# Applications of Artificial Intelligence in Renewable Energy: a Brief Review

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***Abstract*—Renewable energy is a sustainable substitute to fossil fuels, which are depleting and attributing to global warming as well as greenhouse gas emissions. Renewable energy innovations including solar, wind, and geothermal have grown significantly and play a critical role in meeting energy demands recently. Consequently, Artificial Intelligence (AI) could further enhance the benefits of renewable energy systems. The combination of renewable technologies and AI could facilitate the development of smart grids that can better manage energy distribution and storage. AI thus has the potential to optimize the efficiency and reliability of renewable energy systems, reduce costs, and improve their overall performance. This study provides an overview of the applications of algorithms and models of AI as well as its advantages and challenges in renewable energy systems.**

***Keywords—Renewable energy; Artificial Intelligence; Machine Learning; Deep Learning;***

## I. INTRODUCTION

The energy system is vital to the development of the human society, especially in daily life, industry and transportation [1]. With a growing global population and advancing economy and culture, it is inevitable that the need for energy will rise [2, 3]. Renewable energy is being assigned increased responsibility for sustaining energy demands in order to avert an energy crisis and protect the environment from pollution produced by the usage of fossil fuels. One approach to the aforementioned issues is to employ renewable resources and technologies such as solar, wind, and geothermal. Since renewable energy systems are highly impacted by their surroundings, it is imperative to apply methodologies and simulations to predict these changes for enhanced system efficiency and energy dispensation.

To be objective, it is necessary to point out the drawbacks of renewable energy sources like solar and wind power. The main challenge of renewable energy is intermittent supply [4, 5]. In addition to uncertain output fluctuation of renewable energy sources, load demand is also uncertain [5-7]. Therefore, it is important to keep the power system stable in terms of supply–demand balance management [6, 8]. As an example, the output of solar panels can abruptly decrease because of clouds, resulting in a gap between power production and power demand, which can lead to power outages. Alternatively, excessive production of renewable energy production results in energy waste [5, 9]. Therefore, it is significantly vital to improve accuracy forecasting of renewable energy sources to stabilize and secure grid operation [10]. In recent years, there has been an increase in the number of novel techniques and algorithms such as Artificial intelligence (AI) technologies that increase the reliability of forecasts for renewable energy sources [11-14].

AI methods use huge data to develop intelligent machines capable of performing activities that would normally require the intelligence of a human. Since AI techniques including deep learning (DL) and machine learning (ML) are able to address nonlinear and complex data structures, they are gaining popularity in various fields of science and technology in order to solve real-life issues [15]. ML algorithms comprise artificial neural networks (ANNs), kernel and nearest-neighbor (k-NN), extreme learning machine (ELM), support vector machine (SVM), to name a few. These techniques have an advantage over statistical approaches in that they do not require any internal parameters of the solar systems.

AI techniques can be used to design a model of a problem, which can be analyzed to predict the performance, fault diagnostics and control effectively in renewable energy systems. For instance, Bhuiyan et al. [16] employed machine learning models for estimating the speed of wind to analyze wind systems power yield. There are also crucial applications in the renewable field, like planning and forecasting of load demand [17], forecasting of solar energy [18], inverter control of PV systems [19] and maximum power point tracking [20], and battery energy storage [21]. These methods offer opportunities to minimize the risk of failure with whole systems and ensure its reliability. Although AI systems have the potential to be more precise, reliable, and comprehensive than traditional methods, there are still challenging issues such as decreasing the accuracy of renewable energy predictions on cloudy days (i.e., large databases) [22].

This study aims to review state-of-the-art use of AI for major applications in renewable energy like forecasting. Therefore, a detailed review of the latest studies conducted in major applications for two diffeent sources of renewable energy including wind, and solar power projects is carried out. In addition, the view of current topical issues, future trends and challenges are discussed.

