[153]

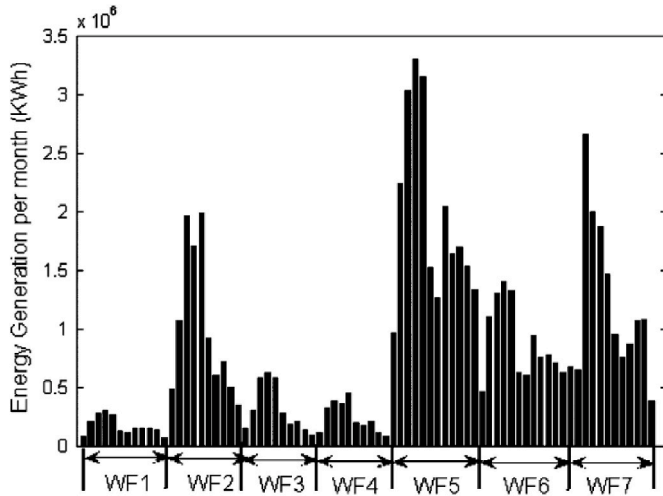


Fig. 7. Prediction of ANN modified model for wind power generation of 7 wind farms in muppandal, Tamil Nadu, India [154].

and solar energy serve as the foundation for the PV-wind hybrid system simulation model [160].

Several PV-wind hybrid system configurations were considered by the simulation model, and an optimization process was carried out to determine which combination would result in the lowest cost. The recommended inverter size optimization method (Fig. 8) worked well for Malaysia in terms of determining the optimal hybrid PV/wind system size. The data suggested that the ideal PV-array (CA), wind-based turbine (Cs), and storage-battery (CB) sizing ratios were 1.1411, 0.7159, and 0.550, in that order. Meanwhile, 1.37 was the appropriate size ratio for the inverter. Utilizing the monthly ideal tilt angle, the PV array's collected yields increased by 7.96 % in the end [159].

Discussion: Global solar radiation (GT) and extraterrestrial solar radiation (G_{extra}) make up the two primary categories of solar radiation. In this case study, the researchers used Eq. (2) and Eq. (3) to obtain G_{extra} and GT. Here, I_0 depicts the solar constant having a value of 1367 W/m², N shows the number of days, and GB and GD are the beam or direct, and diffuse solar radiation.

$$G_{extra} = I_0 + 0.034 \cos \frac{2\pi N}{365} \quad (2)$$

$$G_T = G_B + G_D \quad (3)$$

Since hybrid PV/wind systems are often created with a specific amount of wind speed and solar energy records, the optimal solution is then found by using optimization techniques such as genetic algorithms and graphical solutions to the LPSP. Given that the location coordinates have a significant influence on the system size, the methodologies aim to provide the optimal hybrid PV/wind system size for a given site. Although Malaysia has not yet had its hybrid PV/wind system

