A review of application of artificial intelligence for space vector pulse width modulated inverter-based grid interfaced photovoltaic system

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Article Info

Article history:

Received Jan 23, 2023
Revised Mar 25, 2023
Accepted Apr 6, 2023

Keywords:

Artificial intelligence
Battery monitoring
Photovoltaic system
Power quality
Space vector pulse width Modulation

ABSTRACT

Artificial intelligence (AI) is being proposed for a range of subfields that deal with photovoltaic (PV) systems as a result of improvements in computer power, tool accessibility, and data generation. The methods employed at present in the PV industry for a variety of tasks, including the outcomes of design, forecasting, control, and maintenance, have been found to be relatively inaccurate. Additionally, the use of AI to carry out these tasks has improved in terms of accuracy and precision, which has made the topic itself highly interesting. In light of this, the goal of this article is to examine the effect AI approaches have on the solar value chain. The article involves creating a map of all currently accessible AI technologies, identifying potential future uses for AI, and weighing the advantages and disadvantages of these technologies' relative to more conventional approaches. This article lays special emphasis on discussing AI techniques for improving the power quality in grid systems involving space vector pulse width modulated inverters interfacing the photovoltaic to the grid along with power converter defect monitoring, filter flaw detection, and battery monitoring.

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ABBREVIATIONS

AI	: Artificial intelligence	MLPNN	: Multi-layer perceptron neural network
PV	: Photovoltaic	PCA	: Principal component analysis
DG	: Distributed generation	GMM	: Gaussian mixture model
PQ	: Power quality	CNN	: Convolutional neural network
BESS	: Battery energy storage system	GAP	: Global average pooling
GTI	: Grid tie inverter	ESR	: Equivalent series resistance
MPPT	: Maximum power point tracker	RUL	: Remaining useful life
PWM	: Pulse width modulator	NFN	: Neo-fuzzy neuron
SVPWM	: Space vector pulse width modulation	SUR	: Support vector regression
VSI	: Voltage source inverter	RLS	: Recursive least squares
PI	: Proportional-integral	SOC	: State of Charge
ANN	: Artificial neural network	SOF	: State of Function
GA	: Genetic algorithm	SOH	: State of Health

RF	: Random forest	RVM	: Relevance vector machine
ANFIS	: Adaptive neural fuzzy inference system	AGMM	: Adaptive gaussian mixture model
RF	: Reinforcement learning	TCN	: Temporal convolutional network
DL	: Deep learning	LSTM	: Long short-term memory
DRL	: Deep reinforcement learning	RNN	: Recurrent neural network
DWT	: Discrete wavelet transform	MAB	: Modified adaptive boosting
RBFN	: Radial basis function networks	AOM	: Approaching optimization method
PNN	: Probabilistic neural network		

1. INTRODUCTION

The availability of electricity is very much essential for improving the quality of life. People who require access to power are becoming more numerous. However, the conventional fuels that are used to produce electricity are depleting at a startling rate. In addition, one of the biggest causes for worry is environmental contamination. In order to keep up with rising electricity demand, the liberalisation of the electricity market, and efforts to reduce the amount of greenhouse gas emissions produced by conventional electric power generation facilities, distribution generation (DG) systems are rapidly gaining popularity as a new source of electricity generation. As a result, renewable energy-based technologies are becoming more and more crucial. Solar thermal, solar photovoltaic, and wind power generation are a few examples of such renewable energy systems. The PV is gaining popularity as the main unconventional energy source for electricity production and consumption because of its availability in abundance and non-exhaustible nature [1].

The most common topology used in grid-interfaced PV system is one based on inverters. Inverters, which serve as a connection between utility grid and PV panel and provides for operational stability of PV networks are a key component of any PV system. In the upcoming years, research and development will concentrate on improving the operation of PV grid interfacing inverters [2]–[4]. An inverter in a PV system converts DC voltage from PV modules to AC. In a PV system interfaced to the grid, if the local demands have been satisfied, the extra energy is sent to the grid. However, extra energy is taken from the grid if the local load demand is greater than the PV supply. In this study, PV system is being examined with the goal of providing the electrical power produced by PV panels to the grid. In order to get PV voltage above the grid’s peak voltage, a DC-DC converter is used in between the PV and the inverter [5]. A PV system’s full potential is realised by implementing maximum power point tracking algorithm in DC-DC converter which makes it possible to operate in a variety of air conditions that affects the sun’s intensity and warmth. The popularity of the PV systems that are connected to the grid is rising because they do not require batteries for energy storage and hence may or may not be present in grid-connected PV systems.

One of the biggest difficulties for the electrical industry is the rising usage of delicate electronic circuits in businesses and homes, together with privatisation and competition in the electric energy networks. This makes increasing power quality (PQ) one of the most urgent problems. Power converters are used to connect the PV source to the grid. Because of how they operate, power converters always introduce harmonics into the grid. Harmonics cause the source voltage to become distorted, and unwanted current flowing through the source causes additional loss. Additionally, it could result in malfunctioning relays, mains, and other control equipment. Therefore, it is crucial to reduce the impact of the harmonics that are generated from the presence of PV inverter [6], [7].

Further sections of this review are organized as follows: section 2 discusses the types of grid-interfaced PV systems and the problems associated with them. In section 3, the space vector pulse width modulation technique has been reviewed. The AI techniques for SVPWM are discussed in section 4; the AI for power converter defect monitoring discussed in section 5. The AI techniques for filter flaw detection are discussed in section 6. The trends of AI for battery monitoring are provided in section 7. The findings of the review are concluded in section 8.

2. GRID INTERFACED PHOTOVOLTAIC SYSTEM

The power electronics built-in voltage converter controls the output power, which is all that the inverter actually is. However, it is possible for harmonics to form in the output voltage during the conversion from DC to AC. These harmonics would then be introduced into the system, leading to a number of problems with the grid's power quality. One of two battery systems is frequently used in conjunction with solar PV systems: Depending on the intended use and type of application, either a battery-powered system or one with enough capacity to handle PV generation that occurs intermittently and deliver a stable grid voltage, or a battery energy storage system (BESS) that stores PV generation surplus and delivers it during peak hours to increase grid power supply reliability, may be used. Two power quality-related challenges must be overcome by solar PV systems: one is at the source end of the system (such as PQ problems caused by the nonlinear loads of the PV system), and the other is dealing with PQ problems caused by the sags and switching transients of the network. The nonlinear loads on the PV system are what cause these two difficulties. It is crucial to solve the issue since, generally speaking, these power quality issues lead to a reduction in the efficiency and durability of various machines, capacitors, voltage regulators, and distribution transformers. Renewable energy sources of any kind must be able to meet the standards set for standard power quality in order to be integrated into the grid. voltage and power factor controllers [8], [9].

