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A Type-2 Fuzzy Logic Expert System for AI Selection in Solar Photovoltaic Applications Based on Data and Literature-Driven Decision Framework

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Abstract: Artificial intelligence (AI) has emerged as a transformative tool for optimizing photovoltaic (PV) systems, enhancing energy efficiency, predictive maintenance, and fault detection. This study presents a systematic literature review and bibliometric analysis to identify the most commonly used AI techniques and their applications in PV systems. The review provides details on the advantages, limitations, and optimal use cases of various review techniques, such as Artificial Neural Networks, Fuzzy Logic, Convolutional Neural Networks, Long-Short Term Memory, Support Vector Machines, Decision Trees, Random Forest, k-Nearest Neighbors, and Particle Swarm Optimization. The findings highlight that maximum power point tracking (MPPT) optimization is the most widely researched AI application, followed by solar power forecasting, parameter estimation, fault detection and classification, and solar radiation forecasting. The bibliometric analysis reveals a growing trend in AI-PV research from 2018 to 2024, with China, the United States, and European countries leading in contributions. Furthermore, a type-2 fuzzy logic system is developed in MATLAB R2023b for automating AI technique selection based on the problem type, offering a practical tool for researchers, industry professionals, and policymakers. The study also discusses the practical implications of adopting AI in PV systems and provides future directions for research. This work serves as a comprehensive reference for advancing AI-driven solar PV technologies, contributing to a more efficient, reliable, and sustainable energy future.

Keywords: artificial intelligence; solar photovoltaic energy; fuzzy logic system; literature review

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1. Introduction

Solar photovoltaic (PV) systems have become a cornerstone of the global shift towards renewable energy, providing a sustainable solution to meet growing energy demands while addressing environmental concerns. Their ability to capture abundant solar radiation and convert it into electricity positions them as a leading renewable energy technology [1]. However, several key challenges continue to hinder their widespread adoption and optimal performance. These include efficiency losses caused by environmental variability, shading, and temperature fluctuation; complexities in maintenance; and difficulties integrating with existing grid systems [2].

Artificial intelligence (AI) has emerged as a game-changing technology for addressing the challenges faced by solar PV systems. By applying AI-driven algorithms for predictive maintenance, efficiency optimization, and system monitoring, researchers and industry professionals are enhancing the operational reliability and economic viability of PV systems [3]. Interest in integrating AI with PV technologies has grown significantly in recent years, highlighting their immense potential. For example, advancements in machine learning and big data analytics have greatly improved the accuracy of energy yield predictions and system fault diagnosis [4].

By facilitating advanced solutions such as predictive maintenance, energy forecasting, and real-time fault detection, AI can enhance the efficiency and reliability of PV systems while reducing operational costs and downtime. This integration is especially vital in the context of the global shift toward renewable energy, as the demand for sustainable energy solutions continues to rise. However, despite rapid advancements, the current body of literature often lacks a comprehensive method of synthesis that captures the full range of AI techniques and their applications throughout the PV system lifecycle. Additionally, challenges such as scalability, generalizability, and integration with grid and energy storage systems remain underexplored, highlighting the need for in-depth review to guide future research efforts.

This study aims to address these gaps by systematically reviewing the current body of research on AI applications in solar PV systems. Utilizing the PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analyses) methodology, 163 papers published between 2020 and 2024 were selected from an initial dataset of 774 studies for detailed analysis. The review examines the AI techniques employed, their applications across various stages of the PV system lifecycle, and the challenges and opportunities shaping this field. Furthermore, it introduces an AI selection system.

This study makes several contributions to the field of AI applications in PV systems, providing a comprehensive analysis of AI-driven advancements for improving PV performance, efficiency, and reliability. The key contributions of this work are as follows:

- Presenting a systematic literature review of the most commonly used AI techniques, including Artificial Neural Networks (ANNs), fuzzy logic (FL), Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVMs), Decision Trees (DT), Random Forest (RF), k-Nearest Neighbors (kNN), and Particle Swarm Optimization (PSO). It highlights the advantages and limitations of each technique in PV applications;
- Categorizing the most relevant AI applications in PV systems, identifying Maximum Power Point Tracking (MPPT) optimization, solar power forecasting, parameter estimation, fault detection, and solar radiation forecasting as the most extensively researched areas. The review quantifies the impact of AI on each of these applications;
- This work includes a bibliometric analysis, identifying publication trends, leading countries, and research hotspots;
- Identifying current challenges in AI-driven PV optimization and outlining key future research directions;
- Structuring a decision-making framework for selecting AI techniques based on problem complexity, data availability, and computational requirements;
- Introducing a MATLAB-based type-2 fuzzy system to assist the user in selecting the most suitable AI technique for PV applications by accounting for uncertainty in input variables and expert evaluations;
- Finally, this study serves as a reference for researchers, engineers, and policymakers, as it can contribute to the standardization of AI methodologies in PV systems,

helping the stakeholders involved align their works with emerging trends and technological advancements.

Unlike prior reviews that focus either on technical performance or specific AI models, this study integrates a PRISMA-based literature review with a bibliometric analysis and a Type-2 Fuzzy Logic Expert System to guide AI model selection in solar PV applications. This hybrid methodology offers both a systematic synthesis of current research and a decision-support framework, addressing both academic and practical gaps in the field.

The remainder of this paper is organized as follows. Section 2 outlines the methodology for the literature review, including the use of the PRISMA framework and bibliometric tools. Section 3 presents the findings from the bibliometric analysis and literature review, focusing on key AI techniques and their applications. Section 4 offers recommendations for future research directions. Section 5 shows the recommended decision-making framework for AI selection in PV systems, including the developed MATLAB-based type-2 fuzzy system, while Section 6 presents a discussion of the main insights of this work. Finally, the paper concludes with a summary of the findings and their implications for the field.

2. Methodology: PRISMA

To ensure transparency, methodological rigor, and replicability, this study used the PRISMA framework. This approach offers a structured, step-by-step process for conducting a systematic review, ensuring a thorough and impartial analysis of the existing literature. As established in prior research [5], the methodology is divided into two primary phases:

1. Identification and screening. This initial phase involves defining research questions, creating a review protocol, performing extensive searches across various databases, and assessing the relevance of retrieved studies by reviewing their titles, abstracts, and full texts;
2. Data extraction and synthesis. In this stage, relevant data are systematically gathered using standardized formats, organized effectively, and analyzed through narrative descriptions, statistical methods, or meta-analytical techniques.

By adhering to this methodology, this review aims to address the following research questions:

1. What are the primary AI techniques applied to solar PV systems, and how have they evolved over the years?
2. What are the most common application areas for AI in the lifecycle of solar PV systems, and what challenges do they address?
3. What gaps exist in the current body of research, and what future directions are proposed for integrating AI into solar PV systems?

The systematic literature review workflow is outlined in Figure 1, and it consists of the following stages:

1. **Identification.** A total of 774 papers were retrieved from the Web of Science database. The search strategy targeted titles, abstracts, and keywords using terms such as "artificial intelligence", "AI", "solar photovoltaic", "photovoltaic system", and "photovoltaic panel". The inclusion criteria for this stage were journal articles published between 2020 and 2024 in English or Spanish;
2. **Screening.** After applying filters for document type, publication year, language, and category, 307 papers were retained. At this stage, duplicates and unrelated studies were excluded, resulting in 193 papers. Titles and abstracts were reviewed to eliminate studies irrelevant to the scope of the chosen title. Table 1 provides a detailed summary of the inclusion and exclusion criteria applied during this phase.

3. **Eligibility.** The full texts of the remaining 213 papers were reviewed. Studies that lacked an explicit application of AI or did not focus on solar PV systems were excluded, leaving 163 eligible papers. Exclusions included 50 studies, with 26 full texts unavailable and 6 review papers not meeting inclusion criteria;
4. **Inclusion.** The final dataset comprised 163 papers deemed relevant for inclusion in the review. These papers were selected based on their adherence to the defined criteria and their focus on the application of AI in solar PV systems.

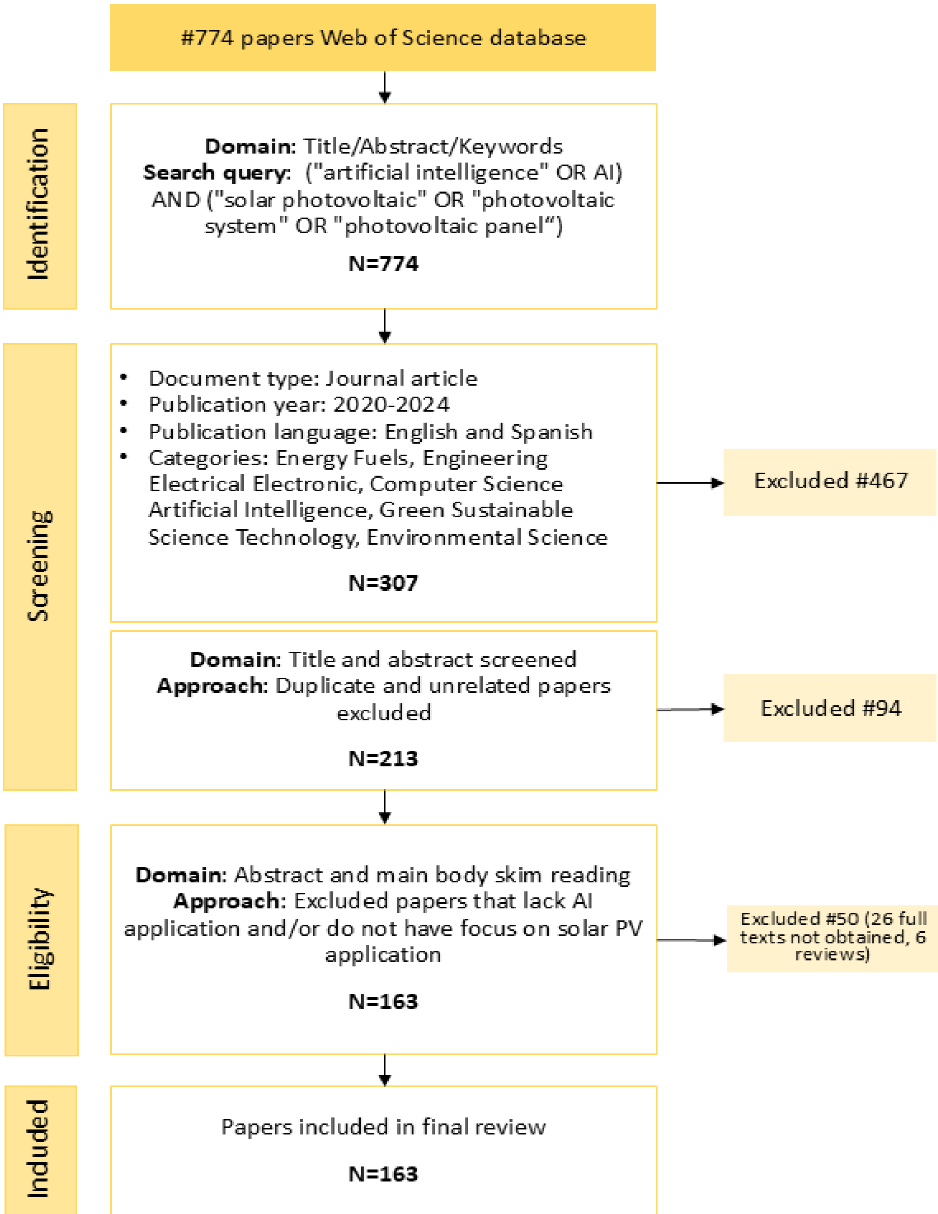

Figure 1. Methodology of the systematic literature search used in this study.