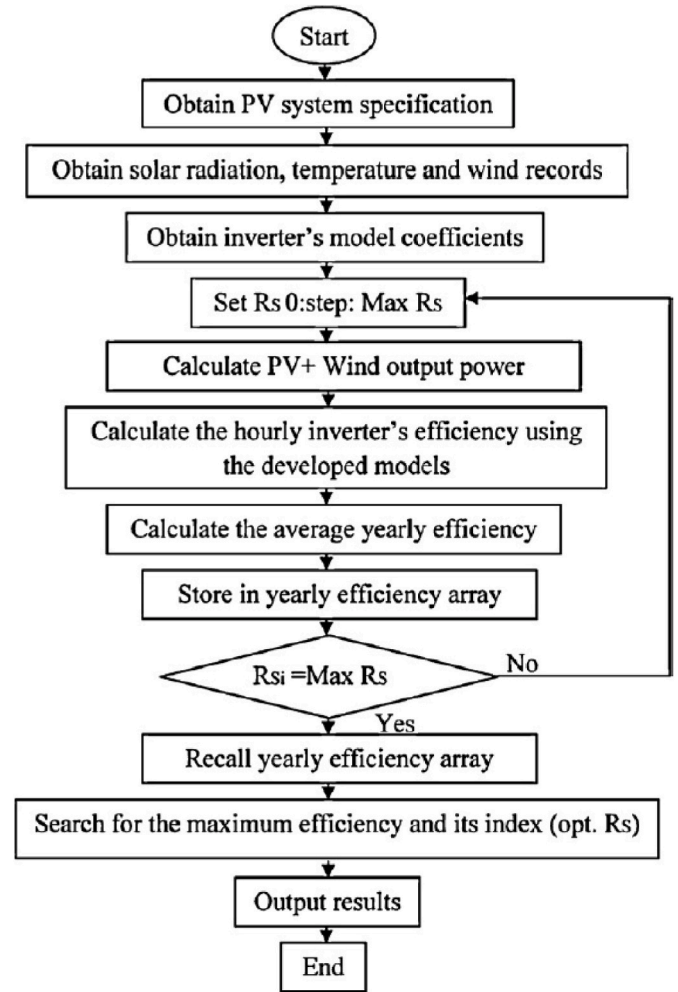


Fig. 8. Ai based iterative model for determination of inverter size [159].

optimized, there are some promising locations, including Kuala Terengganu State, which has relatively high average wind speeds and makes a hybrid PV/wind system a realistic alternative.

Advantages and Limitations: This case study gave the inverter size optimization method for determining the optimal hybrid PV/wind system size that can be a breakthrough to get a size optimization for PV arrays and others with a cost-effective configuration. The PV array, wind turbine, and storage battery sizes that produced the best results also exhibited the greatest improvement in system efficiency. By adjusting the monthly tilt angle, 7.96 % more power by the PV array was produced. However, the limitations associated with this study are that their projected optimization method is useful for sizing hybrid PV/wind systems at the lowest cost for Malaysia. It is unclear whether the

configuration is dependent upon the selection of site area or not, which should be addressed.

3.5.3. Case study 3: ANFIS modeling for PV power supply system in Algeria

Background: Selecting an appropriate model for a photovoltaic power supply system (PVPS) is difficult because of the several daily, monthly, and annual variations in meteorological data. This study used an adaptive neuro-fuzzy inference scheme (ANFIS) to simulate a PVPS system and propose a new expert configuration PVPS system and models [161]. Models of the PVPS system’s various parts, including the battery, regulator, and ANFIS PV generator, see Fig. 9, were found to be able to provide results that were acceptable in a variety of climatic situations, which allowed for testing the system’s dependability and performance. Climate (humidity, global radiation, and temperature) and electrical (photovoltaic, regulator voltage, battery, and current) data were recorded in a database between 1992 and 1997 by a PVPS system placed at Tahifet, south of Algeria.

Potential Results: The PVPS system has been modeled and simulated using this data. The overall ANFIS output from the sum of the node inputs was calculated using Eq. (4) as follows:

$$O_{4,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i \bar{w}_i f_i}{\sum_i \bar{w}_i} \quad (4)$$

The correlation coefficient between the calculated and predicted values by the ANFIS produced a good prediction accuracy of 98 % and 97 % for the delivered power by the system, showing that the simulated system’s reliability and accuracy are great. The RMSE for the training error in the case of the PV generator is 0.00131, for the battery is 0.00165, and in the case of the regulator is 0.00144. Testing results also show that ANFIS outperformed the ANN, another model used to represent the system.

Discussion: The data prophesied from this work can also be used for the following possible applications:

- Examining the yields of the PVPS systems to assess how well they operate.
- Control of the PVPS system (i.e., the maximum power point tracker, or MPPT), which is the optimal location for a PV module to harvest

the most amount of energy; the system ought to be in operation at this moment).

- Monitoring and the fault diagnostic system (FDS) (keeping an eye on regulators, batteries, and PV modules for faults).
- Estimating the electricity generated by the PVPS system.
- Determining the pace of degradation of the photovoltaic plant.

