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Integrating Solar Photovoltaic Systems into the Grid: An Overview of AI Application

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Abstract: *The photovoltaic (PV) system business is seeing an increase in the number of applications for artificial intelligence (AI) as a result of the expansion of powerful computer resources, helpful tools, and an explosion of data. It has been shown that the methods that are currently used for a variety of jobs in the solar photovoltaic (PV) industry, such as design, forecasting, control, and maintenance, provide results that are not totally accurate. Additionally, artificial intelligence (AI) has enhanced the accuracy and precision of these professions, which has allowed them to become a topic of discussion at the present time. Within the context of this specific paradigm, the objective of this study is to investigate the impact that AI techniques have had on the PV value chain. In the course of the study, a cataloging of the current artificial intelligence systems, the compilation of a list of prospective applications of AI in the future, and an analysis of the benefits and drawbacks of these systems in contrast to more conventional approaches are all included..*

Keywords: AI, solar systems, optimum size, irradiance prediction, condition tracking, transition management, dependability

I. INTRODUCTION

The capacity of artificial intelligence (AI) to automate processes for improved efficiency and performance has propelled it to the forefront of academic inquiry in recent decades [1]. Through the application of a set of intricate instructions, it empowers systems to mimic human learning, reasoning, and decision-making abilities. This procedure is widely employed in several sectors and is also used by consumers in their daily lives.

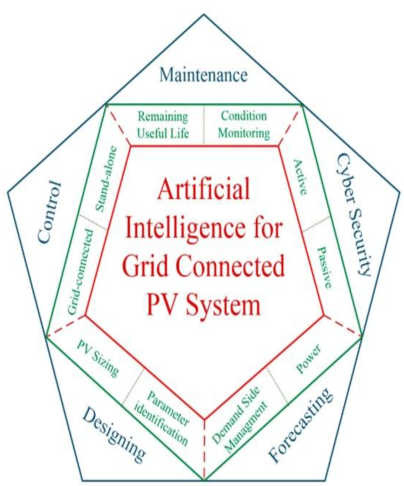

Fig. 1. The implementation of artificial intelligence for the power system industry.

The digital transformation of power systems, which includes the use of AI, has the potential to greatly enhance the network's stability, dependability, dynamic reaction, and other crucial features [2]. The power system is now being designed, forecasted, controlled, optimized, maintained, and protected using AI, as shown in Figure 1. There was hope that emerging cyber security standards will lead to more innovative uses of artificial intelligence in PV power systems in the near future. Thanks to the abundance of data generated by PV power systems, artificial intelligence has made great strides in helping these systems learn how to improve efficiency and reaction time in design, control, and maintenance. In order to tackle the difficult and complicated issues with power systems, this method promoted data-driven research. Figure 2 shows a schematic that connects the methods used by AI in power systems to their respective functions and applications. Although several articles have shown positive outcomes from using AI in solar PV, it is important to remember that many of the suggested solutions were only tested in limited case studies. According to this research, the models have a low relative degree of generalizability and would not provide the same outcomes when used in a new setting.

The AI strategies shown in Figure 2 were used in the supplied situations, and in every relevant component, the majority of the findings demonstrated that they outperformed traditional methods. Data preparation and preprocessing are another critical factor to think about. Data preparation is the most crucial step in using AI since all techniques rely on gathered time-series data, which is prone to noise, missing datasets, and abnormalities.

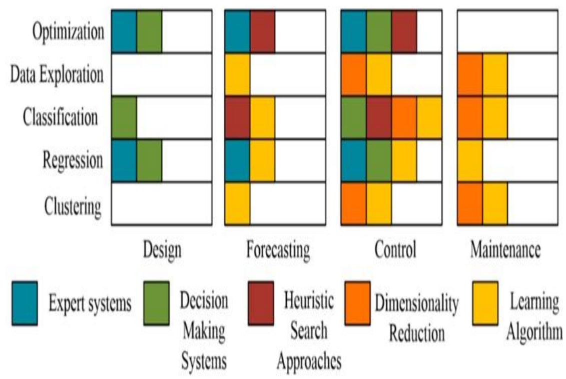

Fig. 2. Integration of various AI applications into grid-connected photovoltaic system design, forecasting, control, and maintenance processes.

