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A Short Review on AI based Solar Power System

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Abstract

Modern, advanced society cannot function without a steady and reliable source of electricity. Much of the work being done on control framework research has moved away from the formal scientific demonstration system, which emerged from the fields of task analysis, control hypothesis, and numerical analysis, and toward the less rigorous and labour-intensive approaches of artificial intelligence (AI). These techniques are used to address a range of control framework, scheduling, forecasting, control, and arrangement. These tactics are able to handle challenging tasks that applications in today's vast power frameworks, which have significantly more interconnections added to satisfy the expanding load requirement, look for. This paper's actual objective is to demonstrate how computerized reasoning processes could play a crucial role in forecasting and illustrating the operation of solar-powered energy frameworks. Through a way for displaying different problems in the many orders of sun-based vitality designing, the paper outlines an understanding of how expert systems and neural systems function.

Keywords: Artificial Intelligence, Artificial Neural Network, Genetic Algorithm, Fuzzy Logic.

Introduction

Solar Power System

Sunlight or solar radiation is other names for solar energy. Electrical energy is produced from solar power using solar energy. It can use photovoltaic (PV) directly, indirectly through concentrated solar energy, or by focusing the sun's light into smaller beams using mirrors and tracking devices. Light is converted into electricity by photovoltaic cells using the photovoltaic effect [1-6].

Artificial Intelligence

Artificial intelligence is an intentional way of thinking, and intelligent people think in the same ways as computers, computer-controlled robots, or software. It is the simulation of human cognitive processes by machines, particularly computer systems. These processes include identification, substantiation (approximate or definitive findings), and learning (knowledge acquisition and usage rules) [5-8].

Need of AI in Solar Power

AI has demonstrated the ability to transfer energy. The research, forecasting, and modeling of the use and management of renewable resources can be aided by installation ingenuity. Numerous accurate data points, like solar radiation, temperature, and wind speed, are needed for the design, construction, and maintenance of solar systems. Such long-term measures are frequently lacking in many areas of interest, or the environment that is now accessible contains additional imperfections (e.g., low-quality data, a dearth of extended footage, etc.). Artificial insemination technology appears to be one of the most effective ways to solve these issues. AI techniques available for solar energy are genetic algorithms, fuzzy logic, and artificial neural networks (ANN, FL, GA). Because artificial intelligence (AI) can automate processes for improved efficiency and performance, it has become one of the most popular research areas over the last few decades [1]. By giving them a sophisticated set of instructions to follow, it gives machines the ability to think, learn, and make decisions much like people do. Both consumers and industries make great use of the process in their daily lives. Moreover, it has been determined that the digital transformation of power systems through the use of AI has enormous potential to support the growth of the power system network in terms of stability, dependability, dynamic responsiveness, and other crucial areas [2]. AI is currently being used to implement the power system's design [3], forecasting [4], control [5], optimization [6], maintenance [7], and security [8], as shown in Figure 1. Among these designated fields of AI application, design, fore-casting, control, and maintenance features are extensively covered in the literature. Cyber security components are evolving and were thought to be the upcoming developments for AI applications in PV power systems. The development of AI to support the system learning process in the design, control, and maintenance aspects for increasing efficiency and decreasing response time has improved due to the availability of data in the operation of PV power systems. This methodology promoted study endeavors from a data-driven standpoint to examine the intricate and demanding issues in power systems.