Advantages and Limitations: The advantage of the ANSIF model proposed in this case study is that it needs only elementary meteorological information as input for its operation. Current numeric or analytic models described in the literature require several pieces of data that are not always available or cannot be easily accessed. This AI-developed model can predict and simulate the electrical data of the PVPS system from only the ambient temperature, solar irradiation, and clearness index. In comparison to artificial neural networks (ANN), the ANFIS model performs better in modeling PV system components under varying climatic circumstances, as evidenced by its high prediction accuracy of 98 %. However, the limitations associated with this case study are the satisfactory accuracy between the measured and estimated electrical data and the experimental set-up configuration.

3.5.4. Case study 4: power output prediction via ANN and TRNSYS in Xinjiang China

Background: To anticipate the output power of RE sources, a case study was conducted in Tikanlik, China’s Xinjiang province. It detailed the creation, validation, and data source of an ANN with adaptation to the TRNSYS model [162]. Tikanlik province is situated at latitudes 87.70°N, longitudes 40.63°E, and an elevation of 847 m. It is rich in solar and wind energy resources. The weather and system output power data serve as the foundation for the ANN model used for training.

Potential Results: Using the simulation results with different original parameters, the training and test data were produced, such as the meteorological data. Of the 8760 data sets that TRNSYS supplied, 75 % were used for training and 25 % were used for testing. There were three layers in the proposed ANN. The 5 input factors of ANN are composed of two time predictors and 3 weather data variables, i.e., wind velocity, temperature, and solar radiation. The entire procedure for estimating the expected system output power value is depicted in Fig. 10. It showed that the relative error of 99.32 % of the test set is less than 3 %,

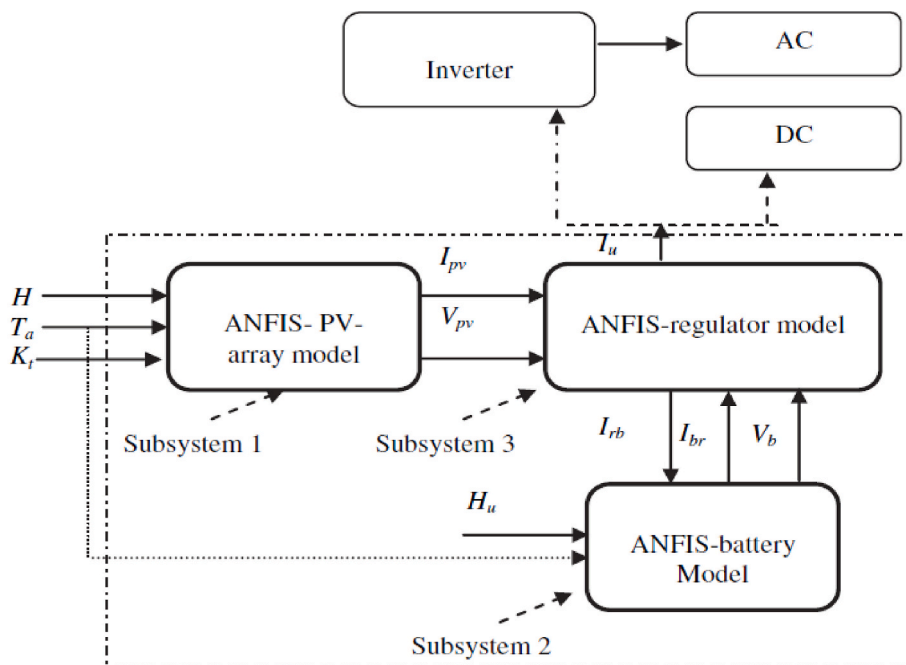


Fig. 9. An illustrative diagram of ANFIS-Based PV array, battery, and regulator model.

