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Recent Progress on Applications of Artificial Intelligence for Sustainability of Solar Energy Technologies: An Extensive Review

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Abstract

Green energy sources are most promising energy sources in the globe, as they are non-pollutant sources. Solar energy sources are among green energy sources that are free and abundant in nature, yet solar energy sources have some shortcoming such as faults on the solar PV modules, improper maintenance and some climatic and environmental impacts. Artificial intelligences are employed to solve most of these shortcoming like prediction of the solar irradiance of the specific sites, parameters estimation on the solar PV modules, fault detection on the solar PV modules surfaces and forecasting of solar PV power output. This paper presents extensive review on application of artificial intelligences to solve problems related to solar energy systems from 2009 to 2024. It was found that from most of the literatures, artificial intelligent algorithms were more accurate and efficient than the conventional methods and it has an ability to solve complex and non-linear data. This work will help scholars to explore the relationship between solar energy technologies and artificial intelligences.

Keywords: *Artificial neural network; Genetic algorithms; Machine learning; Particle swarm optimization; Solar irradiance.*

1. Introduction

To have sustainable and reliable access to energy source at appropriate cost and efficient and cost-effective consumption pattern of energy are two among seventeen goals of sustainable development and utilization of green energy effectively is now a crucial research interest to many academia and industries globally.

Since burning of fuels cause pollution [1] and promoting environmental effects to the atmosphere is another critical problem [2]. Renewable energies continue improving both technical and economical for over a decade [3, 4]. Investment in these energies has been rising in the last years, even with a crisis such as the COVID-19 pandemic [3,4].

Renewable energy includes solar, wind, hydro, biomass, geothermal, etc [5, 6]. In attempt to improve the accuracy and reliability of renewable energy sources, various methods have been developed [7-9]. Nowadays, artificial intelligence techniques are applied to predict future problems and solve the problems that are difficult or impossible to be solved using conventional techniques [10].

Artificial Intelligence (AI) is a comprehensive high-technology that interact with human-based and machine intelligences. It comprises branches such as genetic algorithms (GA) [11], particle swarm optimization (PSO), simulated annealing (SA) [12], artificial neural networks (ANN), and hybrid models [13]. Synthetic intelligence methods are widely applied to renewable energy prediction because they can solve nonlinear and complex data structures [9, 14].

Artificial intelligence techniques are used in many disciplines such as renewable energy systems. In solar energy system, AI techniques can be employed to predict solar PV farms [15, 16]; and also to forecast solar irradiance of the regions [17]. A hybrid approach that combine two or more algorithms is used to improve the accuracy and reliability of power plant [18]. Most of the algorithms used are Particle Swarm Algorithms (PSA), Bee Colony Algorithm (BCA), Genetic Algorithm (GA) in order to optimize the parameters of the prediction model [19–21]. Particle Swarm Optimization (PSO) algorithm is the most widely used algorithm with fast convergence speed [22, 23].

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This paper tends to provide an extensive review on application of artificial intelligence to solve problems in renewable energy systems for sustainable development. The paper consists of four sections namely: section 1 gives general overview of the paper; section 2 provides the artificial intelligence techniques; section 3 consists of artificial intelligence-based solar energy technologies and section 4 drawn-out the conclusions.

2. Artificial Intelligence Techniques

Artificial Intelligence (AI) is new technique to process data processing in order to execute complex task by mimicking human intelligence [24]. Artificial Intelligence (AI) may be incorporated into hardware systems or dependent on software mostly in the virtual world [25]. To improve reliability, stability and performance of the renewable energy systems with complex data, AI is used for optimization, exploration, forecasting/prediction and regression easily [25–28]. Some author categorized AI into machine learning (ML) and deep learning (DL) while some said that deep learning (DL) is a subdivision of machine learning (ML), and thus both are AI techniques as shown in **Figure 1**.

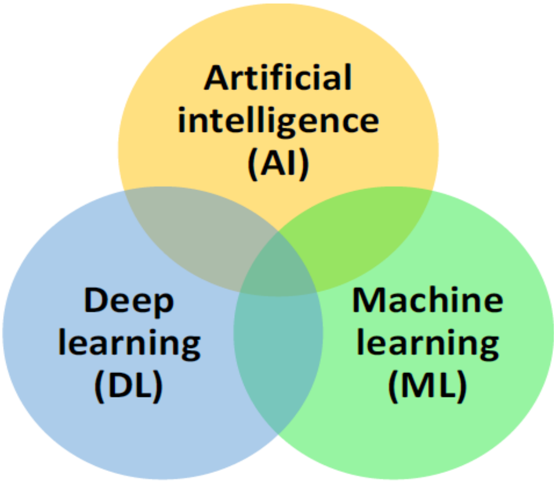

Figure 1. *Venn Diagram Showing the Relationship Between Machine Learning (ML) and Deep Learning (DL) as Categorized by [25]*

2.1. Machine Learning

Machine learning (ML) is an artificial intelligence technique that allow systems to execute a task from the existing data stored in the system automatically without human aid [29]. In machine learning (ML), a raw data is processed by selection time-series data through extraction, training and evaluation of the feature data and then model distribution.

Machine learning (ML) is subdivided in four algorithms namely: supervised, unsupervised, semi-supervised, and reinforcement learning.

2.1.1. Supervised Learning

Supervised learning is a machine learning technique that required supervisor in executing a task (**Figure 2**). The supervisor helps to guide the algorithm in predictions of the desired output and the output may lead to either classification or regression problem. Classification problem deals with a discrete variable of the output data while regression problem deals with a real value of the output data [30]. Examples of supervised learning algorithms include vector support machines, linear and logistic regression, decision trees, k-Nearest Neighbors, Neural Networks, naive Bayes and random forest.