There has been a large degree of conventional power generation dis placement as a result of the current spike in interest in solar energy generation. Additionally, loads with a sizable reactive component may actually result in a drop in the system's power factor. This work emphasises the importance of power factor, power factor correction, reactive power demand, and harmonics which become crucial not only for utilities but also for private consumers as PV plant penetration keeps increasing. Capacitive loads in the grid lead the pack in terms of power factor and voltage, whereas inductive loads are just behind them [4], [10]. This has been proven to be a true reality. The system's low power factor puts a heavy burden (and losses) on the electrical grid during transmission. Due to this, the majority of regulators permit utilities to fine customers who have low power factors, with the bulk of the fine going to large consumers. Regardless of the reactive power requirements of the utility network, the power factor of standard PV systems remains constant at unity. A PV system that is connected to the grid lowers the power factor at the load end. This is due to the fact that the grid supplies the consumer with the leftover active power if the PV's capacity is less than their end load while retaining the same level of reactive power of the connected load. This can be explained by using Figure 1. The structure shown in Figure 1 uses 450 kVAR and 1,000 kW of electricity each day. If the PV capacity is less than the end load system voltage, consumers will receive any remaining active power. In this setup, active power could only come from the grid, lowered if this home were to install a 500 kW PV system with a power factor of 1, but the overall amount of power generated would remain the same. There will be no change in the amount of reactive power that is drawn from the grid. The PV plant will produce 500 kW, and 450 kVAR and 500 kW of power will be pulled from the grid as shown in Figure 2. In reality, the power factor of electricity taken from the grid will be 0.743. The voltage delivered to the load would be significantly lower as a result [11].

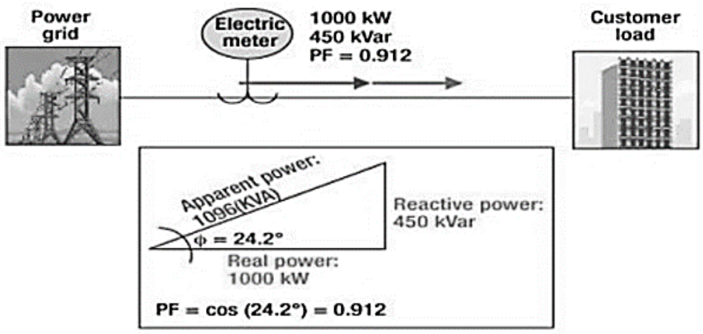

Figure 1. Active and reactive power flow from grid to load [11]

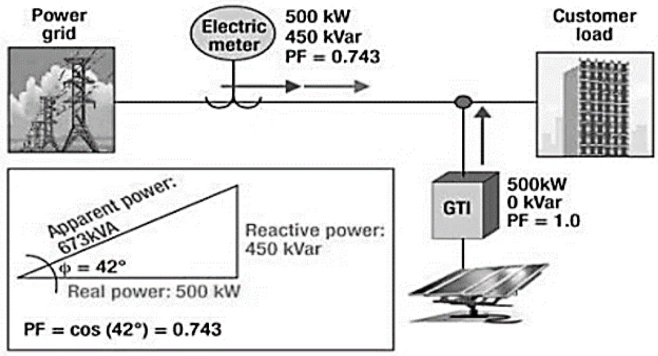

Figure 2. PV power helps in displacing 50% of utility real power [11]

There is a chance of a similar situation involving a degradation of the power factor when the load's power factor is leading. When employed to the purpose of controlling voltages on radial circuits, voltage regulators and capacitors are two frequent components that excel. On the other hand, because distributed power generation uses multiple sources, including PVs, voltage regulation will be more challenging. In Figure 2, PV helped to displace 50% of the actual power from the utility. 500 kW of electricity are being used to power the load in this scenario from both the grid and the PVs. The power factor has dropped to 0.743 and is now seen as being behind because the consumer is only utilising 500 kW of real power and the entire 450 kVA of reactive power from the grid.

Depending on whether or not there is an adequate supply of reactive power, the voltage at the PV end of the network may decrease or increase. Depending on the needs at the grid substation's load end, such as to account for the varying voltage levels in the system, capacitor banks or reactors may need to be turned on and off. This would depend on the circumstances. In some cases, the PV plants may be forced to shut down for their own safety if the voltage changes too much. There will be less generation as a result, which might lead to other problems. However, this weak power factor problem can be resolved and brought under control by selecting the appropriate inverter equipment for PV. Multistage inverters can be configured with reactive power and harmonics control to produce an output power factor that blends active and reactive power generation and control the harmonics and voltage. The output of this setup would have a non-unity power factor. The use of PV inverter technology has the ability to offer a wide range of extra advantages beyond merely producing energy in kilowatt-hours [11].

The same principle underlies how conventional inverters and transformers operate. An electrical system that is linked to the grid includes some intelligent features. The main difference is between the algorithms that run them and the safety features they include. When the grid's primary supply fails or when the voltage or frequency of the grid increases or decreases, the step-up transformer and converter known as grid tie inverter (GTI) can act as an isolator (or disconnector) from the grid and track the PV's power production. In its most basic configuration, a GTI converts a source's changing DC voltage to AC, such as a bank of PV panels, before boosting that AC voltage to enable synchronisation or connections with the electrical grid. When the PV array is working in parallel with the grid, the owner has the option of using this electricity or exporting it to the utility grid. The amount of electricity produced by the PV array and connected to the owner's home determines this. The GTI also aids in maximising the quantity of electricity produced by PVs through the use of maximum power point tracker (MPPT) technology. Multistage inverters can be highly useful for maintaining the power factor and the reactive power while also lowering the amount of harmonics introduced into the grid if they are built, calibrated, and tuned properly. These multistage inverters are built with a combination of capacitance, inductance, and resistance in the circuit to manage reactive power and harmonics at the solar photovoltaic system's output [12].