Data from the selected studies were carefully extracted and compiled into a structured database (Table A1—Appendix A). This included details such as author(s), title, publication year, journal name, AI techniques employed, and their specific applications in solar PV systems. The analysis emphasized identifying key trends, research gaps, and potential opportunities within the field. Furthermore, a bibliometric analysis was performed to better analyze trends in publication frequency, country contributions, and keyword co-occurrence. This methodological approach facilitated an in-depth exploration of the intersection between AI and solar photovoltaic systems, offering valuable insights and highlighting potential directions for future research.

Table 1. Inclusion and exclusion criteria used in the PRISMA review.

Category	Inclusion Criteria	Exclusion Criteria	Justification
Language	English, Spanish	Languages other than English or Spanish (e.g., Chinese, German, French)	Spanish was included due to its relevance in Latin American contexts and the authors' proficiency. Other languages were excluded to ensure consistency in full-text review and due to translation limitations.
Document type	Peer-reviewed journal articles	Editorials, letters, notes, abstracts only, non-peer-reviewed sources	To ensure scientific rigor and reliability of reported results.
Timeframe	Publications from 2020–2024	Publications before 2020	The timeframe reflects the period of significant growth in AI and PV research.
Subject area	AI techniques applied to solar PV systems	Studies on AI unrelated to solar PV or those focusing on other renewable technologies only (e.g., wind, hydro)	Focused on the intersection of AI and solar PV systems to maintain relevance.
Availability	Full-text available online via institutional access or open access	Inaccessible full texts	Full-text access was necessary for accurate content analysis.
Content focus	Application of AI methods (e.g., ML, FL, DL, optimization) to solar PV forecasting, MPPT, fault detection, grid integration, among other applications	Reviews or studies that do not apply or evaluate AI techniques for solar PV systems	The review aimed to synthesize applied AI techniques in the solar PV context specifically.

3. Results

This section presents the results from the bibliometric analysis and the literature review findings.

3.1. Bibliometric Analysis

To provide a comprehensive overview of the research landscape on the application of AI in solar PV systems, a bibliometric analysis was conducted using the 774 papers initially retrieved from the Web of Science database prior to applying inclusion and exclusion criteria. This analysis was performed using the Bibliometrix 4.0.1 [6] tool and VOSviewer 1.6.18 software to examine annual trends, geographical distribution, keyword co-occurrences, and thematic evolution within the field.

The annual distribution of publications on AI applications in solar PV systems, illustrated in Figure 2, shows a significant increase in research activity over the past two decades, with an especially sharp rise in recent years. The number of publications remained relatively low until 2010, after which steady growth was observed. A more pronounced increase is evident from 2018 onward, reflecting the accelerating interest in AI applications for PV systems. The peak in recent years suggests that AI-driven innovations in solar energy are gaining momentum, aligning with global efforts to enhance the efficiency, reliability, and integration of renewable energy technologies. It is important to highlight that the decrease in the scientific production data for the year 2025 is because that year is not included in this study, and the results appearing on the search are "early access".

The geographical distribution of scientific contributions, shown in Figure 3, indicates that research in this field is primarily driven by a few key countries. The United States leads with the highest number of publications, followed by significant contributions from China, India, and several European nations. These countries have invested heavily in AI-driven renewable energy solutions, often supported by governmental policies promoting sustainable energy research. Regions such as South America, the Middle East, and parts of Africa show comparatively lower research activity, pointing to opportunities for greater academic and practical involvement in these areas.

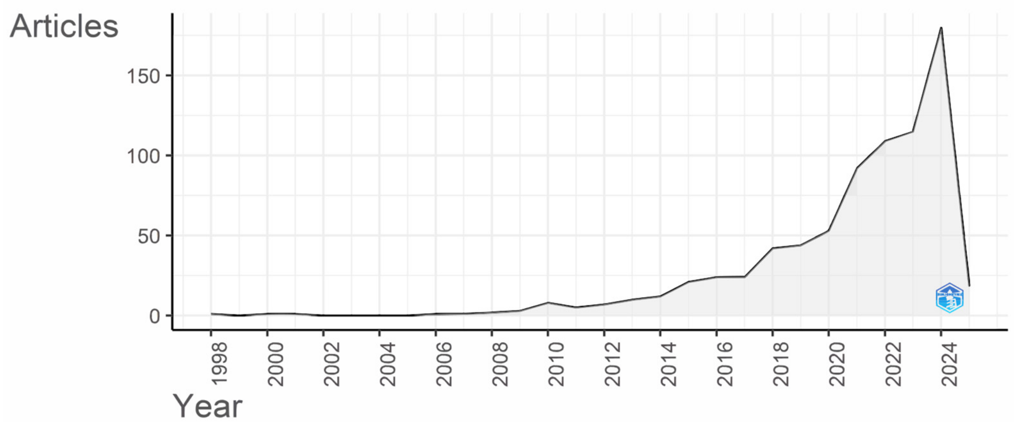

Figure 2. Annual scientific production generated using Bibliometrix 4.0.1.

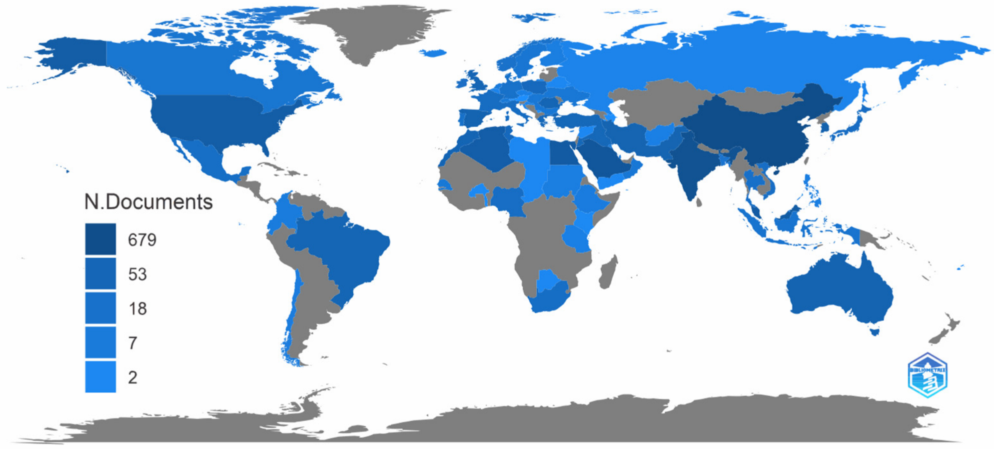

Figure 3. Country scientific production generated using Bibliometrix 4.0.1.

The keyword co-occurrence analysis (Figure 4) highlights the interconnectedness of key themes within this research area. Prominent terms such as "artificial intelligence", "solar energy", "photovoltaic systems", and "optimization" reflect the central focus of the literature. Clusters of related keywords, including "machine learning", "fault detection", and "energy forecasting", showcase the diverse applications of AI in the field. The network further identifies emerging trends such as "predictive maintenance", "energy management", and "real-time monitoring", signaling the evolving directions of research and innovation.

The keyword density visualization, shown in Figure 5, provides additional insight into the intensity and primary focus areas within the research field. The color gradient indicates the frequency and relevance of keyword appearances across the analyzed literature. Warmer colors (yellow and green) represent higher density and stronger co-occurrence between keywords, whereas cooler colors (blue and purple) indicate lower frequency and weaker associations. Dominant keywords like "artificial intelligence", "optimization", and "photovoltaic systems" stand out, surrounded by related topics such as "power forecasting", "fault diagnosis", and "efficiency". The less-dense areas of the map indicate emerging topics, such as AI applications in hybrid energy systems, real-time monitoring, and the integration of AI with smart grids. These patterns reinforce the notion that while certain AI applications in PV systems are well-established, there remains substantial room for exploration in areas such as intelligent grid coordination and advanced energy management systems.

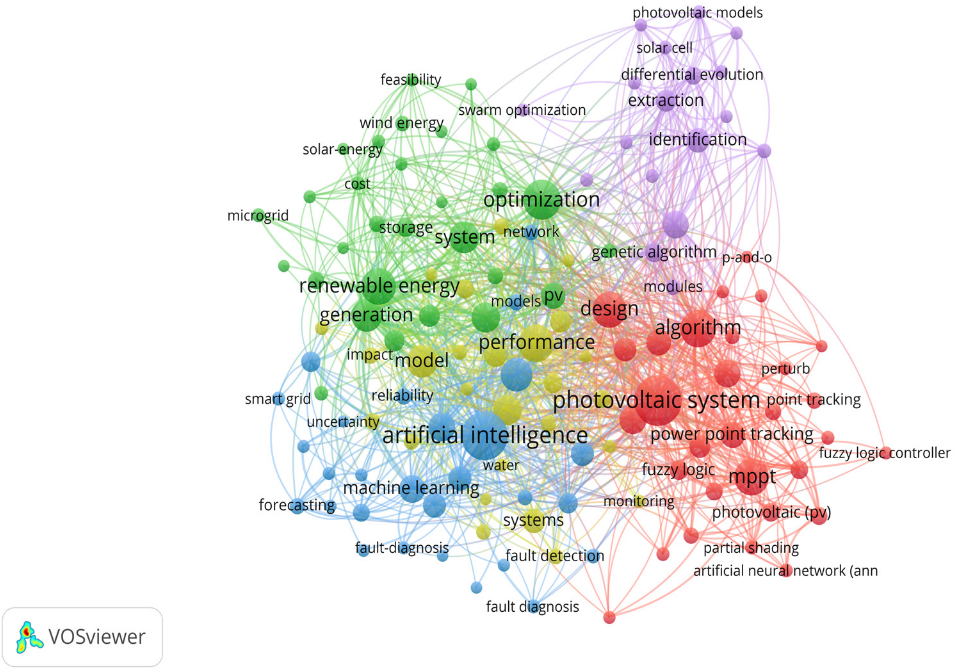

Figure 4. Keyword co-occurrence network generated using VOSviewer 1.6.18.