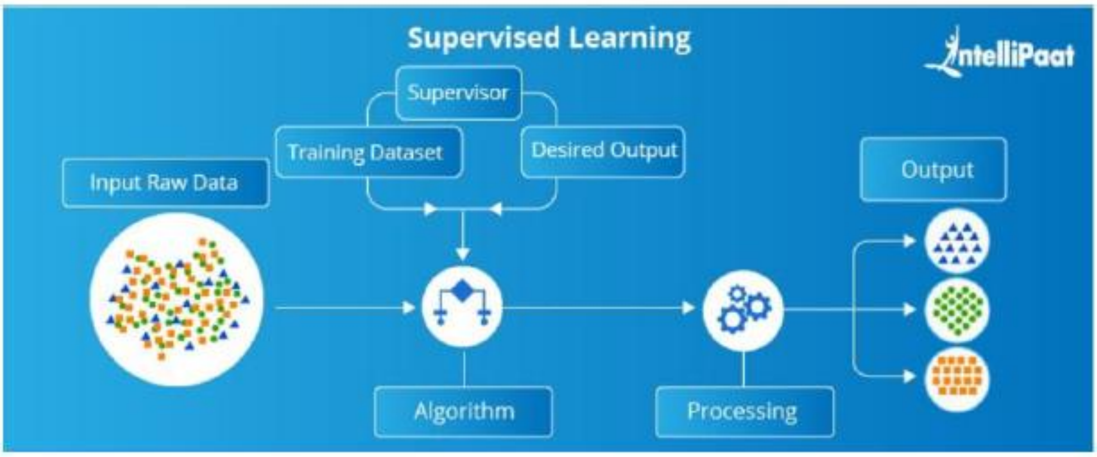

Figure 2. *Schematic of supervised learning [31]*

2.1.2. Unsupervised Learning

Unsupervised learning is a second machine learning techniques that required no supervisor to process the required output (**Figure 3**). Unsupervised learning algorithms trained with unknown data and expected outputs, hence they follow rules and patterns of the available database before being able to understand the actual data [26, 29]. Examples of unsupervised learning are fuzzy means, k-means and hierarchical clustering techniques.

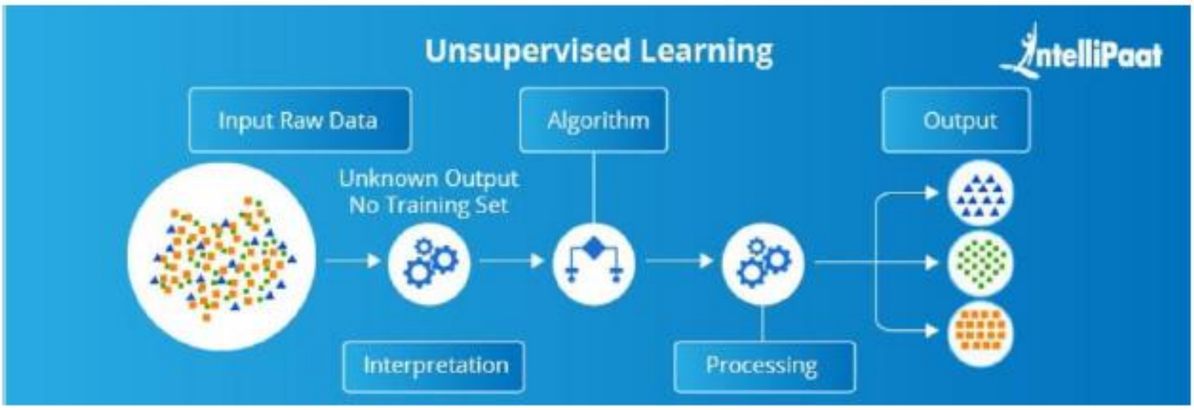

Figure 3. *Schematic of unsupervised learning [31]*

2.1.3. Semi-Supervised Learning

Semi-supervised learning combined features of both supervised and unsupervised learning [32]. This involve training an algorithm to discover a model, and the most common issues that can be solved with it are classification and clustering [25]. Generic and graph-based models are examples of semi-supervised learning.

2.1.4. Reinforcement Learning

Reinforcement learning is a machine learning depend on a searching goal approach by which the learner carried out different tasks to find out which task is the best task to achieve a specific target [33]. **Figure 4** shows the working mechanism of the reinforcement learning, Q-Learning and Monte Carlo methods are common examples of the reinforcement learning.

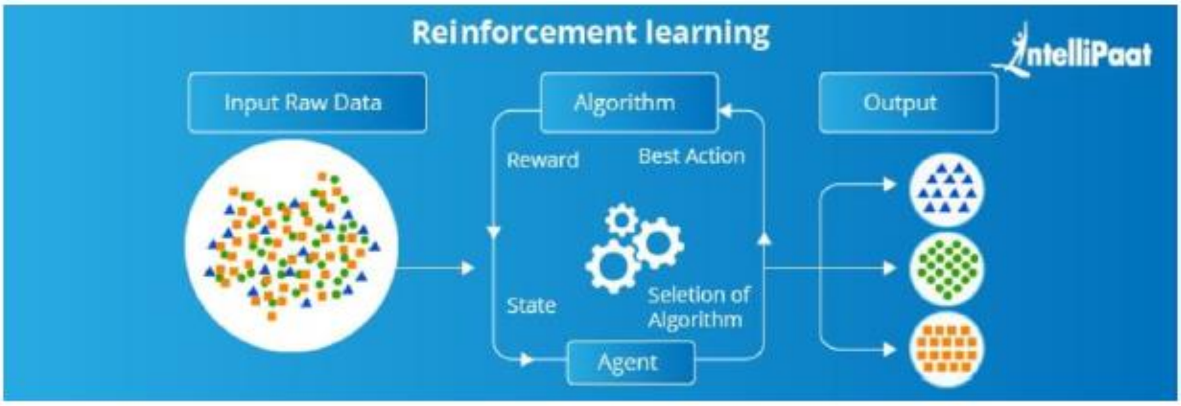

Figure 4. *Schematic of reinforced learning [31]*

2.2. Deep Learning

Deep learning is an artificial intelligence that combine a set of classifiers and train them to predict a single prediction of the classifier [29, 34]. It is used for extraction of features from data sets to model the flexibility in network designs [34]. Deep learning techniques include long short-term memory (LSTM), convolutional neural networks (CNN), generative adversarial networks (GAN), and hybrid combinations [24, 26, 29, 34].