3. SPACE VECTOR PULSE WIDTH MODULATION

For voltage sources that use pulse width modulation (PWM) in three phases voltage source inverter (VSI), an inverter can be used to convert power, synchronise the grid, and optimise control. The main factor in feeding a grid with high-quality power is the current regulation of grid-connected VSI in DG systems. This is due to the fact that, contrary to what the IEEE standards claim, a DG system does not actually regulate the voltage level of common connection. This is so that DG systems do not have to adjust the voltage at the point of common coupling, as required by IEEE standards [1], [13]–[15]. Due to the advantages, they offer, space vector pulse width modulation (SVPWM) -based controllers are currently utilised often in three-phase PWM VSIs. SVPWM has several advantages [16], [17]. This is one of the methods for managing the current that was previously stated. SVPWM, on the other hand, is an open-loop voltage-type modulator and as a result, it differs significantly from current-type modulators with closed loops in a number of important ways. When utilised with an inverter that is linked to the grid, SVPWM-based current controllers may be vulnerable to disruption brought on by the grid's harmonics. Additionally, the delay in control caused by computation and sampling may result in a decline in the output current's quality. Furthermore, there is no built-in safeguard against overcurrent because the SVPWM has direct control over the voltage waveforms generated by the inverter. Since it makes the inverter unstable, this is a particularly challenging problem for grid-connected inverters utilised in DG applications [15]. A modern mistake compensation system is planned as follows: consequently, of paramount importance if one desires to circumvent SVPWM's drawbacks. Current error compensation is often carried out with one of these kinds of regulators due to the simplicity and dependability of standard proportional-integral (PI) regulators. The output current waveforms, however, could be altered if the electromagnetic disturbance brought on by the grid's reverse electromotive force is not properly corrected for [17], [18]. Numerous attempts have been made to enhance traditional PI regulators, such as those found in [19] or fuzzy-tuning PI control. One of these modifications has been the integration of a sine transfer function. These are only two instances of the numerous various strategies that have been used.

But as system parameters change, the system's design becomes considerably more intricate and complex. Since deadbeat predictive control offers excellent performance when it comes to the current control of VSIs, it is usual practise to use it for current error compensation [20]–[23]. However, the control algorithm grows more complex and sensitive as a result of the time and effort needed to calculate and implement it. Mattavelli [24] and Oh *et al*. [25] presented two digital predictive current controllers for three-phase PWM VSIs that operate given immobile coordinates and have control delays that are equivalent to or more than one PWM period. However, even with rectification, the computations were too large, resulting in lower performance.

The inverter can be used with the SVPWM approach to control the speed and torque of electric motors [26]–[28]. SVPWM has become a popular alternative for low-switch-count systems due to its greater efficiency in regulating inverters with fewer switches [29], [30]. The duty cycle of SVPVM is determined by the modulation technique. There are six sectors in the intricate switching vector space plane (a, b). The switching states for the power inverter's turn-on and turn-off are combined to divide the sectors. The switching intervals for all vectors are determined by SVM, which is a more complex technique, using a lookup table and sector identification. The two adjacent switching state vectors are recognised by the reference vectors. To calculate the on and off states of each switch, you will require these vectors. To locate the switching sequences, you will need a microprocessor, intricate algorithms, and an increase in the power inverter's n-level. The fundamental disadvantage of SVM is that it takes a long time to do simple calculations, which causes unneeded delays [31]. To address this issue, sophisticated deadbeat control and multiple reactive system components are used [32]. In terms of fundamental voltage ratios and harmonics correction, SVM methods surpass SPWM. The peak output voltage of SPWM is roughly 15% higher than that of triangle carrier signal-type modulation [33]. Moreover, systems with many levels of power inverters frequently employ the SVM approach, which compares several different-level carrier waves with the reference voltage signals and are used to build an n-level space vector with sector and n-switching states for positive, zero, and negative switching sequences [34], [35]. Value vectors come in three sizes: tiny, medium, and gigantic.

4. ARTIFICIAL INTELLIGENCE BASED SVPWM

The application of artificial intelligence (AI) methods, particularly neural networks, can considerably boost the performance of power electrical controllers. In the broad subject of power electronics, neural networks have uncovered a brand-new and fascinating sector. Neural networks are increasingly being used in motors and power electronics. Neural networks of the feed-forward back-propagation kind are most frequently used in power electronics. It uses supervised error back-propagation training and has a large processing capacity. The neurons of the output layer typically have a linear transfer function, whereas the neurons of the hidden layer often have a hyperbolic tangent sigmoid transfer function. Similar to how synaptic junctions of neurons contribute dispersedly to the memory or intelligence of a biological neural network, synaptic weights of a neural network also contribute dispersedly to the intelligence of the system. As a result, the neural network is able to maintain its core functionality, such as pattern recognition or input-output mapping. It should be emphasised that one of the neural network's unique qualities is its extraordinary speed when doing large-scale parallel processing with the aid of application-specific integrated circuit chips. SVPWM is an example of a feed-forward carrier-based PWM phenomena known as non-linear mapping. This method samples the command phase voltages at the input and establishes the corresponding pulse width patterns at the output [36], [37]. Therefore, it is logical to suppose that an artificial neural network (ANN) of the feed-forward back-propagation type with a high computing capability may implement the SVPWM method. The ANN has a built-in capability for learning, which enables it to deliver improved precision through interpolation, in contrast to the conventional look-up table method. Article on the ANN-based SVPWM modulator for induction motor drive have been published by Pinto *et al*. [38]. The presented ANN-based modulator has a lower computational burden than three-level converters since initial space-vector computations are not necessary for determining the magnitude and angle of the reference vector. Training a multi-layer neural network is more difficult since an even larger number of neurons are required. There is a need for an additional up-down counter, a complex logic circuit, and more switching transitions, all of which contribute to the complexity of segmentation.

Because it can reduce the inverter's harmonic output signals and has lower switching losses than other approaches, the SVPWM approach is the best one for VSI. This technique makes use of implicit modulation functions of SVPWM and necessitates substantial nonlinear calculations. The majority of SVPWM generally requires hard online calculation, which makes real-time implementation difficult. Because more memory is needed for traditional SVPWM, there are fewer switching frequency options available, which reduces the accuracy of the SVPWM algorithm. This problem is solved using a genetic algorithm (GA) based SVPWM. However, the GA is time-consuming to utilise because they must be repeated a lot to produce the best results. Durgasukumar and Pathak [39] used SVPWM based on the adaptive neural fuzzy inference system (ANFIS) for two-level inverters.

Many academicians in the recent years have focused on the creation of unique machine learning algorithms to address the problems that come with artificial intelligence. One of the most crucial of these techniques is the random forests (RF) regression methodology. It has been utilised to create the real image spectra and to boost daytime, night-time, and twilight rainfall rate assignment. The RF based SVPWM was demonstrated by Hannan *et al*. [40] to have a level of robustness that was greater than the ANFIS and ANN controllers in all the scenarios that were examined in terms of damping capability, settling time, steady-state error, and transient response across a variety of different operating conditions.

