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The Role of Computational Intelligence Techniques in the Advancements of Solar Photovoltaic Systems for Sustainable Development: A Review

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ABSTRACT

The use of computational intelligence (CI) in solar photovoltaic (SPV) systems has been on the rise due to the increasing computational power, advancements in power electronics and the availability of data generation tools. CI techniques play an important role in modelling, sizing, forecasting, optimizing, analysing and predicting the performance and control of SPV systems. Thus, CI techniques have become an essential technology as the energy sector seeks to meet the rapidly increasing demand for clean, cheap, and reliable energy. In this context, this review paper aims to investigate the role of CI techniques in the advancements of SPV systems.

The study includes the involvement of CI techniques for parameter identification of solar cells, PV system sizing, maximum power point tracking (MPPT), forecasting, fault detection and diagnosis, inverter control and solar tracking of SPV systems. A performance comparison between CI techniques and conventional methods is also carried out to prove the importance of CI in SPV systems. The findings confirmed the superiority of CI techniques over conventional methods for every application studied and it can be concluded that the continuous improvements and involvement of these techniques can revolutionize the SPV industry and significantly increase the adoption of solar energy.

Index-words: *Solar photovoltaic systems; Computational Intelligence; Maximum power point tracking; Fault detection and diagnosis.*

I. INTRODUCTION

Sustainable development necessitates collective efforts to build an inclusive, sustainable, and resilient future for society and the planet. This means that the three pillars of sustainability; namely, economic growth, social inclusion, and environmental protection, must be balanced. It is in 2015 when the United Nations General Assembly developed seventeen Sustainable Development Goals (SDGs) as part of Agenda 2030 to ensure a sustainable future for all [1].

Fig. 1. Sustainable development goals.

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The SDGs address all aspects of sustainability and represent an ambitious step toward actionable targets for sustainable development across all sectors of society. **Figure 1** shows the SDGs. Sustainable Development Goal 7 (SDG 7) is one of the most crucial goals and it calls for access to affordable, reliable and sustainable energy for all. Energy is a key source of economic growth in every nation and lack of access to energy supplies is a constraint to human and economic development.

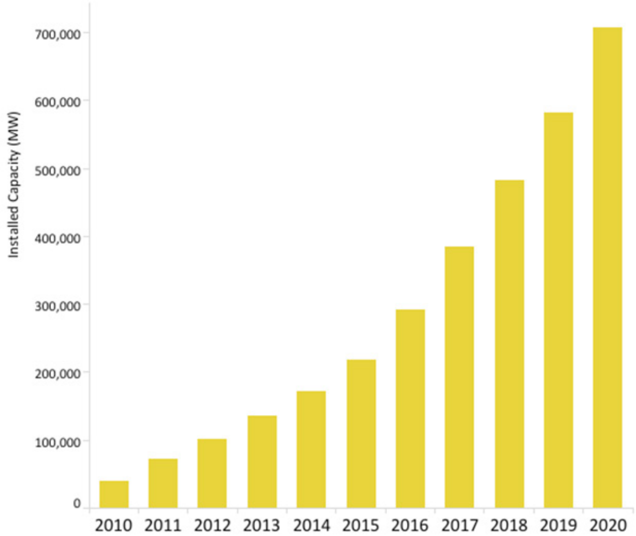

Fig. 2. Installed capacity of SPV.

Presently, fossil fuels provide approximately 80% of the world's energy [2]. The use of fossil fuels emits greenhouse gases and it is a threat to our environment. Thus, concerning SDG 7, for achieving the environmental goals for the future, many nations are strongly promoting the utilization of renewable energy sources. Renewable energy sources are sustainable and very low in pollution. In the same context, among different renewable energy sources, solar PV (SPV) is one of the fastest-growing renewable technologies as given in **Figure 2**.

The global interest in SPV is growing as the prices of photovoltaic (PV) modules and solar batteries continue to fall, as well as advances in power electronics. In addition, there are many new innovative technologies, such as computational intelligence (CI) and the internet of things (IoT), which are being used to advance SPV systems, thereby improving solar energy's competitiveness in the marketplace. CI techniques play an important role in modelling, sizing, forecasting, optimizing, analysing and predicting the performance and control of SPV systems.

They have the potential to reduce energy losses, lower energy costs, and facilitate and accelerate the global adoption of solar energy. CI techniques can also be used during the manufacturing of solar cells, allowing for the production of high-quality solar modules. Thus, CI techniques have become an essential technology as the energy sector seeks to meet the rapidly increasing demand for clean, cheap, and reliable energy.

This paper provides a comprehensive review of the application of CI techniques for modelling, sizing, optimizing, forecasting, fault detection and diagnosis, and control of SPV systems. It also gives a comparison between CI techniques and conventional methods for each application type. The rest of the paper is arranged as follows: **Section 2** gives an overview of commonly used CI techniques. **Section 3** covers the methodology and the involvement of CI techniques in different SPV systems sectors. After that, **Section 4** discusses the findings of the study and **Section 5** provides the conclusion for the study.

II. OVERVIEW OF COMMONLY USED COMPUTATIONAL INTELLIGENCE TECHNIQUES

Computational intelligence refers to the theories, designs, applications and developments of biologically and linguistically inspired computational paradigms [3]. Artificial neural networks, fuzzy systems, and evolutionary computation are the three main pillars of CI. The next section gives an outline of CI techniques.