According to a Crowd Flower assessment of 80 data scientists' time allocation practices, data preparation consumed about 80% of the total [3]. The training procedure ought to be simple given a clean and well-structured dataset. A thorough analysis of AI's role in power systems, with an emphasis on the following areas, is suggested to accomplish this goal: To accomplish an ideal power system design and appropriate resource usage, find the AI solutions that are suitable for PV system size. To determine how much longer certain parts of the system will last, examine how artificial intelligence methods tailored to condition monitoring and reliability analysis were used. To prevent unplanned power outages and maintain control and monitoring, it is important to anticipate emerging trends in artificial intelligence (AI) methods for digital twins and cyber security.

II. ARTIFICIAL INTELLIGENCE ARCHITECTURE FOR PHOTOVOLTAIC SYSTEMS CONNECTED TO THE GRID

A rundown of all the papers written on artificial intelligence in the electricity grid throughout the last few decades. The data was obtained by referring to the significant articles published in various publications. It is clear that the majority of researchers have been focusing on artificial intelligence methods for optimization and control applications in system design in the last several years. Intelligent photovoltaic (PV) plants are envisioned in [4], with system control achieved by model predictive control and array and energy storage system size optimized using linear programming. Here, AI-powered learning methodologies are made possible by the collected data, allowing the system to detect and respond to a wide range of problems and anomalies within the allotted time. Based on the findings, this procedure can be executed online using reinforcement learning techniques.

Data management and categorization allow for precise identification of the many operational phases and characteristics, which is crucial for power system operation, which relies heavily on processing massive volumes of data quickly. Various functioning phases and disruptions in the power system may be identified by monitoring its real-time characteristics, as described in [5]. In addition, the power system employs an expert system analysis to differentiate between various voltage dips and disruptions in [6].

In addition, the data was used to its maximum potential by modifying regression methods for power system power flow analysis, demand side management, and forecasting. To find out how much power to scale up the heterogeneous virtual power plants, the authors of [7] use the K-clustering technique. To accommodate the power system's diverse ESS distribution, this section employs the distributed dynamic clustering technique. By taking power system uncertainty into account, a multi-cluster method is used to optimize ESS sizing for PV production in [8]. Similarly, different power grid linkages are investigated using an ordered clustering spectral approach [9]. The digital shift of in photovoltaic systems connected to the grid with AI is shown in Figure 3, considering all the purposes described before.

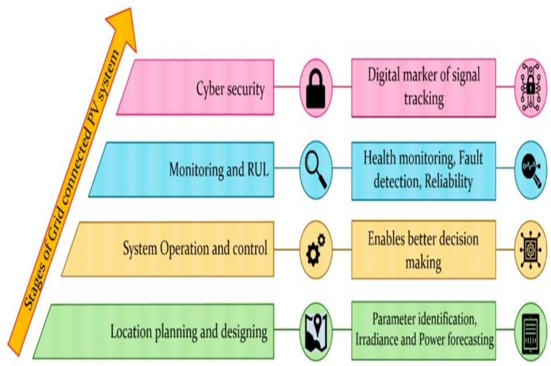

Fig. 3. AI-powered digital transformation of PV installations linked to the grid.

III. USING AI TO DESIGN POWER SYSTEMS

The existing status of artificial intelligence (AI) application in PV system design and optimization with respect to energy yield, costs, and permits is presented in this section. Solar panel equivalent circuit model-based numerical simulations for system operational performance description have long been the subject of discussion [10-11]. Through analytical or numerical methods, the parameters of these models are discovered. The problem with using analytical techniques is that they rely on a lot of assumptions and approximations, which might lead to inaccurate models. In contrast, numerical approaches have consistently shown superior results [12-13]. Despite its computational demands, these approaches include pattern search, non-linear least squares optimization, and the Newton-Raphson method. Also, by using Markov chains, parameter identification was successfully achieved [14].

