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Review

A Review on Artificial Intelligence Applications for Grid-Connected Solar Photovoltaic Systems

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Abstract: The use of artificial intelligence (AI) is increasing in various sectors of photovoltaic (PV) systems, due to the increasing computational power, tools and data generation. The currently employed methods for various functions of the solar PV industry related to design, forecasting, control, and maintenance have been found to deliver relatively inaccurate results. Further, the use of AI to perform these tasks achieved a higher degree of accuracy and precision and is now a highly interesting topic. In this context, this paper aims to investigate how AI techniques impact the PV value chain. The investigation consists of mapping the currently available AI technologies, identifying possible future uses of AI, and also quantifying their advantages and disadvantages in regard to the conventional mechanisms.

Keywords: artificial intelligence; photovoltaic systems; optimal sizing; irradiance forecasting; condition monitoring; transition control; reliability

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1. Introduction

Over the last few decades, artificial intelligence (AI) has emerged as one of the most prominent areas of research, due to its capability to automate systems for enhanced efficiency and performance [1]. It enables systems to learn, reason, and make decisions, much like humans, by training them with a set of complex instructions.

The process is extensively used in industries as well as by consumers in their day-to-day activities. Further, the application of AI for the digital transformation of power systems is identified to have massive potential to aid in improving stability, reliability, dynamic response, and other essential advancements for the power system network [2]. Currently, AI is targeted at implementing the design [3], forecasting [4], control [5], optimization [6], maintenance [7], and security aspects of the power system [8] as illustrated in Figure 1. Out of these identified areas of AI application, the characteristics of design, forecasting, control, and maintenance are widely discussed in the literature. The elements of cybersecurity are developing and were considered the future trends for AI applications in PV power systems. The data availability in PV power systems' operation has advanced the development of AI to assist the system learning process in the design, control, and maintenance aspects for improving efficiency and reducing response time. This approach encouraged research activities in a data-driven perspective to analyze the complex and challenging problems in power systems. A layout identifying the techniques between the function and application of AI in power systems is mapped as shown in Figure 2.

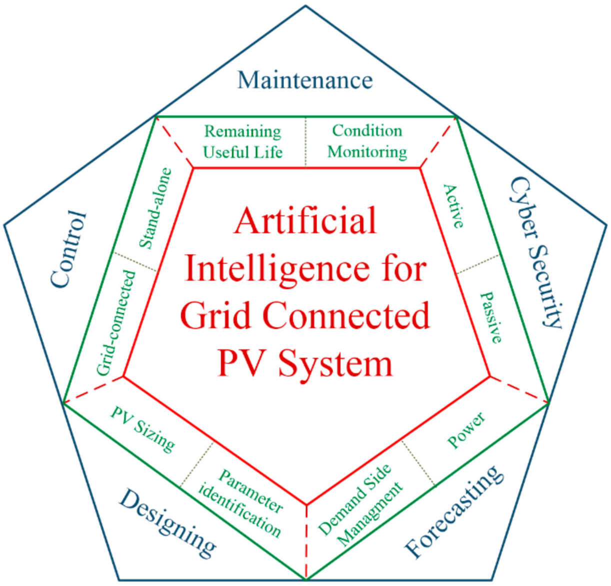


Figure 1. Application of artificial intelligence for power system.

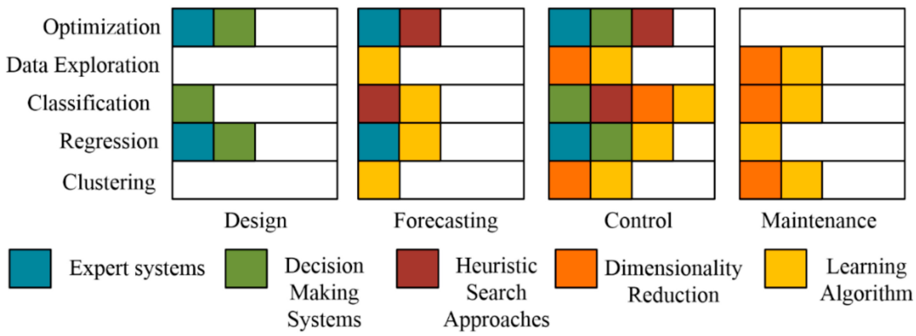


Figure 2. Generalization of different AI applications for the design, control, forecasting and maintenance of grid-tied PV systems.

As the application of AI in solar PV is rather extensive, and several papers have reported good results, it must be noted that many of the proposed methods were performed in narrow case studies. These studies indicate that the relative degree of generalization of the models is low and does not produce similar results if applied to a different environment. In the given settings, the AI techniques in Figure 2 were deployed, and most of the results proved to outperform conventional methods in every applicable section. Another important consideration is the preprocessing of data and data preparation. Every technique is involved with collected time-series data, which will suffer from noise, incomplete datasets and anomalies in the datasets, which is why data preprocessing is the most important task in the utilization of AI. In a survey of about 80 data scientists on how they allocate their time, conducted by CrowdFlower, data preparation accounted for almost 80% of the total time spent [9]. Thus, making sure that the model can be supplied with clean and valid data is a highly demanding task and is responsible for the performance of the model. Provided that the dataset used is clean and well organized, the training process should be straightforward.

In light of the above observations, this paper aims to identify the gaps in the literature and propose a viable solution to enhance the implementation of AI for power system design, forecasting, control, and maintenance. To achieve this, a comprehensive review of AI applications in power systems is proposed, focusing on the following aspects:

- Identify the AI solutions adapted for sizing the PV systems to achieve an optimal power system design and the proper utilization of resources.

- Review the forecasting techniques developed with AI to estimate the mission profile indices, power generated, and load demand.
- Establish the literature on control solutions with AI for power electronic converters to enhance the converter operation for maximizing the output power. Further, the application of AI techniques for grid forming, and grid supporting mode, i.e., islanding detection and fault ride through, are also identified.
- Review the application of AI techniques adapted for condition monitoring and reliability analysis in order to estimate the remaining useful life of different components in the system.
- Identify the future trends of AI techniques for digital twin and cyber security to control, monitor, avoid false data injection, and protect the power system from unscheduled disconnection.

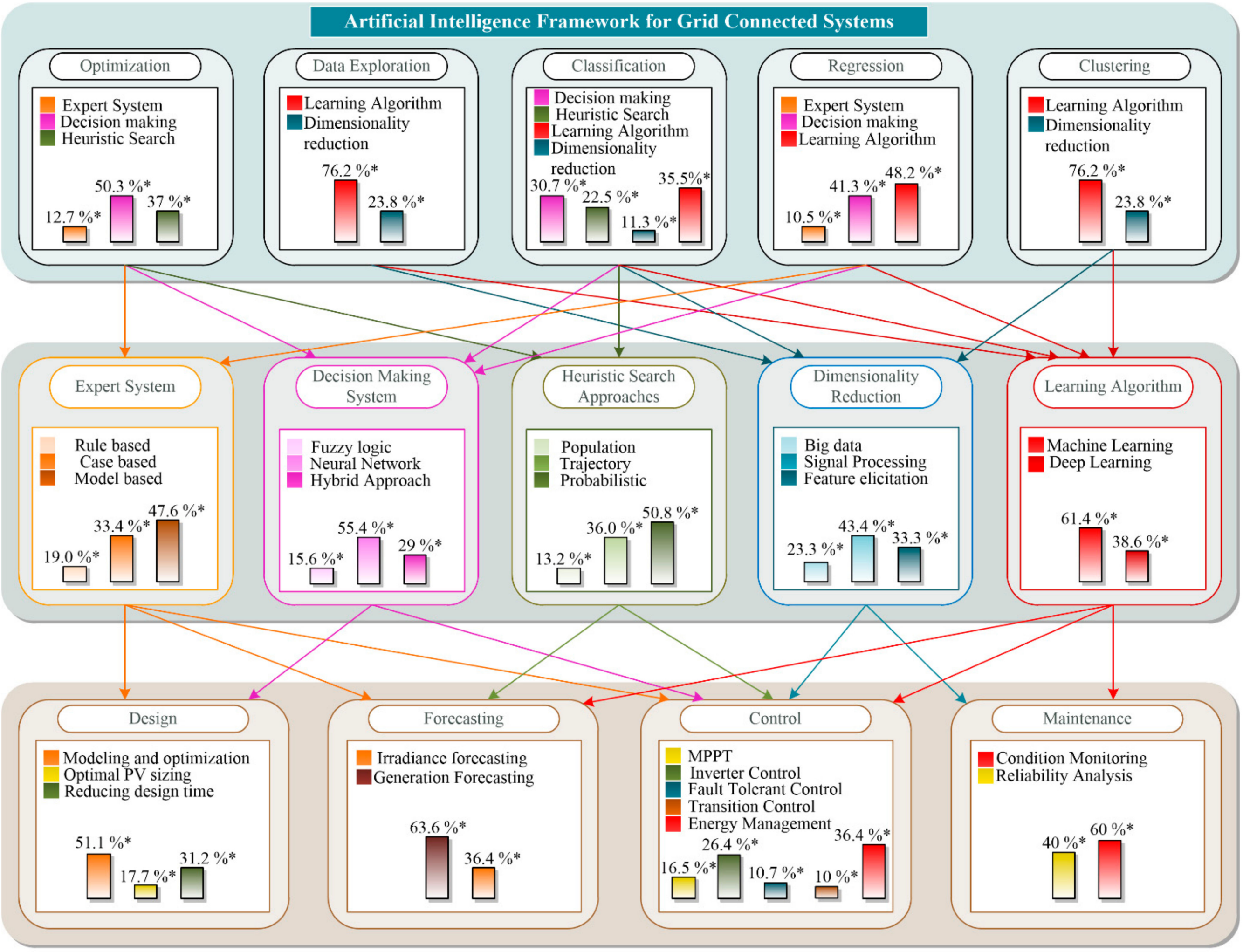
Further sections of this review are organized as follows: Section 2 discusses the AI framework through functions, techniques, and applications for the grid connected PV systems. In Section 3, the AI techniques for parameter identification and optimal sizing are discussed. The AI techniques for irradiance forecasting and output power forecasting are discussed in Section 4; the AI control aspects of both grid-connected, and standalone operation of PV systems is discussed in Section 5. The maintenance aspects in terms of fault diagnosis, condition monitoring, and reliability for grid-connected PV systems with the AI techniques are discussed in Section 6. The future trends of AI with digital twin applications and cyber-security are provided in Section 7. The findings of the review are concluded in Section 8.

2. AI Framework for Grid Connected Photovoltaic Systems

To analyze the challenges of power systems in the field of design, control, monitoring, forecasting and security, the AI is implemented with different techniques. From the literature, AI for power systems is categorized into five classes: optimization, data exploration, classification, regression, and clustering. Figure 3 identifies the number of publications related to AI in the power system over the past few decades. The data were prepared, using the notable contributions from different journals.

It can be identified that in recent years, most of the researchers have been developing AI techniques for system design optimization and control applications. In [10], intelligent PV plants are designed, using linear programming based optimization for sizing of PV arrays and energy storage systems (ESS), and model predictive control for controlling the system. Further, in [11] optimization-based approaches are used for controlling the power system operation by solving the optimal power flow (OPF) problems. The contribution of optimization-based approaches is also extended to reliability analysis of the power system, due to their improved capability in modeling complex problems at low cost. In [12], the network topology optimization (NTO) technologies along with the dynamic thermal rating (DTR) are used to increase the transmission assets and enhance power system reliability. Subsequently, in [13] the stochastic dual dynamic programming along with Monte Carlo methods are implemented for optimal reliability planning. In [14], a robust optimization model for generation and transmission is developed to identify and mitigate the effects of uncertainties and interferences on the reliability of the system.