A. Artificial Neural Networks

An artificial neural network (ANN) is a mathematical method that tries to simulate how biological neural networks work [4]. Artificial neurons learn from previous or given examples so that if they encounter such a situation again in the future, they will be able to solve it. Artificial neural networks (ANNs) have been useful in various areas including the field of medicine, neurology, mathematics, engineering, economics, and meteorology [5].

There are numerous types of ANNs, including feed-forward neural networks, recurrent networks, and radial bias neural networks. ANNs need training data sets and a learning algorithm for them to work. A commonly used learning algorithm is the back-propagation algorithm. When training ANNs, the network is given an input to give an output. The network output is then compared to the desired or correct output and if there is a difference, the synaptic weights are adjusted in such a way that decreases the error [6].

The process of adjusting the weights and running through the inputs is repeated until the errors are within the desired tolerance. After the training has reached the desired level, the weights are then held constant and the network will be ready to be used to make decisions and solve problems.

B. Fuzzy Logic

Lotfi Zadeh developed fuzzy logic (FL) in 1964 to address uncertainty and imprecision that are prevalent in many real-world engineering problems [7]. FL mimics decision-making in humans because it takes all possible intermediate values between "yes" and "no". Fuzzy logic is centred on the fuzzy sets theory, a theory that explains the classes of objects with ambiguous boundaries where the membership is a matter of degree [8]. A fuzzy logic controller consists of a fuzzification module, a rule-based inference system, and a defuzzification module.

The fuzzification module is responsible for transforming crisp system inputs into fuzzy values using membership functions while the inference system determines the output linguistic variables based on the fuzzy rules stored in the knowledge base. The defuzzification module then converts a linguist variable from the inference engine into a crisp output value. Fuzzy logic controllers have been utilized in different applications such as pattern recognition [9], robotics [10], aerospace [11], and many other applications.

C. Evolutionary Computation

Evolutionary computation is a class of population-based metaheuristic optimization algorithms that employ biological evolution-inspired mechanisms such as reproduction, mutation, recombination, and selection [12]. These evolutionary algorithms proved to be highly successful in several applications, especially for non-linear and multi-objective optimization problems. The section below gives an overview of commonly used evolutionary algorithms in PV systems.

1. Genetic Algorithms

A genetic algorithm (GA) is a search and optimization method that is devised to mimic the theory of natural selection [13]. Genetic algorithms are inspired by how living organisms adapt to the severe realities of life. A GA is implemented through three main operators namely; (a) selection operator (b) crossover operator and (c) mutation operator. When using this algorithm, the first stage is to select the initial population of genes. Then a fitness function is calculated for finding the best genes in the population.

The genes that possess the best fitness function values are selected for producing the next generation of genes using the crossover and mutation operators. The crossover operator is used to combine two chromosomes and exchange segments of their genetic material. The mutation operator is responsible for the random changes of some genes in the DNA sequence. GAs can be used for optimizing engineering designs [14], robotics [15], and many other applications. In [16], a genetic algorithm is applied for the optimum design of laminated composite structures.

2. Particle Swarm Optimization

Particle swarm optimization (PSO) is an optimization technique that is inspired by natural phenomena such as bird flocking and fish schooling [17]. Using the flocking analogy, the PSO algorithm maintains a swarm of individuals known as particles, with each particle representing a potential solution. Every particle in the swarm has a fitness value that is mapped using the objective function, and each particle also has an individual velocity that determines its motion's direction and range.

The particles share the information gleaned from their respective search processes. The position of each particle depends on two parameters: (a) the best solution obtained by a particle itself (p_{best}), and (b) the best particle in the neighbourhood (g_{best}). The particles continuously revise their direction and velocity to move towards the best position which ultimately results in each particle moving to the global optimum. PSO has been utilized for several complex applications such as water management [18], central position control in metallurgical processes [19] and robotics [20].

3. Simulated Annealing

Simulated annealing (SA) is a metaheuristic global optimization technique inspired by metallurgical annealing, in which the metal is rapidly heated to a high temperature and then slowly cooled to improve the metal's properties [21]. Using SA, the objective function represents the thermodynamic energy. At high temperatures, the algorithm allows for large movements in the search space, increasing the likelihood of accepting solutions that do not improve on the previously discovered one. This mechanism prevents the algorithm from becoming stuck in a local solution.

At low temperatures, however, the perturbation and likelihood of accepting a worse solution are greatly reduced. SA has been successfully utilized for several applications such as vehicle routing [22], farm layout optimization [23] and mechanical designs [24].

III. SOME NOVEL APPLICATIONS OF CI TECHNIQUES IN SPV SYSTEMS

A. Methodology

The main aim of this review paper is to provide relevant recent achievements of CI techniques in the advancements of SPV systems. Improvements in the applicability of SPV systems increase the renewable energy penetration in the world energy market

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thereby reducing the use of fossil fuels and leading to sustainable development. CI techniques have been the driving force for improving the design and control of SPV systems.

To come up with a comprehensive review paper, a strict selection criterion was used. The research articles used in this work were searched from top academic research databases such as Scopus, Web of Science, IEEE Xplore and ScienceDirect. The articles are in the period, 2010 to 2022. The minimum requirement for each publication used was to have at least 10 citations. This requirement was implemented to make sure that the used material is relevant and credible.

An exception to this requirement was made for articles published in 2021 and 2022 since they did not have enough citations because of the timeframe. After meeting the minimum requirement, the articles were then selected depending on the performance of the CI techniques per given application. The performance of the CI techniques was measured using different indexes such as the root mean square error (RMSE), absolute error (AE) and efficiency (η). The papers with the best performance were then selected.