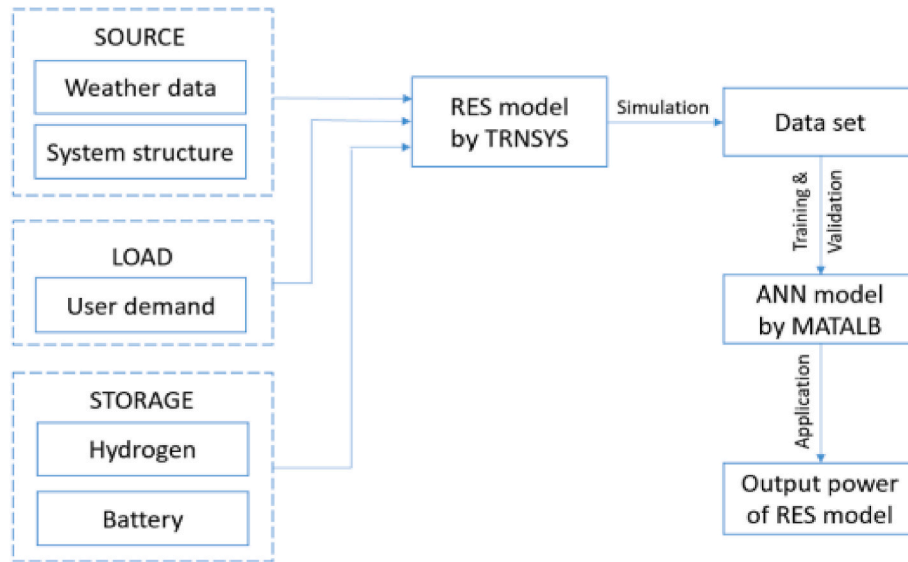


Fig. 10. Flowchart of the ANN and TRYNYS models used [162].

indicating the model’s capacity to generate precise prediction results.

Discussion: The assessment set was chosen at random from the whole set of information to check the precision of the ANN model. Uncertainty in the ANN model is the cause of the biggest relative error value, 15.8 %. 24 data sets were randomly chosen from the test sets to verify the forecast and improve its visual appeal. Although the model values contain some inaccuracy, overall, the expected system output-power levels fit the test data very well. It seems that this ANN model can handle computing and forecasting requirements. Various AI algorithms can further optimize the linked goal functions, including the technical, social, environmental, and economic indicators, based on a more accurate ANN. A viable avenue of research is to combine the ANN model with AI optimization algorithms such as TRNSYS or apply them to more appropriate and specific settings.

Advantages and Limitations: The AI model in this case study gave reliable prediction accuracy, which other related ANN models could not comprehend well to verify the forecast and improve the visual appeal. However, the major limitation of the results of this case study is associated with the relevant errors and predictions in the ANN model, which limits its applications.

4. Challenges and solutions

There are certain disadvantages to RE sources in addition to their many advantages. For instance, the generation discontinuity is brought on by seasonal fluctuations. The majority of RE resources depend on climate change, so using advanced design, planning, and control optimization techniques is necessary for their use. Fortunately, scientists can now tackle these optimization problems with computational resources pertinent to the renewable and sustainable energy area owing to continuous developments in computer hardware and software technologies. Fig. 11 shows the most prevalent problems and obstacles in the predictive maintenance of RE systems.

4.1. Data acquisition and auditing

The availability of high-quality data for model training and evaluation significantly limits the viability and performance of ML models, particularly deep learning, in any given application. One area that lacks good training data is the predictive maintenance of RE systems. Most of the time, it is not viable to implement data-driven approaches because of the high data requirements for these approaches and the lack of high-