Further, with increasing access to the operating data of power system, AI implementation has seen a significant rise along with improved accuracy. Here, the data acquired are used to enable learning approaches with AI for identifying various complications and abnormalities in the system and taking an appropriate action within the stipulated time. In [15], a data-driven approach with a Bayesian ascent algorithm is implemented to achieve the target result by assigning target values for a wind farm operation. Further, the irradiance forecasting with the long short-term memory network is implemented in [16] for estimating the day-ahead mission profile for PV system operation. Theoretically, a mission profile handles the dataset related to environmental factors of a location (irradiance, temperature, humidity, etc.), energy estimation, annual power generation, and other graphical results. This dataset helps the PV system designers in identifying the operating conditions of the PV, and assists in extracting minimum, average, and maximum power outputs. Further, the authors in [17] develop a data-driven approach for power system security, to facilitate the identification of the false data injection in the system control. The research identifies that this process can be performed in online mode with the assistance of reinforcement learning approaches.



* Data for calculating the percentage is by considering the notable contribution (articles with high citation in past five years) the respective field

Figure 3. AI framework for different functions, and techniques in application with grid-connected PV systems.

As most of the power system operation is reliant on processing large amounts of data in a short time, data management and classification facilitate accurate identification of the different operating stages and parameters. In [18], the real-time characteristics of the power system are monitored to classify different operating stages and identify disturbances in the system. Further, in [19], an expert system analysis is performed in the power system for distinguishing different voltage dips and interruptions. In [20], the PV module condition monitoring is achieved by accumulating different failure conditions of the PV panels to create a database and perform a real-time assessment with the trained database. Further in [21], the normalized peak amplitude and phase at a sampled instant is identified using a Fourier linear combiner, and the data are used for diagnostics with the help for fuzzy systems.

Moreover, to emphasize the full potential of the acquired data, regression approaches were adapted for forecasting, demand side management, and power flow analysis for the power system. In [22], the PV power forecasting is performed, using a genetic algorithm in combination with particle swarm optimization and an artificial neural network. Here, the Gaussian regression is used for determining the influence of input parameters on the output power. Further, to improve the power quality, a gradient descent least squares regression-based neural network approach is developed in [23]. This approach tends to reduce noise, minimize the harmonics, and compensate for the DC offset to achieve power improvement for both normal as well as abnormal grid operations. In addition to the above, the power flow analysis can also be performed using regression approaches [24].

Further, to accomplish an efficient modeling of the system with improved performance and operation, the clustering techniques are adapted with the data acquired from the various operating states of the power system [25]. In [26], the *K*-clustering method is implemented to identify the power requirements by scaling the heterogenous virtual power plants. Here, the distributed dynamic clustering algorithm is implemented for heterogeneous distribution of ESS in the power system. In [27], the sizing of ESS for PV generation by considering the uncertainty in the power system is optimized, using a multi cluster algorithm. Similarly, different interconnections in a power grid are analyzed, using a hierarchical spectral clustering methodology [28]. Considering all the above discussed applications, the digital transformation of in grid-connected PV systems with AI is shown in Figure 4. Further, a brief overview of AI solutions and techniques to overcome the drawbacks of conventional systems in different functions of grid-connected PV systems are summarized in Table 1.

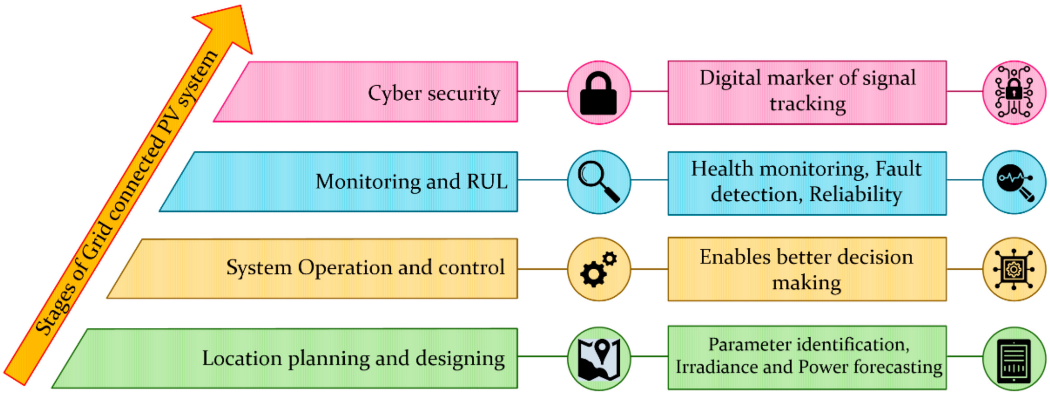


Figure 4. Digital transformation of grid-connected PV systems with AI.

Table 1. Drawbacks of conventional algorithms for different applications and their solution with AI.

Conventional Algorithms	Application	Advantages	Drawback of Conventional Algorithms	Solution with AI	AI Techniques
Predictive and stochastic methods	Monitoring and Maintenance	Simple implementation, Better Interpretability	Sensitive to outliers	Replace Outliers with a suitable value using Quantile Methods	• Machine Learning • Deep learning
Data Minimization Approaches	Maintenance	Flexible framework	Can only be used with clustering and intelligent approaches	Replace data minimization approaches with filtering and normalization approaches	• Memory based and model based collaborative filtering • Machine learning

Table 1. *Cont.*

Conventional Algorithms	Application	Advantages	Drawback of Conventional Algorithms	Solution with AI	AI Techniques
Kernel based approaches	Control and Maintenance	Uncertainty Quantification, Better approximation capability, Computational Efficiency	Probabilistic output, long training time	Probabilistic outcomes are overcome with predictability, which uses statistics to analyze the frequency of past successful and unsuccessful events, and solves training sets locally to minimize the training time.	• Regression algorithms • Neural networks and their hybrid approaches • Machine learning • Expert systems
Randomized Probabilistic approaches	Maintenance	Better Interpretability	Complex computations, and Probabilistic output with random variables	Uses symbolic reasoning to solve complex computations.	• Logical neural networks • Decision trees
Population based methods	Design control and maintenance	Parallel Capability, Achieved global convergence	Complex implementation approach, less convergence speed	Achieves pre-training with a pretty small learning rates to achieve fast convergence	• Machine learning • Heuristic search • Expert systems
Trajectory based methods	Control	Simple implementation, Fast convergence	Has local optima, and no parallel capability	Work on uncertain jump positions and are less susceptible to premature convergence and less likely to be stuck in local optima.	• Heuristic search • Expert systems • Decision making algorithms

3. Application of AI for Power System Design

This section presents the current state of AI implementation within the design and optimization of PV systems in regard to the energy yield, costs and permits. Conventionally, numerical simulations based on the equivalent circuit models for solar panels are discussed to describe the system operational performance [29,30]. The parameters of these models are found, using analytical or numerical approaches. The issue that arises while employing analytical methods are that several assumptions and approximations are made, which causes model errors. Numerical methods, on the other hand, have proven to be a better solution [31,32]. These methods include the Newton–Raphson method, non-linear least squares optimization and pattern search, although these methods are highly computationally demanding. Further, parameter identification was also accomplished, using Markov chains [33]. These methods require data that cover a large timespan; therefore, in the case that these kind of data are not available, these conventional methods cannot be employed.

3.1. Parameter Identification in PV Systems

Parameter identification is highly important when the PV system is modeled and simulated but also in fault diagnosis. There are two types of models that can be used for parameter identification—the single diode model and the double diode model. The error metric employed for optimizing solar cell parameters is the root mean square error (RMSE) for both single and double diode models, compared to empirical I–V curves. In [34], the genetic algorithm approach is used to achieve parameter identification with a double diode solar cell model. The developed approach uses the diode voltages as a function of their temperature to estimate the currents and shunt resistance. The results identify the best individuals from the final generation that closely trace the experimental I–V curve with good convergence. Further, a flexible particle swarm optimization-based parameter identification for single and double diode solar cells is used in [35,36]. The fitness function used is the RMSE, which is dependent on the error function of the single and double diode model, as well as the solar panel. The proposed flexible particle swarm optimization algorithm (FPSO) algorithm produces lower RMSE than the others, and the I–V curves observed from the parameter identification follows the experimental curves under different irradiance and temperature values reasonably well. In [37], an artificial immune system is developed for solar PV panel parameter identification and modeling of the double diode model. The fitness function of the developed approach is based on minimizing the power–voltage curve at the maximum power point (MPP). The results identify that the proposed artificial immune system (AIS) method estimates parameters that are in agreement with the experimental values and compare the outputs with the genetic algorithm and particle swarm optimization. In [38], an artificial bee swarm optimization approach is developed for parameter identification of single and double diode models. The results show that, in terms of RMSE, the developed approach performs the best when compared with other methods developed in the literature. Similarly, in [39], the artificial bee colony is adapted for parameter identification of the single and double diode models of the solar cell. The developed algorithm converges faster and with higher accuracy (lower RMSE) than the other algorithms. Apart from the heuristic search approaches, the neural networks [40,41], and the adaptive neuro fuzzy inference system (ANFIS)-based parameter identification approaches [42] are also widely implemented in the literature. These approaches, when tested on solar panels with unknown parameters, have produced fairly good results. A general overview of implementing parametric identification with the ANFIS approach is shown in Figure 5. Further, a brief overview of various conventional and AI-based parameter identification techniques are compared to identify their accuracy as shown in Table 2.

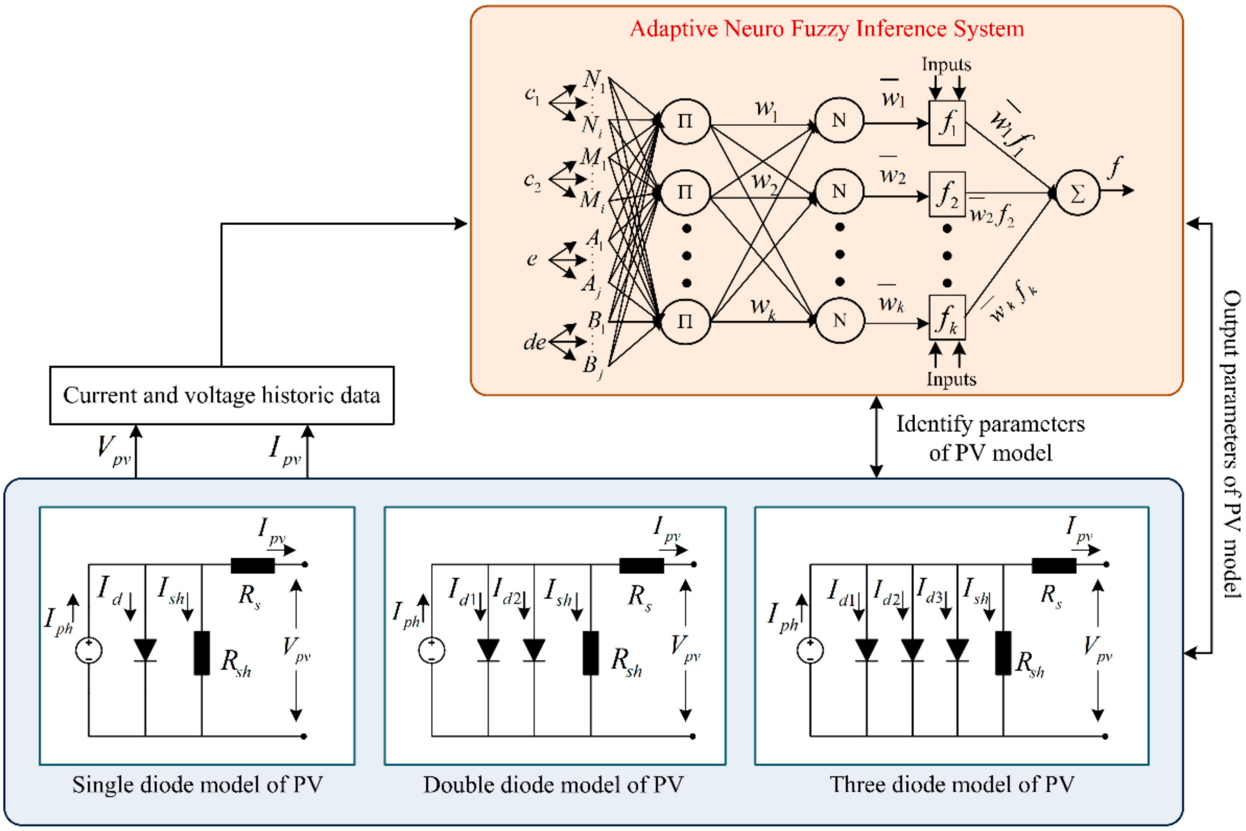


Figure 5. Parameter identification with adaptive neuro fuzzy inference system [43].