Moreover, only the papers that show a clear validation of the performance of the presented CI technique were selected. The best conventional methods per application were also included in this review paper to give a detailed comparison. The articles focused on seven different SPV system areas namely:

- Parameter identification for solar cell modelling.
- PV system sizing.
- Maximum power point tracking.
- Solar irradiance and energy production forecasting.
- Fault detection and diagnosis.
- Inverter control.
- Sun tracking.

B. Parameter Identification for Solar Cell Modelling

Accurate modelling of solar cells is a critical stage in SPV research. Due to the non-linear current-voltage characteristics of solar cells, it is very important to identify appropriate parameters for modelling the equivalent circuits of solar cells. There are two common equivalent circuits used to model solar cells; the single diode model (SD) and the double diode model (DD). The single-diode model has five parameters and the double-diode model has seven parameters. **Figure 3** shows the parameters for the single-diode model.

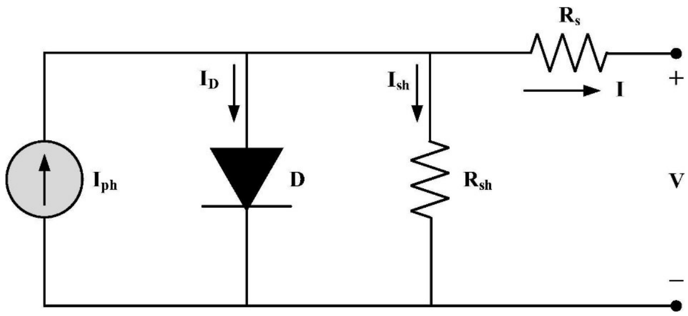

Fig. 3. An equivalent circuit for a single-diode solar cell model.

Finding the optimum values for these parameters is very crucial for modelling, controlling and sizing SPV systems. The literature presents so many methods for accurate estimation of the parameters of the solar cell and these methods can be grouped into two categories: analytical-numerical methods and CI-based methods. Analytical-numerical methods are mostly based on solving equations to determine solar cell parameters.

In [25] and [26], an analytical-numerical method was presented for solar cell parameter identification. The approach was based on curve fitting by utilizing the least square error method to form the system equations and then solving the equations using a modified Newton-Raphson (NR) method. In [27], a fast and accurate method based on the reduced forms of the original five-parameter system and experimental data was presented.

The approach was useful for a more general characterization of a PV model and only works if the experimental data sets for solar irradiance and temperatures are available. Some other analytical-numerical methods proposed for parameter identification of solar cells are given in [28, 29]. These conventional methods are easy to implement but they have many disadvantages such as the need for experimental data and relying on assumptions that can lead to the loss of accuracy when determining the solar cell equivalent circuit parameters.

CI techniques were also suggested for parameter identification of solar cell models because of their ability to solve complex and non-linear problems. In [30], genetic algorithms (GAs) were successfully applied for identifying solar cell parameters. In [31], an efficient approach based on the salp swarm algorithm (SSA) was presented for extracting the parameters of the equivalent circuit of solar cells.

The SSA was evaluated using the sine cosine algorithm, virus colony search algorithm (VCS), ant lion optimizer (ALO), gravitational search algorithm (GSA) and whale optimization algorithm (WOA). The simulation results showed that the SSA provides the highest level of accuracy and can be adopted in designing SPV systems. Other important CI techniques reported in the literature for solving the parameter identification problem include the JAYA optimization algorithm [32], simulated annealing (SA)[33], artificial bee swarm optimization algorithm (ABSO) [34], particle swarm optimization (PSO) [35], ANN [36], and Harris hawks optimization (HHO) [37]. Hybrid techniques have also been suggested for the parameter identification of solar cells. In [38], the Levenberg-Marquardt (LM) method was combined with simulated annealing to estimate the five parameters of a single-diode model. A combination of particle swarm optimization and simulated annealing was also presented for parameter identification [39]. The performance of these methods was evaluated using the root mean square error (RMSE) given by,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \check{y}(i)\|^{2}}{N}} \tag{1}$$

where N is the number of data points, y(i) presenting the ith measurement and $\check{y}$ (i) is its corresponding predicted value. **Table I** gives the performance of different techniques for parameter identification of solar cell models.

TABLE I: COMPARISON OF CI AND CONVENTIONAL TECHNIQUES FOR PARAMETER IDENTIFICATION OF SOLAR CELL MODELS.

Ref	Year	Author	Technique	Classification	Diode model	Performance (RMSE)
[33]	2012	K.M. El-Naggar	SA	CI	SD,DD	1.74×10^{-3}
[36]	2013	M. Karamirad	ANN	CI	SD	4.47×10^{-2}
[34]	2013	A. Askarzadeh	ABSO	CI	SD,DD	9.83×10^{-4}
[26]	2014	M. Hejri	Newton Raphson	Conventional	SD	6.35×10^{-2}
[27]	2014	A. Laudani	Reduced forms	Conventional	SD	7.73×10^{-4}
[38]	2014	F. Dkhichi	Levenberg–Marquardt &SA	CI	SD	9.86×10^{-4}
[28]	2016	M. Hejri	Approximation	Conventional	SD	2.21×10^{-2}
[32]	2017	K. Yu	JAYA	CI	SD,DD	9.83×10^{-4}
[39]	2017	M.A. Mughal	PSO-SA	CI	SD,DD	7.45×10^{-4}
[35]	2018	H.G.G. Nunes	PSO	CI	SD,DD	7.18×10^{-4}
[30]	2019	N. Hamid	GA	CI	SD,DD	2.43×10^{-3}
[25]	2020	A.K. Abdulrazzaq	Newton Raphson	Conventional	SD	1.98×10^{-6}
[31]	**2020**	**R.B. Messaoud**	**SSA**	**CI**	**SD,DD**	$\mathbf{1.30 \times 10^{-8}}$
[37]	2020	H. Chen	HHO	CI	SD,DD	6.40×10^{-4}
[29]	2021	P.J. Gnetchejo	Adaptive-Newton Raphson	Conventional	SD,DD	4.83×10^{-3}