The machine learning technique known as reinforcement learning (RL), teaches an agent to comprehend a dynamic environment by applying actions and gaining rewards through trial and error. As more potent processing units are created, deep learning (DL) is growing in popularity since it has been shown to be capable of resolving a range of extremely challenging issues. The learning approach known as deep reinforcement learning (DRL), which was created when standard reinforcement learning and deep learning were coupled, is relatively new. DRL has been used in a variety of scenarios to simplify issues that might otherwise be challenging. Qashqai *et al*. [41] proposes a new SVM switching method that can learn how to switch an inverter using the inverter's SVM switching states where deep reinforcement learning is the foundation of this approach. A new current regulated SVPWM with grid harmonic compensation in simulation of PV system has been presented by Bhat and Agarwal [42] and Lakshmanan *et al*. [43].

5. ARTIFICIAL INTELLIGENCE FOR POWER CONVERTER DEFECT MONITORING

The detection of converter faults in grid-connected PV systems has been successfully accomplished over the past few years using AI-based data-driven intelligent fault categorization algorithms like the one presented by Kurukuru *et al*. [44]. Artificial intelligence is the driving force behind these methods. For the fault detection and classification of power switches in multilevel H-bridge inverters, ANN are used by Chowdhury *et al*. [45]. The details pertaining to the output voltage from the inverter is collected, and discrete wavelet transform (DWT) is then used to extract properties like signal power, energy, and so forth. After then, the input and output layers are combined to create the training component of the ANN, which also has one hidden layer. For identifying and categorising defects in PV systems connected to the grid radial basis function networks (RBFNs) have been used to build a defect classifier. A variety of time instants' worth of data from the inverter's output are gathered, and after pre-processing, the wavelet transform is utilised to extract important properties. The RBFN receives these features as input, and uses the Gaussian kernel to carry out its analysis. Supervised learning-based probabilistic neural network (PNN) has been proposed for fault diagnosis in diode clamped multilevel inverters by Bhattacharya *et al*. [46]. DWT is used for feature mining with the mother wavelet of the Daubechies order 4 (db4). The use of a multi-layered feedforward PNN is then made, and this time there is no requirement for weight modification iteration. A multi-layer perceptron neural network (MLPNN)-based intelligent condition monitoring strategy for PV systems that are connected to the grid is suggested by Bharath *et al*. [47]. Following the collection of data on the voltage and current faults of the inverter brought on by various switch faults, DWT is applied to calculate the different attributes. Principal component analysis (PCA) is also used to reduce the number of dimensions, and as a consequence, only the features that are relevant to the study are collected. He *et al*. [48] outlines the application of a fault forecasting approach based on fast clustering and the Gaussian mixture model for a photovoltaic inverter that is connected to the grid. The technique entails capturing real-time data on the system, including the inverter's output power, current, voltage, IGBT temperature, and other data. Additionally, the Gaussian mixture model (GMM) is used for fault forecasting, and the fast-clustering approach is used to condense data clusters that are similar to one another. Gong *et al*. [49] advocates utilising a modified version of the convolutional neural network-global average pooling (CNN-GAP) technique for the detection of defects in inverter switches. The raw data from the 1-D time series of the inverter serves as the input for the CNN-GAP model. 2-D feature maps are the end product of this process, which is constructed at the input layer utilising numerous convolution and pooling layers. The output SoftMax layer is where the diagnostic result is ultimately obtained, while the GAP layer is responsible for compressing the final image.

6. ARTIFICIAL INTELLIGENCE FOR FILTER FLAW DETECTION

Keeping an eye out for filter flaws grid-connected PV systems frequently require the installation of filters to lower the quantity of harmonics released by the inverter's output. A simple L filter might be all that is required, but that would require a large inductor and could result in a big drop in voltage. As a result, the LCL filter is suggested by Zhou *et al*. [50] due to the advantage of using components that are more compact in size [49]. The results of the study indicate that capacitors are among the most fragile parts, and that the operating conditions, such as temperature, current, and others, have a significant impact on how well they perform. Equivalent series resistance (ESR) is a metric for electrolytic capacitor health and can be analysed to ascertain the condition of electrolytic capacitors. Monitoring the comparable series resistance will enable you to estimate ESR. Artificial intelligence-based monitoring techniques are used to assess the condition of a capacitor's health. The use of an ANN-based regression technique allows for the remaining useful life (RUL) identification of electrolytic capacitors as proposed by Bhargava *et al*. [51]. Decisions on a person's health prognosis are made using a fuzzy-based approach. Neo-fuzzy neuron (NFN) model-based electrolytic capacitor health monitoring system is presented by Soualhi *et al*. [52]. It is based on the integration of fuzzy logic and artificial neural network-based approaches to effectively monitor the status of capacitors. For the goal of determining the health of capacitors, a comparison is made between the support vector regression (SVR) approach and the recursive least squares (RLS) method for computing regression coefficients by Khalil and Lee [53]. To lay the groundwork for the SVR approach, the model is first determined by offline training. Using supervised learning-based artificial neural networks to perform health status monitoring of electrolytic capacitors has been thoroughly analysed by Soliman *et al*. [54]. However, the use of AI-based methodologies has a lot of untapped potential that may be explored when it comes to the topic of the condition of electrolytic capacitors.