## II. AI TECHNOLOGY FOR OUTPUT POWER FORECASTING

### *A. Forecasting the Output Power of Solar Systems*

Solar energy is generated by converting solar radiation into electrical energy using solar photovoltaic (PV) or solar thermal systems. The International Energy Agency Over show that the worldwide PV capacity exceeded 179 TWh in 2021, a 22% increase over 2020. As a result of the direct and extremely essential effect that solar irradiance has on the production power of solar systems, the accurate forecast of solar radiation plays a vital role in estimating solar power production. The ability to accurately anticipate the amount of electricity that will be produced by photovoltaic cells is essential for a variety of applications including micro-grids, energy optimization and management. The majority of AI models and algorithms are created based on data obtained from solar radiation, which enables them to perform better than other traditional models and approaches [23]. Below are the summaries and findings of a new and interesting studies on this topic.

**Table 1:** Summary of reviewed articles predicting the output power of solar/wind systems

| Year | Reference | Models used | Application |
|---|---|---|---|
| 2012 | Shi et al. [24] | SVM | Solar systems |
| 2022 | Pandu et al. [25] | BDAAI-ENN | |
| 2012 | Mandal et al. [26] | WT-BPNN; WT-RBFNN | |
| 2021 | Ağbulut et al. [27] | SVM; ANN; k-NN; DL | |
| 2013 | Bouzerdoum et al. [28] | SARIMA; SVM | |
| 2022 | Lim et al. [29] | CNN-LSTM | |
| 2020 | Belmahdi et al. [30] | ARMA; ARIMA | |
| 2020 | Karaman et al. [31] | ELM; ANN | |
| 2019 | Yang et al. [32] | ME-EMD-MSSA-ELM<br>ME-EEMD-MSSA-ELM<br>ME-CEEMD-MSSA-ELM<br>ME-VMD-MSSA-ELM | Wind systems |
| 2017 | Lin et al. [33] | VMD-DE-ELM | |
| 2014 | Su et al. [34] | ARIMA-PSO | |
| 2005 | Torres et al. [35] | ARMA; Persistent | |
| 2002 | Sfetsos et al. [36] | Persistent; ANN; ARIMA | |
| 2022 | Gao et al. [37] | DeIS; k-MoGE; WkElm | |
| 2018 | Tian et al. [38] | CEEMDAN-ANNs | |
| 2020 | Hu et al. [39] | EWT-CSA-LSSVM;<br>CSA-LSSVM | |
| 2020 | Li et al. [40] | IDA-SVM; DA-SVM;<br>GA-SVM; Grid-SVM;<br>GPR; BPNN | |
| 2022 | Amoura et al. [41] | ANN; ANFIS | |
| 2016 | Meng et al. [42] | WPD-CSO-NN | |

Note: ENN, Elman Neural Network; RBFNN, radial basis function neural network; BPNN, back propagation neural network; MSSA, multi-objective salp swarm algorithm; VMD, variational mode decomposition; CEEMDAN, complete ensemble EMD with adaptive noise; DeIS, a decomposition and integration strategy, k-MoGE, k point modified multi-objective golden eagle optimizer; WkElm, weight hybrid kernel extreme learning machine; EWT, Empirical Wavelet Transform; CSA, Coupled Simulated Annealing; LSSVM, Least Square Support Vector Machine; GA, genetic algorithm; BPNN, back propagation neural network; GPR, Gaussian process regression; WPD, Wavelet packet decomposition; CSO, crisscross optimization algorithm; NN, Neural Networks.

Shi et al. [24] developed algorithms for estimating the electricity production of PV systems using weather classification and support vector machines (SVM). Four models that matched four standard days were established: cloudy, foggy, rainy, and sunny. While sunny days produced the greatest outcomes (in this case, an MAE of 4.83%), the MRE was 8.64% on average. The findings demonstrate that the recommended forecasting approach for grid-connected PV systems is both effective and promising. This led to integration of big data with AI (BDAAI) as proposed by Pandu et al. [25] to forecast solar radiation. Furthermore, Mandal et al. [26] suggested a combination of wavelet transform (WT) and AI techniques for estimating PV power. Son et al. [43] demonstrated that a six-layer feedforward DNN performs better than other traditional models. However, the accuracy of predictions decreased on summer and cloudy weather.