Table 2. Parameter identification using conventional and intelligent methods.

Algorithm	Diode Model	Accuracy
Genetic Algorithm [34]	Double Diode Model	Moderate RMSE
Particle Swarm Optimization [35,36]	Single and Double Diode Model	High RMSE
Artificial Immune System [37]	Double Diode Model	High RMSE
Artificial Bee Colony [38], [39]	Single and Double Diode Model	High RMSE
Pattern search [44,45]	Single and Double Diode Model	Low RMSE
Neural network [40,41]	Single Diode Model	Moderate RMSE

3.2. Sizing of Solar PV System

Accurate sizing of a solar PV system is of high importance in order to ensure the quality and continuity of a power supply, and for maximizing the economic life-cycle savings. In the literature, the non-AI methods, and the numerical methods applied in the sizing of the system suffer from needing large amounts of data, while the intuitive methods do not produce results with high enough accuracy. Thus, in the case of sizing a PV system at a site at which the required data are missing, research is done for alternative solutions.

In [46], the genetic algorithm approaches are hybridized with the artificial neural network models to achieve the optimization of sizing coefficients for standalone PV systems. The genetic algorithm model optimized the coefficients by minimizing the cost of the system, and the artificial neural network was later trained using these inputs to determine the optimal coefficients in remote areas. Similarly, in [47], the artificial neural network is applied for predicting the optimal sizing parameters for standalone PV systems. The ANN produced results with an RMSE of 0.046 and 0.085 for the PV array size coefficient and the battery storage capacity coefficient, respectively. Further, in [48,49], the Bat algorithm is adapted for size optimization of grid-connected PV systems by maximizing the specific yield. The algorithm is trained from the database of existing PV modules with technical specifications, and the results identified faster optimization with the developed approach when compared to the application of particle swarm optimization. In [50], the generalized regression neural network is used for optimizing the sizing coefficients and estimating the loss of load probability for standalone PV systems. The developed model produced sizing coefficients of 0.6% mean absolute percentage error, and the simulation built using the estimated coefficients and simulated hourly solar irradiance data and load demand produced a loss of load probability of 0.5%. In [51], the particle swarm optimization is implemented for optimal sizing of grid-connected PV systems. The algorithm database contained the technical and economical characteristics of commercially available system devices along with meteorological data for the proposed sites. Further, in [52], the ANFIS model is developed for optimization of the sizing coefficients of standalone PV systems. The developed database has sizing coefficients corresponding to 200 sites in Algeria based on meteorological data. Further, the optimal sizing parameters for these calculated sites were developed, based on the costs of a solar panel. The proposed adaptive neuro fuzzy inference system model produced the most accurate results of the different network architectures, compared to the known sizing parameters of the site. A brief comparison of the above discussed literature is provided in Table 3.

Table 3. Methods for optimum sizing of PV systems.

Algorithm	Advantages	Disadvantages
Genetic Algorithm with ANN [46]	• Efficiently identifies the global optimal in the input data • Applicable to both discrete, continuous, complex, and not well-defined datasets • Intermediate failures do not affect the end solution	• Repeated fitness function evaluation effects the processing time of the approach • If trapped in local optima, this approach will provide incorrect results
Artificial Neural Network [47]	• Easy to implement high precision factor, computational time efficiency	• Lacks robustness, only can consider single objective and single distributed renewable generation at a time
Bat algorithm [48,49]	• Needs few input parameters • Has a simple structure • Robust performance	• Slow convergence speed • Low optimization precision
Generalized Regression Neural Network [50]	• Easily maps the complex relation between independent and dependent variables • Efficiently handles the noise in the dataset	• Becomes trapped in local minima, resulting in over-fitting • High processing time for large structures of the neural networks
Particle Swarm Optimization [51]	• Easy implementation with few parameters for adjustment • Robust enough to handle parallel computation • Efficiently identifies the global optima and achieves fast convergence	• Not suitable for scattered parameters • Premature convergence resulting in local minimum • Difficult to identify initial design parameters
Adaptive-Neuro Fuzzy Inference Systems [52]	• Efficient performance for finding the global optimum, capable of handling complex optimization problems	• Relatively complex implementation process

4. Application of AI for Forecasting in Grids with Photovoltaic Systems

As an increase in grid-connected photovoltaic (PV) systems has been seen over the last few years, having accurate forecasts for the power production fed into the grid has become more of an important issue. The reason for an increase is primarily because of the reduction in investment costs, which decreased 10–20% from 2019 to 2021, but also, factors such as incentives, regulations on technical requirements for building works, and other directives have played a role. As this increase is expected to continue for years ahead, the grid-connected PV systems will lead to higher changes in the electricity grid and can create instabilities, due to sudden changes in weather [53]. Further, the liberalization of the electricity markets has led to the introduction of spot markets for electricity, which played an important role in the balancing of supply and demand. Therefore, generators, retailers, large end customers and communities have to estimate their output and demand accurately. In order to do so, these market players have been using forecasting methods extensively. An overview on the energy market mechanisms and the resulting requirements for forecasts of electricity production by intermittent renewable energy sources is given in Figure 6.

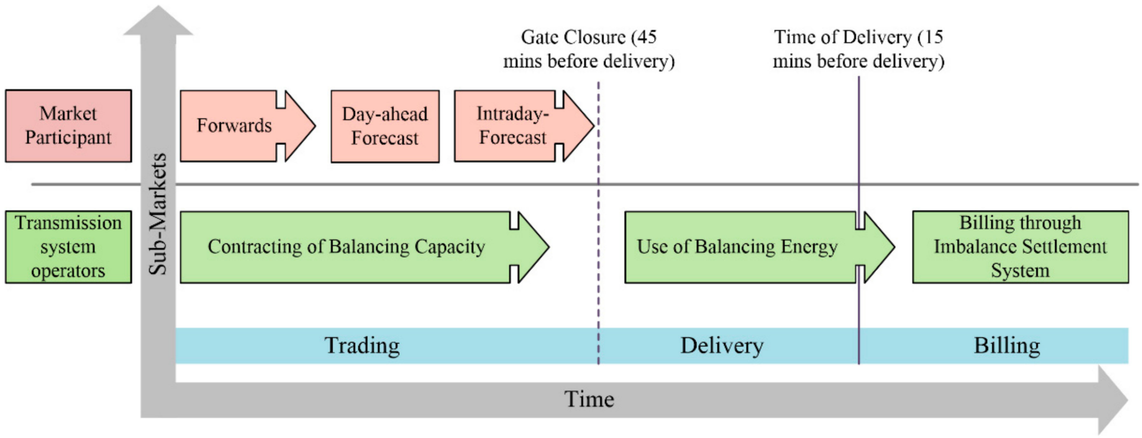


Figure 6. Overview of forecasting requirements for process energy marketing.

This overview helps in balancing the electricity production and consumption, and establishes the markets for energy and control reserves [54]. However, the increasing PV has made it more difficult for market players to manage their systems because they typically have difficulties to forecast solar irradiance, and the PV outputs [55–57]. Moreover, it is identified from the literature that generators and retailers, who are unable to meet their forecasted output or demand, must turn to the balancing market, where they pay high prices for their imbalances. In light of these issues, efficient forecasting models are considered a major requirement for enhanced market mechanisms.

In the early literature, forecasting outputs were used in several aspects for managing grids with distributed energy resources. However, the majority of the work has focused on load forecasts instead of distributed energy resource outputs [58]. A variety of research has used load forecasts for better system operation. Apart from the research that only utilizes forecast outputs, there are also studies that focus on forecasting techniques and accuracy in power grids in order to increase the forecast reliability [59,60]. This literature has identified that the forecasting has significant dependence on weather, which is a chaotic system. Therefore, it is impossible to forecast what will happen over long time scales, e.g., next season. This motivated the development of intelligent techniques that are dependent on statistical and stochastic models, as they enable long-term planning by providing a broad understanding of how distributed energy resources and loads behave.

4.1. AI for Solar Irradiance Forecasting

A review of solar irradiance forecasting using four different machine learning techniques (artificial neural network (ANN), support vector machine (SVM), k-nearest neighbor (k-NN), and deep learning (DL)) are presented in [61]. The comparison between the different techniques identified that ANN algorithm provided the best fitting for the data, followed by the DL, SVM, and k-NN techniques. A summary of the relation between different solar irradiance forecasting models, forecasting horizons, and the related activities with the grid operators are shown in Figure 7 [62,63]. Further, the DL techniques, and gradient boosted trees are used in [64] to forecast the solar irradiance directly from an extracted sub-image surrounding the sun. A detailed overview of different DL models for solar irradiance forecasting are discussed in [65–69]. In [66,68,69], a long short-term memory (LSTM) neural network technique is used to develop a multi-time scale model for solar irradiance forecasting. The developed approach achieved efficient resource sharing between multiple tasks with highly consistent performance, and improved metric results. Further, in [70], the wavelet decomposition-based convolution LSTM networks are used for developing the solar irradiance forecasting approach. The wavelet decomposition improves the operation of the network model by decomposing the raw solar irradiance into several subsequences. This enhances the forecasting ability and accuracy when compared to the conventional DL-based forecasting approaches. Similarly, in [67], the DL methodologies are adapted to develop time series models for solar irradiance forecasting in different areas. The developed models consider both single location and multilocation univariate data to achieve improved accuracy, performance, and reliability for both forecasting and the system operation. In [71,72], the ANN model is developed by customizing it based on the particular season of the year to provide an accurate forecasting approach. The developed approach is assisted with the Pearson correlation approach to provide the most suitable set of inputs for the ANN model. This improves the computational capacity of the model to furnish accurate predictions, even under strong irregularities and rapidly changing scenarios. Further, in [73,74], the solar irradiance forecasting is achieved by evaluating the potential of Gaussian process regression. This research opens a new avenue for the development of probabilistic renewable energy management systems to support energy trading platforms and help the smart grid operators with critical decision making during the inherent uncertainty of stochastic power systems. Apart from the deep learning and neural network approaches, the use of machine-learning classifiers, such as the multilayer perceptron neural network [75], Naïve Bayes approach [76], and k-nearest neighbor neural network [77], and evolutionary algorithms, such as multigene genetic programming [75], are also widely adapted for solar irradiance forecasting. A brief comparison of the discussed literature on solar irradiance forecasting is provided in Table 4.

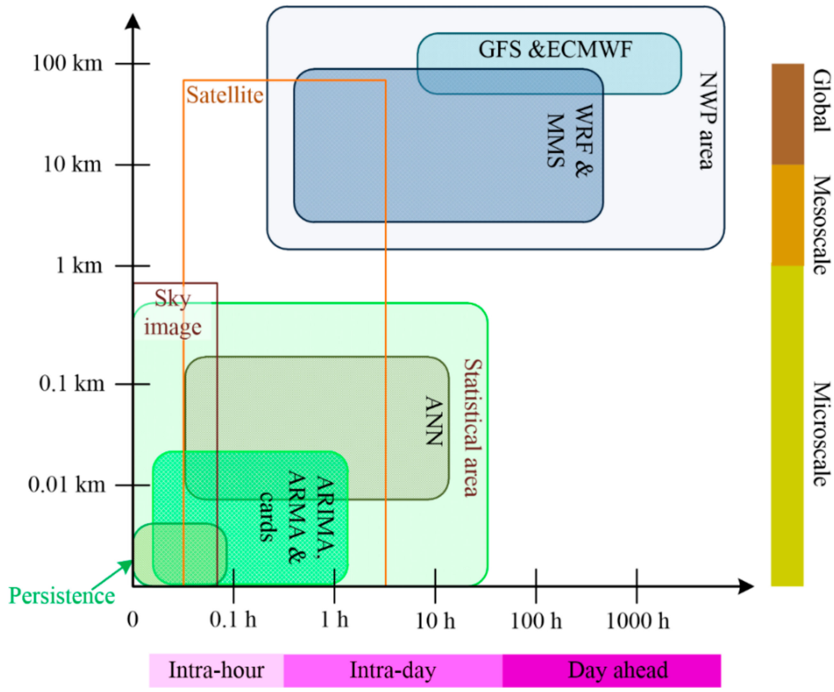


Figure 7. Temporal and spatial resolution for irradiance forecasting.