7. ARTIFICIAL INTELLIGENCE FOR BATTERY MONITORING

Synthetic intelligence monitoring for battery malfunctions and deterioration, state of charge (SOC), state of function (SOF), and state of health (SOH), as well as a range of other parameters, are used to assess the performance of batteries in PV systems that are connected to the grid. The diagnostic and prognostic technologies required to monitor the health of batteries have been studied. There has been some study on AI-based battery diagnosis tools. Yu [57] created a Bayesian regression with the goal of estimating RUL for batteries. To get a battery's RUL rating, a statistical model is integrated with a process-based, electrochemistry-based model. Additionally, one option is the relevance vector machine (RVM) methodology explored with the goal of determining the battery's condition. An adaptive gaussian mixture model (AGMM) based system for monitoring the health of batteries is proposed by Yu [55]. It is an online battery degradation diagnostic tool that works with a learning rate schedule and recursive component t parameter changes. The Gaussian distribution's components are continuously updated online, and the component with the highest probability is chosen to further increase efficiency. Samadi and Saif [56] chose to monitor the batteries using a Takagi-Sugeno fuzzy technique. Even though the nonlinear dynamics of a battery include complex electrochemical equations, it can be managed in a reasonable way. A temporal convolutional network (TCN) is suggested for use in battery monitoring to forecast SOH and estimate RUL by Zhou *et al*. [57]. It is a fairly recent method that is data-driven and deep learning-based and offers a high-precision assessment of the state of health of the specified component. Long short-term memory (LSTM) and the recurrent neural network (RNN) are used in tandem to create the battery fault diagnostic as is reported by Li *et al.* [58]. By acquiring large volumes of data on batteries from the real world, the resilience of the combined method is acquired. Along with it, to find the model's hyperparameters, the method combines the benefits of a modified adaptive boosting (MAB) coupling module with an approaching optimization method (AOM) optimization tool to improve diagnostic reliability. Thus, the authors have discussed use of artificial intelligence for reliability. Reliability refers to a device's ability to perform a defined duty within a predetermined set of operating circumstances as given by Huai *et al.* [59]. The likelihood of success and failure is one of the criteria used to gauge reliability as suggested by Yang *et al.* [60]. The objective of the reliability analysis is being carried out to provide an estimate of the operational lifespan and, in the event of a breakdown, to recalibrate the lifetime and provide the remaining useful life. Operating systems perform the reliability study for the design modification. Electronic equipment is powered in a regulated environment. The device's thermal model might be developed after accounting for the inverter's power loss. After the thermographic profile has been established, cycle counting utilizing the rain flow counting method can be performed using a variety of lifespan computing models, including Coffin-Mason [61], Monte-Carlo [62], and LESIT [63] for the purpose of calculating the device's lifespan. However, the analytical analysis methodologies could have numerous flaws, such as quick convergence in analysis. To solve these problems, it is possible to incorporate the rapidly changing load on components into the AI-based lifespan estimate. It is brought on by the ride-through procedure [62], which will ultimately lead to a better lifespan forecast capability. In contrast to the paper [64], which establishes a function-based connection between dependability and design parameter, the paper [63] uses ANN to estimate lifespan in order to analyze the various operating scenarios. The analysis is carried out using an ANN. It is first trained, after which surrogate models are used. A generalized schematic for the deployment of artificial intelligence applications for fault detection and status monitoring in grid-connected solar systems is shown in Figure 3. Figure 4 displays the typical practice of lifespan estimation where Markov analysis or Monte Carlo methods are used [65], [66].

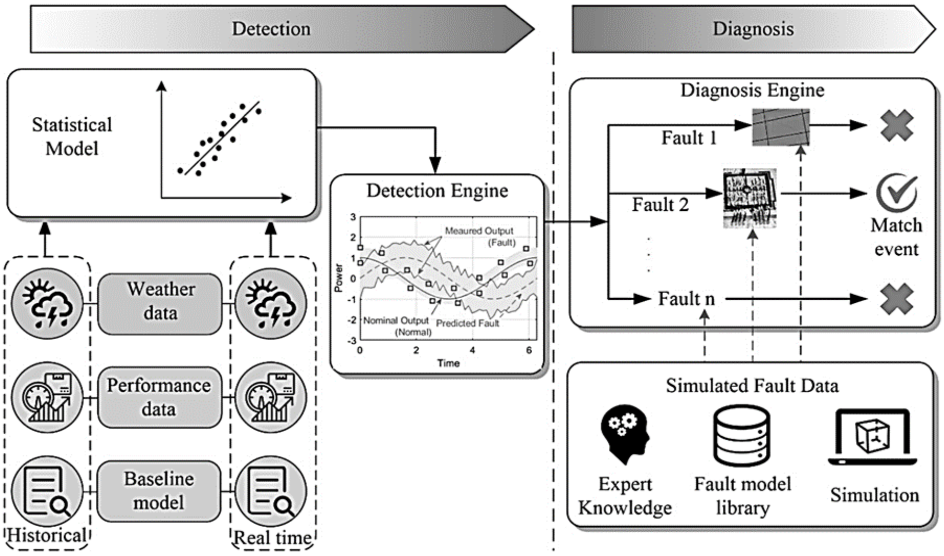

Figure 3. Generalised schematic for the deployment of artificial intelligence applications for fault detection and status monitoring in grid-connected photovoltaic systems [66]

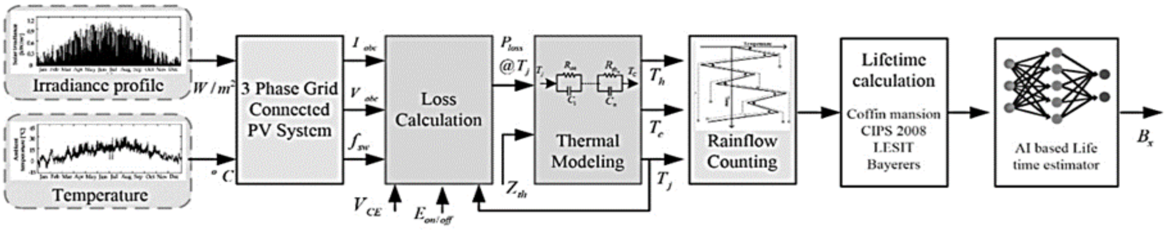

Figure 4. Typical practice of lifespan estimation, Markov analysis or Monte Carlo methods are used [66]

8. CONCLUSION

This article describes a technique for improving the power quality in grid interfaced photovoltaic (PV) system using space vector pulse width modulation (SVPWM). The grid voltage, grid current, and grid harmonic correction of the PV system are used in the execution of the current controlled SVPWM technique. In order to meet the rising demand for electricity, PV systems that are connected to the grid are currently in a strong position to increase both energy efficiency and power quality. A unique current-regulated SVPWM with grid harmonic compensation is used in this study of a PV system that is hooked into the grid. Using artificial neural network (ANN), lessens the mathematical complexity related to the SVPWM. If the ANN-SVPWM is appropriately developed, the mathematical complexity related to the SVPWM may be significantly reduced. In an effort to improve the quality of the power supplied by grid systems, the discoveries made throughout the course of this inquiry will be put to use in later artificial intelligence-based technologies.

REFERENCES

[1] J. M. Carrasco *et al.*, "Power-electronic systems for the grid integration of renewable energy sources: A survey," *IEEE Transactions on Industrial Electronics*, vol. 53, no. 4, pp. 1002–1016, 2006, doi: 10.1109/TIE.2006.878356.
[2] B. Renders, K. De Gusseme, W. R. Ryckaert, K. Stockman, L. Vandevelde, and M. H. J. Bollen, "Distributed Generation for Mitigating Voltage Dips in Low-Voltage Distribution Grids," *IEEE Transactions on Power Delivery*, vol. 23, no. 3, pp. 1581–1588, 2008, doi: 10.1109/TPWRD.2007.916162.