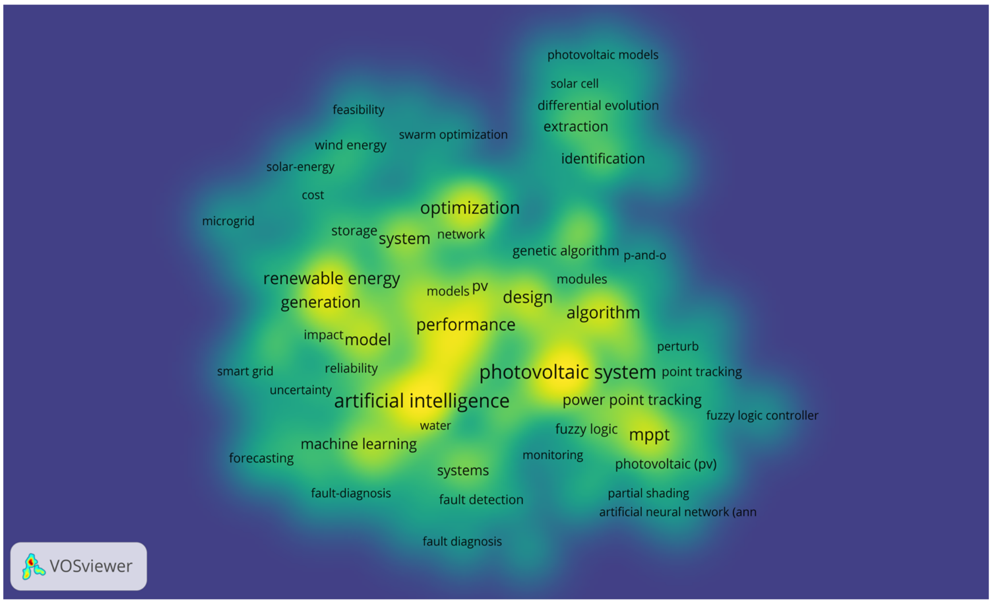

Figure 5. Keyword density network generated using VOSviewer 1.6.18. Warmer colors (yellow/green) indicate higher keyword co-occurrence density, while cooler colors (blue/purple) indicate lower density.

The thematic evolution network (Figure 6) illustrates the progression of research themes over time. This Sankey diagram visualizes how key research themes and keywords have evolved. The left side represents the dominant themes and keywords used in the literature between 1998 and 2019, while the right side shows the themes that emerged or remained relevant from 2020 to 2025. The connecting lines (or flows) indicate the semantic or conceptual continuity between themes across the two periods, based on co-word and co-occurrence analysis.

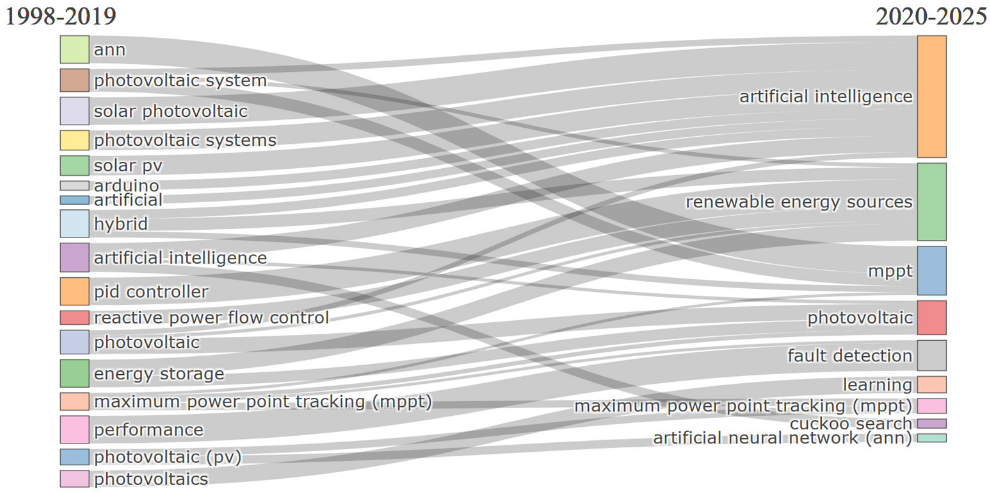

Figure 6. Thematic evolution network generated using Bibliometrix 4.0.1.

The line thickness represents the strength of the connection, that is, how strongly a topic in the earlier period is linked to a theme in the later period, based on shared keywords and context in the reviewed publications.

For example, themes like "photovoltaic system", "solar PV", and "photovoltaic (PV)" evolved into more specific or refined concepts such as "photovoltaic", "MPPT", and "fault detection". Similarly, broad early topics like "artificial intelligence" and "hybrid" transitioned into more applied and granular research themes like "renewable energy sources", "learning", and "artificial neural network (ANN)" in the later period.

The bibliometric analysis underscores the rapid expansion and global reach of research on AI applications in solar PV systems. It highlights leading contributors, key research themes, and their development over time. These insights offer a valuable foundation for understanding the current state of the field and pinpointing areas for future exploration.

3.2. Literature Review Findings

This subsection shows the insights from the 163 papers chosen (Table A1—Appendix A) for in-depth analysis, emphasizing the application of AI techniques in solar PV systems. The review highlights the variety of AI methodologies, their application across different stages of the PV system's lifecycle, and the emerging trends, challenges, and gaps within the existing research.

3.2.1. AI Techniques Applied in Solar PV Systems

The reviewed studies highlight a variety of AI techniques designed to tackle specific challenges in solar PV systems. The reviewed techniques can be broadly classified into categories such as supervised learning (e.g., ANN, SVM, DT, RF, kNN), deep learning (e.g., CNN, LSTM), optimization methods (e.g., PSO), and fuzzy logic-based reasoning systems (e.g., FL). The most common include the following.

- **Artificial Neural Networks (ANNs)**

ANNs are popular for modeling nonlinear relationships and learning from historical data. The topology of ANNs, including the number of hidden layers, neurons per layer, and activation functions, plays a crucial role in its performance. Improper topology selection can lead to underfitting or overfitting, reducing the model's ability to generalize to new data [7,8]. To address this, optimal topologies are often identified empirically or through optimization algorithms, such as particle swarm optimization (PSO) and genetic algorithms (GA), particularly in applications like PV system forecasting and fault detection [9].

Several studies demonstrated that ANN-based MPPT controllers significantly enhance power extraction efficiency, with methods such as wavelet-assisted ANN MPPT achieving a tracking efficiency of 99.9%, outperforming traditional Perturb and Observe methods (P&O) [10]. Similarly, ANN-driven adaptive MPPT for grid-connected PV systems resulted in a 12% efficiency improvement, ensuring stable voltage regulation despite fluctuating solar conditions [11]. ANN-based fault detection and diagnosis models also proved highly effective, with hybrid ANN-Fireworks Algorithm (FWA) techniques achieving 99.98% accuracy and significantly reducing diagnostic time [12]. In PV inverter fault tolerance, ANN-based real-time control reduced total harmonic distortion (THD) to 8.24%, thereby enhancing system stability and resilience [13].

ANN-based forecasting models also demonstrated high accuracy in predicting solar energy generation and urban energy demand, with Decision Support Systems achieving 99% predictive accuracy [14]. Hybrid ANN approaches, such as ANN-FLC and variable step P&O, further improved MPPT performance under partial shading conditions, tracking power with >99.65% efficiency while reducing steady-state oscillations [15]. These findings underscore ANN's ability to optimize PV efficiency, enhance grid reliability, and support intelligent energy management in smart cities.

- **Fuzzy Logic (FL)**

FL systems are used for decision-making under uncertainty by applying rule-based reasoning. Studies have demonstrated that FL-based MPPT algorithms outperform conventional techniques like P&O by providing faster adaptation to varying irradiance and temperature conditions. A comparative study showed that an FL-enhanced P&O method reduced oscillations in steady-state conditions while achieving a higher power yield [16]. Additionally, a hybrid FL-MPPT system integrating genetic algorithms (GA) and PSO improved tracking accuracy and reduced power loss, leading to a tracking efficiency above 99.5% [17].

A study comparing FL and ANNs used in real-time PV fault detection demonstrated that FL achieved 99.2% accuracy in identifying six common fault types, including partial shading, bypass diode failures, and soiling [18]. Another study integrating FL-based voltage source control with a multilevel inverter showed a significant reduction in THD, with voltage THD as low as 1.13% and current THD below 1.52%, ensuring smoother grid integration [19].

The emergence of hybrid AI controllers, such as FL–ANN and FL–Genetic Algorithm combinations, presents a promising avenue for further research. These approaches leverage FL's rule-based adaptability and ANN's pattern recognition capabilities, offering higher precision and robustness in dynamic PV environments [20].

- **Convolutional Neural Networks (CNNs)**

CNNs are powerful in processing spatial data, and have been widely used for fault detection through image classification.

A key application of CNNs is in fault detection and the classification of PV panel defects. One study employed a Visual Geometry Group (VGG-16)-based CNN model for detecting physical and electrical anomalies in PV systems using radiometric infrared thermography. The system achieved 91.46% accuracy in classifying common defects [21]. Another investigation implemented CNN-based aerial imaging to detect hotspots and cracks in PV panels, demonstrating 93.3% classification accuracy [22]. A hybrid CNN–Multilayer Perceptron (MLP) outperformed traditional statistical models by effectively predicting global solar radiation with high spatial accuracy [23]. Furthermore, CNN-driven geospatial mapping techniques have been used to detect and quantify rooftop installations, achieving an average precision rate of 93% [24]. These findings indicate that CNN-based approaches significantly enhance PV system reliability, efficiency, and integration into energy grids.

- **Long Short-Term Memory (LSTM)**

LSTM networks are a type of recurrent neural network designed to capture temporal dependencies in time-series data.

LSTM-based solar power forecasting models have proven superior to traditional statistical methods, particularly in handling nonlinear meteorological data. A hybrid CNN-LSTM model was developed for PV power estimation, achieving R^2 values above 0.98 across varying weather conditions, and thus demonstrating high reliability in forecasting [25]. The R^2 value, also known as the coefficient of determination, shows how well the model's predictions match the actual data—values closer to 1.0 mean better accuracy. Similarly, an LSTM-based smart grid recommender system optimized energy harvesting strategies, reducing the gap between predicted and actual PV energy generation, and improving grid demand response management [26].

An LSTM model was compared against ANNs and regression-based approaches for tracking global maximum power points. The results indicate that LSTM reduced power tracking errors by 31% compared to ANN models, proving its efficiency in the real-time optimization of PV systems under partial shading conditions [27]. Furthermore, hybrid wavelet–LSTM models have been successfully applied to solar tracking systems, achieving higher accuracy in power estimation for dual-axis PV trackers, enabling real-time position adjustments based on forecasted solar intensity [28].

These findings highlight the robustness of LSTM-based models in addressing solar energy intermittency, optimizing power generation, and enhancing MPPT efficiency.

- **Support Vector Machine (SVM)**

SVMs are supervised learning models effective for use in classification tasks with small datasets. A study utilizing a Least Squares SVM (LSSVM) model combined with Variational Mode Decomposition (VMD) and Whale Optimization Algorithm (WOA) achieved a 17.17% reduction in Mean Absolute Percentage Error compared to conventional SVM approaches [29]. Another study implemented an SVM-based prediction framework for residential PV power estimation in Saudi Arabia, achieving higher accuracy than conventional regression models when applied to real-time weather and irradiance datasets [30]. A cloud-computing-integrated SVM fault detection system was validated using MATLAB/Simulink simulations and achieved 97.4% classification accuracy in differentiating various PV system faults [31]. Another study proposed an ensemble learning model combining SVM with k-Nearest Neighbors (kNN) and Decision Trees, achieving high precision in detecting snail trail faults, microcracks, and panel delamination issues [32]. An SVM-based islanding detection technique integrated with Gaussian Radial Basis Function kernels achieved 99.2% detection accuracy while minimizing false alarms to 0.2%, significantly outperforming traditional passive and active islanding detection methods [33]. These findings confirm that SVM-based approaches are highly effective in PV fault diagnostics, short-term energy forecasting, and grid stability assessments.