C. *PV System Sizing*

Accurate sizing is one of the crucial elements to consider when designing PV systems. This includes finding the optimum number of PV modules, optimum battery storage, MPPT controllers and inverter sizes as well as the optimum placement and tilt angles of PV modules. Accurate sizing is essential because it ensures that the load demand is met and allows the design of cost-effective systems that are practically credible in the renewable energy marketplace. Analytical methods have been used for sizing PV systems. In [40], an analytical model based on the statistical analysis of the solar irradiation data was presented. The model showed satisfying results after validation. The performance of these proposed techniques was measured in terms of the correlation coefficient (r) given by,

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 . \sum(y_i - \bar{y})^2}} \tag{2}$$

where x_i represents values of the x-variable in the sample, $\bar{x}$ is the mean of the x-variable, y_i represents the values of the y-variable in the sample and $\bar{y}$ is the mean of the y-variable. In [41], the authors suggested a technique based on the Markov chain and beta probability density function for the sizing

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of photovoltaic generators. The obtained results were compared with the Sandia method, in which the proposed method proved to be more reliable. A model based on artificial neural networks and genetic algorithms was presented in [42] to generate the sizing curve for a stand-alone PV system. The technique was compared to the numerical methods and was considered very promising. Another technique for PV system sizing worth noting is the radial bias function neural network (RBFNN) method reported in [43]. **Table II** presents the performance of different techniques for PV system sizing.

TABLE II: COMPARISON OF CI AND CONVENTIONAL TECHNIQUES FOR PV SYSTEM SIZING.

Ref	Year	Author	Technique	Classification	Performance (r)
[41]	2010	C.V.T. Cabral	Markov chain	Conventional	0.9650
[42]	**2010**	**A. Mellit**	**ANN-GA**	**AI**	**0.9998**
[43]	2010	M. Benghanem	RBFNN	AI	0.9880
[40]	2012	E. Kaplani	Statistical analysis	Conventional	0.9500

D. *Maximum Power Point Tracking*

Maximum power point tracking (MPPT) controllers are algorithms that are included in PV battery charge controllers or inverters to extract the maximum available power from a PV module for any given temperature and irradiance [44]. For any set of temperatures and irradiance, the operating point of a PV module corresponds to a unique point on the current-voltage (I-V) curve. The operating point on the I-V curve also corresponds to some point on the power-voltage (P-V). For the PV module to produce the highest power output, its operating point must correspond to the maximum point on the P-V curve known as the Maximum Power Point (MPP) as shown in **Figure 4**.

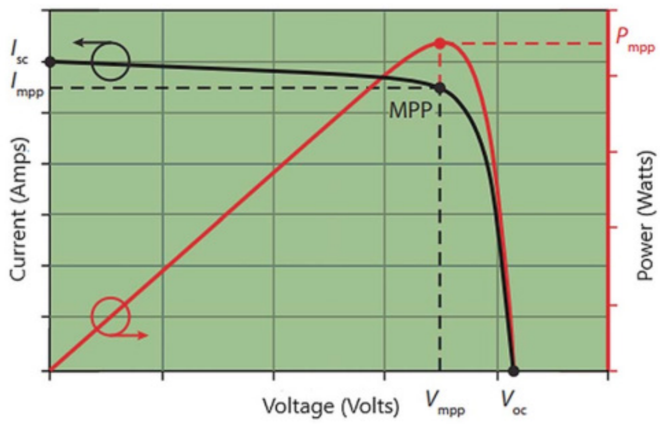

Fig. 4: I-V and P-V curves of a PV module.

If the irradiance or temperature changes, the position of the MPP also shifts. Therefore, it is the responsibility of the MPPT controller to continuously track the position of the MPPT for any given environmental condition. Generally, an MPPT controller is comprised of a DC-DC converter which is controlled by an algorithm to force the solar module's operating point to be at MPP at all times. Connecting the PV module directly to the load makes the module's operating point dictated by the load. Thus, the PV module only operates at MPP if the load impedance matches the input impedance to the DC-DC converter as seen by the PV module, otherwise it can operate at any point on the P-V curve which might not be the MPP.

MPPT techniques can be categorized as conventional techniques and CI-based techniques. The performance of the MPPT controllers was evaluated in terms of tracking efficiency calculated using the following,

$$T_{Eff} = \frac{\int_0^t P_{MPP}\,dt}{\int_0^t P_{ideal\ MPP}\,dt} \times 100\% \qquad (3)$$

where P_{MPP} represents the measured maximum power point for each controller and $P_{ideal\ MPP}$ represents the desired/ideal maximum power point for given environmental conditions. One of the widely used conventional MPPT techniques is the Perturbation and Observation (P&O) controller.