Conventional approaches cannot be used if data covering a broad time range is not accessible, since these methods rely on this data. When modeling and simulating the PV system, as well as when diagnosing faults, parameter identification is crucial. A method for estimating currents and shunt resistance based on the temperature dependence of diode voltages has been devised. The top performers from the last generation are selected based on how closely they follow the experimental I-V curve with excellent convergence. When compared to other approaches found in the literature, the findings demonstrate that the created strategy performs the best in terms of RMSE. A similar approach is used in [15] to identify parameters of the solar cell's single and double diode models using an artificial bee colony. Compared to the previous algorithms, the one that was designed converges more quickly and with better accuracy (lower RMSE). In addition to heuristic search methods, other popular techniques include neural networks [16-17] and parameter identification methods based on the adaptive neuro fuzzy inference system (ANFIS) [18]. These methods have shown promising outcomes when used to solar panels whose parameters are not known. Figure 5 provides a high-level overview of how the ANFIS technique may be used to perform parametric identification. Table 1 also provides a high-level summary of the many traditional and AI-based parameter identification methods, with the goal of determining which methods are more accurate.

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Table 1. Identification of parameters using traditional and advanced techniques.

S. No.	*Algorithm*	*Diode Model*	*Accuracy*
1	GA	Model with Two Diodes	Standard Reduced Mean Square Error
2	PSO	Models of Single and Double Diodes	HIgh Reduced Mean Square Error
3	AIS	Model with Two Diodes	HIgh Reduced Mean Square
4	ABC	Models of Single and Double Diodes	HIgh Reduced Mean Square
5	PS	Models of Single and Double Diodes	Low Reduced Mean Square
6	ANN	Model for a Single Diode	Standard Reduced Mean Square Error

Solar photovoltaic (PV) systems must be appropriately sized to maximize economic life-cycle savings, provide a constant and high-quality power supply, and avoid power outages. There is a lack of sufficient precision in the findings produced by intuitive techniques, and both the non-AI and numerical approaches to system sizing in the literature need excessive quantities of data. Therefore, when there is a lack of necessary data for PV system size at a given location, other alternatives are investigated. Results showed that the created method achieved quicker optimization than the use of particle swarm optimization; the algorithm was trained using a database of current PV modules with technical specs. Technical and financial details of commercially available system devices were included in the algorithm database, together with climatic data for the suggested locations. The literature that was discussed is included in Table 2.

Table 2. Strategies for best PV system sizing.

S. No.	**Algorithm**	**Advantage**	**Disadvantage**
1	GA	Finds the worldwide best using the provided data efficiently Workable with complicated, not-well-defined datasets as well as discrete and continuous models When steps in the solution fail, the final product is unaffected.	It takes more time for the method to handle data when fitness functions are evaluated many times. This method will provide erroneous outcomes if it becomes stuck in local optima.
2	PSO	Simple to set up and tweak with few settings Capable of enduring simultaneous computation Locates global optima efficiently and reaches convergence quickly	Unsuitable for parameters that are distributed Loss of local minimum due to convergence occurring too soon. Identifying basic design parameters is a challenging task.
3	AIS	Effectiveness in determining the global optimum, even when faced with difficult optimization challenges	Implementation method that is quite complicated
4	BA	Does not need many input parameters. The construction is straightforward. Strong performance overall.	The pace of convergence is slow, and the accuracy of optimization is poor.
5	GRNN	Easily maps the intricate relationship that exists between the independent factors and the dependent variables, Handles the noise in the dataset in an effective manner	It becomes stuck in local minima, which leads to over-fitting of the distribution. A significant amount of time is required for processing massive neural network architectures.
6	ANN	The computing time efficiency, ease of implementation, and high precision factor	Has limited scalability; it can only handle a single goal and a single distributed renewable energy source simultaneously.