- **Decision Trees (DT) and Random Forest (RF)**

DTs offer interpretable rule-based structures for decision-making, while RF is an ensemble learning technique that constructs a collection of decision trees and averages their outputs to enhance accuracy and generalization.

A major application of RF and DT models is in solar PV power forecasting, where they outperform traditional statistical models in predicting short-term and long-term energy generation. A study integrating Random Forest with Data Envelopment Analysis for PV site selection demonstrated that RF models effectively predict solar panel efficiency across various locations, helping policymakers and energy planners optimize solar farm placement [34]. Another investigation in PV power forecasting under soiling conditions showed that RF models incorporating a Cleanness Index significantly improved accuracy, reducing the Mean Absolute Error from 1.24% to 0.22%, highlighting the effectiveness of feature selection in RF models [35].

A DT-based diagnostic framework for PV systems successfully classified inverter failures, bypass diode malfunctions, and partial shading faults with an accuracy exceeding 95% [36]. Additionally, an ensemble learning model combining DT, SVM, and kNN achieved 99.8% accuracy in detecting line-to-line and open-circuit faults [32].

A recent study on building-integrated PV (BIPV) systems combined RF and LSTM models, reducing the Root Mean Square Error (RMSE) from 4.75 to 2.97 for horizontal surfaces and significantly improving forecasting accuracy [37]. These findings highlight the strength of tree-based machine learning models in enhancing PV system performance, improving fault detection accuracy, and optimizing energy forecasting.

- **k-Nearest Neighbor (kNN)**

The kNN algorithm classifies instances based on similarity to neighboring data points.

A key application of kNN is in solar energy forecasting, where it has been employed to estimate solar radiation and PV power generation. One study applied a kNN-based forecasting model to predict short-term PV power output, achieving 10% to 25% improvement compared to reference persistence methods [38].

kNN models have also been utilized in the fault detection and diagnosis of PV systems. A hybrid kNN–SVM–DT ensemble learning approach was successfully implemented to classify PV panel faults, including snail trail degradation and microcracks, achieving 97.4% fault classification accuracy [32]. Additionally, a study on cloud computing-integrated PV monitoring employed kNN for real-time fault detection, reducing false alarms and misclassifications [31]. In PV site selection and power estimation, kNN has been applied in combination with geospatial analysis and clustering techniques to determine optimal locations for solar panel installation, improving solar harvesting potential while considering environmental conditions [39].

These findings highlight kNN's versatility and accuracy in forecasting, fault detection, and system optimization for PV applications.

- **Particle Swarm Optimization**

PSO is a bio-inspired optimization algorithm that mimics the behavior of bird flocks or fish schools to identify optimal solutions.

One study introduced a fuzzy adaptive PSO-based MPPT approach that dynamically adjusts PSO parameters, leading to a 14% faster convergence under shading conditions and 30% faster under uniform irradiation compared to conventional PSO [40]. Similarly, another study implemented a hybrid PSO-based MPPT for electric vehicles, optimizing power transfer from triple-junction solar cells to a DC–DC converter. The proposed approach outperformed P&O and other heuristic algorithms in terms of response time and efficiency [41].

In solar PV modeling and parameter estimation, PSO has been utilized to accurately identify PV cell parameters for both single-diode and double-diode models. An enhanced PSO method achieved higher parameter estimation accuracy with lower computational complexity than traditional numerical methods [42]. Additionally, a hybrid PSO–Grey Wolf Optimization (PSO-GWO) algorithm demonstrated superior accuracy in extracting PV panel parameters, minimizing RMSE values compared to standalone optimization techniques [43].

A PSO-based two-axis solar tracker optimized panel positioning without requiring a mathematical sun movement model, achieving an increase in energy capture efficiency while reducing computational load [44]. These findings highlight the effectiveness of PSO-based approaches in enhancing MPPT performance, improving parameter estimation accuracy, and optimizing solar tracking systems.

A variety of software tools and platforms are commonly used to implement AI algorithms in solar PV applications, as can be observed in Table 2.

Table 2. Common software platforms used for implementing AI techniques in solar PV applications.

AI Technique	Common Software Tools
ANN, SVM, DT, RF	Python (Scikit-learn), MATLAB (ML Toolbox) [45,46]
CNN, LSTM	Python (TensorFlow, Keras, PyTorch), MATLAB (Deep Learning Toolbox) [21,47]
PSO, GA	MATLAB (Global Optimization Toolbox), Python (PyGAD, DEAP) [48]
FL	MATLAB (Fuzzy Logic Toolbox), Python (scikit-fuzzy) [16]
Reinforcement learning	Python (OpenAI Gym, Stable Baselines), MATLAB (Reinforcement Learning Toolbox) [49]

3.2.2. Applications Across the PV System Lifecycle

AI techniques have been utilized effectively across different stages of the solar PV system lifecycle. The five most common applications include the following.

- **Maximum Power Point Tracking (MPPT)**

MPPT is a technique used in PV systems to continuously adjust operating conditions and maximize power output under varying environmental conditions such as irradiance and temperature.

Among the reviewed studies, MPPT emerged as the most common application of AI in PV systems, with 39 studies dedicated to this topic. MPPT plays a critical role in optimizing energy yield from PV systems, particularly under fluctuating environmental conditions. The surveyed literature highlights a broad spectrum of AI-enhanced MPPT techniques, including machine learning, FL, ANNs, and metaheuristic optimization approaches. Metaheuristic optimization refers to flexible, nature-inspired algorithms used to solve complex optimization problems where traditional methods are inefficient or fail [50].

The studies revealed that hybrid AI-based MPPT strategies provide superior performance compared to traditional P&O or incremental conductance methods. For example, a neuro-fuzzy MPPT control strategy demonstrated an 8.2% increase in average power generation and 60% reduction in tracking time compared to conventional techniques [51]. Additionally, an AI-enhanced MPPT algorithm leveraging PSO and FL achieved a tracking efficiency of 99%, outperforming traditional approaches in dynamic irradiance scenarios [52]. Another study introduced a novel metaheuristic-based MPPT algorithm that significantly improved convergence speed and power stability under partial shading conditions [53].

Furthermore, studies integrating deep learning models for MPPT highlighted the potential for predictive control strategies, which anticipate changes in solar irradiance and adjust the duty cycle of the power converter in real time [27].

- **Power forecasting**

Solar power forecasting estimates the actual electricity output of a PV system, incorporating variables such as system configuration, inverter efficiency, and temperature.

Among the reviewed papers, solar power forecasting emerged as the second most common AI application in PV systems, with 36 studies dedicated to this topic. The accurate forecasting of solar PV power plays a critical role in grid stability, energy management, and economic planning, particularly given the intermittency and nonlinearity of solar energy generation. The reviewed literature showcases a diverse range of AI-driven methodologies aimed at improving forecasting accuracy, resilience to missing data, and adaptability to weather fluctuations.

The studies highlight that deep learning-based models, particularly LSTM networks and hybrid CNN-LSTM architectures, offer superior performance over traditional statistical methods. A notable study developed an attention-based CNN-LSTM model, achieving significant reductions in forecast error compared to ARIMA and SVR models, improving short-term forecasting accuracy [54]. Another paper introduced a hybrid transformer-based probabilistic forecasting model, which demonstrated superior uncertainty quantification capabilities over conventional ANN and gradient boosting approaches [55].

A missing-data tolerant LSTM model demonstrated robust performance in handling incomplete datasets while maintaining high forecasting accuracy across different weather conditions [56]. Similarly, a randomized learning ensemble method combining Extreme Learning Machines (ELM), Stochastic Configuration Networks (SCN), and Randomized Vector Functional Links (RVFL) improved probabilistic forecasting precision, reducing mean absolute percentage error (MAPE) by up to 35% [57].

Overall, the literature confirms that hybrid AI-based forecasting models outperform traditional methods in handling solar energy variability, uncertainty, and real-time adaptability.

- **Parameter estimation**

Parameter estimation involves identifying the optimal values of a PV system's internal model parameters (e.g., diode factors, resistances) to accurately simulate or control system behavior.

Parameter estimation emerged as the third most common application of AI in PV systems, with 27 studies dedicated to this topic. Accurate parameter estimation is essential for optimizing PV models, improving energy yield, and enhancing system efficiency under varying environmental conditions. The reviewed literature highlights a range of AI-based optimization approaches, including metaheuristic algorithms, deep learning models, and hybrid AI frameworks, aimed at accurately extracting key parameters of PV models.

The studies reveal that metaheuristic optimization algorithms significantly enhance parameter estimation accuracy. A hybrid Chimp-Sine Cosine Algorithm (HCSCA) demonstrated superior performance in estimating single-diode and double-diode model parameters, achieving an error reduction below 10^{-10} across multiple execution runs [58]. Similarly, an enhanced Slime Mould Algorithm (SMA) incorporating random learning and Nelder–Mead simplex methods exhibited higher convergence speed and robustness compared to traditional optimization approaches [59].

Deep learning models have also been integrated into parameter estimation frameworks, where a Multilayer Perceptron (MLP) model optimized using Marine Predators Optimization (MPO) successfully predicted PV system parameters with high accuracy, demonstrating its potential for real-time system tuning [60]. Another study employed a Gradient-Based Optimizer (GBO), which outperformed traditional swarm intelligence algorithms in extracting PV parameters, particularly under noisy and uncertain data conditions [61].

The findings indicate that hybrid AI-based parameter estimation models provide superior accuracy, faster convergence, and greater robustness in PV system modeling.

- **Fault detection/diagnosis/classification**

Fault detection refers to the identification and diagnosis of abnormal conditions or failures (e.g., shading, inverter faults) in PV systems to ensure reliability, safety, and performance.

Fault detection, diagnosis, and classification in PV systems emerged as the fourth most common application of AI, with 14 studies dedicated to this topic. Accurate and automated fault detection is crucial for maintaining PV system reliability, optimizing performance, and preventing energy losses due to faulty modules, shading, and inverter failures. The reviewed literature highlights a range of AI-driven fault detection techniques, including deep learning models, hybrid AI frameworks, and statistical learning approaches, to improve the accuracy and efficiency of PV fault classification.

A hybrid CNN–Generative Adversarial Network model significantly enhanced PV fault detection by generating high-quality synthetic fault data, improving classification accuracy by 23% on small datasets [62]. Additionally, a multi-scale CNN-based deep learning model was developed to classify 11 different types of PV defects, achieving a fault classification accuracy of 97.32% [63].

Machine learning models such as SVM, DT, and RF were also extensively used in real-time monitoring and predictive maintenance. A DT-based classification model for grid-connected PV systems achieved 99.5% fault detection accuracy, effectively distinguishing between grid anomalies, inverter malfunctions, and module failures [64].

Furthermore, hybrid models have demonstrated robust real-time performance in fault detection and predictive maintenance. An adaptive neuro-fuzzy inference system (ANFIS) integrated with SVM achieved a classification accuracy of 95% in detecting partial shading, open-circuit, and bypass diode faults [65].