2.2.1. Long Short-term Memory (LSTM)

Long Short-term Memory (LSTM) is time series approach designed to process time-dependent variables of the data sets [34]. The recurrent neural network (RNN) is an algorithm of long short-term memory (LSTM) is applied when dependent input data is used. In renewable energy application, solar irradiance can be forecast using LSTM [34, 35]. Generally, LSTM is applied to improve efficiency, reliability and predictability of the systems [34].

2.2.2. Convolutional Neural Networks (CNNs)

Convolutional neural network (CNN) is deep learning technique whereby convolution replaced matrix multiplication in one or more layers of the conventional neural networks (NNs) [24, 35]. Forward and backward stages are involved in convolutional neural network, whereby input image with the existing parameters is served as a forward stage while executing of each parameter's gradient is a backward stage [26, 29, 34]. Convolutional neural network is usually applicable in managing and fault detection of large solar PV farms [34].

2.2.3. Generative Adversarial Networks (GANs)

Generative adversarial network (GAN) is another deep learning technique developed to improve performance, training stability and to generate high-quality samples [25, 26, 29, 34]. Virtual batch normalizing, feature matching and one-side label smoothing are heuristic techniques applied to enhance the training stability of generative adversarial network (GAN) [34, 36].

3. AI-Based Solar Energy Technologies

Artificial Intelligence is applicable in solar energy technology for prediction of solar irradiance, solar energy harnessing, fault detections on solar PV grids and so on. Many researchers conducted researches related to these and some of their findings were as follows:

Benghanem et al. [37] have developed models that forecast the daily global solar radiation using artificial neural network (ANN). The input parameters used to develop these models were air temperature, sunshine hours, relative humidity, and day of year. The authors developed six artificial neural network (ANN) and for each model, the output is the daily global solar radiation. Their findings revealed that artificial neural network (ANN) was best algorithm for forecasting global solar radiation as its correlation coefficient were 97% for each models developed.

Esen et al., [38] used artificial neural network (ANN) and wavelet neural network (WNN) algorithms for modelling of a solar air heating system. The experimental measureable parameters were used as input parameters. A comparative analysis was done between the experimental and predicted results and it was found that the developed models were more accuracy than the experimental results in terms of the efficiency of the solar air heating system.

Fadare [39] forecast the potential of solar energy utilization in Nigeria using artificial neural network (ANN). The input parameters used to develop the model were sunshine hours, mean daily temperature, relative humidity, altitude, days of the year, longitude and latitude. These parameters were obtained from database of Nigerian Airspace Agency (NASA). The result revealed that the correlation coefficient of the predicted model was 96% accurate that the measured results.

A Multi-Layer Perceptron (MLP) network to predict one day ahead solar irradiance was presented by Mellit and Pavan [40]. The input parameters used in this work were mean daily solar irradiance and the mean daily air temperature. They compared the power produced by a 20 kWp Grid Connected Photovoltaic Plant and the predicted one using the developed MLP predictor and the result shows that MLP predicted solar irradiance performed better for the subsequent four sunny days.

A simple multi-layer feedforward perceptron was developed by Sanusi et al., [41] to forecast the sizing of solar PV array in Nigeria. The input data were the analytical parameters used for sizing solar PV array that were calculated using location's meteorological parameters obtained from Nigeria Meteorological Agency (NIMEC) and Nigerian Airspace Agency (NASA). The result obtained in the study shows that the model developed have root mean square error (RMSE) of 0.085 and 0.046 for the battery storage and solar PV array size respectively which is more accurate than the analytically derived parameters.

Bartler et al., [42] adopted VGG16 architecture using CNN consisting of 13 convolutional layers. The EL camera was used to capture the photographs of the solar modules and these photographs were serve as the datasets. To reduce the error, data augmentation and over-sampling were used to train the model. It was found that a Balance Error Rate (BER) of 7.73% was achieved if both data augmentation and over-sampling were employed.

In 2018, Deitsch and coauthors conducted a comparative study between SVM and Convolutional Neural Networks by composing of 2624 EL images of the solar modules [43]. The ELPV data sets were trained using SVM of different feature descriptors. Silicon-type solar modules (Polycrystalline and Monocrystalline solar modules) were used to test the models. This models were developed using Python with the aid of Keras for the Neural Network (NN) and the finding of this study is achieved with the accuracy of 82.4%.

A new network for optimizing the ANN for MPPT was presented by Duman et al., [44]. For real-time applications, the ANN was structured with 2-3-3-1 structure. The input of the network were solar irradiance and temperature and output of the network was maximum voltage. The authors compared P&O and conventional NN and their results revealed that the network provides more stability and efficiency.

Faragola et al., [45] developed a hybrid model that combines artificial neural network (ANN) with Support Vector Machines (SVM) [46]. The datasets which consists of solar irradiance and temperature were improved via Course Gaussian Support Vector Machine (CGSVM). The artificial neural network (ANN) was composed of two inputs, one output and a single hidden layer with 13 neurons. The results are slightly worse on power than the ANFIS, but the required time was significantly less than the ANFIS.

In the same year, Karimi et al., [47] developed a similar algorithm using SVM and CNN. The CNN was composed of two convolutional layers with leaky-relu and max-pooling. The SVM was trained with different features extracted from the images. A module with 540 cells was used to test the algorithm using its 90 images as the data sets. An accuracy of 98% was achieved in this study.

A new model with six convolutional layers using different regularization techniques was presented by Akram et al., [48]. The dataset used was the ELPV dataset that composed 2624 images. The algorithms were run on Tensorflow. The accuracy of the model was 93%.

Abdel-Naseer and Mahmoud [49] conducted a comparative analysis of five (5) different architectures of RNN: A fundamental Long Short-Term Memory (LSTM), a Long Short-Term Memory (LSTM) integrated with the window technique, Long Short-Term Memory (LSTM), incorporated with time steps, Long Short-Term Memory (LSTM) with memory between batches and stacked Long Short-Term Memory (LSTM) with memory between batches. Two datasets of different cities were used to test the three (3) models. The results show the Long Short-Term Memory (LSTM), incorporated with time steps is more reliable and have high accuracy than others since it has an RMSE of 82.15 in the first dataset and an RMSE of 136,87 in the second, which uses prior time steps in the PV series as inputs when compared with Artificial Neural Network (ANN).