4.2. Literature Review of Solar Power Forecasting

For grid operators to be able to handle sudden changes in power in the grid, accurate predictions of the output power from PV systems can contribute to reveal important information to regulate the electricity grid more efficiently. Variation in solar irradiance due to weather fluctuations causes variations in the power production from PV systems, and, as the use of large-scale grid-connected PV systems is increasing, it is important to strengthen the prediction of the PV system output power. Further, with the advantage of AI techniques to overcome the limitations of traditional methods and to solve complex problems that are difficult to model and analyze, they are viewed as a convenient method to forecast the solar radiation intensity and power output of PV systems [78]. The requirements for developing generation forecasting models with AI techniques are shown in Figure 8.

Table 4. Conventional and intelligent methods for solar irradiance forecasting.

Algorithm	Objective	Advantages	Disadvantages
LSTM neural network technique [66,68,69]	Develop a multi-time scale model	• Efficiently handles nonlinear data • Memorizes long temporal relationships in the data	• Longer training times • Easy to overfit • Sensitive to random weight initializations
Wavelet decomposition [70]	Decompose the raw solar irradiance data into subsequence	• Efficiently models nonstationary environmental parameters without losing information • Effectively handles short time-scale solar irradiance	• Choice of decomposition level • Redundant representation of data
ANN [71,72]	Accurate forecasting under strong irregularities and rapidly changing scenarios	• Modeling abilities with the different elements of the input data to form a relation in the network structure	• Sensitive to the dimensionality of data • Identifying preliminary settings and functions according to the input data
Gaussian process regression [73,74]	Develop probabilistic renewable energy management systems	• Directly captures the uncertainties in data • Probabilistic prediction for computing empirical confidence intervals	• Require large datasets for prediction • Less efficient in high dimension spaces

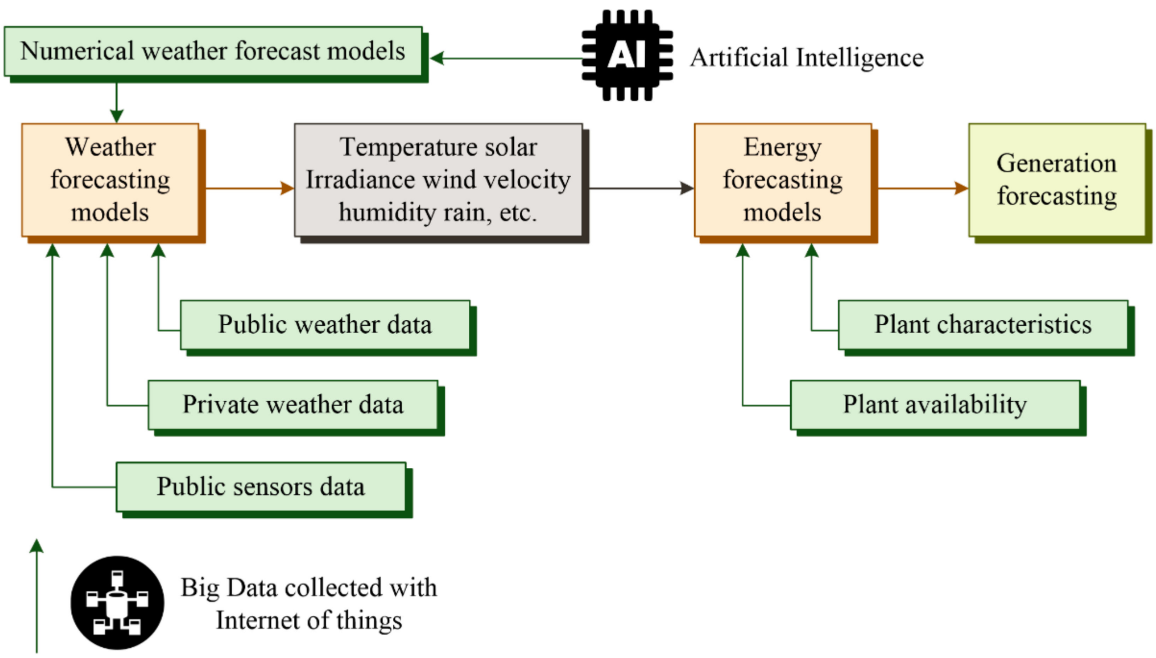


Figure 8. Requirements for solar power forecasting with AI techniques.

A review of photovoltaic power forecasting in [79,80] assesses different techniques and approaches to improve the accuracy and reduce uncertainty in prediction models. The review concludes that ANNs are the most used machine-learning techniques among solar power forecasting, as they have proven useful in a wide variety of situations and with many input variables. The next most used techniques are the support vector machines that use supervised modeling methods. They are strong when it comes to their generalization capacity and have a great ability to deal with non-linear problems. Further, the research in [81,82] used ANN and ensemble approaches to predict power output with input variables global horizontal irradiance, wind speed, air temperature, pressure, humidity cloud cover, and time of year and day. The results from this study showed that averaging the output forecasts from an ensemble of similar configuration networks are likely to perform better, regarding day-ahead forecasting, than a single network of the same configurations. Kudo et al. [83] suggest the use of normalized solar radiation when training an ANN for solar power based on weather parameters. The weather varies for different seasons, and the use of only one season for a model would require a large amount of data; therefore, it is suggested that the normalized radiation could give the model better performance. The normalized radiation is obtained by dividing the solar radiation with the extraterrestrial radiation. The study by Liu et al. [84] aimed to see the correlation between the output power from a PV system with solar irradiance and air temperature. The output power indicates a linear correlation with the solar irradiance intensity, while the air temperature gives neither a positive nor negative linear correlation, meaning that the power output has a non-linear correlation with the air temperature. Similarly, the detailed review on forecasting photovoltaic power generation in [85,86] defines three different models to train a feedforward neural network, involving different input variables. A detailed overview of different photovoltaic power generation forecasting models available in the literature is discussed in Table 5.

Table 5. Comparison of intelligent techniques for output power forecasting.

Algorithm	Advantages	Disadvantages
Wavelet and ANN [87,88]	• Does not require multi-channel signals • Automatic and online forecasting can be achieved	• Removing a large amount of useful information from the original signal • Time consuming
Fuzzy Logic [89]	• Intuitive design, and quick response • Fuzzy rules demonstrate the flexibility in forecasting action • Does not demand the exact model of the system	• Cannot predict varying process with time delays • Multiple tuning parameters affect the stability of the approach
Artificial Neural Network [79,80,83]	• Intuitive design, and quick response • The forecasting action is demonstrated just by the definition of weights along the layers	• Adjustment of abundant parameters affects the stability of the approach • Choice of network size and structure affects the prediction accuracy • Shape of accepted input functions needs to be checked for accurate results
Back Propagation Neural Network [90,91]	• No additional parameters for tuning. • Continuous learning to identify the relevancy and difference in the input data • No prior knowledge is required for learning makes the approach flexible	• Performance is solely dependent on the input data • Sensitive to outliers and noise in the data

5. Application of AI for Power Electronics Converter Control

The control of power electronic converters can be further classified as (a) grid-connected control and (b) standalone control, based on the mode of operation [92]. A conventional controller comprises a dual cascade loop in which the outer loop controls the power and the voltage of the inverter, whereas the inner loop is responsible for regulating the current and maintaining the power quality [93]. The detailed explanations are as follows.

5.1. Grid-Connected Inverter Control

The aim of the inverter controller is to regulate the power and frequency at the AC side of the inverter and reduce the harmonics in the system. The switches present in the inverter are controlled by implementing an inverter control algorithm. Conventional controllers are based on PI- and PR-based algorithms, but with the AI, the accuracy of the controller along with the response time of the inverter controller to transient errors is improved significantly. In [94], fuzzy-based inverter control is discussed, whereas in [95], fuzzy is used for tuning the PID controller for improving the accuracy and performing as a robust controller. Further, in [96], an artificial neural network based controller is simulated, whereas in [97], the ANFIS-based inverter controller is discussed. All the AI-based inverter controllers result in low THD output. The overview of the grid-connected inverter control is presented in Figure 9 when operating at point 2.

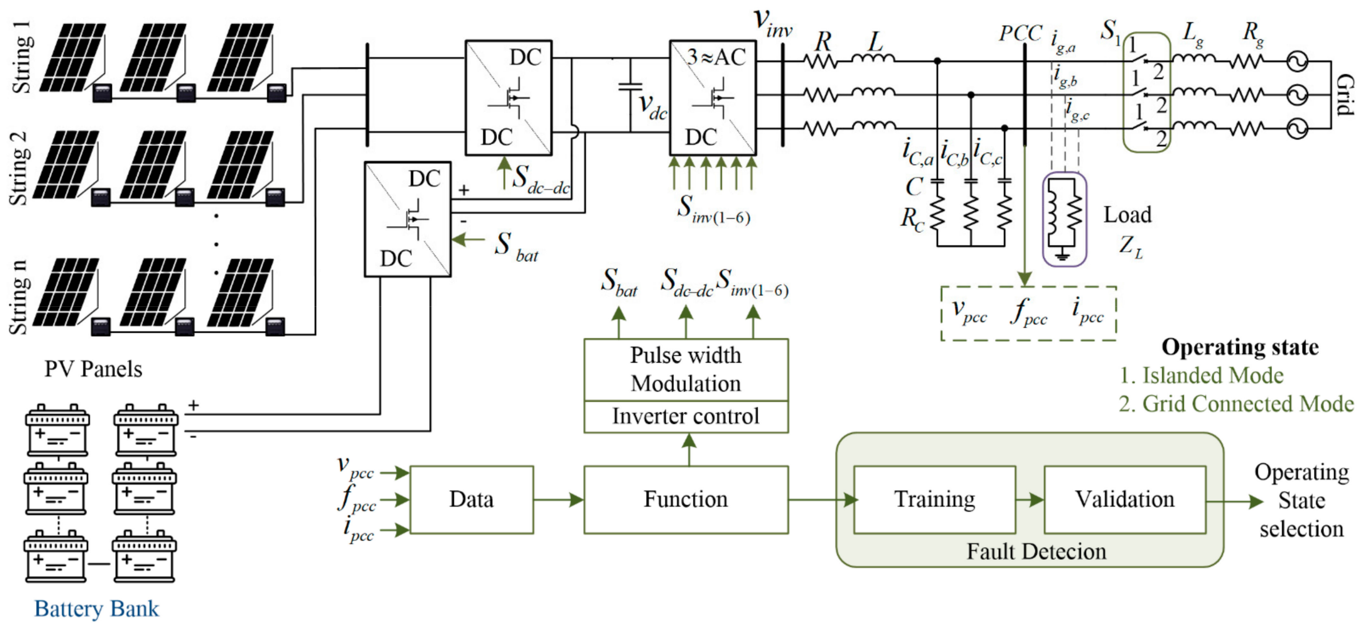


Figure 9. Overview of grid-connected inverter control.