[3] M. Singh, V. Khadkikar, A. Chandra, and R. K. Varma, “Grid interconnection of renewable energy sources at the distribution level with power-quality improvement features,” *IEEE Transactions on Power Delivery*, vol. 26, no. 1, pp. 307–315, 2011, doi: 10.1109/TPWRD.2010.2081384.

[4] S. B. Kjaer, J. K. Pedersen, and F. Blaabjerg, “A review of single-phase grid-connected inverters for photovoltaic modules,” *IEEE Transactions on Industry Applications*, vol. 41, no. 5, pp. 1292–1306, 2005, doi: 10.1109/TIA.2005.853371.

[5] L. S. Czarecki, “Power related phenomena in three-phase unbalanced systems,” *IEEE Transactions on Power Delivery*, vol. 10, no. 3, pp. 1168–1176, 1995, doi: 10.1109/61.400893.

[6] F. S. Pai and S. J. Huang, “Design and operation of power converter for microturbine powered distributed generator with capacity expansion capability,” *IEEE Transactions on Energy Conversion*, vol. 23, no. 1, pp. 110–118, 2008, doi: 10.1109/TEC.2007.895853.

[7] S. Riyaz and K. S. Kumar, “Power-Management Strategies for a Grid-Connected PV-FC Hybrid System,” *International Journal of Engineering and Computer Science*, 2015, doi: 10.18535/ijecs/v4i8.64.

[8] N. Y. Dahlan, M. A. Jusoh, and W. N. A. W. Abdullah, “Solar grid parity for Malaysia: Analysis using experience curves,” *Proceedings of the 2014 IEEE 8th International Power Engineering and Optimization Conference, PEOCO 2014*, 2014, pp. 461–466, doi: 10.1109/PEOCO.2014.6814473.

[9] S. Reichelstein and M. Yorston, “The Prospects for Cost Competitive Solar PV Power,” *SSRN Electronic Journal*, 2012, doi: 10.2139/ssrn.2182828.

[10] Y. Chen and K. M. Smedley, “A cost-effective single-stage inverter with maximum power point tracking,” *IEEE Transactions on Power Electronics*, vol. 19, no. 5, pp. 1289–1294, 2004, doi: 10.1109/TPEL.2004.833458.

[11] “Concept paper on the assessment of solar PV (SPV) system for power quality and safety issues,” *Central Electricity Authority*, 2018.

[12] B. Subudhi and R. Pradhan, “A comparative study on maximum power point tracking techniques for photovoltaic power systems,” *IEEE Transactions on Sustainable Energy*, vol. 4, no. 1, pp. 89–98, 2013, doi: 10.1109/TSTE.2012.2202294.

[13] L. Chang and H. M. Kojabadi, “Review of interconnection standards for distributed power generation,” *LESCOPE 2002 - 2002 Large Engineering Systems Conference on Power Engineering: Energy for the Future, Conference Proceedings*, 2002, pp. 36–40, doi: 10.1109/LESCPE.2002.1020664.

[14] IEEE Standards, “IEEE Standard for Interconnecting Distributed Resources With Electric Power Systems,” 2003, doi: 10.1109/IEEESTD.2003.94285.

[15] M. P. Kazmierkowski and L. Malesani, “Current control techniques for three-phase voltage-source pwm converters: A survey,” *IEEE Transactions on Industrial Electronics*, vol. 45, no. 5, pp. 691–703, 1998, doi: 10.1109/41.720325.

[16] Q. Zeng, L. Chang, and P. Song, “SVPWM-based current controller with grid harmonic compensation for three-phase grid-connected VSI,” *PESC Record - IEEE Annual Power Electronics Specialists Conference*, vol. 4, pp. 2494–2500, 2004, doi: 10.1109/PESC.2004.1355221.

[17] S. H. Song, S. Il Kang, and N. K. Hahm, “Implementation and control of grid connected AC-DC-AC power converter for variable speed wind energy conversion system,” *Conference Proceedings - IEEE Applied Power Electronics Conference and Exposition - APEC*, 2003, vol. 1, pp. 154–158, doi: 10.1109/apec.2003.1179207.

[18] E. Twining and D. G. Holmes, “Grid current regulation of a three-phase voltage source inverter with an LCL input filter,” *PESC Record - IEEE Annual Power Electronics Specialists Conference*, vol. 3, pp. 1189–1194, 2002, doi: 10.1109/psec.2002.1022337.

[19] S. Fukuda and R. Imamura, “Application of a sinusoidal internal model to current control of three phase utility-interface-converters,” *PESC Record - IEEE Annual Power Electronics Specialists Conference*, vol. 3, pp. 1301–1306, 2003, doi: 10.1109/pesc.2003.1216776.

[20] M. Prodanovic and T. C. Green, “Control and Filter Design of Three-Phase Inverters for High Power Quality Grid Connection,” *IEEE Transactions on Power Electronics*, vol. 18, no. 1, pp. 373–380, 2003, 10.1109/TPEL.2002.807166.

[21] J. Svensson and M. Lindgren, “Vector current controlled grid connected voltage source converter-influence of nonlinearities on the performance,” *PESC Record - IEEE Annual Power Electronics Specialists Conference*, vol. 1, pp. 531–537, 1998, doi: 10.1109/PESC.1998.701949.

[22] H. Abu-Rub, J. Guziński, Z. Krzeminski, and H. A. Toliyat, “Predictive current control of voltage-source inverters,” *IEEE Transactions on Industrial Electronics*, vol. 51, no. 3, pp. 585–593, 2004, doi: 10.1109/TIE.2004.825364.

[23] D. G. Holmes and D. A. Martin, “Implementation of a direct digital predictive current controller for single and three phase voltage source inverters,” *Conference Record - IAS Annual Meeting (IEEE Industry Applications Society)*, 1996, vol. 2, pp. 906–913, doi: 10.1109/ias.1996.560191.

[24] P. Mattavelli, “An improved deadbeat control for UPS using disturbance observers,” *IEEE Transactions on Industrial Electronics*, vol. 52, no. 1, pp. 206–212, 2005, doi: 10.1109/TIE.2004.837912.