Overall, the literature confirms that AI-driven fault detection and classification techniques significantly enhance the reliability, accuracy, and efficiency of PV system monitoring.

- **Solar radiation forecasting/prediction**

Solar radiation forecasting focuses on predicting the intensity of solar irradiance reaching the Earth's surface, which is primarily used for input resource planning.

Among the reviewed papers, solar radiation forecasting has emerged as the fifth most common application of AI in PV systems, with seven studies dedicated to this topic. Accurate solar radiation prediction is crucial for optimizing PV system performance, energy management, and grid stability, as solar irradiance variations significantly impact PV power generation. The reviewed literature highlights a range of machine learning (ML) and deep learning (DL) models, integrating satellite imagery, meteorological data, and hybrid AI frameworks for improved forecasting accuracy.

One study proposed a hybrid CNN-MLP model, which successfully integrated global climate model data with observational meteorological inputs. The proposed model outperformed traditional statistical and standalone AI models, achieving lower RMSE and higher forecasting accuracy across multiple time scales [23]. Another study employed satellite imagery with a Convolutional Long Short-Term Memory (ConvLSTM) model, demonstrating a 3% improvement in RMSE compared to traditional time-series models [66].

A study integrating wavelet decomposition with feedforward neural networks (FFNNs) for intra-hour solar radiation forecasting achieved a forecast deviation of less than 4% in 90.6% of test cases, significantly outperforming persistence models [67]. Additionally, a hybrid ensemble learning approach combining extreme gradient boosting, light gradient boosting, and categorical boosting methods demonstrated high adaptability for real-time solar radiation forecasting in smart grid applications, further reducing forecasting errors [68].

The findings highlight that hybrid AI approaches, integrating deep learning, ensemble learning, and metaheuristic optimization techniques, significantly enhance solar radiation forecasting accuracy.

3.2.3. Trends over Time

The analysis of the reviewed literature highlights a clear progression in research focus over time, as follows:

- **2020–2022—**Early studies concentrated on exploratory applications of AI, primarily focusing on energy forecasting and fault detection;

- **2023–2024**—More recent research shows a shift towards integrated solutions, including hybrid AI models for MPPT, AI-enabled IoT system for real-time monitoring, and methods for managing environmental factors such as dust and shading.

This progressive evolution was identified using two main criteria. The first one is the thematic evolution network, which shows how keywords and research themes have shifted between the periods of 1998–2019 and 2020–2025, based on co-word analysis and keyword clustering. The second criterion is the keyword frequency and co-occurrence analysis, since the shift in research focus was further supported by the frequency of keywords in the reviewed publications.

4. Future Directions

The findings from this literature review point to several emerging trends poised to shape the future of AI applications in solar PV systems. As research progresses, these trends indicate a movement toward more integrated, resilient, and sustainable solutions aimed at tackling both technical and environmental challenges within renewable energy systems.

4.1. Hybrid AI Models for Enhanced Performance

The growing use of hybrid AI models is expected to persist as researchers aim to address the limitations of single-method approaches. By integrating techniques like fuzzy logic, neural networks, and optimization algorithms, hybrid models provide the flexibility and adaptability required to manage the inherent complexities of PV systems. These models are anticipated to become increasingly sophisticated, harnessing advancements in ensemble learning and metaheuristic optimization to enhance accuracy and efficiency in critical tasks such as MPPT and fault detection.

4.2. Integration of AI with IoT and Edge Computing

The integration of AI with IoT technologies and edge computing is poised to transform real-time monitoring and decision-making in PV systems. IoT-enabled sensors and edge devices can deliver continuous data streams, allowing AI models to process and respond to these data instantly. This approach will significantly improve predictive maintenance, fault detection, and energy management while minimizing the latency and computational demand of cloud-based systems. These advancements are expected to lead to autonomous PV systems capable of seamlessly adapting to dynamic environmental and operational conditions.

4.3. AI-Driven Energy Storage and Grid Integration

With the growing demand for renewable energy, integrating AI into energy storage systems and grid management will become increasingly vital. Future research is expected to prioritize AI models that optimize battery charging and discharging cycles, enhance energy storage efficiency, and ensure stable grid operations. AI's ability to forecast energy demand and generation patterns will play a crucial role in managing the variability of solar power and maintaining a balanced energy supply. This development is particularly significant for regions transitioning to smart grids and renewable energy-based infrastructures.

Despite its potential, the integration of AI with energy storage and grid systems remains relatively underexplored due to several challenges, including the lack of standardized real-time data, limited interoperability between PV, storage, and grid components, and the complexity of managing hybrid systems under uncertainty. Practical barriers such as regulatory constraints and cybersecurity concerns also limit deployment. Future research should focus on developing open-access datasets, simulation tools like digital twins, and modular AI frameworks adaptable to diverse energy infrastructures.

4.4. Increased Focus on Environmental and Operation Robustness

Future research also will focus on developing AI models capable of operating reliably under a wide range of climatic operational conditions. Improving the generalizability and robustness of these systems will ensure consistent performance despite variations in solar irradiance, temperature, and dust accumulation. This emphasis will be crucial for successfully deploying PV systems in geographically and environmentally diverse regions, including areas with harsh or unpredictable conditions.

4.5. Generative AI and Advanced Neural Architectures

Generative AI and advanced neural architectures, such as transformers, are poised to revolutionize the future of PV systems. These models hold the potential to improve the design and optimization of PV components, accurately predict long-term systems performance, and simulate intricate interactions within energy systems. Their applications may also include optimizing solar panel manufacturing processes, promoting both economic efficiency and environmental sustainability.

4.6. Standardization and Open-Source Data Sharing

The absence of standardized datasets remains a significant challenge in the field. Future efforts are likely to prioritize the development of open-source data repositories and the establishment of benchmarking standards for AI models in solar PV systems. These initiatives will foster collaboration, enhance model training, and improve the reproducibility of research outcomes. Standardization will also allow for fair comparisons between different AI approaches, driving faster innovation and more efficient deployment.

4.7. Localized and Context-Specific Solutions

With an increasing emphasis on equitable energy access, future research is expected to emphasize localized AI solutions designed to meet the unique needs of developing regions. These solutions can tackle challenges such as affordability, infrastructure constraints, and energy poverty. By creating context-sensitive AI models, researchers can help ensure that the advantages of AI-powered PV systems reach underserved communities, contributing to global sustainability objectives.

The future of AI in solar PV systems is set for transformative advancements, fueled by hybrid modeling, IoT integration, energy storage optimization, and the adoption of cutting-edge AI techniques. These developments promise to improve the efficiency and reliability of PV systems while addressing broader challenges in renewable energy adoption and sustainability. By prioritizing robust, scalable, and context-sensitive solutions, the research community can help drive the transition to a cleaner and more sustainable energy future.

5. Selecting the Right AI Technique Depending on the Problem

AI offers a diverse range of techniques for optimizing PV systems, each with distinct strengths and limitations. Selecting the right AI technique depends on the specific problem to be addressed, such as power optimization, energy forecasting, fault detection, or predictive maintenance. This section serves as a practical guide for identifying PV challenges and matching them with the most suitable AI solutions.

Different AI models exhibit varying performance characteristics depending on the complexity, data availability, and real-time processing requirements of PV applications. Table 3 summarizes AI techniques, as well as their advantages, disadvantages, and ideal use cases.

Table 3. Advantages and disadvantages of AI techniques for PV challenges.

PV Challenge	Recommended AI Technique(s)	Advantages	Disadvantages
MPPT optimization	ANNs, FL, PSO	High adaptability to changing conditions, improved tracking efficiency, reduced oscillations [69–71].	High computational complexity for ANN, FL requires well-defined rules, PSO may get stuck in local optima [69–71].
Solar power forecasting	LSTM networks, CNN-LSTM hybrid, SVMs, DT	Captures temporal dependencies, effective for time-series data, with high accuracy in long-term prediction [72–74].	LSTM requires large datasets, SVMs struggle with high-dimensional input, DT may overfit [72–74].
Fault detection and diagnosis	CNNs, SVMs, R, kNN	High classification accuracy, suitable for image-based defect detection, real-time monitoring [38,72,75,76].	CNNs require labeled datasets and high processing power, SVMs slow with large data; kNN sensitive to noise [38,72,75,76].
Parameter estimation for PV models	PSO, ANNs, DT, GA	Fast optimization, efficient for non-linear problems, useful in PV model tuning [14,44,77,78].	PSO prone to local optima, ANN requires extensive training, GA computationally expensive [14,44,77,78].
Solar radiation prediction	LSTM, CNNs, Ensemble Learning RF, gradient boosting, ANFIS	Handles multiple meteorological variables, improves PV system planning [35,37,65,79,80].	Computationally intensive for deep learning models, require high-quality datasets [35,37,65,79,80].
Real-time grid stability and island detection	DT, RF, RL	Fast execution, effective for real-time grid monitoring, interpretable models [81–83].	DT prone to overfitting, RL requires extensive training and simulation [81–83].

Selecting the right AI model also depends on the nature of the data and computational constraints. The following guidelines can help determine the most suitable approach.

- **For small datasets or limited computational power** (rule-based AI and traditional ML models):
  - FL is ideal when expert knowledge can define system behavior (e.g., MPPT control);
  - SVMs and kNN work well when labeled datasets are small but need accurate classification (e.g., fault detection);
  - DT and RF provide fast, interpretable results for fault classification and grid monitoring.
- **For large, complex datasets with time dependencies** (DL models):
  - LSTM networks excel in forecasting applications where historical patterns impact future outcomes (e.g., power generation prediction);
  - CNNs are ideal for image-based defect detection (e.g., microcracks, panel degradation);
  - Hybrid CNN-LSTM models combine the strengths of spatial and temporal learning, improving solar energy prediction.
- **For real-time, dynamic optimization** (swarm intelligence and RL):
  - PSO, as part of swarm intelligence, mimics the collective behavior of decentralized systems such as bird flocks to efficiently explore and optimize solutions. It is widely used for MPPT control and parameter estimation, optimizing PV performance in changing conditions;
  - RL operates through trial-and-error learning, where an agent interacts with its environment to learn the best actions over time based on feedback. Thus, it is an emerging technique for adaptive grid management and real-time decision-making.

Furthermore, recent advancements highlight the importance of hybrid AI techniques, which combine multiple models to enhance performance and mitigate individual weaknesses. Some common hybrid approaches include the following:

- **FL-ANN for MPPT optimization**—Combines the adaptability of ANN with the interpretability of FL for real-time control;
- **CNN-SVM for fault detection**—Uses CNN for feature extraction and SVM for efficient classification;
- **LSTM-PSO for energy forecasting**—Leverages PSO for hyperparameter tuning in solar power prediction models;
- **RF + RL for learning for grid stability**—RF helps classify grid anomalies, while RL adapts to dynamic energy fluctuations.

To assist in selecting the appropriate AI techniques, the decision-making framework observed in Figure 7 can be used.