Anti-Islanding Protection: The aim of the protection scheme is to identify the abnormality in the system and disconnect the utilities from the DGs. There is much research on attaining fast detection times with a smaller non-detection zone [98]. Based on the method implemented to identify abnormality, the anti-islanding protection scheme is categorized into active [99], passive [100] and hybrid [101] islanding detection. In active islanding detection, an external perturbation is added into the system, and variation in the signal is observed to identify any abnormality. However, the active method presents challenges while operating in a multi-inverter system and causes concern related to power quality. In the case of the passive islanding detection technique, the operating parameters (voltage, current, frequency, etc.) of the system are closely monitored, and if they surpass the threshold limit, then the abnormality is identified. The threshold identification makes false classification a concern for this type of islanding protection method. Based on the drawbacks of both techniques, a new approach was proposed in which the threshold identifies the abnormality and then perturbation is added in the system to verify whether the abnormality exists in the system or not. This method is known as hybrid islanding detection. However, the process is slow in abnormality identification, as both the methods are combined in its operation.

Based on the identified limitation, a faster and accurate abnormality identification approach is presented by artificial intelligence, as it analyzes the incoming signal, which is used to create a database of all the possible abnormalities and train the classifier to identify the operating condition by assessing the real-time signals [102]. For improving the abnormality identification accuracy, the signals are pre-processed, and features are extracted, which enhances the data matrix and improves identification capability. A brief account of the islanding detection algorithm is presented in Table 6.

Table 6. Comparison of islanding detection technique.

Islanding Method	Principle Methods	Detection	Advantage	Disadvantage
Active	Goertzel algorithm [103]	0.4 s	• Accuracy • Relatively simple	• Power quality detriment • Stability hazard in case of multi generation system
	Virtual resistor method [104]	39 ms		
	Voltage positive feedback [105]	250 ms		
Passive	Switching frequency [106]	20 ms	• Simplicity • Can be used for multi system operation	• Error in detection under unbalanced power condition • Threshold setting needs to be performed carefully
	Grid voltage sensor-less [107]	45 ms		
Hybrid	Wavelet and S-transform [108]	Less than 20 ms	• Has a small non-detection zone • Perturbation is only introducing once islanding is suspected	• Detection time is slow • Perturbation often leads to power quality degradation
	Combination of voltage amplitude and frequency [109]	150 ms		
	Voltage unbalance and THD [110]	Within 2 s		
Artificial Intelligence based approach	Fuzzy with S-transform [111]	Less than 20 ms	• Good accuracy with the ability to handle multi-inverter-based grid-connected DG • Easy to categorize the different states of operation and can be used with multiple distributed generation systems	• The result is abstract and is based on a set of predefined rulesets • The requirement of a large database for training makes it difficult to implement and compute
	Wavelet with neural network [102]	Less than 0.2 s		
	Adaptive neuro-fuzzy inference system (ANFIS) [112]	Less than 0.4 s		

Low Voltage Ride Through (LVRT): Once the abnormality in the grid is identified, it is not recommended to disconnect DGs instantaneously, as it may affect the grid stability [113]. Hence, it is recommended by the grid codes to impose fault ride through or low voltage ride through, which involve the PV system remaining connected with the grid and injecting a reactive current into the grid to maintain power stability and assist in voltage recovery [114,115].

The ride through operation can be performed by using external devices (i.e., a flexible alternating current transmission system (FACT) device) or by modification of the controller of the inverter. The controller modification is an easy and much more economical method to achieve LVRT. In [116], a dual current controller is implemented, which controls the negative and positive sequence of the inverter under fault condition and injects reactive power into the grid as per the grid code regulation. In [117], a droop-based LVRT technique is discussed in which the variation in the DC link voltage is monitored and in the case of a drop, maximum power point tracking (MPPT) is switched to the ride through mode of the controller. Further, in [118], a coordinated reactive power injection control is proposed that utilizes the FACT device along with the inverter control for reactive power injection based on the priority assigned and injection requirement.

Further, to enhance the LVRT capability of the inverter controller, AI-based techniques, such as fuzzy logic control (FLC) [119], and computation-based techniques, such as particle swarm optimization (PSO) [120], are also implemented. The PSO tends to improve the LVRT capability for the nonlinear system, whereas FLC-based control utilizes a vector control plot for the DC- link voltage and performs LVRT safely. A brief overview of achieving LVRT with intelligent approaches is shown in Figure 10, and different LVRT techniques are compared in Table 7.

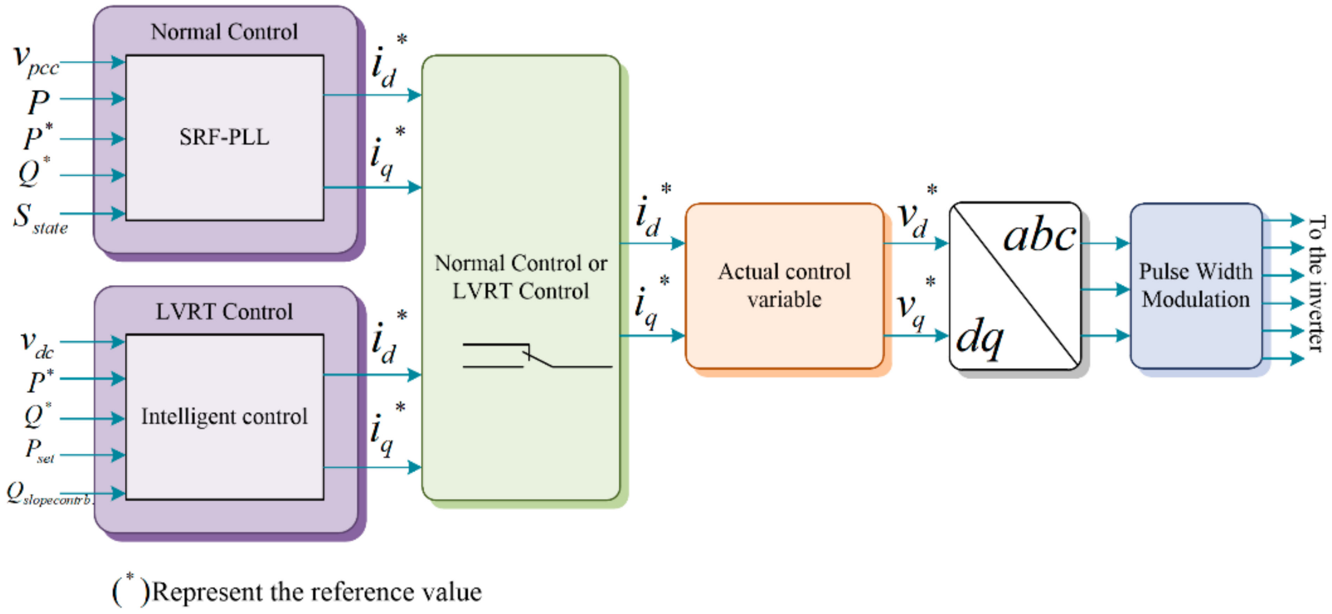


Figure 10. AI approach for low voltage ride through in grid-connected PV systems.

Table 7. Comparison of low voltage ride through techniques.

Algorithm	Computation Burden	Reactive Current Injection	Advantage	Disadvantage
Dynamic voltage restorer [121]	High	Sufficient	• Reactive current injection • Weak grid voltage stability	• Voltage-dependent reactive control • Instability
Static synchronous compensator [118]	High	Good	• Efficient control of reactive power • Drop in voltage negative sequence	• Low capacity in supplying active power • Coupling transformers introduce many switches
PSO [120]	Low	Sufficient	Fast response Hight efficiency	Presence of oscillation and overshooting
FLC [119]	Low	Sufficient	Simple and flexible No overlapping	Presence of oscillation and overshooting

MPPT Control: At the DC/DC conversion stage of the inverter, it is necessary to attain maximum power from the PV array. In the perturb and observation method, a PV curve is monitored, and a hill climbing algorithm is implemented to find the peak. However, the step size increment does not make the system very accurate. With AI, the optimization and regulation with variation in mission profile is performed faster.

The MPPT is performed, using a fuzzy logic controller to track the maximum operating point considering the mission profile [122], whereas in [123], a genetic algorithm is used to optimize the neural network controller for tracking the maximum point of operation. A brief analysis of different algorithms is presented in Table 8. The comparison distinguishes between the output response, feasibility of implementation, power loss and transients in the output power, and learning capabilities of different algorithms used for MPPT. The output response indicates the time taken by the algorithm to perform the MPP operation, and the feasibility identifies its ease of implementation in any given system. Further, the power consumption discusses the output power loss incurred with the use of a specific algorithm for MPP operation, and the transients indicates the harmonics and disturbances in the tracked power output. From the analysis, it is identified that the P&O and incremental conductance MPPT techniques are simple to implement but have slow response rates and high power loss, and the transients in the output can be commonly observed, whereas the other algorithms have a complex implementation process but are efficient in other processes.

Table 8. Analysis of maximum power point tracking techniques in the literature.

Algorithm	Output Response	Feasibility	Power Consumption	Learning	Transients
P&O, Incremental Conductance [124]	Slow	Simple	Loss	No	Common
Particle Swarm Optimization [125]	Slow	Complex	Efficient	No	Common
Hopfield Neural Network	Fast	Complex	Efficient	Yes	No
Neural Network	Fast	Complex	Efficient	Yes	No
Ant Colony Optimization	Fast	Simple	Efficient	Yes	Common
Genetic Algorithm [123]	Fast	Complex	Efficient	Yes	Common
Fuzzy Logic Control [122]	Fast	Complex	Efficient	No	No
Genetic Algorithm-Neural Network	Fast	Very Complex	Efficient	Yes	No
Adaptive Neuro Fuzzy Inference System	Fast	Very Complex	Efficient	Yes	No
Reinforcement Learning	Fast	Very Complex	Efficient	Yes	No
Adaptive Neuro Fuzzy Inference System-Genetic Algorithm	Fast	Very Complex	Efficient	Yes	No

Seamless Transition: Once the fault is identified and the LVRT is unable to recover the system, then the grid is disconnected from the DGs. It is necessary to control the disconnection and reconnection action of the DGs from the grid so that the transient voltage is minimized, and frequency runaway does not take place. Further, to achieve seamless transition, in [126], a static control switch is used to change the controller when the transition takes place, whereas in [127], a single control structure is used for controlling both the modes of operation by utilizing the outer loop as a reference generator for the current loop in the case of a standalone mode of operation. In these techniques, there is a substantial response delay along with the presence of transients in the case of a static switch base control.

With the implementation of AI in transition techniques, the switching between the modes has become transition free. In [128,129], a fuzzy logic (FL)-based transition is proposed, which tends to generate a reference trajectory and enable smooth transition. Further, in [130], a model predictive control based transition controller is proposed, which has stable output and is much easier to implement with a small modification to the pre-existing control algorithm.

5.2. Stand Alone Inverter Control

After the grid is disconnected from the DGs, the DG needs to operate and satisfy the local load. In this mode of operation, the DGs must be able to address the balance between load and supply, while regulating the voltage and frequency simultaneously. Conventionally, the stand alone mode of inverter was operated using space vector pulse width modulation (PWM) [131], carrier based PWM [132] and repetitive control techniques [133]. Even dual loop control strategy was implemented with a hybrid frame of reference to attain better accuracy. However, all the conventional controls failed to optimize the operation and reduce the THD for the output post transition. Hence, to achieve faster recovery and reliable control, AI-based standalone techniques have been proposed. In [134], a fuzzy based inverter control strategy is proposed to overcome the drawback. However, the rule-based approach reduces the adaptive nature of the controller. Hence, to overcome the issue, fuzzy is implemented with a neural network and multiple heuristic algorithms [135,136]. The operation is represented in Figure 9 when operating in switch position 1.