Karimi et al., [50] present new models of two solar PV modules images with cracks and corrosion. The solar PV modules images were snapped with EL camera and 5400 images were used as data sets. The authors used SVM and CNN algorithms whereas Keras and Tensorflow were adopted to validated the algorithms experimentally. The CNN is composed of two convolutional layers. The SVM parameters are optimized by a grid search. An improved result of 99% accuracy was obtained using this models.

Another work was done by Torress et al., [51] using a multi-step method which decomposes the prediction challenges with Big Data and Deep Learning approach. They used to next-day-ahead forecast in 30 min intervals. Three (3) hidden layers with 12 and 32 neurons as differences was found to be the best structure. Deep learning (DL) was found to be directly proportional to the training time as the big solar data was found using deep learning approach and it more accurate than other approaches.

A modified RNN was achieved by Yao et al., [52]. The authors applied Echo State Network (ESN) as demonstrated by [53]. In this work, Echo State Network (ESN) used to replace the conventional hidden layers of RNN as a dynamical reservoir. And the number of dynamic reservoirs and input data sets were obtained using restricted Boltzmann machine (RBM) [54] and principal component analysis (PCA) [55]. These networks can obtain better results than typical RNN. A DFP Quasi-Newton algorithm [56] was employed to determine the parameters of the networks. Their findings revealed that this approach can improve the prediction of solar PV with MAPE of 0.00195% against other solar PV irradiance prediction methods.

A PSO algorithm was employed to optimize the initial weights of the neural network by Al-Majidi et al., [57]. The input datasets used by the authors are solar irradiance and temperature and power of solar PV was the output. The model proved to be more effective under various weather conditions than other ANN techniques.

Balzategui et al., [58] developed a new network with Convolutional Neural Networks using U-net approach. The input datasets used was 542 EL images with 21 convolutional layers of different sizes. The authors used Keras and Tensorflow to implement the algorithms. It was found that it was better to accept a slight decrease in the performance in order to improve the speed of the system.

A combination of static Wavelet Transform and discrete Wavelet Transform was used by Mathias et al., [59] to harness edge and textural features of the solar modules. The authors used 2300 EL images for input datasets while SVM and FFNN were employed as the classifiers. The result of the study revealed that SVM is less accurate with 92.6% and 93.6% for the FFNN.

A complex hybrid algorithm using Neural Network (NN) was developed by Niu et al., [60]. To determine the most essential factors that affect solar PV performance, the authors used a Random Forest (RF) [61] and a Complementary Ensemble Empirical Mode Decomposition (CEEMD) was employed to decomposed the original sequence of the data sets [62], this will help to stabilized the original data sets and to ensured that the quality of the data sets was enhanced. The authors modified the PSO by optimizing the neural network (NN) using dynamic inertial factor particle swarm optimization (DIFPSO) [63, 64]. They finally improved the accuracy of the solar PV irradiance prediction with MAE of 2.84, 13.01 and 10.12 on sunny hours, rainy hours and cloudy hours respectively.

A hybrid algorithm integrated with Wavelet Transform (WT), PSO and Radial Basic Neural Feed Networks (RBFNN) was applied for prediction from 1 to 6 hours ahead by Wen et al., [65]. Data selection (Filtering) on the immediate fifteen (15) days before prediction days was done using Wavelet Transform (WT), and optimization of RBFNN was done using PSO algorithm. The solar irradiance and temperature were used as the input data sets. The authors achieved the network with better performance than the other methods, and MAE of 4.22%, 7.04% and 9.13% for a 1-hour-ahead prediction, for a 3-hour-ahead prediction and 9.13% for 6-hour- ahead prediction.

Zhang et al., [66] used Dendritic Neuron Network (DNN) as a new Neural Network (NN) for prediction of solar PV power. Synaptic layer, branch layer, membrane layer and cell-body layer are the layers of Dendritic Neuron Network (DNN) [67]. The temperature and irradiance of the city (Input data sets) were feed to the first (synaptic) layers which transformed the input data sets and selected the essential data sets and moved them to the second (branch) layer, the numerical work was done by cell-body layer. When the selected data sets exceed a required threshold, the cell-body layer will move them to other neurons through the axon. The findings of this work show that using MATLAB, this approach performed better with MAPE of 4.55 and 10.9 with weak data fluctuations and with strong data fluctuations respectively.

Deep-Feature-Based network was developed using convolutional neural networks by Demirci et al., [68]. The SVM and forward neural network (FNN) algorithms were used as classifiers of the convolutional neural networks. 2624 images of the solar cells were served as the data sets of the study. DarkNet-19, Resnet-50, VGG-16 and VGG-19 were selected to extract the features of the data sets. The result shows that SVM with 89.63% and 94.52% accuracies in four-class and in two-class classification were better than forward neural network (FNN) algorithms.

Sattar et al., [69] presents a Marine Predator Algorithm [70] to estimate parameters of the solar PV modules. The algorithm developed was run using MATLAB to extracted solar PV and it was found that the RSME on a single-diode of the solar cell and double-diode of the solar cell were 0.000773 and 0.000765 respectively.

Sibtain et al., [71] developed a multistage hybrid model for forecasting solar irradiance based on a multivariate meteorological data. They initially evaluate five standalone models, including recurrent deterministic policy gradient (RDPG), long short term memory (LSTM) neural network, extreme gradient boosting (XGB), Gaussian process regression (GPR), and support vector regression (SVR). The RDPG model outperforms the standalone counterparts by demonstrating 2.485 W/m^2, 20.591 W/m^2, 18.316 W/m^2 and 23.176 W/m^2 reductions in RMSE compared to the LSTM, XGB, GPR, and SVR models. Afterward, the performance of the RDPG model is further enhanced, by developing two-stage hybrid models, including improved complete ensemble empirical mode decomposition with additive noise-RDPG (ICEEMDAN-RDPG) and variational mode decomposition-RDPG (VMD-RDPG). The subsequent construction of the hybrid model

ICEEMDANSE-VMD-RDPG (ISVR) results in the further improvement of the two-stage hybrid models. The ISVR surpasses all the established models including VMD-RDPG, ICEEMDAN-RDPG, RDPG, LSTM, XGB, GPR, and SVR by displaying 18.401 W/m^2, 13.908 W/m^2, 33.223 W/m^2, 53.111 W/m^2, 67.704 W/m^2, 67.502 W/m^2 and 69.943 W/m^2 respectively, decrease in RMSE.