Application of AI in Solar Power System

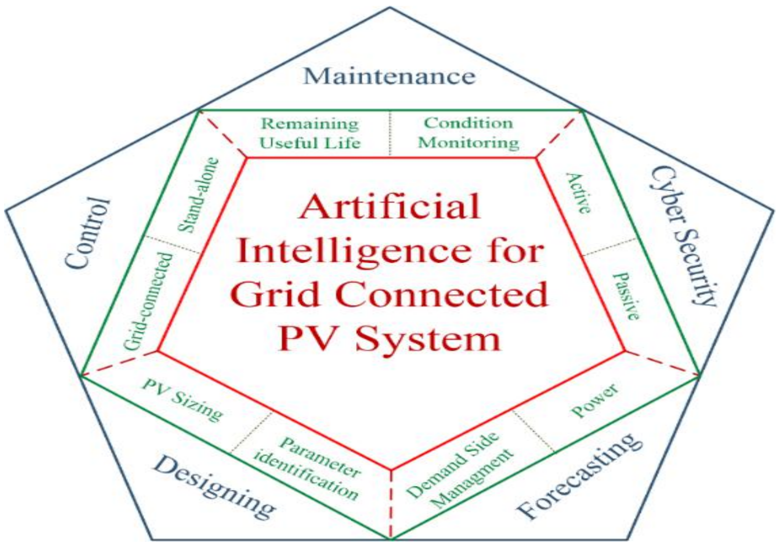

Figure 1: Application of AI in power systems

Solar Power Forecasting

Accurate estimates of PV system output power can help reveal critical information to better regulate the energy grid, enabling grid operators to handle rapid changes in power in the system. The power production from photovoltaic systems varies due to variations in solar irradiation caused by weather fluctuations. Therefore, as the use of large-scale grid-connected PV systems is growing, it is crucial to improve the prediction of the PV system output power. Furthermore, AI techniques are seen as a practical way to predict the solar radiation intensity and power production of PV systems because of their ability to overcome the drawbacks of conventional methods and to address complicated problems that are challenging to describe and analyze [10]. Figure 2 displays the requirements needed to create generation forecasting models using AI approaches.