IV. USING AI FOR GRID FORECASTING IN PV SYSTEMS

Having precise predictions for the power generation delivered into the grid has grown in importance due to the recent uptick in grid-connected photovoltaic (PV) installations. The decline in investment costs—10–20% between 2019 and

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2021—is the main driver of the growth, while other variables including incentives, rules governing technical requirements for construction projects, and other directives have also contributed. There will be more fluctuations in the power grid and the possibility of instability owing to unexpected weather changes as a result of grid-connected PV systems, and this trend is projected to persist for the foreseeable future [19]. In addition, spot markets for electricity were established as a result of energy market deregulation; these markets were crucial in regulating the supply and demand for power. This means that communities, merchants, generators, and major end users all need to have precise demand and production estimates. This has been made possible by the heavy use of forecasting techniques by these market participants. Figure 4 provides a high-level picture of the energy market mechanics, which in turn necessitates predictions of power output from intermittent renewable sources.

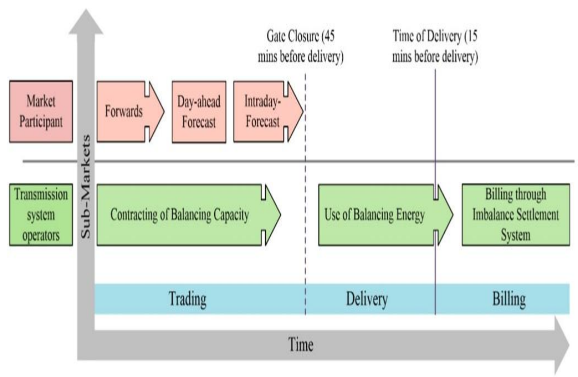

Fig. 4. An overview of the criteria for forecasting in the process energy marketing industry.

This synopsis is useful for controlling reserves, creating energy markets, and balancing power output and consumption [20]. Market participants often struggle to predict solar irradiance and PV outputs, which has made system management more challenging as PV has increased [21-23]. In addition, the literature identifies the balancing market as a place where merchants and generators pay hefty charges for their imbalances when they fail to fulfill their predicted demand or production. Because of these problems, improved market processes rely heavily on accurate forecasting models.

On the other hand, distributed energy resource outputs have not received nearly as much attention as load projections [24]. Improved system functioning has been achieved via the use of load projections in several studies. In order to improve the dependability of forecasts, there is research that looks at both the methods and accuracy of power grid forecasting, in addition to studies that just use forecast outputs [25-26]. The literature has shown that weather, a chaotic system, is very dependent on forecasting. So, looking far into the future, like into the following season, is completely out of the question [27].

In addition, the use of AI approaches offers a solution to the constraints of conventional methods and enables the resolution of intricate issues that are difficult to model and evaluate. The research indicates that artificial neural networks (ANNs) are the predominant machine-learning approaches used in solar power forecasting due to their shown efficacy in many scenarios and with multiple input variables. Support vector machines are the second most often utilized methodology, using supervised modeling methods. They possess robust generalization capabilities and excel at solving non-linear issues. Due to the fluctuating weather conditions over multiple seasons, using data from just one season for a model would need a substantial quantity of information. As a result, it is recommended that the model's performance might be improved by using normalized radiation.

V. ANTICIPATED DEVELOPMENTS AND PROSPECTS

A. Virtual Twin

By integrating AI methods with grid-connected PV systems' many functionalities, we have shown that digitization is a widely accepted process. Even more so, this prompted the creation of a plethora of novel methods, which in turn enhanced grid integration with contemporary energy systems. The advent of the digital twin (DT) has dramatically altered the trajectory of scientific inquiry by greatly expanding the interconnections among real-world objects, their associated data, and digital simulations. By creating a model of the energy system in a digital and virtual environment, this method paved the way for real-time synchronization, monitoring, and other services [28-29]. In order to learn about the system's status in real time, this method employs intelligent analytics in conjunction with visualization software [30] and real-time data [31-32]. The voltage source inverter's sensing and actuation capabilities were used to create this strategy, which aims to improve system performance. The DT framework typically receives as contribution the fallout of the insight period and the data-gathering modus operandi at the PV system. Furthermore, energy forecasting, the energy internet, the internet of things (IoT) platform, and sophisticated data analytics are all crucial technologies linked to the DT framework that ensure the system runs smoothly. Connected devices, the Internet of Things (IoT), and artificial intelligence (AI) data mining capabilities are laying the groundwork for a data-driven future in product design, production, and service via the DT framework [33-34]. In order to build the DT framework, the IoT platforms additionally integrate data produced by the physical system with historical datasets acquired from the grid-connected PV systems' prior operations [35]. A more efficient and consumer-oriented DT framework may be achieved by enhancing data processing skills using AI. In addition, most of the PV system's functions are incompatible with the raw data due to its high stochasticity. Data preprocessing using the DT framework is crucial for feature extraction in datasets [36]. These characteristics shouldn't impede the uniqueness of the measured data, but they should take into account the elements impacting the dynamics of the PV system's operation.