Su et al., [72] presents Complementary Attention Network (CAN) that consist of subnetwork connected with a spatial attention subnetwork. As stated by [73] Complementary Attention Network (CAN) is grouped with any CNN, Fast R. 2129 and 2029 EL images were used as datasets. The authors used Python to implement the algorithms of the developed network. The model developed achieved an accuracy of 99.17% and a precision of 87.38%.

Solar Power Generation Prediction System was developed by Lee and Shin [74]. Neural network, SVM, and deep learning were used as prediction algorithms, and the optimal algorithm was selected by using the root mean square error (RMSE). They developed a predictive model that improve the prediction rate by changing the algorithm structure and modifying constants. Then, a defect detection system is developed by applying the predicted results to the domestic regional data.

Martinez Lopez et al., [75] quantified the existing relation between irradiance variations and efficiency loss of the logic of the Perturb-and-Observe MPPT algorithm, along with the sensitivity of the MPPT to its control parameters. It was found that when the algorithm parameters are not tuned properly, its efficiency will drop to nearly 2% and the solar irradiance variability causes a systematic energy loss of the algorithm that can only be quantified by ignoring the hardware components. The authors provide an additional efficiency loss to be considered in the calculations in order to improve the energy yield estimation.

A novel hybrid GWO–PSO-based maximum power point tracking for photovoltaic systems operating under partial shading conditions was presented by Smail et al., [76]. The feasibility and effectiveness of the hybrid GWO–PSO-based MPPT method were verified via a co-simulation technique that combines MATLAB/SIMULINK and PSIM software environments, while comparing its performance against GWO, PSO and P&O based MPPT methods. The simulation results carried out under dynamic environmental conditions have shown the satisfactory effectiveness of the hybrid MPPT method in terms of tracking accuracy, convergence speed to GMPP and efficiency, compared to other methods.

In solar water pumping system, Sumathi and Abitha [77] presented a novel system which consisted a hybridized MPPT technique based on Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO). The dynamic and steady-state performance of a permanent magnet brushless DC (BLDC) motor coupled to a centrifugal water pump fed by the SPV array-SEPIC was assessed, and its applicability was confirmed using simulated results in the MATLAB/Simulink environment. The Cuk converter and Single Ended Primary Inductor Converter (CUKSEPIC) achieves high settling time of 0.9 for a 5.0 kW output power, improving power efficiency.

Sangsang et al., [78] designed an optimum system for harnessing solar energy system using Fuzzy Logic (FL). They developed a maximum power point tracking (MPPT) to optimize the energy potential harvested from the solar PV system and Fuzzy logic (FL) was used to operate the MPPT technique on the converter. And the result of the study proved that FL's tracking speed algorithm for tracking MPP is twice as fast as conventional P&O.

A novel hybrid optimization approach for fault detection in Photovoltaic arrays and inverters using Artificial Intelligence (AI) and statistical learning techniques was developed by Abubakar et al., [79]. Their proposed technique integrated Elman neural network (ENN), boosted tree algorithms (BTA), multi-layer perceptron (MLP), and Gaussian processes regression (GPR) for enhanced accuracy and reliability in fault diagnosis. Feature engineering-based sensitivity analysis was utilized for feature extraction. The fault detection and diagnosis were assessed using several statistical criteria including PBAIS, MAE, NSE, RMSE, and MAPE. Two intelligent learning scenarios are carried out. The first scenario was conducted for PV array fault detection with DC power (DCP) as output. The second scenario was conducted for inverter fault detection with AC power (ACP) as the output. The proposed technique was capable of detecting faults in PV arrays and inverters, providing a reliable solution for enhancing the performance and reliability of solar energy systems. A real-world solar energy dataset was used to evaluate the proposed technique with results compared to existing detection techniques and obtained results showing that it outperforms existing fault detection techniques, achieving higher accuracy and better performance. The GPR-M4 optimization justified its reliably among all the models with MAPE = 0.0393 and MAE = 0.002 for inverter fault detection, and MAPE = 0.091 and MAE = 0.000 for PV array fault detection.

Alba et al., [80] worked on the effect of climate on Photovoltaic yield prediction using machine learning models. An extensive data gathering process was performed and open-data sources were prioritized. A website www.tudelft.nl/ open-source-pv-power-databases was created with all found open data sources for future research. Five machine learning algorithms and a baseline one was trained for each solar PV system. Their results showed that the performance ranking of the algorithms was independent of climate. Systems in dry climates depict on average the lowest Normalized Root Mean Squared Error (NRMSE) of 47.6 %, while those in tropical presented the highest of 60.2%. In mild and continental climates, the NRMSEs were 51.6% and 54.5%, respectively. When using a model trained in one climate to predict the power of a system located in another climate, on average systems located in cold climates show a lower generalization error, with an additional NRMSE as low as 5.6% depending on the climate of the test set. Robustness evaluations were also conducted that increase the validity of the results.

Arash et al., [81] proposed a global solar radiation forecasting approach based on federated learning (FL) and convolutional neural network (CNN). CNN input for network training in each client used were data related to eight regions of Iran with different climatic features. To test the effectiveness of the global supermodel, data related to three new regions of Iran named Abadeh, Jarqavieh, and Arak were used. It can be seen that the global forecasting supermodel was able to forecast solar radiation for Abadeh, Jarqavieh, and Arak regions with 95%, 92%, and 90% accuracy coefficients, respectively. Finally, in a comparative scenario, various conventional machine learning and deep learning models were employed to forecast solar radiation in each of the study regions. The results of the above approaches were compared and evaluated with the results of the proposed FL-based method. The results show that, since no training data were available from regions of Abadeh, Jarqavieh, and Arak, the conventional methods were not able to forecast solar radiation in these regions. This evaluation confirms the high ability of the presented FL approach to make acceptable predictions while preserving privacy and eliminating model reliance on training data.