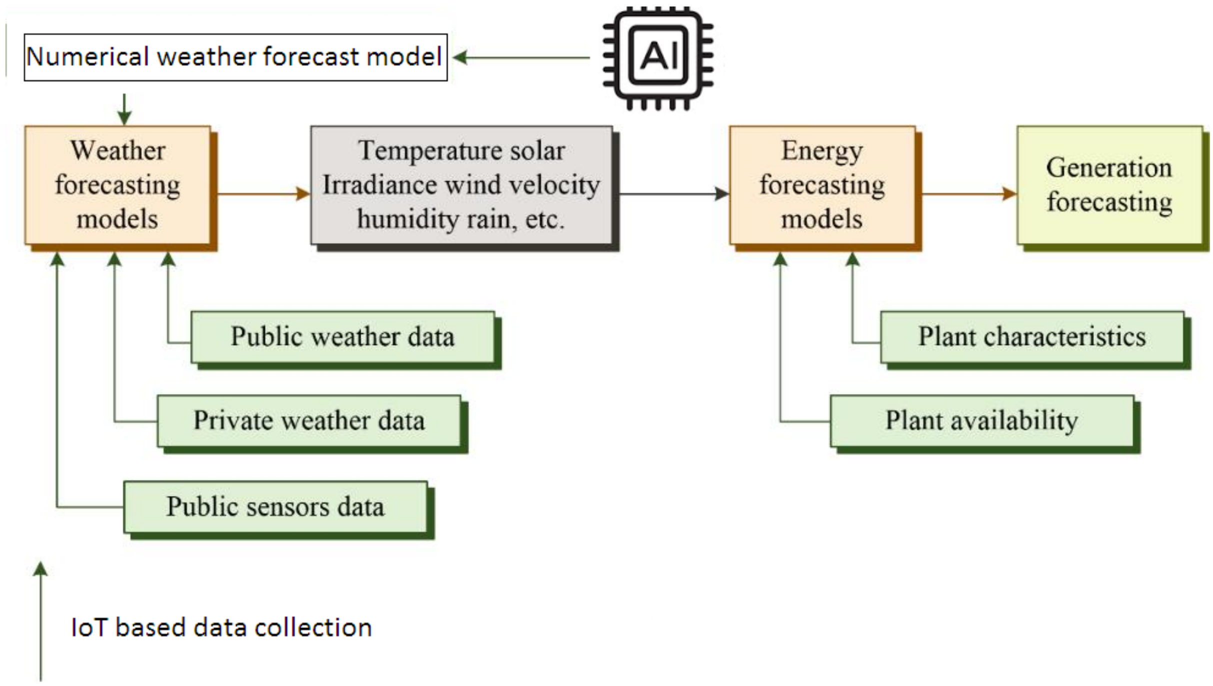

Figure 2: Block diagram of solar power forecasting with AI techniques

A review of solar power forecasting in [11-12] evaluates several methods and strategies to raise prediction models' precision and lower their uncertainty. According to the review, ANNs are the most popular machine-learning methods for solar power forecasting since they work well in a wide range of scenarios and with a large number of input variables. Support vector machines, which employ supervised modeling techniques, are the next most popular methodology. They are highly proficient at handling non-linear problems and have a robust generalization capacity. Furthermore, with input factors including global horizontal irradiance, wind speed, air temperature, pressure, humidity, cloud cover, and time of day and year, the research in [13-14] employed ANN and ensemble techniques to forecast power production. The study's findings demonstrated that, when it comes to day-ahead forecasting, an ensemble of comparable configuration networks with their output forecasts averaged out should likely perform better than a single network with the same settings. Normalized solar radiation is recommended by Kudo et al. [15] for training an ANN for solar power based on meteorological parameters.. It is proposed that the normalized radiation could improve the model's performance because the weather fluctuates with the seasons and using a single season would require a lot of data. By splitting the solar radiation by the alien radiation, one can obtain the normalized radiation. The goal of the study by Liu et al. [16] was to determine how air temperature and sun irradiation affected a photovoltaic system's output power. The solar irradiance intensity and the output power show a linear association, while the air temperature shows no positive or negative linear correlation, indicating a non-linear relationship between the two. In a similar vein, three distinct models including various input variables are defined in the comprehensive review on forecasting photovoltaic power generation in [17-18].

AI for Power System Design

The current status of AI application in PV system design and optimization with respect to energy yield, costs, and permits is discussed in this section. Traditionally, the operational performance of the system is described by numerical simulations based on the equivalent circuit models for solar panels [19-20]. These models' parameters are determined by analytical or numerical methods. One problem with using analytical methods is that many approximations and assumptions are made, leading to model inaccuracies. Conversely, numerical techniques have shown to be superior [21-22]. The Newton-Raphson method, non-linear least squares optimization and pattern search are some of these techniques, but they require a lot of processing power. Additionally, parameter identification was achieved through the application of Markov chains [23]. These techniques necessitate data spanning a significant amount of time; hence, these traditional approaches cannot be used if such data are not accessible.

Sizing of Solar PV System

Precise system size for photovoltaics is crucial for guaranteeing the reliability and durability of power supply as well as optimizing financial life-cycle savings. The literature shows that while intuitive methods do not yield findings with high enough accuracy, non-AI methods and numerical methods used in system sizing suffer from the necessity for vast volumes of data. Therefore, research is done for alternate methods when sizing a PV system at a site where the necessary data are absent.

In order to optimize the sizing coefficients for standalone PV systems, [24] hybridizes evolutionary algorithm approaches with artificial neural net-work models. The artificial neural network was trained with these inputs to find the ideal coefficients in remote places after the evolutionary algorithm model optimized the coefficients by reducing the system's cost. Similar to this, in [25], the ideal sizing parameters for freestanding PV systems are predicted using an artificial neural network. For the PV array size coefficient and the battery storage capacity coefficient, the ANN yielded values with RMSEs of 0.046 and 0.085, respectively. Additionally, in [26-27], the Bat algorithm is modified to maximize the specific yield in order to optimize the size of grid-connected photovoltaic systems. The new approach yielded faster optimization results compared to particle swarm optimization. The algorithm was trained using a library of technical specifications from existing PV modules. The generalized regression neural network is employed in [28] to estimate the risk of load loss and optimize the sizing coefficients for standalone photovoltaic systems. With the help of simulated hourly solar irradiance data, load demand, and the created model, sizing coefficients with a mean absolute percentage error of 0.6% were obtained. The simulation resulted in a 0.5% loss of load probability. Particle swarm optimization is integrated for grid-connected photovoltaic systems' ideal sizing in [29]. The algorithm database included meteorological information for the suggested locations as well as the technical and financial features of systems that are commercially available. Additionally, the ANFIS model is created in [30] in order to optimize the size coefficients of independent photovoltaic systems. Based on climatic data, the generated database contains size coefficients corresponding to 200 sites in Algeria. In addition, depending on solar panel pricing, the ideal sizing criteria were created for these predicted sites. When compared to the site's known sizing parameters, the suggested adaptive neural fuzzy inference system model yielded the most accurate findings across all network configurations.