B. Internet safety

As digitalization incentives have spread across all industries and ICTs have proliferated, cyber security has become an increasingly pressing issue. Adaptive control via digital twins, condition monitoring, predictive maintenance, and fault diagnostics are only a few of the activities made possible by data centric methods, as described in the preceding part. Nevertheless, they simultaneously increase susceptibility to cyber-attacks. Changes to PV systems are likely to be substantial when new cyber security requirements for DERs are developed. Figure 5 provides a bird's-eye view of the situation by comparing data-driven [37-39] and physics-informed [40] solutions in terms of speed, selectivity, and accuracy.

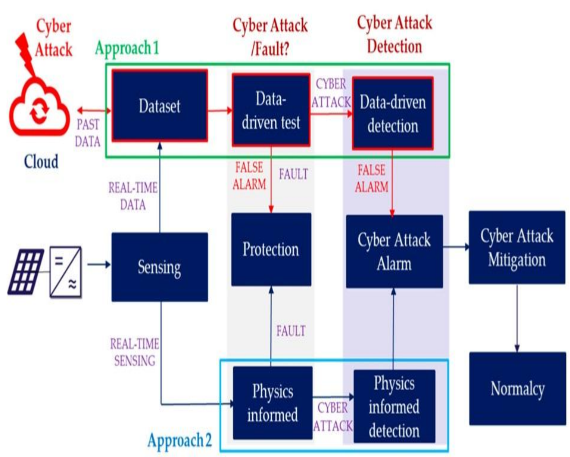

Fig. 5. presents a viewpoint on the cybersecurity methods used for photovoltaic (PV) systems. It provides a comparative assessment of artificial intelligence (AI) techniques and physics-informed approaches.

Figure 5 shows that in Approach 1, grid-tied PV systems' historical data can be used to build cyber security technologies that are both fast and accurate. Because of this, anomaly detection may end up going off more often than it should. The precision and discrimination of data-driven cyber security systems may be readily undermined in this manner. But with method 2, you can only influence the physics-guided tools' decision-making from the real-time sensing stage, and that's already taken into consideration. The outcome is that method 2's decision-making process is more confident than method 1's. To effectively create data-driven cyber security solutions, this calls for further study into this area to account for the opaque character of AI tools.

VI. CONCLUSIONS

According to this paper's review of the literature, numerous studies use different AI methods for different purposes at the structure level of the solar power plant value chain. While specific AI methods may differ depending on the task at hand, artificial neural networks and related sub-architectures are often used. Optimizing generally makes use of adaptive algorithms like PSO and GA, even though artificial neural networks ANN have shown to be highly effective when working with historical data, such in sunlight projection or electrical prediction. Despite their prevalence for management and upkeep, methods of learning, based on data methods, and reasoning frameworks have shown to be too problem-or condition-specific to be useful in other contexts or with different datasets.

Even though most of the publications claim to have achieved considerable results, it should be pointed out that they only tweaked one model while leaving the others with their default values. On top of that, it's likely that some of the suggested models aren't generalizable given the input data. There will very certainly be improvements to the existing AI methods in the not-too-distant future. The industry is currently experiencing a data discrepancy, but this is expected to change as a result of advancements in internet of things solutions, widespread sensor deployment, drone video streams for maintenance purposes, and natural language processing techniques.

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