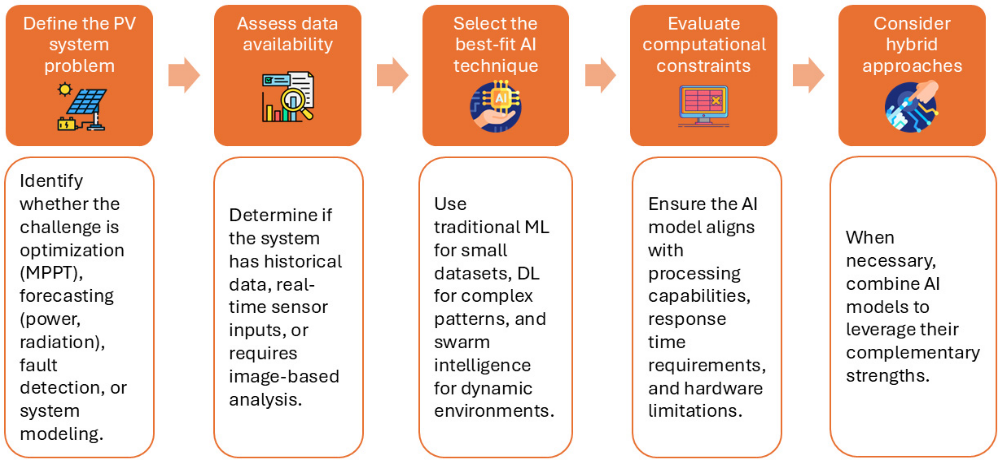

Figure 7. Decision-making framework for selecting AI technique.

5.1. *Fuzzy Expert System for AI Selection in Solar PV Energy Applications*

To enhance decision-making in selecting the most suitable AI technique for PV system optimization, a fuzzy expert system was developed in MATLAB using the Fuzzy Logic Designer tool based on the AI selection framework outlined in the literature review. This system automates the AI selection process based on problem type and system characteristics, enabling users—regardless of their AI expertise—to obtain precise recommendations for fault detection, energy forecasting, MPPT optimization, and other solar energy applications. These problem types correspond to the major areas of AI research in solar PV systems, ensuring that the fuzzy logic system is designed to address real-world challenges.

This system provides multiple benefits that make it a powerful and flexible decision-support tool for the solar PV energy sector. The system eliminates the need for manual AI selection by automatically recommending the most suitable technique based on input parameters, which saves time and ensures the most effective AI selection. The system also allows users to modify membership functions and rule sets in MATLAB's Fuzzy Logic Designer, enabling customization as new AI techniques emerge or as system requirements evolve. Furthermore, unlike static decision models, this fuzzy system evaluates multiple AI techniques to provide the most effective approach for each problem.

The fuzzy system operates by taking a problem definition as input and recommending an AI technique as output, as can be observed in Figure 8.

For the inputs, the user specifies the type of PV system problem to be solved. For the outputs, based on the problem type, the fuzzy system provides a recommendation for the most effective AI technique, as shown in Table 4.

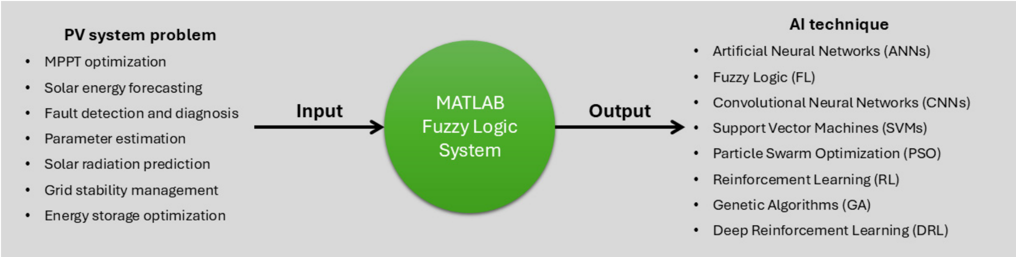

Figure 8. Fuzzy logic system—input and output diagram.

Table 4. PV systems' most common problems and AI techniques recommended to solve them.

PV System Problem	Recommended AI Technique(s)
• **MPPT optimization:** Selecting AI techniques that improve energy harvesting efficiency. • **Solar energy forecasting:** Identifying suitable models for predicting solar power generation trends. • **Fault detection and diagnosis**: Selecting AI approaches that enhance PV system monitoring and predictive maintenance. • **Parameter estimation:** Recommending techniques that tune system models for better performance. • **Solar radiation prediction:** Identifying AI-driven weather prediction and irradiance modeling solution. • **Grid stability management:** Choosing AI techniques for balancing PV output with grid demands. • **Energy storage optimization:** Selecting methods that improve battery management and energy dispatching.	• **ANNs:** Suitable for pattern recognition, forecasting, and MPPT optimization. • **FL:** Ideal for handling uncertainty in fault detection and real-time energy adjustments. • **CNNs:** Best for image-based fault detection (e.g., thermal imaging, microcrack analysis). • **SVMs:** Recommended for classification-based fault detection and efficiency diagnosis. • **PSO:** Effective in finding optimal MPPT settings and tuning model parameters. • **RL:** Applied to self-learning grid management and dynamic energy optimization. • **GA:** used in system optimization tasks where multiple variables need fine-tuning. • **DRL:** Applied in autonomous grid management and self-optimizing PV systems.

The Fuzzy Logic Designer in MATLAB enables users to modify the system based on evolving AI advancements. By adjusting the membership functions, rule sets, and decision parameters, the system can accommodate new AI techniques and adapt to different PV applications. This ensures that the model remains relevant and scalable for future developments in solar energy and AI research. Figure 9 illustrates the fuzzy logic system developed in MATLAB. To run the system, the user provides an input (e.g., "MPPT Optimization") and obtains an AI recommendation (e.g., "PSO or ANN").

The fuzzy system applies rule-based logic derived from findings in the literature to match input conditions with AI technique recommendations. These rules integrate knowledge from multiple studies evaluating AI models in terms of accuracy, computational efficiency, and adaptability. For example, if the problem complexity is high and data availability is low, FL or DT is recommended due to the lower computational demands of both. If the system requires MPPT optimization, the literature suggests that PSO and ANNs are the most effective, as they have demonstrated superior performance in tracking the maximum power point. Similarly, for fault detection applications requiring image-based analysis, CNNs are prioritized due to their high classification accuracy.

A total of 25 if–then rules were developed, linking specific PV challenges to recommended AI approaches. All rules were assigned equal weight in the current system configuration, reflecting equal importance across decision criteria. Table 5 shows the rules integrated into the system.

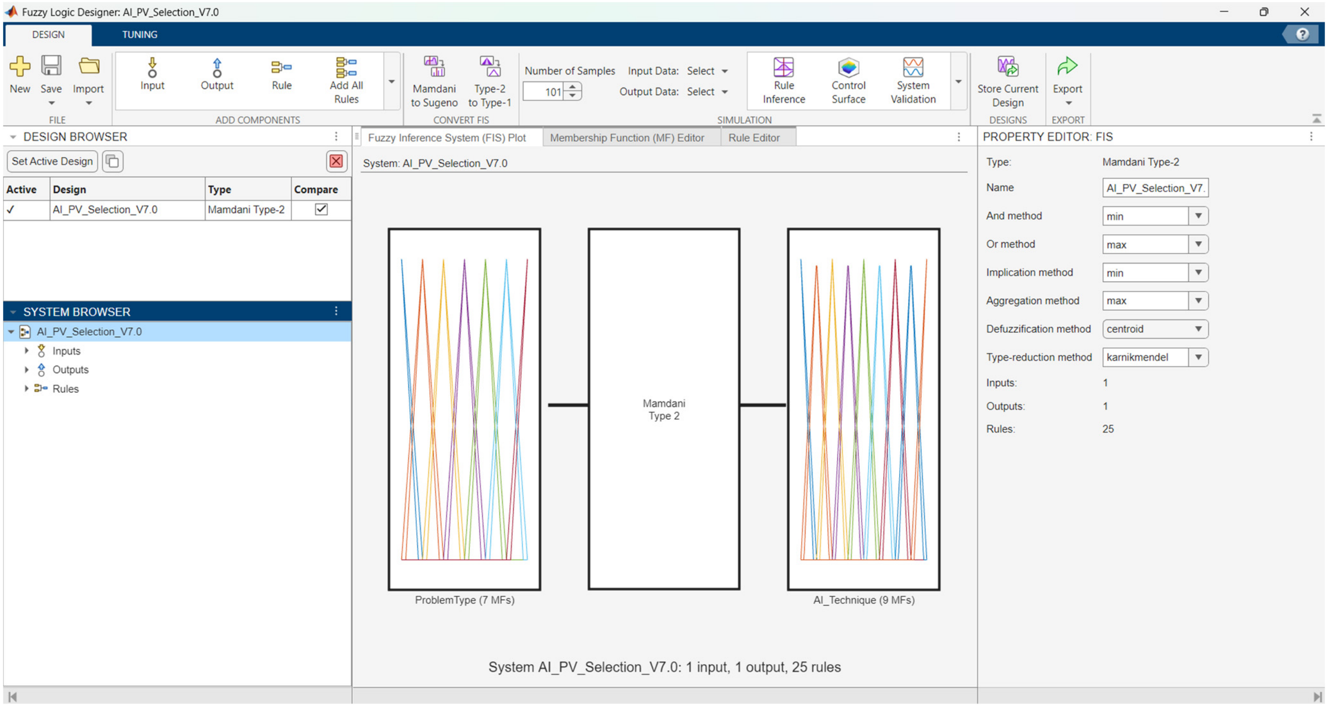

Figure 9. Fuzzy logic system for solar PV energy problems.

Table 5. If–then rules for PV energy problems and AI techniques.

Rule No.	IF Problem Type	THEN AI Technique
1	MPPT Optimization	ANN
2	MPPT Optimization	Fuzzy Logic
3	MPPT Optimization	PSO
4	MPPT Optimization	Hybrid AI
5	Solar Power Forecasting	Fuzzy Logic
6	Solar Power Forecasting	CNN
7	Solar Power Forecasting	Hybrid AI
8	Solar Power Forecasting	Genetic Algorithm (GA)
9	Fault Detection	CNN
10	Fault Detection	SVM
11	Fault Detection	Hybrid AI
12	Fault Detection	Genetic Algorithm (GA)
13	Parameter Estimation	SVM
14	Parameter Estimation	PSO
15	Parameter Estimation	Hybrid AI
16	Parameter Estimation	Genetic Algorithm (GA)
17	Solar Radiation Prediction	PSO
18	Solar Radiation Prediction	Reinforcement Learning
19	Solar Radiation Prediction	Hybrid AI
20	Solar Radiation Prediction	Deep Reinforcement Learning
21	Grid Stability Management	Reinforcement Learning
22	Grid Stability Management	Hybrid AI
23	Grid Stability Management	Deep Reinforcement Learning
24	Energy Storage Optimization	Energy Storage Optimization
25	Energy Storage Optimization	Deep Reinforcement Learning

The membership functions were designed using Gaussian shapes to model uncertainty smoothly across input and output variables. Placement was determined based on the categorization of PV problems and AI techniques identified in the review. Each function was centered on a specific problem type or technique, with overlapping ranges to allow flexible reasoning during fuzzy inference. Fine-tuning was performed manually using MATLAB's Fuzzy Logic Designer.