The studies [45-47] have shown how different types of the P&O method have been utilized by several researchers. Another well-known conventional technique is the incremental conductance (InCon) technique. Refs [48, 49] present the applications of different types of the InCon technique for maximum power point tracking. Some other conventional MPPT techniques include the Fractional Open-Circuit Voltage (FOCV) [50], and Fractional Short-Circuit Current (FSC) [51]. Recently, CI-based MPPT methods have been utilized and proved to be highly successful to solve the MPPT problem. In [52-54], fuzzy logic controllers were utilized for MPPT and they showed better tracking efficiency as compared to conventional techniques. Artificial neural networks were used for MPPT in Refs [55-57] and their performance was satisfactory.

Hybrid MPPT techniques were also reported in the literature where either a conventional technique is combined with a CI-based technique or combining two CI-based MPPT techniques. Examples of hybrid techniques are the GA-ANN based MPPT technique given in [58], a grey wolf–assisted perturb and observe algorithm (GWO-P&O) [59] and an adaptive neuro-fuzzy inference system (ANFIS) based technique [60]. Other CI-based MPPT techniques of interest include ANFIS-PSO-based technique [61] and genetic algorithms [62]. **Table III** presents the performance comparison of different techniques for MPPT.

TABLE III: COMPARISON OF CI AND CONVENTIONAL TECHNIQUES FOR MPPT.

Ref	Year	Author	Technique	Classification	Performance (Efficiency)
[58]	2011	R. Ramaprabha	GA-ANN	CI	99.94 %
[47]	2012	J.S. Kumari	P&O	Conventional	94.38 %
[62]	2014	S. Daraban	GA	CI	97.70 %
[53]	2014	C.L. Liu	FL	CI	99.93 %
[51]	2014	A. Sandali	FSC	Conventional	98.54 %
[49]	2015	P. Sivakumar	InCon	Conventional	96.60 %
[48]	2016	N.E. Zakzouk	InCon	Conventional	99.70 %
[50]	2016	D. Baimel	FOCV	Conventional	98.19 %
[59]	2016	S. Mohanty	GWO-P&O	CI	99.84 %
[46]	2017	V.R. Kota	P&O	Conventional	99.75 %
[54]	2017	S. Ozdemir	FL	CI	99.10 %
[45]	2018	M. Abdel-Salam	P&O	Conventional	99.48 %
[52]	2018	U. Yilmaz	FL	CI	99.40 %
[57]	2019	R. Divyasharon	ANN	CI	99.70 %
[61]	2019	N. Priyadarshi	ANFIS-PSO	CI	99.51 %
[55]	2022	S. Chahar	ANN	CI	96.48 %
[56]	2022	S.R. Kiran	ANN	CI	98.15 %
[60]	**2022**	**R.T. Moyo**	**ANFIS**	**CI**	**99.97 %**

E. Forecasting

Forecasting in SPV systems can be grouped into two types named: (a) solar irradiance forecasting and (b) forecasting of energy production. Solar irradiance forecasting involves the estimation of the irradiance expected to be received over a certain period. Energy production forecasting focuses on the estimation of the power output from the PV modules. The forecast information is very crucial for the management and control of solar PV hybrids systems as well as for energy trading [63]. Several methods of different architecture and complexity have been explored to solve this forecasting problem. Forecasting in SPV systems can also be grouped as short-term, mid-term or long-term forecasting and different forecasting methodologies have been utilized depending on the type of problem. The performance of the techniques in this category was evaluated using the RMSE given by Equation (1).

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1. Irradiance Forecasting

Forecasting solar irradiance is essential for grid-connected photovoltaic (PV) plant performance and power estimation. Both conventional and modern techniques have been used for irradiance forecasting. In [64], the authors presented a statistical Fourier trend model for short-term solar irradiance forecasting. Their model was able to achieve around 90% forecasting accuracy and produced better results as compared to other popular statistical models. In [65], an automated convolutional neural network long short-term memory (CNN-LSTM) architecture was designed for forecasting solar irradiance.

The proposed model outperformed other models in terms of the MAE, RMSE and Pearson metrics. Other techniques that show better results as applied to solar irradiance forecasting include deep recurrent neural networks (DRNNs) [66] and convolutional neural networks. Table IV shows a review of different techniques as applied to solar irradiance forecasting as well as their performances.

TABLE IV: COMPARISON OF CI AND CONVENTIONAL TECHNIQUES FOR SOLAR IRRADIANCE FORECASTING.

Ref	Year	Author	Technique	Classification	Performance (RMSE)
[64]	2013	Z. Dong	Statistical Fourier trend model	Conventional	0.1964
[66]	2017	A. Alzahrani	DRNNs	C1	0.0860
[67]	2019	S. Ghimire	Convolutional neural networks	CI	0.1801
[65]	**2021**	**S.M.J. Jalali**	**CNN-LSTM**	**CI**	**0.0136**

2. Forecasting of the Power Production

The power generated by photovoltaic modules is affected by solar irradiation and temperature. As a result, predicting the output power is a hot topic for photovoltaic experts to research. The literature reports different kinds of methods to tackle this problem. In [68], a seasonal decomposition least-square support vector regression model was proposed to forecast monthly solar power output.

After a comparative study, it was found that the ESDLS-SVR model performed better as compared to other statistical models such as the autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA).

Another method was presented in [69], to forecast a day-ahead power output from PV plants based on the least-square optimization technique. To validate the model, the methodology was compared with previous studies and the results were promising.

An ANN-based model was also used to forecast the average power output from PV modules [70]. In this model, GAs were utilized to optimize the parameters of the ANN architecture. The findings showed that the proposed model performs better than other forecasting models such as ARIMA.