Numerous methods based on artificial intelligence (AI) were proposed by Azad et al., [82] to address the issue of the appearance of multiple peaks in the performance of solar panels caused by partial shading. The authors presented the energy-valley optimizer-based optimization (EVO) technique, which is designed to efficiently and dependably tackle the issue of partial shading (PS) in detecting the maximum power point (MPP) for photovoltaic (PV) systems. The EVO algorithm enhanced the speed of tracking and minimized the power output fluctuations during the tracking phase. Extensive validation of the proposed technique was conducted using the Typhoon hardware-in-the-loop (HIL) 402 emulator. The effectiveness of the suggested method was compared with the established cuckoo search algorithm for achieving maximum power point tracking (MPPT) within a photovoltaic (PV) system. This comparison takes place under equivalent conditions to ensure a fair performance evaluation.

Another solar PV power prediction model was developed based on Wavelet Neural Network (WNN) by Bo et al., [83]. The authors provide data reference for the scheduling department through the prediction of distributed PV power. Initially, they studied sensing layer, prediction layer, and service layer on the distributed PV power prediction architecture, and then the specific functions of the prediction layer were designed based on a wavelet neural network. They finally concluded that the proposed model can effectively achieve the power prediction of distributed PV.

Dae et al., [84] proposed an approach to develop a solar radiation model with spatial portability based on deep neural networks (DNNs). The data for development and internal testing of the DNNs, respectively were collected from weather station networks in South Korea between 33.5–37.9◦ N latitude. Multiple sets of weather station data were selected for cross-validation of the DNNs by standard distance deviation (SDD) among training sites. The DNNs tended to have greater spatial portability when a threshold of spatial dispersion among training sites, e.g. 190 km of SDD, was met. The final formulation of the deep solar radiation (DSR) model was obtained from training sites associated with the threshold of SDD. The DSR model had RMSE values <4 $MJm^{-2}d^{-1}$ at external test sites in Japan that were within ±6◦ of the latitude boundary of the training sites. The relative difference between the outputs of crop yield simulations using observed versus estimated solar radiation inputs from the DSR model was about 4% at the test sites within the given boundary. These results indicate that the identification of the spatial dispersion threshold among training sites would aid the development of DNN models with reasonable spatial portability for estimation of solar radiation.

John et al., [85] developed a maximum power point tracking of a partially shaded solar photovoltaic system using a modified firefly algorithm-based controller. They modified firefly algorithm-based controller, tied operationally with a DC–DC boost converter. A model was developed and simulated on MATLAB, for tracking the maximum power point of the system, both at constant solar irradiance and at PSC.

Khamees et al., [86] evaluated three radiation Schemes of the WRF Solar model for global surface solar radiation forecast in Egypt. Dudhia, rrtmg, and Goddard schemes were used to simulate Global Horizontal Irradiance (SR) during 2017. Sixteen stations were selected to represent the different climate conditions in Egypt. The observed SR data is only available at five stations and used to evaluate the accuracy of ERA5 and WRF output. SR data at the other eleven stations were extracted from ERA5 to evaluate the corresponding values from WRF simulation. The results showed that ERA5 and WRF Dudhia scheme have reliable results as compared to the observations at the five stations. Also, the WRF Dudhia scheme simulates the SR at the other eleven stations better than rrtmg, and Goddard schemes as compared to ERA5 dataset. Where, the three WRF radiation schemes overestimate the SR along the eleven stations and underestimate at Alexandria station by -0.15 KWh/m^2, which may due to the weather conditions over these sites. But the Dudhia scheme over the eleven stations has the lowest MBE (< 0.34 KWh/m^2), RMSE (< 0.58 KWh/m^2), and MAPE (< -2 %), with R^2 more than 0.985 at most stations.

A Dual-Stage model that forecast the solar power to reflects uncertainties in weather forecasts was generated by Lee et al., [87] aiming to minimize the prediction errors during solar time. The proposed method comprises two stages. The first stage was the construction of the Solar Base Model by extracting characteristics from input variables. In the second stage, the prediction error period was detected using the Solar Change Point, which measures the difference between the predicted output from the Solar Base Model and the actual power generation. The performance evaluation was restricted to July and August. The average improvement rate in predicted power generation was 24.5%. Using the proposed model, updates to weather forecast status information were implemented, leading to enhanced accuracy in predicting solar power generation.

Lu et al., [88] compared with physical models, WRF-Solar, as an excellent numerical forecasting model, includes abundant novel cloud physical and dynamical processes, which enables the high-frequency output of radiation components which are urgently needed by the solar energy industry. This study assessed the accuracy of the improved numerical weather prediction (WRF-Solar) model in simulating global and diffuse radiation. Aerosol optical properties at 550 nm, which were provided by a moderate resolution imaging spectroradiometer, were used as input to analyze the differences in accuracies obtained by the model with/without aerosol input. The sensitivity of WRF-Solar to aerosol and cloud optical properties and solar zenith angle (SZA) was also analyzed. The results show the superiority of WRF-Solar to WRF-Dudhia in terms of their root mean square error (RMSE) and mean absolute error (MAE). The coefficients of determination between WRF-Solar and WRF-Dudhia revealed no statistically significant difference, with values greater than 0.9 for the parent and nested domains. In addition, the relative RMSE (RRMSE%) reached 46.60%. The experiment on WRF-Solar and WRF-Dudhia revealed a negative bias for global radiation, but WRF-Solar attained a slightly lower RMSE and higher correlation coefficient than WRF-Dudhia. The WRF-Solar-simulated results on diffuse radiation under clear sky conditions were slightly poorer, with RMSE, RRMSE, mean percentage error and MAE of 181.93 Wm^{-2}, 170.52%, 93.04% and 138 Wm^{-2}, respectively.