To further illustrate the structure of the developed fuzzy expert system, Figure 10 presents the conceptual architecture, outlining the main components involved in processing input data to generate AI technique recommendations.

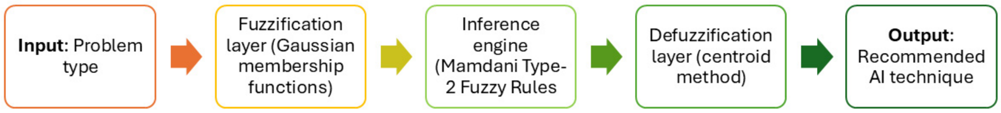

Figure 10. Conceptual architecture of the Type-2 Fuzzy Logic Expert System developed for AI technique selection in solar PV applications.

The fuzzy system does not provide a single crisp output, but instead ranks AI techniques based on membership values, allowing for flexible decision-making. If a user specifies MPPT optimization with high computational constraints, the system might rank PSO as the most suitable, followed by ANN and FL, with decreasing membership values. This ranking process is based on literature-backed evaluations of AI techniques rather than arbitrary selection, ensuring that the system's recommendations align with empirical research.

5.1.1. Type-2 Fuzzy Logic System

The literature review highlights that solar PV optimization involves high uncertainty due to environmental variability, incomplete data, and fluctuating operational conditions. Traditional type-1 fuzzy logic assigns fixed membership values, which may not fully capture the uncertainty present in AI selection for PV applications [84]. To address this limitation, the developed fuzzy expert system utilizes type-2 fuzzy logic, which incorporates Upper and Lower Membership Functions (UMF and LMF) to create a Footprint of Uncertainty (FOU) [85]. This approach allows the system to handle data variability more effectively, ensuring robust AI recommendations even under uncertain conditions [86]; thus, the additional degree of flexibility makes it highly suitable for complex and dynamically changing environments, such as solar PV systems. Studies in the literature emphasize the importance of adaptable AI selection frameworks, making type-2 fuzzy logic a suitable choice for this decision-support tool [87,88].

The system is designed to reflect real-world PV system problems identified in research, ensuring that its AI selection methodology is based on scientific evidence rather than subjective choice. The rule-based structure of the fuzzy system is supported by empirical studies on AI performance in different PV applications, making it a reliable tool for researchers, industry professionals, and policymakers. By incorporating type-2 fuzzy logic, the system further enhances decision-making by addressing the inherent uncertainty in AI model selection. The integration of knowledge from 163 reviewed studies ensures that the fuzzy logic system is scientifically grounded, practical for industry applications, and adaptable to future advancements in AI for solar PV optimization.

One of the main reasons why type-2 fuzzy logic is a better option is its ability to manage the high uncertainty in AI selection for PV applications. The selection of an AI model depends on multiple uncertain factors, all of which may fluctuate in real-world scenarios. In a type-1 fuzzy system, membership values are fixed, which means the system may not accurately capture variations in AI suitability due to unpredictable changes in solar irradiance, temperature, or cloud cover. A type-2 fuzzy system, on the other hand, introduces an extra layer of flexibility by considering a range of possible membership values, ensuring the AI selection remains robust even when input conditions are highly uncertain [84].

Another key advantage of type-2 fuzzy logic is its enhanced ability to handle noisy and imprecise data. In solar PV systems, sensor readings may have errors, missing data, or inconsistencies due to environmental disturbances. Type-1 fuzzy logic struggles in these cases since it assigns a single membership value, which may not adequately reflect the uncertainty present in the data. Type-2 fuzzy logic compensates for this by allowing multiple possible membership values, providing a more reliable decision-making process. This ensures that even if sensor data fluctuate or contain noise, the AI selection remains stable and less affected by anomalies [89].

Furthermore, the type-2 fuzzy logic system improves the generalization ability in decision-making frameworks. Since it inherently accounts for uncertainty, it provides more stable AI recommendations across different solar PV installations, locations, and datasets [90]. In contrast, type-1 fuzzy logic may be overfitted to specific conditions, requiring manual tuning when applied to different environments [91]. Type-2 fuzzy logic enables a more universal AI selection model, reducing the need for constant recalibration when applied to new datasets or operational conditions [86].

In the context of AI selection for PV applications, a type-2 fuzzy system enhances decision reliability by ensuring that AI recommendations are not overly sensitive to variations in input data. If different AI techniques have overlapping suitability levels due to fluctuating conditions, a type-1 system may struggle to differentiate them precisely. A type-2 fuzzy system resolves this issue by accommodating a range of potential values, allowing for more nuanced AI ranking and selection.

Overall, type-2 fuzzy logic is a superior option for AI selection in solar PV applications because it handles uncertainty more effectively, reduces sensitivity to noise, enhances adaptability to changing conditions, and improves generalization across different environments. Its ability to model imprecise and dynamic membership values ensures that AI selection remains robust, flexible, and optimized for real-world PV system challenges. By implementing type-2 fuzzy logic in AI selection frameworks, researchers and industry professionals can achieve more reliable, scalable, and adaptive AI-driven solar PV optimization.

5.1.2. Fuzzy Values

The fuzzy values in the fuzzy expert system for AI selection in solar PV applications handle uncertainty and imprecise information in decision-making. Unlike crisp values, which provide binary or exact outcomes, fuzzy values represent degrees of membership within a defined range, typically between 0 and 1. This allows the system to determine the suitability of different AI techniques rather than providing a single fixed answer.

Recent studies have extended fuzzy logic with multi-criteria decision-making methods, such as fuzzy AHP for process optimization in laser cutting applications [92], and health system monitoring [93]. These works highlight the versatility of fuzzy frameworks in structured decision problems, and support the relevance of our expert system approach in energy domains.

In the first step, fuzzification is applied to convert input parameters, such as problem complexity, data availability, and computational cost, into fuzzy linguistic terms such as “low”, “medium”, or “high”. For instance, if the computational cost is at 75%, the system may classify it as “high”, with a membership value of 0.8, and “medium” with a membership value of 0.2. This classification ensures that the AI selection process considers multiple possible techniques instead of defaulting to a single approach.

Once the inputs have been fuzzified, the system evaluates predefined fuzzy rules to determine the best AI technique for a given problem. A typical rule might state that if problem complexity is high and data availability is low, then FL or DT should be prioritized over computationally intensive models such as CNNs or LSTM networks. The membership functions play a key role in this process by ensuring that different AI techniques are ranked according to their suitability rather than being strictly classified as either acceptable or unacceptable.

Following the rule evaluation, the fuzzy system aggregates the results in the defuzzification stage. This process translates fuzzy outputs into a ranked list of AI techniques, where each technique receives a numerical score indicating its relative appropriateness. If, for example, the system evaluates AI techniques for a fault detection problem and assigns membership values of 0.90 to FL, 0.80 to DT, 0.75 to PSO, 0.65 to ANN, and 0.50 to CNN, then FL and DT would be recommended first. At the same time, ANN and CNN would be deprioritized due to their lower suitability scores.

The fuzzy system's ability to process and rank AI techniques based on membership values rather than absolute classification provides several advantages. It accommodates uncertainty in AI selection by considering multiple AI techniques rather than forcing a strict binary choice. It also provides adaptability by ensuring that AI recommendations dynamically update as system conditions evolve. Additionally, it enhances decision-making transparency by providing a structured ranking of AI techniques based on well-defined criteria.

In practice, when selecting an AI technique for fault detection in a PV system, the fuzzy system processes input conditions such as problem complexity, computational cost, and data availability. It assigns membership values to these parameters, influencing the ranking of AI techniques. Suppose problem complexity is classified as high with a membership value of 0.75, computational cost as medium with a membership value of 0.60, and data availability as low with a membership value of 0.40. In that case, the system evaluates these inputs against predefined fuzzy rules. As a result, the fuzzy system may determine that FL is the best choice with a membership value of 0.85, followed by SVM at 0.75, ANN at 0.60, and CNN at 0.40. This outcome ensures that FL and SVM are prioritized for fault detection in this specific scenario, while CNN is deprioritized due to its higher computational cost and lower suitability under the given conditions.

6. Discussion

The bibliometric analysis revealed key trends in AI applications for PV systems, with a steady increase in research publications over the past decade, reflecting the growing academic and industrial interest in AI-driven PV optimization. The highest number of publications appeared between 2018 and 2023, indicating a surge in AI research for renewable energy integration. Geographic trends in the analysis showed that China, the United States, and European countries contributed the largest share of publications, likely due to their investments in AI research and solar energy projects.

The systematic literature review highlights the increasing role of AI in enhancing PV systems by improving efficiency, reliability, and operational stability. The analysis identified ANNs, FL, CNNs, LSTM networks, SVMs, DT, RF, kNN, and PSO as the most frequently employed AI techniques in PV applications. Among these, ANNs were the most commonly used, particularly in MPPT, fault detection, and power forecasting, achieving power tracking efficiencies of up to 99.9% and fault diagnosis accuracies exceeding 99%. The use of hybrid AI models (e.g., ANN-FL, CNN-LSTM, PSO-FL, DT-RF) has demonstrated superior performance, consistently outperforming standalone techniques by leveraging multiple optimization and learning strategies.

Metaheuristic approaches such as PSO and GA have also been widely applied, particularly for parameter estimation, MPPT optimization, and solar tracking, with studies showing significant reductions in convergence time and improved tracking accuracy under dynamic environmental conditions. Hybrid models that integrate metaheuristic algorithms with machine learning approaches have further enhanced PV system adaptability, ensuring higher resilience against uncertainties in solar power generation. The literature confirms that combining AI with optimization techniques significantly improves energy efficiency and fault-tolerant capabilities, making these methodologies highly relevant for real-world PV system applications.

The review has also identified the most common AI applications in PV systems, with MPPT emerging as the most extensively researched area, followed by solar power forecasting, parameter estimation, fault detection, and solar radiation forecasting.

The fuzzy expert system developed for AI selection in solar PV applications is based on the systematic literature review, which identifies key AI techniques used for solar PV optimization, categorizes their applications, and evaluates their effectiveness in different scenarios. The literature review provides a foundation by analyzing 163 studies that highlight the strengths and limitations of various AI methods, such as ANNs for MPPT optimization and power forecasting, FL for handling uncertain conditions and fault detection, CNNs for image-based defect identification, LSTM networks for time-series-based solar forecasting, and SVMs for classification-based efficiency diagnosis. Other methods, including DT, RF, kNN, PSO, and RL, have also been identified as useful for different aspects of PV system optimization.

Applying the fuzzy expert system in AI selection for solar PV applications ensures that rigid classifications do not restrict decision-making, but that this latter is instead guided by a nuanced and adaptable ranking system. This approach significantly improves the efficiency of AI selection by considering multiple influencing factors simultaneously and adjusting recommendations based on real-time conditions. The fuzzy system enhances the reliability, accuracy, and scalability of AI-driven decision-making in solar energy applications through membership values.

Future work will involve the practical validation of the fuzzy expert system through case studies in industrial solar PV projects. This will include applying the system to real-world scenarios, collecting feedback from domain experts, and comparing its output with existing expert decision-making practices. Such validation will be essential to assessing the system's applicability, trustworthiness, and value in operational environments.