Other important techniques that have been used for forecasting the output power of PV modules include the variation auto-encoder-driven deep learning approach [71] and gated recurrent unit recurrent neural networks (GRU-RNN) [72]. **Table V** shows the performance of different techniques for energy production forecasting.

TABLE V: COMPARISON OF CI AND CONVENTIONAL TECHNIQUES FOR ENERGY PRODUCTION FORECASTING.

Ref	Year	Author	Technique	Classification	Performance (RMSE)
[70]	2012	H.T.C. Pedro	ANN-GA model	CI	0.1307
[68]	2016	K.P. Lin	ESDLS-SVR	Conventional	0.1618
[69]	2016	D.P. Larson	Least-squares optimization model	Conventional	0.1020
[71]	2020	A. Dairi	Deep learning	CI	0.1731
[72]	**2021**	**A.A. Du Plessis**	**GRU-RNN**	**CI**	**0.0802**

F. *Fault Detection and Diagnosis*

PV systems typically operate in harsh outdoor environments. The PV system is prone to different types of system faults and defects when operating in such a setting. These faults and defects can come from the PV array itself or the components connected to it. PV array-related faults can be grouped into three categories depending on their time characteristics. **Figure 5** shows PV array-related faults. Other faults that come from components connected to the PV arrays include MPPT faults and inverter faults.

Numerous fault detection and diagnosis techniques have been developed and suggested to identify the type and location of different failures in a PV system. The main idea is to develop a robust technique that can detect evolving faults quickly to increase the system's reliability and lifetime. Fault detection methods listed in the literature include visual methods, imaging techniques, electrical methods and computational intelligence techniques. For this application, the techniques were evaluated using the prediction efficiency given by,

$$\eta = \frac{P_c}{N} \times 100\% \quad (4)$$

where P_c is the number of correct predictions made and N is the total number of test examples. In [73], a fault and diagnosis procedure based on the probabilistic neural networks (PNN) was presented. The proposed technique demonstrated a higher efficiency as compared to the feed-forward back-propagation artificial neural networks for noiseless and noisy data.

An enhanced ensemble learning technique was utilized in [74] to detect and diagnose the faults in a grid-connected PV system. The testing results of this technique indicated a high prediction accuracy of 99.96 %. In [75], a technique based on supervised machine learning was presented.

The technique was tested using real grid-connected PV data and the results showed the effectiveness of the proposed method. A statistical technique based on the univariate and multivariate exponentially weighted moving average (EWMA) was also used for fault detection of PV systems [76].

This technique was implemented using real data and the results proved its capabilities in detecting partial shading. Some other fault detection techniques worth noting are the decision tree algorithm [77], laterally primed adaptive resonance theory (LAPART) [78], regression-based approach [79], machine learning (k-nearest neighbours) [80], fine-tuning naive bayesian model [81] and ANFIS [82]. **Table IV** presents the performance analysis of different techniques for fault detection and diagnosis.

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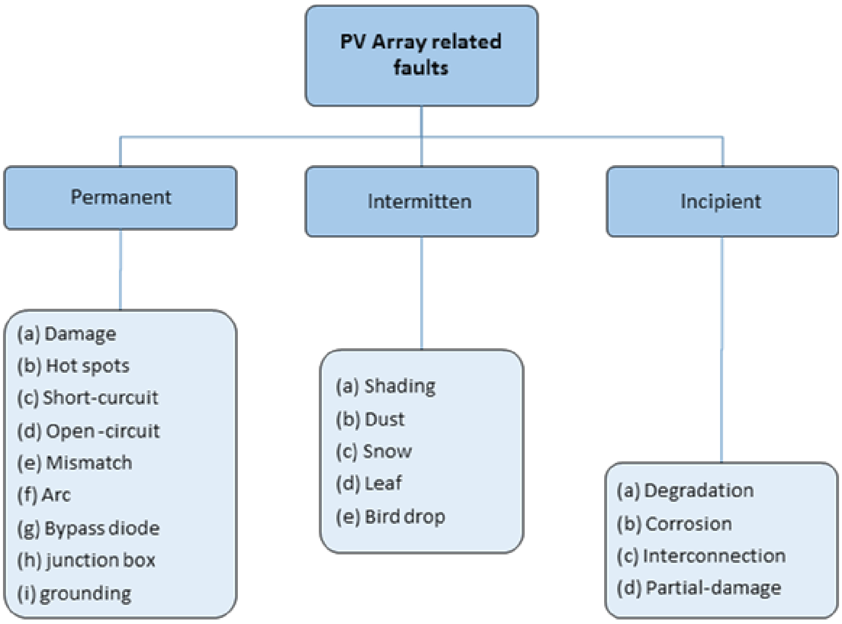

Fig. 5. PV array-related faults.

TABLE VI: COMPARISON OF CI AND CONVENTIONAL TECHNIQUES FOR FAULT DETECTION AND DIAGNOSIS.