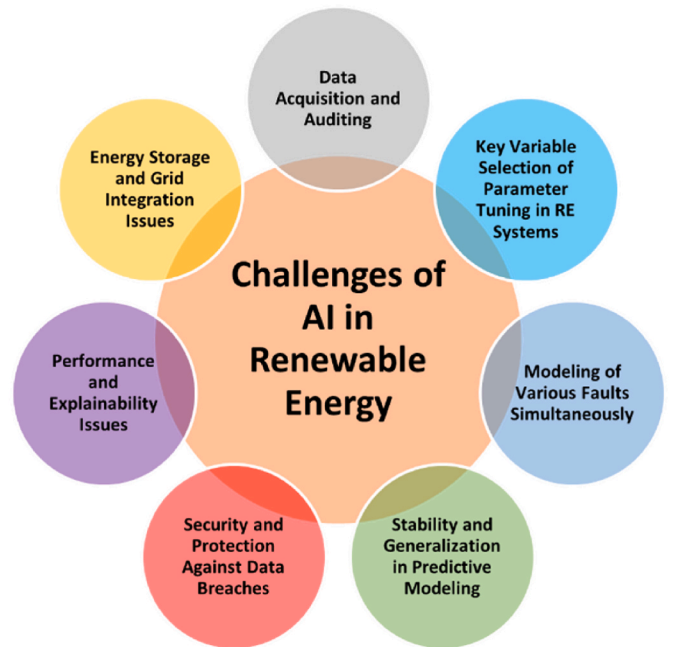


Fig. 11. The challenges and open issues of AI approaches in RE systems [163].

quality data, particularly for recently created systems. Additionally, outcomes may be impacted by overfitting and overgeneralization that occur during algorithm training as a result of a lack of high-quality data [164].

Auditing the data, which is the act of evaluating the suitability and quality of the data for a specific use, is crucial for predictive maintenance in energy plants because measurements are made alongside noise produced by the mechanical parts. For this reason, it’s critical to examine the measurements and data to recognize and maintain noisy and multivariate data. Additionally, it is advised to determine the dangers connected to the noisy data and how they could affect the predictive models’ performance. To achieve this goal, regular tests and audits are required to guarantee the algorithms’ validity over time and that they learned the appropriate lessons [165].

4.2. Key variable selection of parameter tuning in RE systems

One of the crucial stages of predictive maintenance for RE systems is key variable selection, during which important characteristics—that is, variables relating to the models' results—are determined. This extremely difficult procedure is typically carried out either manually or automatically while being supervised by a specialist model that determines how much the chosen strategy must comprehend the technical domain knowledge, underlying failures, and data-gathering process. While expert and fuzzy systems require a moderate level of information, neural networks can be applied without a highly deep understanding of the failure processes. To address this challenge, utilization of the physical models and a thorough understanding of the domain is crucial to understand in addition to the physical mechanisms and environmental elements that influence the failure processes. But this forecasting process is also a bit complicated if it is not handled appropriately and can result in power outages or shortages of RE generation. Furthermore, major epidemics, extreme disasters, and other emergencies also cause greater and more contests to AI prediction techniques [166].

4.3. Modeling of various faults simultaneously

Since modeling multiple failures simultaneously requires processing large datasets, it can significantly impact the algorithm's real-time performance, making it computationally demanding. The performance uncertainty in simultaneous modeling, particularly in predicting Renewable Energy (RE) systems through AI-based approaches, arises from numerous uncertainties associated with RE generation systems. These include stochastic features in source-grid-load storage, generation, transmission, and distribution within RE systems. Such uncertainties represent some of the most significant challenges in developing AI prediction techniques and modeling approaches [167]. Nevertheless, this challenge can be overcome with the right tools and careful methodology to carry out a modeling of faults while implementing the AI approaches to the systems.

4.4. Stability and generalization in predictive modeling

Occasionally, the reliability of results is compromised by either the lack of physical information in the system or the novelty of the flaws that have occurred, making intuition insufficient. Consequently, it is critical to develop models resilient enough to handle and adapt to new errors. The hybrid applicability of current smart control equipment opens avenues for trials in developing AI models. However, the existing equipment for control and modeling falls short of supporting the new RE network generation and the development of robust models. Therefore, it is imperative to advance and update existing control devices to facilitate robust modeling and design innovations in the energy sector. To address this challenge it is valuable to explore advanced AI models and algorithms that can achieve synergistic operations between current and newly advanced apparatus, which is crucial for the large-scale development of RE systems [168].