6. Application of AI for Monitoring

6.1. Condition Monitoring of Grid Connected PV System

Grid-connected PV systems typically operate in rigorous and complex working conditions. They may suffer from various fault events, both at the component level or system level. The safety and reliability of grid-connected PV systems are of the utmost importance to ensure efficient operation of the system. Maintenance activities, including preventive maintenance, incorporating condition monitoring, fault diagnosis, remaining useful life (RUL) prediction, etc., are employed to improve reliability. Proper health monitoring at the component level and at the system level is required to ensure intended operation of the grid-connected PV system. It consists of firstly establishing the knowledge regarding the system behavior and dynamics based on the available information. Then, based on anomaly detection and parameter identification for the offline model dynamics, the knowledge gathered can be applied to real-time health monitoring or online monitoring (OLM) [137]. Detailed identification of various faults in the grid-connected PV systems are discussed in Figure 11 and Table 9.

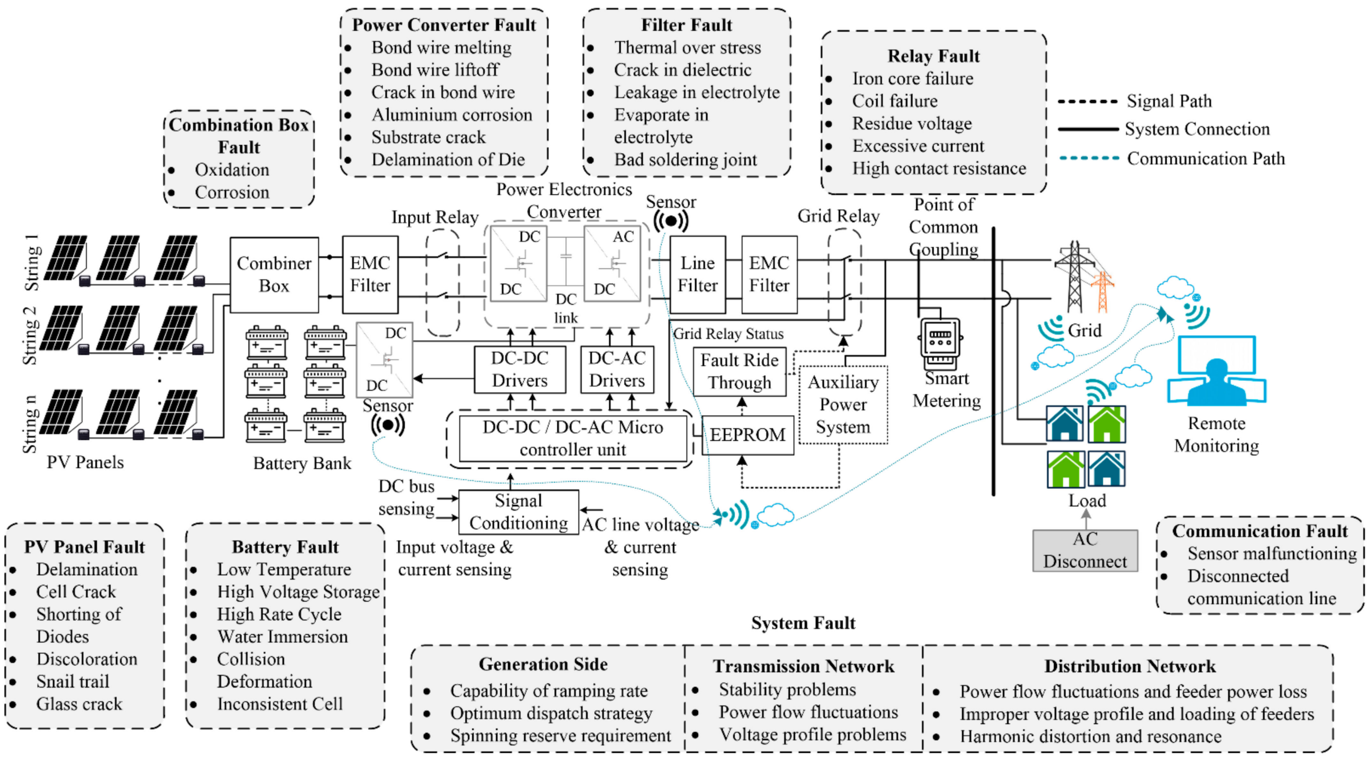


Figure 11. Fault layout for grid-connected PV system.

Table 9. Faults in grid-connected PV system.

Fault Location	Fault	Cause	Impact	Detection Technique
PV Panel Fault	Delamination	Over exposed to direct sunlight	All the faults in the panel will result in reduction of solar panel output and increase the burden on the DC–DC converter	• Visual inspection • Thermography based detection • Image processing-based fault identification • Signal processing-based detection
	Cell Crack	Physical damage		
	Shorting of Diode	Overheating		
	Discoloration	Over exposed to direct sunlight		
	Snail Trial	Moisture in atmosphere		
	Glass Crack	Physical Damage		
Combination Box Fault	Oxidation	Environmental impact	Reduce the power flow	Visual inspection and signal-based monitoring
	Corrosion	Environmental impact		
Power Converter Fault	Bond wire melting	Overheating of thermal joints	Cause stress on the inverter operation, wear out in the inverter components, and reduces the operating lifetime of inverter	• Temperature sensitive electrical parameters • Operating characteristics-based monitoring, using signal, and learning approaches • Thermal model, and physics-based modeling approaches
	Bond wire lift-off	Overheating		
	Crack in bond wire	Stress on the bond wire		
	Aluminum corrosion	Environmental impact		
	Substrate crack	Thermal Stress on substrate		
	Delamination of Die	Overheating of Power electronic switch		
Filter Fault	Thermal over stress	Overheating	• Increase in the harmonics at the AC end of the inverter • Poor power quality. • May cause a false trip signal	• Monitor output signals and use learning-based approaches. • Implementation of thermal image-based learning approaches
	Crack in dielectric	Sudden change in temperature		
	Leakage in electrolyte	Expose to thermal stress during storage		
	Evaporate in electrolyte	Expose to thermal stress during storage		
Relay Fault	Iron core failure	Leakage current	• Humming due to the failure of electromagnetic • Abnormal noise during operation and no contact continuity • Complete cut-off of applied voltage	• Signal processing and machine learning approaches through the measurement of contact resistance, coil resistance, and operating voltages
	Coil failure	Short-circuit of counter electromotive voltage absorbing diode		
	Residue voltage	Semiconductor control circuit with residual voltage		
	Excessive current	Allowable inrush current exceeded		
	High contact resistance	Contact carbonization		
Battery Fault	Ageing	Stress factors (Temperature, depth of discharge, C-rate)	• Loss of active anode/cathode material • Capacity fade • Power fade • Thermal run-away • Longer charging time	• Data driven models for state of health estimation • Thermal inspection • Incremental capacity analysis • Remaining useful life prediction measures characteristics and capacity estimation
	Loss of cooling	Lithium plating/dendrite formulation		
	Cell failure	Electrolyte decomposition,		
	Battery management system failure	Failure of converter control circuit		

6.1.1. AI Monitoring for PV Array Faults

In order to enhance the power conversion efficiency, status monitoring of PV modules is imperative. PV panels may be affected by faults, such as delamination, discoloration, cell crack, short circuit due to bypass diode, snail trail, glass crack, etc. In [138], the supervised learning-based random forest (RF) methods are used for fault diagnosis in PV panels. The array voltage and string current are observed in the simulation for different solar irradiance and temperature conditions, and it is pre-processed to make it suitable for training. The prediction accuracy is quantified by the decision tree's majority voting, and it is found that, along with a very high accuracy, it is capable of dealing with overfitting issues. A multi-layer perceptron neural network (MLPNN)-based condition monitoring and fault diagnostic tool for PV faults is developed [20]. The signal processing technique based on discrete wavelet transform (DWT) is applied to extract the features of the IV characteristics. The extracted features are provided to MLPNN for training, and it is able to achieve 100% accuracy for the given fault data. Further, a fault diagnosis approach for PV panels is developed in [139] based on the probabilistic neural network (PNN), and radial basis networks. This fault diagnostic tool is observed to be less affected by the outliers and provides good generalization accuracy. In [140], a novel approach focused on kernel-based extreme learning machines for PV array health monitoring is proposed. The developed approach arbitrarily constitutes the input biases and weights of the corresponding hidden layer, and consequently determines the output weights through the Moore–Penrose generalized technique. Further, a swarm intelligence-based artificial bee colony (ABC) method is utilized for fault diagnosis in PV panels in [141]. This technique is a semi-supervised extreme learning-based method that utilizes mostly unlabeled fault data acquired after various fault simulations. In [142], a deep learning-based fault classification approach for PV arrays utilizing the convolutional neural network (CNN) is presented. This supervised learning-based classification technique consists of collecting IV characteristic data, converting the acquired data into two-dimensional time-frequency representations or scalograms, and providing them as inputs to the finely tuned AlexNet for the classification task.

6.1.2. AI Monitoring for Power Electronic Converter Faults

In recent years, AI-based data-driven intelligent fault classification techniques have proved to be highly accurate and effective for converter fault diagnosis in grid-connected PV systems. Artificial neural network (ANN)-based power switch fault identification and classification for multilevel H-bridge inverters is implemented [143]. Inverter output voltage information is collected, and DWT is applied to obtain features, such as signal power, energy, etc. After that, ANN, having one hidden layer along with input and output layers, is implemented for training. A radial basis function network (RBFN)-based fault classifier is developed for grid-connected PV system faults [7]. Inverter output data at different time instants are acquired and pre-processed, using wavelet transform for extracting relevant features. These features are utilized as input to the RBFN, which further makes use of the Gaussian kernel. Supervised learning based PNN is proposed for fault diagnosis in diode clamped multilevel inverters [144]. DWT is adopted for feature mining through the Daubechies order 4 (db4) mother wavelet. Then, multi-layered feedforward PNN is utilized without requiring any iteration for weight adjustment. An intelligent condition monitoring method based on MLPNN for grid-connected PV systems is proposed [145]. Inverter voltage and current information for various switch faults is gathered, and DWT is applied for calculating different features. Further, principal component analysis (PCA) is applied for dimensionality reduction so that only relevant features are obtained. A fault prognostic technique for a grid-connected PV inverter based on fast clustering and Gaussian mixture model is implemented [146]. The technique is based on acquiring real-time system information, including inverter output power, current, voltage, IGBT temperature, etc. Further, the fast-clustering approach is utilized for containing similar data clusters together, and the Gaussian mixture model is applied for fault prognosis. A modified CNN- GAP (global average pooling) method is proposed for inverter switch fault diagnosis [147]. The inverter 1D time-series raw data are directly provided as input to the CNN-GAP model. In the input layer, 2D feature maps are constituted through several convolution and pooling layers. The GAP layer is responsible for compressing the output image and finally, the diagnostic result is obtained in the output softmax layer.

6.1.3. AI Monitoring for Faults in Filter

In grid-connected PV systems, filters are usually required for harmonic attenuation of the inverter output. An L filter may be sufficient, but it would require a bulky inductor and may produce a high voltage drop. Therefore, the LCL filter is preferred, due to the advantage of utilizing small-sized components [148]. It is found in research that capacitors are one of the most vulnerable components, and they are greatly influenced by their operational conditions, such as temperature, current, etc. The status monitoring for electrolytic capacitors can be achieved through analyzing equivalent series resistance (ESR), which manifests itself as a measure of the electrolytic capacitor health. AI-based monitoring techniques are utilized for capacitors health estimation. An ANN-based regression technique is incorporated for RUL detection of electrolytic capacitors [149]. Decision regarding health prognostics is determined through a fuzzy-based system. Another electrolytic capacitor health monitoring technique utilizing the neo-fuzzy neuron (NFN) model approach is proposed [150]. It is based on combining fuzzy and ANN-based techniques for successful condition monitoring of capacitors. A comparison between the recursive least square (RLS) method and support vector regression (SVR) method for capacitor health estimation is made [151]. The SVR method is based on firstly identifying the model through offline training. The health status monitoring for electrolytic capacitors, using supervised learning-based ANN, is investigated thoroughly [152]. However, there is more potential that can be explored, utilizing AI-based techniques in the field of electrolytic capacitors health monitoring.