Ref	Year	Author	Technique	Classification	Performance (Efficiency)
[78]	2015	C.B. Jones	LAPART	Conventional	86.00 %
[73]	2017	E. Garoudja	PNN	CI	98.09 %
[77]	2018	R. Benkercha	Decision tree algorithm	CI	99.80 %
[82]	2018	M. Dhimish	ANFIS	CI	92.10 %
[80]	2018	S.R. Madeti	Machine learning	CI	98.70 %
[76]	2018	F. Harrou	EWMA	Conventional	95.00 %
[79]	2019	A. Dhoke	Regression-based approach	Conventional	97.00 %
[75]	2021	M. Hajji	Machine learning	CI	99.03 %
[74]	**2021**	**K. Dhibi**	**Enhanced ensemble learning**	**CI**	**99.96 %**
[81]	2021	W. He	Fine-Tuning Naive Bayesian Model	Conventional	98.59 %

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G. Inverter Control

In PV systems, there exist DC/AC inverters responsible for generating the 3-phase AC voltage for the load. The main aim of inverter control is to regulate the AC output voltage and frequency to make sure that it has low harmonic distortions. This is to make sure that the power that is being supplied to the load is of good quality. Different techniques have been developed and suggested for inverter control of PV systems. The performance of the proposed techniques in this section was evaluated using total harmonic distortion (THD) given by,

$$THD_{(v)}(\%) = \frac{1}{V_1}\sqrt{\sum_{h=2}^{\infty} V_h^2} \times 100 \qquad (5)$$

where V_1 is the fundamental voltage and V_h represents the h[th] harmonic voltage. In [83], the authors proposed a multilevel inverter for SPV systems based on fuzzy logic control. The proposed system showed improved performance as compared to two-level inverters and under low to medium power range. In [84], a technique based on the IoT and ANN was proposed for monitoring and controlling a SPV system. The proposed method was simulated in MATLAB/ Simulink environment and the results were compared to the proportional-integral (PI) controller.

The results showed that the proposed technique was efficient and able to monitor the THD, voltages and phase angle variations within the required limits. In [85], a 3-phase three-level inverter was designed and implemented for controlling the current and voltage of a SPV system. The control was realized using a PI controller. The performance of this technique was satisfying and it can also be applied for very high powers. A quasi-Z-source inverter was also suggested for inverter control of SPV systems [86]. The developed topology was implemented using a proportional-integral sinusoidal (PIS) controller. In [87], an adaptive sliding mode (SM) control was utilized for a two-level inverter to control a grid-connected SPV system.

The proposed technique showed better results as compared to other schemes at different load and solar irradiance levels. Some other inverter control techniques worth noting include the adaptive neuro-fuzzy inference system and proportional-integral-derivative control (ANFIS-PID) [88], pulse-width-modulation (PWM) control scheme [89] and vector control (VC) [90]. **Table VII** shows the performance of different techniques for inverter control.

TABLE VII: COMPARISON OF CI AND CONVENTIONAL TECHNIQUES FOR INVERTER CONTROL.

Ref	Year	Author	Technique	Classification	Performance (THD)
[83]	2010	C. Cecati	FL	CI	3.10 %
[86]	2010	M .Shahparasti	PIS	Conventional	3.62 %
[89]	2010	N.A. Rahim	PWM	Conventional	3.90 %
[85]	2014	S. Ozdemir	PI	Conventional	3.45 %
[87]	2015	N. Kumar	SM	Conventional	4.75 %
[88]	2017	N. Mahmud	ANFIS-PID	CI	2.70 %
[90]	2019	N. Kumar	VC	Conventional	2.96 %
[84]	**2020**	**J. Gupta**	**IoT-ANN**	**CI**	**2.61 %**

H. Solar Tracking System

Solar tracking systems are controllers used to guide PV modules towards the sun. They improve the efficiency of PV modules by making sure that the modules are always aligned with the rotating sun. It was proven that solar trackers increase the power output of solar panels up to 60% more than a stationery system [91].

There are mainly two types of solar trackers; single-axis and dual-axis tracking controllers. Different mechanisms have been developed and proposed for solar tracking. The performance of these techniques is measured in terms of the increase in power output (IPO) as compared to a stationary system.

$$IPO(\%) = \left(\frac{P_T - P_F}{P_F}\right) \times 100 \qquad (6)$$

where P_T is the power generated by the studied tracking system and P_F is the power from a fixed flat-plate system. In [92], a dual-axis programmable logical controller (PLC) was designed and implemented for solar tracking. The controller was compared with

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a fixed-angle PV system and the results confirmed the superiority of the proposed method. In [93], an ultraviolet (UV) sensor-based dual-axis solar tracking system was presented. For validation, the proposed technique was compared to a fixed-angle system and a light-depended resistors (LDRs) based solar tracking system. The results showed that the proposed technique is reliable and profitable. An FL controller is suggested for the design of a dual-axis solar tracking system as reported in [94]. This controller was fully automatic and it was able to consider the changes in weather patterns. In [95], a technique based on DELTA PLC was proposed. The tracking was performed with the help of LDR sensors and magnetic reed switches to control the direction and the speed of the gear motor. The power generation from the proposed system showed a significant increase as compared to that obtained from a fixed system. **Table VIII** presents the performance of different techniques for solar tracking.

TABLE VIII: COMPARISON OF CI AND CONVENTIONAL TECHNIQUES FOR SOLAR TRACKING SYSTEMS.

Ref	Year	Author	Technique	Classification	Performance (IPO)
[92]	2013	T.S. Zhan	PLC	Conventional	25.00 %
[94]	**2016**	**C.H. Huang**	**FL**	**CI**	**36.00 %**
[95]	2016	B.K.S. Vastav,	DELTA PLC	Conventional	25.00 %
[93]	2021	C. Jamroen	UV	Conventional	19.97 %

IV. DISCUSSION

In this paper, more than 300 articles were reviewed. The main emphasis was to provide relevant achievements of CI techniques in SPV systems. The paper gives a comparison of different CI techniques as well as conventional methods in each application in terms of their performance. This section provides the findings of the study.