AI for Forecasting in Grids with Photovoltaic Systems

Accurate forecasting of the power production fed into the grid has become increasingly crucial due to the increase in grid-connected photovoltaic (PV) systems observed in recent years. The reduction in investment costs, which fell by ten percent between 2019 and 2021, is the main driver of the growth; however, other variables including incentives and rules governing the technical specifications for construction projects have also contributed. With this predicted growth continuing for years to come, grid-connected photovoltaic systems may cause more frequent fluctuations in the electrical grid and may even cause instability because of abrupt weather variations [31]. Additionally, spot markets for electricity were introduced as a result of the liberalization of the energy markets, and these markets were crucial in maintaining the balance between supply and demand. As a result, producers, merchants, major clients, and communities must precisely project their output and demand. These market participants have been heavily utilizing forecasting techniques to achieve this. Figure 3 provides an overview of the energy market operations and the ensuing specifications for power output estimates from intermittent renewable energy sources.

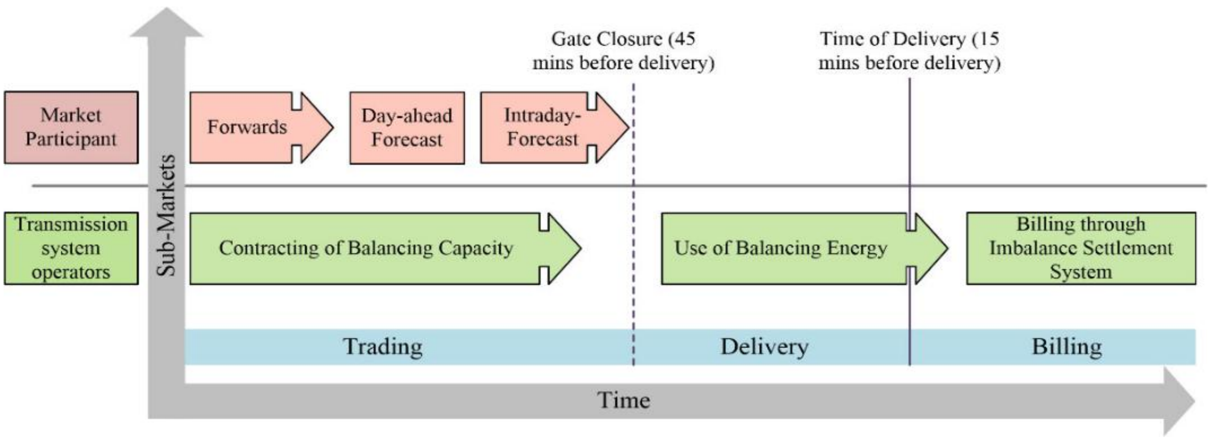

Figure 3: Block diagram of a summary of the forecasting needs for process energy marketing

This summary creates energy markets, controls reserves, and aids in maintaining a balance between the supply and use of power [32]. But because market participants usually struggle to predict solar irradiance and PV outputs, the growing PV has made it harder for them to manage their systems [33-35]. Furthermore, it is clear from the literature that merchants and generators who are unable to achieve demand or output projections are forced to turn to the balancing market, where they must pay exorbitant costs to correct their imbalances. Given these problems, effective forecasting models are thought to be a crucial component of improved market systems.