4.5. Security and protection against data breaches

The decision-making and application of AI are based on hefty volumes of complex data and are sometimes personal. These applications make it quite exposed to serious issues, for example, data infringements and data identity theft. Aside from predictive maintenance models, other machine learning applications for smart grids and energy systems are vulnerable to adversarial and security threats. For example, the great majority of approaches for predictive maintenance of energy systems rely on deep learning, cloud computing, and Internet of Things (IoT) sensors. IoT deployments and deep learning methods are vulnerable to hostile and cyber-security threats. Hence, the lack of a strong security support system is also one of the critical challenges affecting the

application of AI techniques in RE-based technologies [169]. The possible solution to this challenge is to develop some security configurations and tools to avoid data breaches simultaneously to AI tool implementation.

4.6. Performance and explainability issues

One of the desired properties of machine learning algorithms is explainability, which is the capacity of ML models to defend their judgments and predictions. The performance of the models is what the researchers are more interested in, rather than explainability as a necessary feature or primary concern. Nonetheless, one of the most important areas where predictions and choices made by machine learning models should be comprehensible to humans is the predictive maintenance of RE systems. Certain recent studies depend on deep learning-based approaches for the analytical maintenance of energy systems, even though the great majority of the literature still uses classic machine learning techniques and rule-based methodologies. While more explicable, classic machine learning algorithms and rule-based approaches produce less accurate predictions. Conversely, deep learning has demonstrated remarkable efficacy in making predictions; yet, these techniques are opaque and do not offer a rationale for the prediction. Maintaining an equilibrium between the decision-making procedure and outcome in the predictive maintenance of energy systems is extremely difficult [170]. For the solution to this issue, deep learning-based approaches for the analytical maintenance of energy systems should be examined and developed.

4.7. Energy storage and grid integration issues

Energy storage can be a solution for the grid integration of renewable energy sources. It can avoid the problems of the intermittency of renewable energy. Energy storage has its problems that must be solved such as cost, energy density, power density, and lifetime. Using AI, imaging processing, and characterization devices are providing insight into energy storage on an atomic and molecular level. This knowledge can be used to design next-generation energy storage devices that have higher charge density and longer lifetimes by minimizing degradation from charge-discharge cycles [171].

For example, hydropower has two main problems which are energy storage and grid integration. Solutions can be found using ChatGPT and generative AI, by forecasting patterns of energy generation and consumption, generative AI can maximize the integration of hydropower into the larger energy system. For example, ChatGPT can forecast times of high energy demand and low hydropower generation by analyzing past data. The possible solution to these issues is development of energy storage technologies, such as pumped hydroelectric storage or sophisticated battery systems, which would be capable to store excess energy during times of abundance and release it when demand surges. This increases the sustainability of hydropower as a source of energy and guarantees a steady supply of energy for users [172].

5. Recent advancements and future trends

The possibilities in the constantly changing field of renewable energy are endless, due to the integration of cutting-edge technology and unrelenting innovation. In addition to offering improvements over existing practices, the "Future Trends" in renewable energy also portend the introduction of revolutionary ideas that have the potential to completely reshape the sources, stores, and distribution of energy. It is crucial to investigate and predict the trends that will probably influence the future of sustainable energy as scientists around the globe are heading to new age. This section aims to encapsulate these emerging trends by offering a picture of a future in which energy is not only more accessible and integrated with the AI digital revolution, but also cleaner and more efficient.