In another study, the researchers evaluated and compared four models of ML algorithms, like support vector machine (SVM), artificial neural network (ANN), kernel and nearest-neighbor (k-NN), and DL to forecast everyday solar radiation expending data from the two preceding years. The findings demonstrated that four models with high accuracy and reliability may be employed for prediction; where the ANN method outperforms among all algorithms, followed by DL, SVM, and k-NN [27]. Moreover, Voyant et al. [44] show that the ANN algorithm outperforms the other three algorithms (Support Vector Regression, General Regression Neural Network, and Random Forest) in terms of accuracy of prediction, computational time, and error.

This led to the development of a hybrid model by Bouzerdoum et al. [28] who combined the cyclical auto-regressive integrated moving average method (SARIMA) and SVM for short-term power forecasting. The findings indicated that the developed hybrid model outperformed the SVM and SARIMA model. On the other hand, Lim et al. [29] developed a hybrid model comprising a convolutional neural network (CNN) and long short-term memory (LSTM) to precisely forecast the amount of power that will be generated.

### *B. Forecasting the Output Power of Wind Systems*

Recently, wind energy is growing in popularity worldwide as it is a green source of power, inexpensive, and limitless. The wind turbine is a promising example of renewable energy because it contributes directly to the decrease of emissions. Nevertheless, predicting wind energy remains difficult due to its temporal variability and uncontrollable fluctuations, leading to challenges in generating constant wind power. Hence, developing a reliable model for forecasting wind energy is essential [32]. Several predicting methods for wind power have been developed, including the physical, conventional statistical, and intelligent forecasting approaches [33]. Since there is a correlation amid wind speed, route and the power productivity of wind systems, the majority of AI simulations and algorithms are revolutionized using wind speed statistics.

Physical approaches are more apt for longstanding wind energy conjectures [34, 45] although conventional statistics perform better for short-term forecasting such as the autoregressive moving average (ARMA) [35] and the autoregressive integrated moving average (ARIMA) model [36]. While statistical models provide highly precise extrapolations for linear components of data, nonlinear data render inaccurate predictions [37]. Statistical methods are thus more computationally effective compared to corporeal and intelligent learning approaches.

With the fast development of AI, intelligent forecasting models and algorithms have been effectively developed and used in wind energy forecasting [46], such as ANN [38, 47] and SVM [39, 40]. Scholars proposed and compared two models, ANN and adaptive neuro-fuzzy inference system (ANFIS), to predict the speed of wind. The findings illustrated that the ANFIS algorithm performs better than ANN [41]. Authors demonstrated that ANN model accurately predicted wind power and outperformed analytical models.

In recent years, many hybrid systems for predicting wind speed have been proposed because they achieve better single method forecasting performance [42]. For example, hybrid systems named empirical mode decomposition (EMD)-ENN is developed by Wang et al. [48] to forecast wind power production. In another study, authors have suggested hybrid SVM models to improve forecast precision [47]. Moreover, the Improved Dragonfly Algorithm and an SVM were used in a hybrid forecasting prototype to predict temporary wind power yield [40].

## III. CONCLUSIONS

In this review, a brief appraisal of the application of AI in renewable energy is given. In forecasting the output power, numerous studies proposed models of AI algorithms that have high prediction accuracy, less computational time, and less error. Therefore, AI can also be used to keep the power system stable in terms of supply–demand balance management when renewable energy source is intermittent. However, AI systems need to solve issues such as the accuracy of an AI model for cloudy days, and the availability of quality data to train and evaluate the models. Regarding the ageing of PV panels, a suitable AI system for power production also needs to be developed [49].

In the future, more research can be conducted on a variety of other renewable system issues, such as energy storage systems and enhancement of model precision for cloudy days. Also, to improve AI-based forecasts, huge datasets with proficient data are superior. Comparable results of testing using specific wind and solar energy models in various geographical regions with distinct overall patterns would further improve its accuracy.

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