6.1.4. AI Monitoring for Battery Faults and Degradation

In grid-connected PV systems, batteries play a significant role, and it is required that they deliver the desired performance. Various diagnostics and prognostics for battery health monitoring have been explored, such as state of charge (SOC), state of function (SOF), state of health (SOH), etc. AI-based diagnostic techniques have been surveyed for battery faults. A Bayesian regression for RUL estimation in batteries is developed in [153]. An electrochemical process-based model is merged with a statistical model to assess the RUL for batteries. In addition, the relevance vector machine (RVM) approach is explored for analyzing battery health. A battery health monitoring system based on an adaptive Gaussian mixture model (AGMM) is proposed [153]. It is an online battery degradation diagnostic tool that utilizes component recursive parameters updates with a learning rate schedule. The Gaussian components keep updating online, and to further improve the efficiency, the highest probability component selection is made. A Takagi–Sugeno fuzzy method for battery monitoring is implemented [154]. It is able to deal with battery nonlinear dynamics involving the complicated electrochemical equations in a satisfactory manner. Temporal convolutional network (TCN)-based SOH prediction and RUL estimation for battery monitoring is proposed [155]. It is a recent, data-driven deep learning-based approach that delivers high-precision health estimation of the given component. The battery fault diagnosis based on combined long-short term memory (LSTM) and the recurrent neural network (RNN) is presented [156]. Real-world battery related data with a large volume are attained to realize the robustness of the combined approach. It also combines the advantages of a modified adaptive boosting (MAB) coupling module and approach optimization method (AOM) for deriving the hyperparameters.

The generalized schematic for implementing the above discussed applications of AI for fault detection and condition monitoring in grid-connected PV systems is shown in Figure 12.

6.2. Application of AI for Reliability

The reliability is defined as the ability of a particular device to perform a particular function under certain operating conditions [157]. The probability of survival and failure are the parameters on which the reliability is measured [158]. The aim of this reliability analysis is to estimate the lifetime of operation and, in the case of a failure, recalibrate the lifetime and provide the remaining useful life. To perform the reliability analysis for design modification, the power electronic device is operated in a controlled environment, and the power loss of the inverter is used for thermal modeling of the device. Once the thermal profile is obtained, then Rainflow counting is used for cycle counting and many of the lifetime calculation models, i.e., coffin mason [159], CIPS2008 [160], and LESIT [161], can be used for the lifetime calculation. Conventionally, for the lifetime estimation, Monte Carlo or Markov analyses are used as represented in Figure 13. However, the analytical analysis methods may present many gaps in the analysis, such as rapid convergence. Hence, to overcome such issues, the AI-based lifetime estimation can incorporate the sudden fault in the analysis or sudden change in the stress of the components, due to the ride through operation [162] and further lead to enhancing the lifetime prediction capability. In [163], the lifetime estimation is performed, using ANN to analyze the different operating conditions, whereas in [164], a function-based relationship is established between reliability and design parameter. The analysis is carried out by training ANN and implementing it on surrogate models. Further, in Table 10, a brief analysis of conventional lifetime estimation techniques is presented.

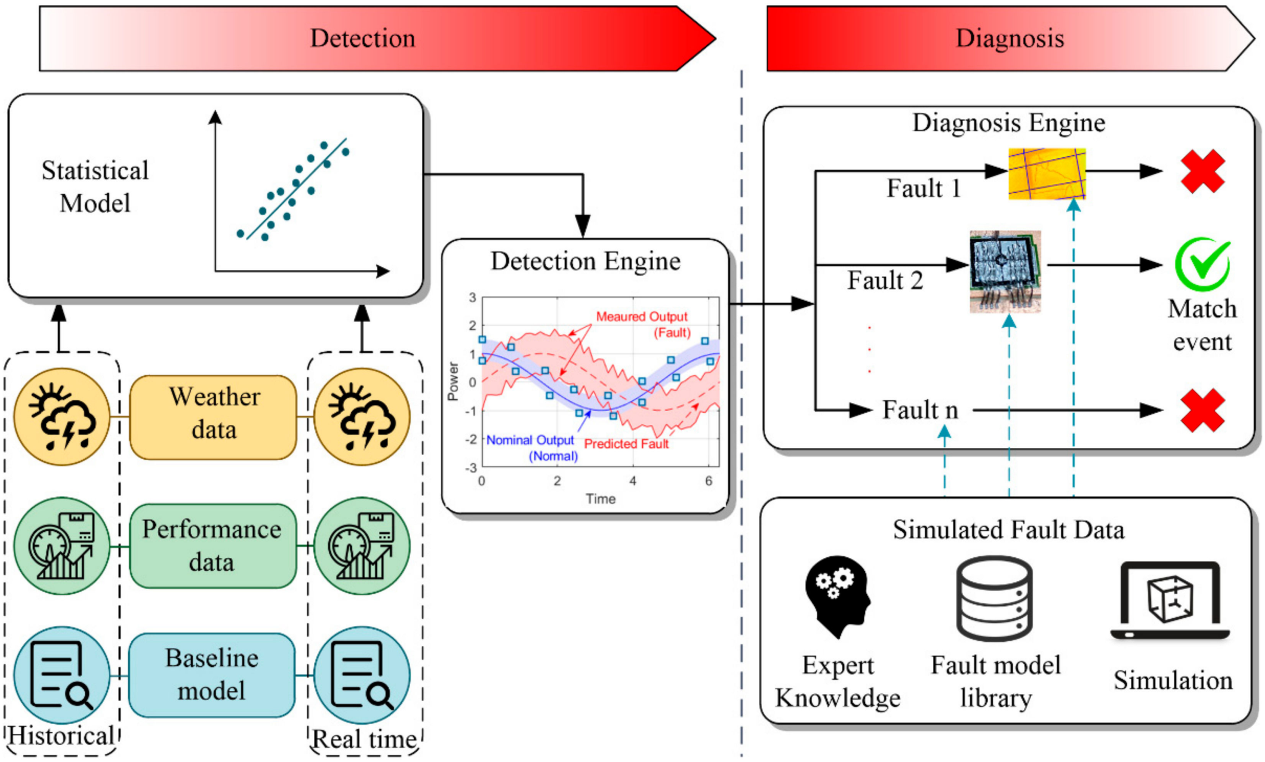


Figure 12. Schematic for implementing AI techniques for fault detection in grid-connected PV systems.

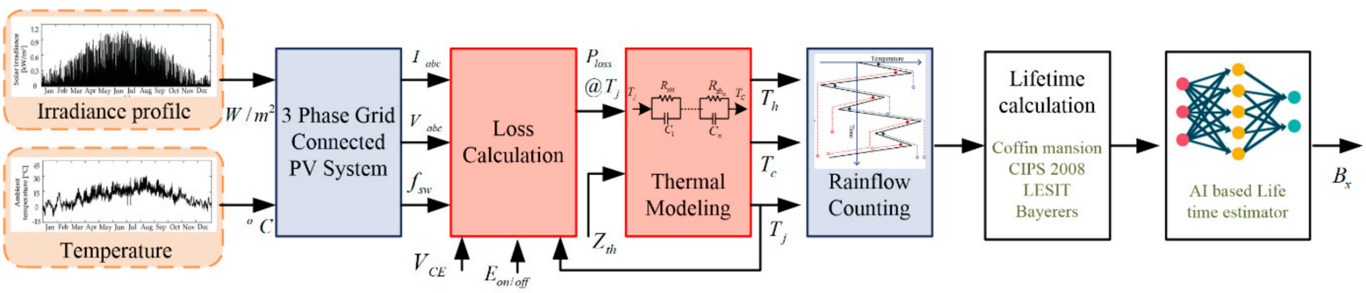


Figure 13. Reliability analysis of a power electronics device.

Table 10. Comparison of convention algorithm for lifetime estimation.

Conventional Algorithms	Application to Power Electronics	Advantages	Drawback of Conventional Algorithms
Reliability Block Diagram	Analysis of component fault by representing them as a block	Simple for implementation	External cases, such as human interference and priority-based events, are not considered
Fault Tree Analysis [165]	Identification of probability of each fault.	External factors accounted for and also assisted in designing	Interdependence is not analyzed adequately
Monte Carlo [166]	Generates random events in a computer model to count the instance of occurring for a specific condition.	High precision, less work in calculation and rapid convergence	Canonical problems are identified while estimating the functional exception of a lifetime model for repairable and non-repairable components
Markov Analysis [167]	Identification of transition rate based on failure and repair rate	Easy to implement for a system where repair is possible	The modeling is large due to state base modeling with a constant repair and failure rate

7. Future Trends and Outlook

7.1. Digital Twin

The application of AI techniques with the different functions of grid-connected PV systems has identified that the process of digitization has a universal acceptance. Further, this led to the development of various new approaches, which increased the integration of modern energy systems with the grid. In a major shift of research trends, the development of digital twin (DT) has effortlessly increased the connectivity between the physical environment, their data, and virtual machines. This technique created an approach for synchronization, monitoring, and other services of the energy systems in real time through a computerized and virtual world modeling [168,169]. This approach is supported with a visualization software [170], and uses intelligent analytics along with the real-time data [169,171] to gather the information about the system operating state [172]. Further, from the point of a grid-connected PV system, the DT framework can be derived with different modeling methodologies that integrate energy forecasting, demand side management, control, monitoring, and data visualization. The research in [169] focuses on the application of DTs to develop control algorithms for a power system. In [173], the analytical evaluation of residual error is realized with a DT approach to achieve fault diagnosis of a real-time PV system. This approach is developed by leveraging the sensing properties, and actuation capabilities of the voltage source inverter to enhance the system performance. Further, the work in [174] discusses the application of DT for energy benchmarking to achieve optimal energy decision making with energy retrofitting and real-time energy management systems. Similarly, in [175,176], the DT-based multilayered approach is adopted for developing an energy model to achieve efficient energy consumption in a power system network. From all the literature discussed above, the major aspects of DTs in the modeling, control, and monitoring of the grid-connected PV system components is identified with reference to AI techniques as shown in Figure 14.

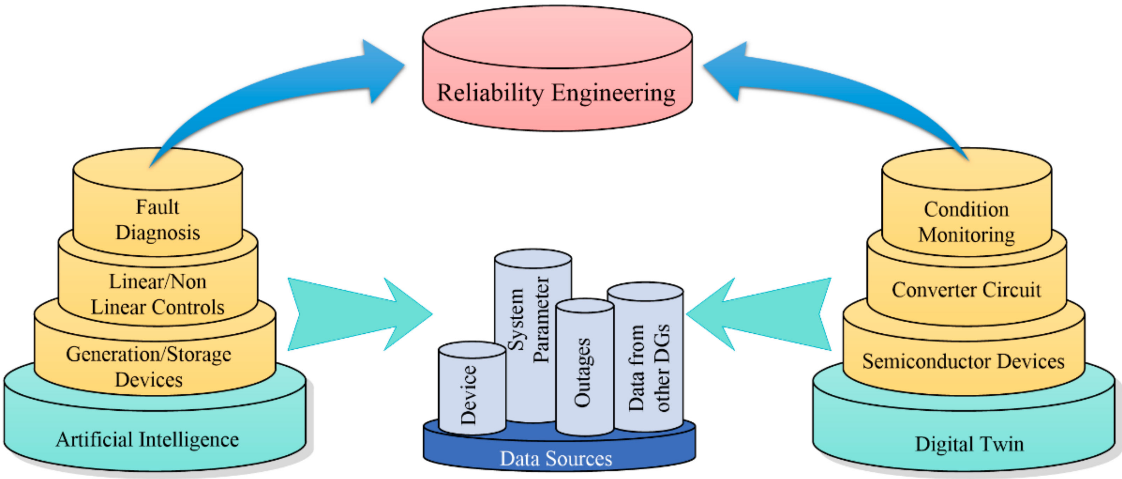


Figure 14. Application of digital twin for different functions with PV system.