5.1. Exploring possibilities of AI in solar energy

As technology advances, scientists and engineers are delving into new fields and expanding the applications of AI in solar energy. One of the primary focus areas for future AI-driven solar energy research will be the development of novel materials and inventive solar cell designs. AI systems can examine vast amounts of data on material properties, performance metrics, and production methods to identify new materials with enhanced stability, efficacy, and affordability. AI-driven simulations and machine learning techniques can help researchers find and optimize materials with desired features for solar cell applications more quickly. To improve overall device performance, lower recombination losses, and increase light absorption, new material compositions, nanostructures, and hybrid systems need to be investigated. An exciting new field of study in AI for solar energy will be the integration of AI with other cutting-edge techniques, such as quantum computing, machine vision, and nanotechnology [40].

5.2. Future trends in microgrids (MGs)

Finding the best AI-based solutions to create, produce, develop, and run new generations of industrial systems as effectively, dependably, and strongly as possible has proven to be a never-ending problem for academics. Microgrid digital twins will be the next trend in advancement in MGs [173]. The first phase will be the system modeling and identification process, which will gather sufficient statistics about the system that will be modeled. To create an effective model, the modeling objectives must also be stated clearly. It is possible to model industrial systems for condition monitoring, fault diagnosis and detection, sensor validation, system identification or design, and control system optimization. Fuzzy logic and ANN are two examples of AI techniques that possess the computational capacity to address a wide range of intricate issues. These include function fitting, pattern recognition, approximation, clustering, image matching, noise reduction, classification, feature extraction, extrapolation (based on historical data), dynamic modeling, and prediction [174].

5.3. Cloud computing/deployment and adversarial robust models

The SCADA systems, which comprise the prognostic maintenance, control, and monitoring systems, are often installed on-site. However, the trend is moving toward cloud deployment of such systems because of the geographical difficulties associated with doing so on-site, which are typically placed on top of mountains or in the middle of the ocean, and the improvement in cloud computing. There have already been several initiatives in this regard. As with other fields, ML/DL algorithms used in smart energy schemes are vulnerable to various adversarial and security threats, particularly when they are implemented on the cloud. The goal of these assaults is to interfere with ML/DL algorithms' ability to make predictions. An adversarial assault, for example, on an ML/DL model for predictive maintenance could lead to erroneous alerts about problems in an energy system. One intriguing area of research for the analytical maintenance of renewable smart energy systems is the creation of adversarial robust ML/DL models [175].

5.4. State-of-the-art sensor technologies

The majority of the foundation of traditional condition-based maintenance (CBM) systems is temperature and vibration analysis. The prognostics and CBM systems' efficiency are impacted by the low signal-to-noise ratio caused by the majority of these sensors and accelerometers being installed atop housings. It could be an intriguing advancement to employ small sensors close to the bearings. Furthermore, it would be possible to examine and take advantage of the effects on prognostic and CBM system performance and efficiency of substituting more cutting-edge methods for conventional sensing

technologies, such as hydrogen sensors and Barkhausen noise inspection [176].

5.5. Scarcity of data and novelty detection

Given the rarity of power plant faults, obtaining defective historical data to train and test the model presents a significant problem. It can be very beneficial and efficient to provide a publicly accessible dataset that contains both accurate and inaccurate SCADA data, particularly from hydropower stations. The scarcity of defects in intricate energy systems has resulted in a restricted supply of failure data [177]. As such, it casts doubt on the ML/DL algorithms' inherent resilience and dependability. One possible solution to this problem is to apply the novelty detection approach. Therefore, more investigation is required into the integration of novelty detection methods with the prognostic and CBM systems [178].