A new feature selection approach for Photovoltaic power forecasting using Sequential Forward Selection (SFS) with Kernel Conditional Density Estimator (KCDE) was presented by Macaire et al., [89] as forward selection (FS) to forecast day-ahead regional PV power production in French Guiana. This method was compared to three other FS methods used in earlier studies: The Pearson correlation method, the RReliefF (RRF) method, and SFS using a linear regression. It has been shown that SFS-KCDE outperforms other FS methods, particularly for overcast sky conditions. Moreover, Wrapper methods show better forecasting performance than filter methods and should be used.

A novel multi-scale ensemble method and multi-scale ensemble neural network was presented by Qin et al., [90]. The neural network uses long short-term memory, gate recurrent units, and temporal convolutional network as the basic model. By coupling the stochastic weight averaging ensemble method and differential evolution ensemble method, these deep learning networks were assembled from single-model scale and multi-model scale, respectively, thereby effectively improving the model prediction accuracy. For predicting the power load of Hubei Province in China, meteorological features and time features were in consideration. The proposed model was trained and compared with eleven intelligent short-term load forecasting models, including machine learning, deep learning and ensemble deep learning models. Simulations show that the proposed model has the best comprehensive prediction performance. This study highlights the power of ensemble deep learning models coupled with multiple ensemble techniques and the promising prospect of our proposed model in short-term load forecasting.

Ribeiro and Fanzeres [91] present descriptive analytics of the time-linked hourly-based daily dynamics of wind speed and solar irradiance in the main resourceful regions of Brazil. They focused on identifying similar days over the years, Representative Days, that can depict the fundamental underlying behavior of each source using Leveraging on unsupervised Machine Learning methods. Their analysis was based on a historical dataset of different sites with the highest potential and installed capacity of each source spread over the country: three in the Northeast and one in the South Regions, for wind speed; and three in the Northeast and one in the Southeast Regions, for solar irradiance. They used two Partitioning Methods (K-Means and K-Medoids), the Hierarchical Ward's Method, and a Model-Based Method (Self-Organizing Maps). And identified that wind speed and solar irradiance can be effectively represented, respectively, by only two representative days, and two or three days, depending on the region and method (segments data with respect to the intensity of each source). Analysis with higher Representative Days highlighted important hidden patterns such as different wind speed modulations and solar irradiance peak-hours along the days.

Sebastian et al., [92] introduces a novel approach for site adaptation of solar irradiance based on machine learning techniques. They analyzed seven machine-learning algorithms and compared with conventional statistical approaches to identify Sweden's most accurate algorithms for site adaptation. Solar irradiance data gathered from three weather stations of SMHI were used for training and validation. The results show that machine learning can substantially improve the STRÅNG model's accuracy. However, due to the spatiotemporal heterogeneity in model performance, no universal machine learning model can be identified, which suggests that site adaptation was a location-dependent procedure.

Sheng et al., [93] proposed a support vector machine (SVM) model based on hybrid competitive particle swarm optimization (HCPSO) with consideration of spatial correlation (SC), for realizing short-term PV power prediction tasks. Firstly, the spatial correlation analysis was conducted on the distributed PV stations. The k-means clustering method based on morphological similarity distance improvement and mutual information function was used to select the best reference station and the best delay, which generates strongly correlated solar PV sequences. Then, a hybrid algorithm of particle swarm optimization (PSO) and sine cosine algorithm (SCA) in a competitive framework (HCPSO) was proposed, aiming to fuse the fast convergence capability of PSO algorithm with the global search capability of SCA algorithm, while enabling the algorithm to effectively handle high-dimensional optimization problems based on a competitive mechanism. Finally, the HCPSO algorithm was combined with SVM algorithm, which expands the applicable scenarios of the SVM model and effectively improves the accuracy of PV short-term prediction.

Shihan et al., [94] decomposed the normalized and pre-processed raw solar PV data into different components by the quadratic frequency domain decomposition method, and they then used the random forest algorithm and the GRU prediction neural network optimized by the genetic algorithm to process the different components, and then reconstructed the results of the different prediction methods to obtain a short-term PV forecasting model. The improved quadratic frequency domain decomposition forecasting model was applied to the forecasting problem and compared with the traditional forecasting method, and the improved quadratic frequency domain decomposition forecasting model was proved to obtain more accurate forecasting results.

A theoretical model was developed to determine the Shockley–Queisser efficiency limit of solar thermophotovoltaic (STPV) cells with single- or double-junction photovoltaic (PV) cells and a simple radiation shield considering the divergence nature of concentrated solar radiation by Wen and Bhaskar [95]. A combination of adaptive parametric sweep and graphic-based methods was developed to solve the highly nonlinear correlations of energy and carrier transports in the theoretical model to find the optimized operating conditions of STPVs with high stability. The theoretical model predicts that the Shockley–Queisser efficiency limit of STPV under 1000 times solar concentration and a simple radiation shield is ~50.1% with InGaAsSb PV cells, ~49.1% with GaSb PV cells, and ~53.2% with InGaAsSb/GaSb double-junction PV cells. The operating temperatures are ~1719.5 K, ~1794.1 K, and 1640.0 K, respectively.

Zhao et al., [96] conducted a research study on solar PV power prediction using long-term monitoring data of output power, various meteorological data, and solar irradiation intensity of photovoltaic modules. The authors developed the functional relationship between the output power of photovoltaic modules and the irradiation intensity through Pearson correlation analysis. By deducing the distribution relationship of irradiation intensity, the prediction model of irradiation intensity based on peak sunshine hours and sunshine duration was constructed and based on 340 sites across the country 64 years peak sunshine hours and sunshine duration query database. And the theoretical value of the prediction model on sunny days was averagely 0.952 which is close to the measured value. The solar radiation intensity on rainy days is weak, and the prediction accuracy is low ($R^2 = 0.884$). The relative errors between the sunshine duration and the peak sunshine hours in the database are less than 4.55% and 4.79%, respectively, under sunny conditions in each quarter, indicating that the accuracy of the database meets the actual needs.