Condition Monitoring of Grid Connected PV System

PV systems connected to the grid usually face demanding and intricate working circumstances. They might experience a range of fault events, either at the system or component level. For grid-connected photovoltaic systems to operate efficiently, safety and dependability are critical components. Reliability is increased through the use of maintenance procedures including preventative maintenance, which integrates condition monitoring, fault detection, remaining usable life (RUL) forecast, etc. To guarantee the intended functioning of the grid-connected photovoltaic system, appropriate health monitoring at the component and system levels is necessary. It starts with determining what is known about the dynamics and behaviour of the system from the data that is at hand. The information obtained can then be used for online monitoring (OLM) or real-time health monitoring based on anomaly detection and parameter identification for the offline model dynamics [36].

AI Monitoring for PV Array Faults

PV module status monitoring is essential for improving power conversion efficiency. Failures including delaminating, discoloration, cell cracking, bypass diode short circuit, snail trail, glass cracking, etc. can impact photovoltaic panels. The random forest (RF) approaches based on supervised learning are employed in [37] for PV panel defect diagnostics. Pre-processed to make it acceptable for training, the array voltage and string current are measured in the simulation for various sun irradiation and temperature conditions. The decision tree's majority voting is used to measure prediction accuracy, and it is discovered that in addition to having a very high accuracy, this technique can also handle over fitting problems. A condition monitoring and fault diagnostic tool for photovoltaic defects based on multi-layer perceptron neural networks (MLPNNs) is created [9]. The discrete wavelet transform (DWT)-based signal processing technique is utilized to extract the properties of the IV features. When MLPNN is trained with the retrieved features, it is able to attain 100% accuracy for the given fault data. Moreover, a method for diagnosing faults in PV panels is created in [38] using radial basis networks and probabilistic neural networks (PNNs). It has been noticed that this fault diagnostic method is less impacted by outliers and offers good generalization accuracy. A unique method for PV array health monitoring that focuses on kernel-based extreme learning machines is proposed in [39]. The presented method uses the Moore-Penrose generalized procedure to calculate the output weights after randomly determining the input biases and weights of the corresponding hidden layer. Additionally, [40] uses an artificial bee colony (ABC) technology based on swarm intelligence to diagnose faults in PV panels. This method is based on semi-supervised extreme learning and uses primarily unlabeled fault data that was obtained from different fault simulations. A convolutional neural network (CNN)-based deep learning-based fault classification method for PV arrays is proposed in [41]. In order to use this supervised learning-based classification technique, IV characteristic data must be gathered, transformed into two-dimensional time-frequency representations, or scalograms, and then fed into an AlexNet that has been precisely calibrated for the classification task.

Application of AI for Reliability

The ability of specific equipment to carry out a specific function under specific operating conditions is known as reliability [42]. The parameters that determine the reliability are the likelihood of survival and failure [43]. Estimating the operational lifespan and, in the event of a failure, recalibrating the lifetime and providing the remaining useful life are the two goals of this reliability study. The power electronic device is operated in a controlled environment in order to do the reliability analysis for de-sign modification. The device's thermal modeling is based on the inverter's power loss. Several lifespan calculation models, such as coffin mason [44], CIPS2008 [45], and LESIT [46], can be utilized for the lifetime calculation after the thermal profile has been acquired. Rainflow counting is then employed for cycle counting. But the analytical analysis techniques-like fast convergence-may leave a lot of holes in the analysis. Therefore, in order to address these problems, AI-based lifetime estimation can include transient faults in the analysis or abrupt changes in component stress as a result of ride-through operations [47], which will also improve the lifetime forecast capabilities. In [48], the lifespan estimation is accomplished, utilizing ANN to study the different operating situations, whereas in [49], a function-based link is constructed between reliability and design parameter.