[25] D. S. Oh, K. Y. Cho, and M. J. Youn, “A Discretized Current Control Technique with Delayed Input Voltage Feedback for a Voltage-Fed PWM Inverter,” *IEEE Transactions on Power Electronics*, vol. 7, no. 2, pp. 364–373, 1992, doi: 10.1109/63.136254.

[26] H. Ahmad, M. Z. Zulkifli, A. A. Latif, K. Thambiratnam, and S. W. Harun, “Overview of Control and Grid Synchronization for Distributed Power Generation Systems,” *Microwave and Optical Technology Letters*, vol. 62, no. 1, pp. 46–52, 2020.

[27] Y. Y. Tzou and S. Y. Lin, “Fuzzy-tuning current-vector control of a three-phase PWM inverter for high-performance ac drives,” *IEEE Transactions on Industrial Electronics*, vol. 45, no. 5, pp. 782–791, 1998, doi: 10.1109/41.720335.

[28] M. Cheng, Q. Sun, and E. Zhou, “New self-tuning fuzzy PI control of a novel doubly salient permanent-magnet motor drive,” *IEEE Transactions on Industrial Electronics*, vol. 53, no. 3, pp. 814–821, 2006, doi: 10.1109/TIE.2006.874269.

[29] Y. Zhang, X. Wu, and X. Yuan, “A Simplified Branch and Bound Approach for Model Predictive Control of Multilevel Cascaded H-Bridge STATCOM,” *IEEE Transactions on Industrial Electronics*, vol. 64, no. 10, pp. 7634–7644, 2017, doi: 10.1109/TIE.2017.2698360.

[30] J. L. Monroy-Morales, D. Campos-Gaona, M. Hernández-Ángeles, R. Peña-Alzola, and J. L. Guardado-Zavala, “An active power filter based on a three-level inverter and 3D-SVPWM for selective harmonic and reactive compensation,” *Energies*, vol. 10, no. 3, 2017, doi: 10.3390/en10030297.

[31] S. M. D. Dehnavi, M. Mohamadian, A. Yazdian, and F. Ashrafzadeh, “Space vectors modulation for nine-switch converters,” *IEEE Transactions on Power Electronics*, vol. 25, no. 6, pp. 1488–1496, 2010, doi: 10.1109/TPEL.2009.2037001.

[32] R. Palanisamy, P. Aravindh, and K. Vijayakumar, “Experimental and numerical analysis on SVPWM based grid connected photovoltaic system,” *Materials Today: Proceedings*, vol. 45, pp. 1583–1590, 2021, doi: 10.1016/j.matpr.2020.08.382.

[33] M. B. Latran and A. Teke, “Investigation of multilevel multifunctional grid connected inverter topologies and control strategies used in photovoltaic systems,” *Renewable and Sustainable Energy Reviews*, vol. 42, pp. 361–376, 2015, doi: 10.1016/j.rser.2014.10.030.