Parameter identification of solar cell models is very crucial since it is the backbone for SPV modelling and design. Several techniques of different complexities were proposed to tackle this problem. Generally, the CI techniques showed better performances as compared to conventional methods with the SSA achieving the RMSE of 1.30×10^{-8} for both the SD and DD models. Other CI techniques that performed well for both the SD and DD models are the GA, JAYA algorithm, PSO and SA.

The best conventional method was the Newton-Raphson technique with the RMSE of 1.98×10^{-6}. However, this technique was only tested for a SD model. A conventional method which was tested for both the SD and DD models is the Adaptive-Newton Raphson and it performed fairly with a RMSE of 4.83×10^{-3}. It can be concluded that CI techniques have significantly improved the parameter estimation of solar cell models and it is very vital for the accurate modelling of SPV systems.

Accurate sizing of the components of a SPV system is very important when designing solar systems. Over-sizing of SPV systems would lead to unnecessary higher investments whereas under-sizing may cause an insufficient power supply to connected loads. Both conventional and CI techniques were utilized for sizing SPV systems. The performance of these techniques was measured using the correlation coefficient. A CI technique based on ANN and GAs was found to be the best with a correlation coefficient of 0.9998 followed by the RBFNN method. The best conventional method was the Markov chain technique which showed a correlation coefficient of 0.9650. For this application, it can be concluded that the involvement of CI has improved the sizing of SPV systems.

Maximum power point tracking controllers play a pivotal role in maximizing the power output of solar modules. In general, a MPPT controller is a DC-DC power converter controlled by an algorithm to always force the PV module to operate at its MPP. The best of both the conventional and CI techniques were reviewed and they all showed an outstanding performance for MPPT. The best technique was a CI-based method (ANFIS) with an efficiency of 99.97%. A GA-ANN method also gave an outstanding performance with an efficiency of 99.94%. Some other CI techniques that performed well for this application are FL, ANFIS-PSO and GWO-P&O. Conventional techniques also showed an impressive performance with the best technique (P&O) with an efficiency of 99.75%. The incremental conductance was the second-best conventional technique with an efficiency of 99.70%. From the above-presented analysis, it is clear that CI techniques have been instrumental in designing MPPT controllers.

Forecasting in SPV systems involves solar irradiance forecasting and energy production forecasting. Solar irradiance forecasting focuses on estimating the irradiance to be received at a particular place and time whereas energy production forecasting deals with predicting the power output from PV modules.

Generally, it was observed that forecasting is very difficult when it comes to SPV systems and it was deduced from high RMSE values in both cases. However, CI techniques performed better than conventional methods and the automated CNN-LSTM was the best technique for irradiance forecasting with a RMSE of 0.0136. A conventional technique that showed better results for irradiance forecasting was the statistical Fourier trend model with a RMSE of 0.1964. For energy production forecasting, the GRU-RNN was found to be the best with a RMSE of 0.0802. The least-squares optimization model was the conventional technique with better results for energy production forecasting with a RMSE of 0.1020. It can be then concluded that CI techniques have improved both irradiance forecasting and energy production forecasting of SPV systems.

Fault detection and diagnosis techniques are very important to ensure the maximum performance of SPV systems. Several methods were developed and suggested for fault detection and diagnosis. CI techniques proved to be more efficient in this application as compared to conventional methods. A technique based on enhanced ensemble learning was found to be the best with an efficiency of 99.96%. Other CI techniques that performed well include decision tree algorithm, PNN and different machine learning techniques. A conventional method that performed fairly was the Fine-Tuning Naïve Bayesian model, with an efficiency of 98.59%. Based on the given analysis, it can be concluded that the adoption of CI techniques for fault detection and diagnosis has a greater impact on the development of SPV systems.

In PV systems, inverters are used to transform DC to AC for the loads. Inverter control involves regulating the output AC voltage and frequency to ensure the supply of power of good quality to the loads. In this application, both the conventional and CI techniques demonstrated outstanding performance for inverter control. The best technique was the IoT-ANN, a CI technique, with a maximum THD of 2.61%. An ANFIS-PID method was the second best with a THD of 2.70%. Conventional techniques proved their relevance for this application with their best technique with a THD of 2.96%. For this application, CI techniques were the best, but conventional methods were also competing in the same range.

Solar tracking systems are important for ensuring that the PV modules are always aligned with the rotating sun. All techniques presented for this application performed well. The FL controller was the best technique with an IPO of 36% and it was the only CI technique in this application. Conventional methods that showed better performance were the PLC and DELTA PLC, both with an IPO of 25%. It can be concluded that CI techniques have shown an improvement as far as solar tracking is concerned but there is still room for the adoption of more CI for solving this particular problem.

V. CONCLUSIONS

This paper explores the role of CI techniques in the advancements of SPV systems for sustainable development. The conclusion that can be drawn from this work is that CI techniques are involved in every aspect of SPV systems and have significantly improved the adoption of SPV systems. This paper compares different CI techniques and conventional methods in terms of performance. In all SPV areas studied, CI techniques proved to be superior to conventional methods. In the literature, several CI techniques have been developed and suggested for different applications, however, selecting an appropriate technique for a given application is of prime importance. Thus, the findings from this work can assist other researchers to choose suitable CI techniques for a given application. This paper also serves as a reference for all academics interested in studying the application of computational intelligence in SPV systems.

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