Digital Twin

The utilization of artificial intelligence techniques in conjunction with the many functions of photovoltaic systems connected to the grid has revealed that the digitization process is widely accepted. Additionally, this prompted the creation of numerous fresh strategies that improved the integration of contemporary energy systems with the grid. The development of digital twins (DT) has significantly changed research patterns by readily increasing the connectivity between virtual computers, their data, and the actual environment. Through computerized and virtual world modeling, this technology developed a method for real-time energy system synchronization, monitoring, and other services [50-51]. This method is supported by a visualization program [52], and it collects data on the working status of the system [54] by means of intelligent analytics and real-time data [51,53]. Furthermore, using several modeling approaches that include energy forecasting, demand side management, control, monitoring, and data visualization, the DT framework may be constructed from the perspective of a grid-connected PV system. The study in [51] is centered on using DTs to create power system control algorithms. In [55], fault diagnosis of a real-time PV system is accomplished through the analytical evaluation of residual error through the use of a DT technique. In order to improve system performance, this strategy makes use of the voltage source inverter's sensing and actuation capabilities. Additionally, the study in [56] addresses the use of DT for energy bench-marking to attain the best possible energy decision-making using real-time energy management systems and energy retrofitting. Comparably, the DT-based multilayered strategy is used in [57-58] to create an energy model that will lead to efficient energy use in a power system network. Based on the literature reviewed above, Figure 4 highlights the key characteristics of DTs in modeling, controlling, and monitoring grid-connected photovoltaic system components using artificial intelligence approaches.

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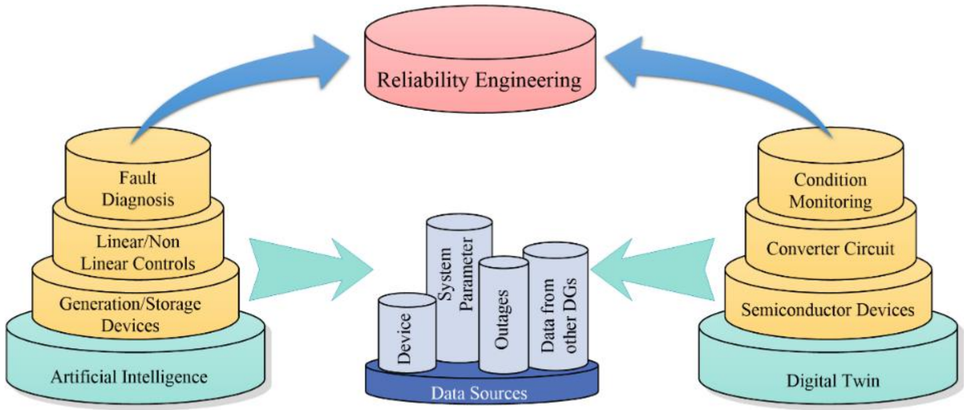

Figure 4: Block diagram of digital twins in PV systems for various purposes.

It is crucial to determine the critical parameters and supporting technologies [53,59] in order to use the DT framework to significantly improve the operation of grid-connected PV systems. Typically, the output from the insight stage and the PV system's data collection phase is fed into the DT framework. Moreover, energy forecasting, the internet of things (IoT) platform, energy internet, and sophisticated data analytics are crucial technologies linked to the DT framework for the efficient operation of the system [60-61].

Conclusions

The review undertaken in this work leads to the following conclusions: at the system level in the solar PV value chain, there are a large number of published research publications that use various AI techniques for various goals. Depending on the use case, ANNs and its sub-architectures are the most commonly utilized AI approaches. Evolutionary algorithms like PSO and GA are commonly utilized in optimization, whereas ANNs are highly effective when applied to time-series data like power forecasting or irradiance prediction. Furthermore, it is found that the extensive use of learning methodologies, data-driven algorithms, and inference models for control and maintenance are more tailored to a particular situation, issue, or dataset and do not have universal applicability for the same characteristics. Even though most of the articles show excellent results, it is important to remember that these successes are dependent on modifying one model while leaving the other models' parameters unchanged. Furthermore, a number of the models that have been suggested, derived from the input data, are most likely not universal. It's highly likely that the currently known AI techniques will experience advancements in the near future. There appears to be a data discrepancy in the industry at the moment, but this is expected to change as internet of things solutions, a large number of sensors deployed, drone video streams used for maintenance, and natural language processing techniques become more prevalent.

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