[34] W. Wang, A. Luo, X. Xu, L. Fang, T. M. Chau, and Z. Li, "Space vector pulse-width modulation algorithm and DC-side voltage control strategy of three-phase four-switch active power filters," *IET Power Electronics*, vol. 6, no. 1, pp. 125–135, 2013, doi: 10.1049/iet-pel.2012.0391.
[35] A. Camacho, M. Castilla, J. Miret, L. G. De Vicuna, and R. Guzman, "Positive and Negative Sequence Control Strategies to Maximize the Voltage Support in Resistive-Inductive Grids during Grid Faults," *IEEE Transactions on Power Electronics*, vol. 33, no. 6, pp. 5362–5373, 2018, doi: 10.1109/TPEL.2017.2732452.
[36] M. Jayabalan, B. Jeevarathinam, and T. Sandirasegarane, "Reduced switch count pulse width modulated multilevel inverter," *IET Power Electronics*, vol. 10, no. 1, pp. 10–17, 2017, doi: 10.1049/iet-pel.2015.0720.
[37] L. Yacoubi, K. Al-Haddad, F. Fnaiech, and L. A. Dessaint, "A DSP-based implementation of a new nonlinear control for a three-phase neutral point clamped boost rectifier prototype," *IEEE Transactions on Industrial Electronics*, vol. 52, no. 1, pp. 197–205, 2005, doi: 10.1109/TIE.2004.837913.
[38] J. O. P. Pinto, B. K. Bose, L. E. B. Da Silva, and M. P. Kazmierkowski, "A neural-network-based space-vector PWM controller for voltage-fed inverter induction motor drive," *IEEE Transactions on Industry Applications*, vol. 36, no. 6, pp. 1628–1636, 2000, doi: 10.1109/28.887215.
[39] G. Durgasukumar and M. K. Pathak, "Comparison of adaptive Neuro-Fuzzy-based space-vector modulation for two-level inverter," *International Journal of Electrical Power and Energy Systems*, vol. 38, no. 1, pp. 9–19, 2012, doi: 10.1016/j.ijepes.2011.10.017.
[40] M. A. Hannan, J. A. Ali, A. Mohamed, and M. N. Uddin, "A Random Forest Regression Based Space Vector PWM Inverter Controller for the Induction Motor Drive," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 4, pp. 2689–2699, 2017, doi: 10.1109/TIE.2016.2631121.
[41] P. Qashqai, K. Al-Haddad, and R. Zgheib, "A New Model-Free Space Vector Modulation Technique for Multilevel Inverters Based on Deep Reinforcement Learning," *IECON Proceedings (Industrial Electronics Conference)*, 2020, pp. 2407–2411, doi: 10.1109/IECON43393.2020.9254989.
[42] A. H. Bhat and P. Agarwal, "Implementation of a neural-network-based space-vector pulse-width modulation for a three-phase neutral-point clamped high-power factor converter," *Electric Power Components and Systems*, vol. 37, no. 2, pp. 210–233, 2009, doi: 10.1080/15325000802388914.
[43] S. A. Lakshmanan, B. S. Rajpourhit, and A. Jain, "A novel current controlled SVPWM technique for grid connected solar PV system," *IEEE Power and Energy Society General Meeting*, 2014, pp. 1–5, doi: 10.1109/PESGM.2014.6939787.
[44] V. S. Bharath Kurukuru, F. Blaabjerg, M. A. Khan, and A. Haque, "A novel fault classification approach for photovoltaic systems," *Energies*, vol. 13, no. 2, 2020, doi: 10.3390/en13020308.
[45] D. Chowdhury, M. Bhattacharya, D. Khan, S. Saha, and A. Dasgupta, "Wavelet decomposition based fault detection in cascaded H-bridge multilevel inverter using artificial neural network," in *2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, May 2017, pp. 1931–1935. doi: 10.1109/RTEICT.2017.8256934.
[46] M. Bhattacharya, S. Saha, D. Khan, and T. Nag, "Wavelet based component fault detection in diode clamped multilevel inverter using probabilistic neural network," *2017 2nd International Conference for Convergence in Technology, I2CT 2017*, 2017, pp. 1163–1168, doi: 10.1109/I2CT.2017.8226310.
[47] K. V. S. Bharath, A. Haque, and M. A. Khan, "Condition monitoring of photovoltaic systems using machine leaming techniques," *2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems, ICPEICES 2018*, 2018, pp. 870–875, doi: 10.1109/ICPEICES.2018.8897413.
[48] Z. He, X. Zhang, C. Liu, and T. Han, "Fault prognostics for photovoltaic inverter based on fast clustering algorithm and Gaussian mixture model," *Energies*, vol. 13, no. 18, 2020, doi: 10.3390/en13184901.
[49] W. Gong, H. Chen, Z. Zhang, M. Zhang, and H. Gao, "A Data-Driven-Based Fault Diagnosis Approach for Electrical Power DC-DC Inverter by Using Modified Convolutional Neural Network with Global Average Pooling and 2-D Feature Image," *IEEE Access*, vol. 8, pp. 73677–73697, 2020, doi: 10.1109/ACCESS.2020.2988323.
[50] D. Zhou, H. Wang, H. Wang, and F. Blaabjerg, "Reliability analysis of grid-interfaced filter capacitors," *Chinese Journal of Electrical Engineering*, vol. 4, no. 3, pp. 21–28, 2018, doi: 10.23919/CJEE.2018.8471286.
[51] C. Bhargava, V. K. Banga, and Y. Singh, "An intelligent prognostic model for electrolytic capacitors health monitoring: A design of experiments approach," *Advances in Mechanical Engineering*, vol. 10, no. 10, 2018, doi: 10.1177/1687814018781170.
[52] A. Soualhi *et al.*, "Heath Monitoring of Capacitors and Supercapacitors Using the Neo-Fuzzy Neural Approach," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 1, pp. 24–34, 2018, doi: 10.1109/TII.2017.2701823.
[53] A. G. Abo-Khalil and D. C. Lee, "DC-link capacitance estimation in AC/DC/AC PWM converters using voltage injection," *IEEE Transactions on Industry Applications*, vol. 44, no. 5, pp. 1631–1637, 2008, doi: 10.1109/TIA.2008.2002181.
[54] H. Soliman, H. Wang, B. Gadalla, and F. Blaabjerg, "Condition monitoring for DC-link capacitors based on artificial neural network algorithm," *International Conference on Power Engineering, Energy and Electrical Drives*, 2015, pp. 587–591, doi: 10.1109/PowerEng.2015.7266382.
[55] J. Yu, "Health degradation detection and monitoring of lithium-ion battery based on adaptive learning method," *IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 7, pp. 1709–1721, 2014, doi: 10.1109/TIM.2013.2293234.
[56] M. F. Samadi and M. Saif, "State-Space Modeling and Observer Design of Li-Ion Batteries Using Takagi-Sugeno Fuzzy System," *IEEE Transactions on Control Systems Technology*, vol. 25, no. 1, pp. 301–308, 2017, doi: 10.1109/TCST.2016.2549270.
[57] D. Zhou, Z. Li, J. Zhu, H. Zhang, and L. Hou, "State of Health Monitoring and Remaining Useful Life Prediction of Lithium-Ion Batteries Based on Temporal Convolutional Network," *IEEE Access*, vol. 8, pp. 53307–53320, 2020, doi: 10.1109/ACCESS.2020.2981261.
[58] D. Li, Z. Zhang, P. Liu, Z. Wang, and L. Zhang, "Battery Fault Diagnosis for Electric Vehicles Based on Voltage Abnormality by Combining the Long Short-Term Memory Neural Network and the Equivalent Circuit Model," *IEEE Transactions on Power Electronics*, vol. 36, no. 2, pp. 1303–1315, 2021, doi: 10.1109/TPEL.2020.3008194.
[59] W. Huai *et al.*, "Transitioning to physics-of-failure as a reliability driver in power electronics," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 2, no. 1, pp. 97–114, 2014, doi: 10.1109/JESTPE.2013.2290282.
[60] Y. Yang, H. Wang, A. Sangwongwanich, and F. Blaabjerg, "Design for Reliability of Power Electronic Systems," *Power Electronics Handbook, Fourth Edition*, Oxford, UK: Butterworth-Heinemann, 2018, pp. 1423–1440, doi: 10.1016/B978-0-12-811407-0.00051-9.
[61] A. Testa, S. De Caro, and S. Russo, "A reliability model for power MOSFETs working in avalanche mode based on an experimental temperature distribution analysis," *IEEE Transactions on Power Electronics*, vol. 27, no. 6, pp. 3093–3100, 2012, doi: 10.1109/TPEL.2011.2177279.

[62] U. M. Choi, I. Vernica, D. Zhou, and F. Blaabjerg, "Comparative evaluation of reliability assessment methods of power modules in motor drive inverter," *Microelectronics Reliability*, vol. 114, 2020, doi: 10.1016/j.microrel.2020.113730.

[63] L. Han, L. Liang, W. Xin, and F. Luo, "Influence of Wire-Bonding Layout on Reliability in IGBT Module," *2020 22nd European Conference on Power Electronics and Applications, EPE 2020 ECCE Europe*, 2020, doi: 10.23919/EPE20ECCEEurope43536.2020.9215733.

[64] M. A. Khan, A. Haque, and V. S. Bharath Kurukuru, "Reliability analysis of a solar inverter during reactive power injection," *9th IEEE International Conference on Power Electronics, Drives and Energy Systems, PEDES 2020*, 2020, doi: 10.1109/PEDES49360.2020.9379776.

[65] T. Dragicevic, P. Wheeler, and F. Blaabjerg, "Artificial Intelligence Aided Automated Design for Reliability of Power Electronic Systems," *IEEE Transactions on Power Electronics*, vol. 34, no. 8, pp. 7161–7171, 2019, doi: 10.1109/TPEL.2018.2883947.

[66] V. S. B. Kurukuru, A. Haque, M. A. Khan, S. Sahoo, A. Malik, and F. Blaabjerg, "A review on artificial intelligence applications for grid-connected solar photovoltaic systems," *Energies*, vol. 14, no. 15, 2021, doi: 10.3390/en14154690.

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