Zhu et al., [97] present SL-Transformer as a novel method rooted in the deep learning paradigm tailored for green energy power forecasting. They employed the SG filter and LOF algorithm for data cleansing and incorporating the system with a self-attention mechanism, to improve the model's ability to discern and dynamically fine-tune input data weights. For solar energy forecasting, the SL-Transformer has achieved a SMAPE of 4.2156%, signifying a commendable improvement of 15% over competing models.

Li et al., [98] proposed a novel deep learning-based model named PLSTNet for ultra-short-term prediction of photovoltaic power over a 5 min time span. This model is a novel dual-path prediction. On one hand, it effectively captures short-term fluctuations in time series data by combining CNN and RNN. On the other hand, it further captures and analyzes long-term trends in fluctuations through the use of a smoothing layer and RNN's recurrent skip layer. In one-step and multi-step forecasting experiments on annual and seasonal datasets, the authors compared the performance of the PLSTNet model with LSTNet, PHILNet, TCN_GRU, and ResCNN to assess its performance. In one-step and multi-step forecasting using the annual dataset, the MAE of the PLSTNet model is at least 15.5% lower than that of other models. Similarly, for seasonal datasets, the MAE of the PLSTNet model is at least 13.2% lower than other models.

Liu and Li [99] proposes a regional PV power forecasting model based on an improved time-series dense encoder and graph attention network (ITDE-GAT), which takes into account the spatio-temporal correlations among the regional PV plants. Firstly, an improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) was used to extract the clear-sky and fluctuation components from solar PV data. Secondly, the combined ITDE-GAT was applied to perform the regional solar PV power forecasting. The authors constructed an improved dense encoder network (ITDE) in order to extract the temporal and spatial relationships of regional solar PV. Graph attention network (GAT) was then utilized to explore the spatial correlations among the regional solar PV. The results demonstrate that compared to various advanced deep learning methods, the R^2 evaluation metric of the approach proposed in this paper demonstrates, respectively, maximum improvements of 3.4 %, 6.5 %, and 7.8 % for the 1 h, 3 h, and 6 h ahead predictions.

Murugan et al., [100] estimated the photovoltaic models using an enhanced Henry gas solubility optimization algorithm with first-order adaptive damping Berndt-Hall-Hall-Hausman method. The designed algorithm was done by incorporating the first-order Berndt-Hall-Hall-Hausman (BHHH) numerical method, along with the non-linear damping parameter of the Levenberg-Marquardt technique (LM). By implementing this approach, the authors have significantly improved the precision and reliability of estimating the initial root parameters in solar PV models, effectively filling the theoretical void in this specific research area. Then in terms of methodology, the Enhanced Henry Gas Solubility Optimization (EHGSO) algorithm was combined with the Sine-Cosine mutualism phase of Symbiotic Organisms Search (SOS) for efficiently estimating the unknown parameters of PV models. The keystone of EHGSO in terms of methodology enhances exploration at the beginning of optimization and intensifies exploitation in later iterations. The proposed EHGSO methodology based on the adaptive damping BHHH technique (EHGSOAdBHHH) was tested on Single Diode (SD), and Double Diode (DD) solar PV models using actual experimental data. EHGSOAdBHHH exhibits outstanding accordance with attained experimental data compared with other algorithms, and its superiority was validated using several statistical criteria.

The hourly solar PV production was estimated using two models based on feedforward neural networks (FFNNs) by Nicoletti and Bevilacqua [101]. The numerical weather prediction (NWP) data: ambient temperature, relative humidity, and wind speed were used input data. They used multiple inputs in the first proposed model, while the second one used only the necessary information. It was concluded that the hourly temperature trend was the most important variable for prediction. The models' accuracy was tested using experimental and NWP data, with the second model having almost the same accuracy as the first despite using fewer input data. The results obtained using experimental data as inputs show a coefficient of determination (R^2) of 0.95 for the hourly solar PV energy produced. The RMSE was about 6.4% of the panel peak power. When NWP data were used as inputs, R^2 was 0.879 and the RMSE was 10.5%. These models can have a significant impact by enabling individual energy communities to make their forecasts, resulting in energy savings and increased self-consumed energy.

A long short-term memory (LSTM)-based multi-step prediction model to forecast and fill in missing data was presented by Wang et al., [102]. The authors proposed a federated-learning-based stacking ensemble gate recurrent unit algorithm (FL-SE-GRU) for electricity theft detection and cyberattack classification, and its effectiveness is verified by comparison with existing methods. The results of experiments show that the LSTM-based multi-step prediction model exhibits a remarkable data interpolation effect. Meanwhile, FL-SE-GRU achieves 95.0% accuracy, 96.6% precision, 93.8% sensitivity, and 95.1% F1 score in detecting electricity theft, and reaches 96.8% accuracy, 96.1% precision, 97.4% sensitivity, and 96.7% F1 score in classifying 9 kinds of cyberattacks, respectively.

4. Conclusion

Solar energy technologies are green technologies that generates electricity and heat using solar PV modules and solar collectors respectively without emission of the pollution or harmful to the environment. With these applications of solar energy technology, yet it has some problems that hinder the efficiency of the system such as partial shading, mismatching of the components, inadequate monitoring and maintenance practices, unforeseen fault in solar PV cells, inefficient inverters and improper design or sizing.

Artificial Intelligence is a promising technique that employed to solve real-life problems in the areas of engineering, medicine, business and so on. In renewable energy, Artificial intelligence is used to solve problems with complex and non-linear datasets. Solar irradiance and power prediction, fault detection, solar PV parameters, MPPT modeling and so on.

This paper explored the literatures that applied artificial intelligence to solve the problems in solar energy systems. Various Artificial intelligence techniques used in solar energy systems have been reviewed. Available literature summaries published in this area is also presented. To have convenient reading, the authors explained the difficulties and contributions of different authors in the area of solar energy technology. Based on results, machine learning and deep learning are used to improve the efficiency of the solar energy systems, detection of faults in the surface of solar PV modules, estimation of model parameters. Moreover, hybrid learning techniques is more accurate and efficient for optimizing solar energy systems. Therefore, it is recommended to use hybrid Artificial Intelligence learning techniques in the future to deal with solar energy generation problems.

Declaration of interest

The authors declare that there is no conflict of interest.

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