To achieve a significant improvement in the operation of the grid-connected PV systems by using the DT framework, it is important to identify the key parameters and technologies [171,177] supporting it. A DT framework of a physical system with the PV system is shown in Figure 15. In general, the output obtained from the insight stage, and data-gathering process at the PV system are provided as an input to the DT framework. Further, the key technologies associated with the DT framework for smooth running of the system include energy forecasting, internet of things (IoT) platform, energy internet [178,179], and advanced data analytics.

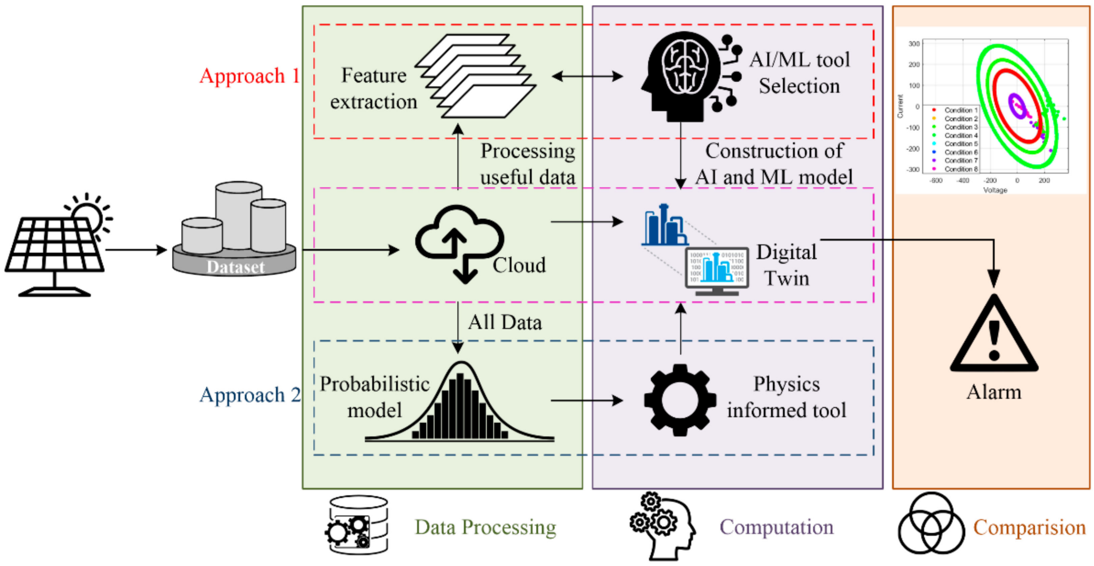


Figure 15. Digital twin framework of a physical system.

To pave a way for a new era of data-driven product design, manufacturing, and service with the DT framework, IoT technology is coupled with the services of smart devices, and supported by the data mining ability of AI [180,181]. The IoT platforms also combines the data generated from the physical system with the historic dataset obtained from previous operations of the grid-connected PV systems for the development of the DT framework [182]. Similarly, the advancements in IoT technologies, such as smart and industrial internet of things [183,184], and energy internet, also provide intelligent sensing and data acquisition capabilities, along with a secure transition network. This improves the data handling capabilities with AI for achieving an efficient and consumer-oriented

DT framework. Further, the data in their raw form have high stochasticity, making them difficult to use with most of the functions of the PV system. Therefore, it is important to adopt data preprocessing with the DT framework for extracting important features of the datasets [172,185]. These features must consider the factors influencing the dynamics of the PV system operation and should not hamper the originality of the measured information. The details of the literature corresponding to DT and its application to power system operation are discussed in Table 11.

Table 11. Related work grid-connected system with digital twins.

Methodology	Function	Advantages	Drawbacks
Dynamic digital mirror [169]	Power management	Operates faster than the supervisory control and data acquisition	Difficult to provide a comprehensive model of the power system
Ontological modeling language [175]	Hybrid operation of distributed generation units	Acts a medium for DT application in the energy sector	Data synchronization cannot be automated
Regression [174]	Power flow management	Energy benchmarking by analyzing the temporal dimensions	Less efficiency
Deep neural network [186]	Application with smart grid functions	Improved performance with volatile electricity load forecasting to achieve balance and stability	Stochasticity and uncertainty in the data
Predictive analytics model [187]	Virtual power plants	Offers efficient coefficient estimation	Regulatory and institutional policies act as barrier to deployment

7.2. Cybersecurity

Cybersecurity has been a growing concern with the proliferation of information and communication technologies (ICT) and digitalization incentives across all sectors. In a power electronics dominated grid, the grid-tied converters are remotely controlled by a plant controller and a SCADA via power line communication (PLC), optical fiber or wireless communications, such as Zigbee, cellular (3G), and LTE (4G) [188]. As outlined in the previous subsection, data centric measures have facilitated various operations, such as predictive maintenance, fault diagnostics, condition monitoring, and adaptive control via digital twins. However, they augment vulnerabilities to cyber-attacks at the same time. These attacks include, but are not limited to, data integrity attack (DIA) [189] and denial of service (DoS) [190].

The development of new standards for distributed energy resource (DER) cybersecurity will have a big impact on PV systems. California Rule 21 mandates that new DER must be ready to communicate with the host utility, using the IEEE 2030.5-2018 standard, which includes the requirement of transport layer security (TLS) and strong encryption. Currently, the new IEEE 1547.3 standard (Guide and Recommendations for Cybersecurity for DER) is under development to fill the cybersecurity gap in IEEE 1547-2018, which includes necessary and optional recommendations based on IEC 62351 and other standards and is expected to be effective in 2022. To provide security against these cyber intrusions, many solutions were provided in the past for power electronics systems. To summarize them, a perspective is provided in Figure 16, where data-driven [191–193] and physics-informed solutions [194–198] are compared on the basis of accuracy, selectivity, and speed.

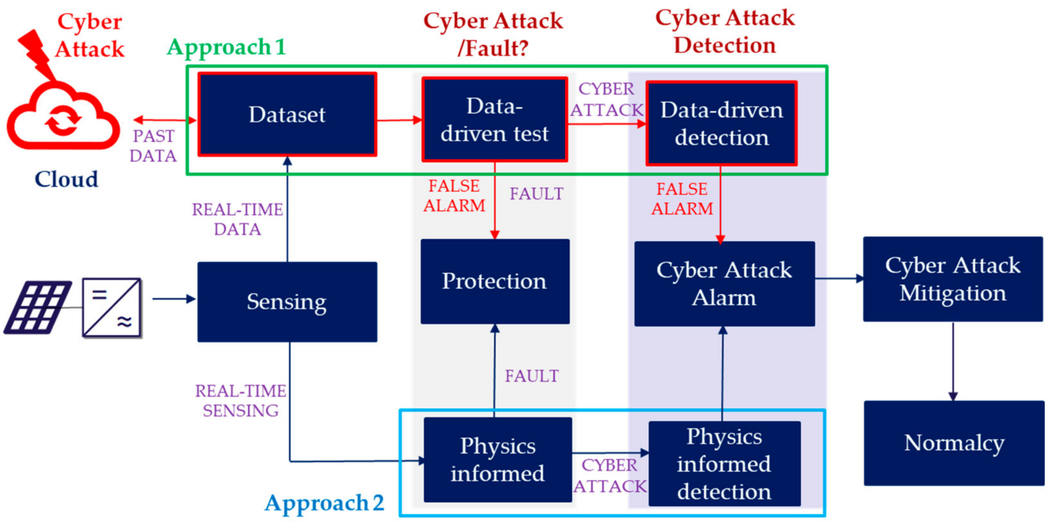


Figure 16. A perspective of cybersecurity approaches for PV systems: comparative evaluation between AI and physics-informed approaches.

As shown in Figure 16, in Approach 1, although the historic data of grid-tied PV systems may provide significant knowledge about their intrinsic characteristics to design faster and accurate cybersecurity technologies, they can be prone to failure simply at the data storage platform (cloud storage in Figure 16), where the adversary may malign historic data strategically. Considering real-time sensing from the physical network as the biggest vulnerability, the possibility of having cyber-attack elements in historic data is often ignored. Consequently, it may result in many false alarms for anomaly detection. In this way, the accuracy and selectivity of data-driven cybersecurity technology can be easily compromised. However, in approach 2, the possibility to affect the decision-making process of the physics-guided tools can only be manipulated from the real-time sensing stage, which is already accounted for. As a result, the degree of confidence of the decision-making process for approach 2 exceeds that of approach 1. This mandates future research in this direction to accommodate the black-box nature of AI tools for the efficient design of data-driven cybersecurity technologies.

8. Conclusions

The conclusions that can be drawn from the review conducted in this paper are that there exist numerous published research articles using different AI techniques for different purposes at the system level in the value chain of solar PV. ANNs and its sub-architectures are the most widely used AI techniques, but this depends on the use case. In the case of optimization, evolutionary algorithms, such as PSO and GA, are widely used, while in the case of time-series data, as in irradiance prediction or power forecasting, ANNs are used with great success. Further, the wide use of inference models, data-driven algorithms, and learning approaches for control and maintenance are identified to be more specific to a condition, problem, or dataset and lack universal applicability for the same aspects. However, even if the majority of the papers report great success, it must be noted that the success is based on tweaking a specific model while maintaining the other models with default parameters. Additionally, several of the proposed models, based on the input data, are probably not generalized. In the near future, advances in the currently available AI techniques are very likely to be seen. Currently, there seems to be a data discrepancy in the industry but with the emergence of internet of things solutions, deployment of a large number of sensors, video streams provided by drones in maintenance purpose as well as natural language processing techniques, the issue of a lack of data is likely to disappear.

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Acronyms

AI	Artificial Intelligence	ABC	Artificial Bee Colony
PV	Photovoltaic	CNN	Convolutional Neural Network
ESS	Energy Storage System	RBFN	Radial Basis Function Network
OPF	Optimal Power Flow	db4	Daubechies Order 4
NTO	Network Topology Optimization	PCA	Principal Component Analysis
DTR	Dynamic Thermal Rating	GAP	Global Average Pooling
RMSE	Root Mean Square Error	ESR	Equivalent Series Resistance
I-V	Current Voltage	NFN	Neo-Fuzzy Neuron
THD	Total Harmonic Distortion	RUL	Remaining Useful Life
PID	Proportional, Integral, Derivative	RLS	Recursive Least Square
PI	Proportional-Integral	SVR	Support Vector Regression
PR	Proportional-Resonant	SOC	State Of Charge
LSTM	Long Short-Term Memory	SOF	State Of Function
DL	Deep Learning	SOH	State Of Health
k-NN	K-Nearest Neighbor	TCN	Temporal Convolutional Network
ANN	Artificial Neural Network	RVM	Relevance Vector Machine
SVM	Support Vector Machine	LSTM	Long Short-Term Memory
ANFIS	Adaptive Neuro Fuzzy Inference System	AGMM	Adaptive Gaussian Mixture Model
FPSO	Flexible particle swarm optimization algorithm	TLS	Transport Layer Security
MPP	Maximum Power Point	DoS	Denial Of Service
AIS	Artificial Immune System	DIA	Data Integrity Attack
LVRT	Low Voltage Ride Through	PLC	Power Line Communication
FACT	Flexible Alternating Current Transmission System	ICT	Information And Communication Technologies
FLC	Fuzzy Logic Control	IoT	Internet of Things
PSO	Particle Swarm Optimization	DT	Digital Twin
DGs	Distributed Generation	AOM	Approach Optimization Method
PWM	Pulse Width Modulation	RNN	Recurrent Neural Network
OLM	On-Line Monitoring	MAB	Modified Adaptive Boosting
RF	Random Forest	SCADA	Supervisory Control and Data Acquisition
MLPNN	Multi-Layer Perceptron Neural Network	DER	Distributed Energy Resource
DWT	Discrete Wavelet Transform	PSO	Particle Swarm Optimization
PNN	Probabilistic Neural Network	GA	Genetic Algorithm

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