6. Conclusion

This review was aimed to provide a single source data for the scientists, engineers and researchers looking for recent advances and challenges associated with the role of AI-based algorithms and approaches play in advancing a wide range of renewable and sustainable energy systems and technologies. The current state of research reports and experimental developments reported in the form of case studies for both single and hybrid RE systems and applicability of AI were retrieved and evaluated in the review. The role of AI in various areas of RE specifically solar energy, photovoltaics, microgrid integration for energy storage and power management, and wind, and geothermal energy were comprehensively evaluated. In solar energy, various AI simulation techniques have been reviewed along with their potential benefits. They provided a potent substitute for traditional physical modeling approaches because these simulations can produce a compact solution for multi-variable issues, require less computational work, and don't require knowledge of internal system parameters. AI approaches have gathered a lot of applications in PV technology that have been documented, and research is being done on its ability to process large datasets regarding solar cell materials and their performance parameters. These were able to spot complicated correlations that would be tough to find using conventional approaches. AI techniques that are applied in the MGs by various research reports were also summarized. In the WTO, scientists and engineers have successfully applied AI and machine learning algorithms and models to predict, monitor, and control wind turbines. In geothermal energy, AI approaches and models have been reported to have a promising application in handling the challenges. Using both surface and subsurface data, AI was initially applied to a fairway analysis of geothermal potential. Additionally, a summary of the function of AI techniques in simulation, control, decision-making, and the RE system's optimization is provided. The state-of-the-art recent research results and case studies in the field of AI applications to RE systems and technologies are discussed comprehensively. The potential challenges, their possible solutions, and future trends are discussed to have a greater outlook on the domain. The specific gap addressed in this review is the site-specific data and suitability analysis of different geographical regions for implementation of AI in RE systems which will be considered in our future work. AI tools have great promise and should be properly used in future research to find new sources of RE. The application of innovative and hybrid AI techniques will enhance RE technology performance and contribute to global prosperity.

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

Data will be made available on request.

List of Abbreviations

AI	Artificial Intelligence
RE	Renewable Energy
GHGs	Greenhouse Gas Emissions
IEA	International Energy Agency
PV	Photovoltaic
ESS	Energy Storage System
IoT	Internet of Things
NN	Neural Network
SVM	Support Vector Machines
BPNN	Back-Propagation Neural Network
FFBPNN	Feed-forward Backpropagation Neural
ANFIS	Adaptive Neuro-Fuzzy Inference System
NB	Naïve Bayes
GA	Genetic Algorithm
ANN	Artificial Neural Network
STD	Standard Deviation
RBFNN	Radial Basis Function Neural Networks
SARIMA	Seasonal Autoregressive Integrated Moving Average
HISIMI	Historical Similar Mining
TRNSYS	Transient System Simulation Tool
GMDHNN	Group Method of Data Handling Neural Network
RBF	Radial Basis Function
ARIMA	Autoregressive Integrated Moving Average
RMSE	Root Mean Square error
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
MSE	Mean Square Error
R2	Determination Coefficient
rMBE	Relative Mean Bias Error
rRMSE	Relative Root Mean Square Error
SDM	Single Diode Model
DDM	Double Diode Model
ISOA	Improved Snake Optimization Algorithm
MGs	Microgrids
BFO	Bacterial Foraging Optimization
PSO	Particle Swarm Optimization
WTB	Wind Turbine Blades
SOA	Swarm Optimization Algorithms
SERI	Solar Energy Research Institute
LLPs	Loss-of-load probability
PVPS	Photovoltaic Power Supply
ANFIS	Adaptive Neuro-Fuzzy Inference Scheme
CBM	Condition-based Maintenance
SCADA	Supervisory Control and Data Acquisition
BPSO	Binary Particle Swarm Optimization
SCPP	Solar Chimney Power Plant
BANN	Bootstrap Aggregated Neural Networks
CNN	Convolutional Neural Network
SVR	Support Vector Regression
WPD	Wavelet Packet Decomposition
LSTM	Long Short-Term Memory
MLP	Multi-Layer Perceptron network
RT	Regression Tree
ISCE	Improved Shuffled Complex Evolution Algorithm
RFR	Random Forest Regressor
PSO-RF	PSO based on Repulsion Factor
PSO-CF	PSO with Constriction Factor
PSO-W	PSO with Adaptive Inertia Weight
MGWO	Modified Grey Wolf Optimizer
BFOA	Bacterial Foraging Optimization Algorithm

GT	Global solar radiation
Gextra	Extraterrestrial solar radiation

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