6.1. Challenges and Gaps

Despite the significant progress made in applying AI to solar PV systems, several challenges and gaps remain. A key issue identified in the reviewed literature is the lack of standardized, high-quality datasets. This limitation hampers the training, validation, and benchmarking of AI models, making it difficult to compare results across studies or implement solutions on a larger scale. Furthermore, the scalability and real-time performance of AI systems present notable challenges, particularly for large-scale PV installations. While advanced models offer high accuracy, their substantial computational demands often impede their use in real-time applications.

Another important gap lies in the limited exploration of AI-driven integration with energy storage and grid management systems. While significant progress has been made in standalone PV systems, research on coordinating solar energy with storage solutions or ensuring grid stability remains scarce. Additionally, many AI models face challenges in generalizing across diverse operational conditions and climatic environments. Variations in solar irradiance, temperature, and other contextual factors can greatly impact the performance of these algorithms, highlighting the need for robust and adaptable models.

Addressing these challenges is crucial for fully harnessing AI's potential to accelerate the shift toward sustainable energy systems.

Another significant insight is the prominence of fault detection and predictive maintenance as leading application areas. This focus underscores the industry's priority on improving system reliability and lowering operational costs—key factors for the broader adoption of solar PV technology. In recent years, there has been a notable shift toward real-time AI applications, fueled by the integration of advanced AI techniques with IoT and edge computing. This trend emphasizes the increasing importance of rapid decision-making and continuous system monitoring in the operation of modern PV systems.

Tailored AI applications in these areas could address unique challenges, including energy access, affordability, and infrastructure limitations, paving the way for more inclusive advancements in renewable energy.

In selecting the appropriate AI technique for PV system optimization, it is crucial to consider the specific problem, data availability, and computational constraints, as observed in Figure 7. A problem-driven approach to AI selection ensures that PV systems benefit from the most effective computational intelligence techniques, leading to higher efficiency, reliability, and scalability in real-world applications.

A crucial consideration in adopting AI techniques for solar PV system applications is the trustworthiness and reliability of these methods. AI models, particularly those developed through machine learning and generative approaches, inherently depend on the quality and representativeness of the data used for training. The validation of AI models typically involves rigorous methodologies such as cross-validation, comparison with real operational data, and sensitivity analyses to ensure robustness and accuracy. In this work, the authors have selected techniques that have been extensively validated in the literature, and prioritize those with proven accuracy and reliability in empirical applications. Additionally, they acknowledge that Generative AI models can sometimes produce inaccurate or misleading information if not properly trained or guided. To address this, all AI-generated content in this study was manually verified against original literature sources and validated using expert judgement to ensure correctness and relevance. Deep learning models, in particular, often require large, high-quality datasets and are prone to overfitting if not carefully regularized, which can limit their generalizability in real-world PV scenarios. Moreover, the proposed type-2 fuzzy logic expert system inherently accounts for uncertainty, enhancing decision reliability under variable operational and environmental conditions. However, users should remain cautious, continually validating and updating AI models with new data, particularly when they are deployed in dynamic real-world scenarios.

6.2. Practical Implications for Researchers, Industry, and Policymakers

The integration of AI in PV systems has significant practical implications for various stakeholders, including researchers, industry professionals, and policymakers. As AI-driven techniques continue to advance, understanding their real-world applicability is essential for bridging the gap between academic research, industrial deployment, and regulatory frameworks.

For researchers, the findings of this study highlight the importance of selecting the right AI technique depending on the specific PV application. Future research should focus on developing lightweight AI models that can operate in real time on edge computing devices, reducing reliance on cloud processing. Additionally, the lack of standardized datasets and benchmarking frameworks for AI-based PV optimization remains a challenge. Open-access datasets, standardized testing environments, and collaborative AI modeling efforts can enhance reproducibility and accelerate innovation in the field.

For industry, AI presents significant opportunities for enhancing efficiency, reducing maintenance costs, and improving grid integration. AI-based fault detection and predictive maintenance systems can enable proactive monitoring, minimizing energy losses and reducing downtime. Companies investing in AI-driven MPPT optimization can achieve higher energy yields, improving the financial viability of PV installations. Moreover, AI-powered forecasting models can help PV operators better integrate renewable energy into the grid, reducing fluctuations and improving demand–response strategies. However, to fully leverage AI, the industry must invest in scalable AI solutions that can be seamlessly integrated with existing PV monitoring systems and energy management platforms.

Policymakers play a crucial role in facilitating AI adoption in the solar energy sector by implementing supportive regulations and incentives. Data-sharing policies should be established to promote collaborative AI model development, allowing researchers and industry stakeholders to access real-world PV system data. Governments can also encourage investment in AI research for renewable energy through grants, subsidies, and regulatory frameworks that incentive AI-based energy optimization. Finally, ethical and environmental considerations, such as AI's energy consumption and data privacy concerns, must be addressed to ensure sustainable and responsible AI deployment in the PV sector.

7. Conclusions

This review underscores the transformative impact of AI in advancing solar PV systems, highlighting its ability to tackle critical challenges such as efficiency optimization, fault detection, energy forecasting, and system reliability. Through a systematic analysis of 163 studies published between 2020 and 2024, this study explores a diverse range of AI techniques—including machine learning, neural networks, fuzzy logic, and hybrid approaches—applied across different stages of the PV system lifecycle. The findings highlight key trends, such as the increasing use of hybrid AI models, the integration of AI with IoT for real-time applications, and a growing focus on addressing practical, system-level challenges.

This work offers valuable contributions by presenting a comprehensive synthesis of global research trends, emerging themes, and existing gaps in the field. Key challenges identified include the absence of standardized datasets, scalability issues for large-scale deployments, and the limited integration of AI with energy storage and grid systems. While these challenges pose obstacles, they also create opportunities for further research and innovation. By tackling these issues, researches and practitioners can harness AI's full potential to enhance the efficiency and sustainability of PV systems. To maximize the benefits of AI in PV systems, stronger collaboration between researchers, industry leaders, and policymakers is needed.

A major contribution of this work is the development of a type-2 fuzzy logic system in MATLAB, designed to automate AI selection for PV applications. This system enables researchers, engineers, and industry professionals to identify the most appropriate AI technique for a given PV problem, reducing manual effort and improving decision-making efficiency. This approach significantly improves the efficiency of AI selection by considering multiple influencing factors simultaneously and adjusting recommendations based on real-time conditions.

Looking forward, future research should prioritize the development of scalable, real-time AI models for large-scale PV systems, the integration of AI with energy storage and grid management technologies, and the creation of standardized datasets to enable benchmarking and collaboration. In parallel, increasing attention should be paid to explainable AI (XAI) techniques, which can improve the transparency and interpretability of AI-driven decisions, particularly in critical infrastructure such as solar energy systems. Furthermore, designing localized AI solutions tailored to the specific needs of developing regions can be instrumental in enhancing energy access and infrastructure. Addressing these challenges will allow AI to further drive advancements in solar PV systems and play a pivotal role in the global transition to a sustainable energy future.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
PV	Photovoltaic
PRISMA	Preferred Reporting Items for Systematic Review and Meta-Analyses
ANNs	Artificial Neural Networks
FL	Fuzzy Logic
CNNs	Convolutional Neural Networks
LSTM	Long Short-Term Memory
SVMs	Support Vector Machines
DT	Decision Trees
RF	Random Forest
kNN	k-Nearest Neighbors
PSO	Particle Swarm Optimization
MPPT	Maximum Power Point Tracking
PCA	Principal Component Analysis
PDet	Progressive Deformable Transformer
Extra Trees	Extremely Randomized Trees
LR	Linear Regression
ABOD	Angle-Based Outlier Detection
O&M	Operation and Maintenance
NN	Neural Networks
GAI	Generative AI
AOA	Arithmetic Optimized Algorithm
ELM	Extreme Learning Machine
CSA	Crow Search Algorithm
SENMSSA	Super-Evolutionary Nelder–Mead Salp Swarm Algorithm
GRU	Gate Recurrent Unit
CVO	Coronavirus Optimization
ANFHC	Adaptive Neuro–Fuzzy Hybrid Controller
FFNN	Feedforward Neural Network
MsSCNN	Multiscale Siamese Convolutional Neural Network
P&O	Perturb and Observe

P2P	Peer-to-peer
DAGRU	Dual-attention Gated Recurrent Units
LCA	Life Cycle Assessment
FES	Fuzzy Expert System
DRL	Deep Reinforcement Learning
PSM	Proportional Selection Method
RSM	Random Selection Method (RSM)
DSF	Dense and Successive Features
HFPE	Hierarchical Feature Precision and Extraction
CCEAF	Contextual Characteristics Extraction and Attribute Fusion
MFO	Moth Flame Optimization
MLP	Multilayer Perceptron
TSFS	Two-stage Feature Selection
ICMODA	Improved Chaotic Multi-objective Dragonfly Algorithm
SMFTS	Seasonal Multivariable Fuzzy Time Series
ORELM	Outlier-robust Extreme Learning Machine
1D-CNN	One-dimensional Convolutional Neural Network
MPC	Model Predictive Control
MFSO	Modified Fluid Search Optimization
ANFIS	Adaptive Neural-fuzzy Inference System
FLC	Fuzzy logic controller
GA	Genetic Algorithm
ABC	Artificial Bee Colony
TLBO	Teaching Learning-based Optimization
DTBO	Driving Training-based Optimization
HYTREM	Hybrid Tree-based Ensemble Learning Model
ELADE	Elite Learning Adaptive Differential Evolution
NFN	Neuro Fuzzy Network
NF	Nonlinear Function
SMC	Sliding Mode Control
FPA	Flower Pollination
CSA	Cuckoo Search Algorithm
WGAN	Wasserstein Generative Adversarial Network
RERNN	Recalling-enhanced Recurrent Neural Network
SGO	Shell Game Optimization
MRAC	Model Reference Adaptive Control
FCM	Fuzzy C-means
WOA	Whale Optimization Algorithm
LSSVM	Least Squares Support Vector Machine
ISSA	Improved Sparrow Search Algorithm
DNN	Deep Neural Network
ECANet	Efficient Channel Attention Module
TCN	Temporal Convolutional Network
VGG	Visual Geometry Group
RESNET	Residual Neural Network
ICSA	Chameleon Swarm Algorithm
RPNN	Recurrent Perceptron Neural Network
MLP	Multi-layer Perceptron
BSA	Backtracking Search Optimization Algorithm
GWO	Grey Wolf Optimizer
HHO	Harris Hawks Optimization
LGBM	Light Gradient Boosting
UPQC	Unified Power Quality Conditioner

EHO	Elephant Herding Optimization
ABWO	Adaptive Black Widow Optimization Algorithm
SDA	Similar Day Analysis
ECPA	Enhanced Colony Predation Algorithm
LNMHGS	Laplacian Nelder–Mead Hunger Games Search
TFT	Temporal Fusion Transformer
HBA	Honey Badger Algorithm
DLH	Dimensional Learning Hunting
DE	Differential Evolution
SAR	Search and Rescue Optimization Algorithm
HGS	Hunger Games Search
ASMA	Adaptive Slime Mould Algorithm
ET	Extra Tress
GB	Gradient Boosting
HCSCA	Hybrid Chimp–Sine Cosine Algorithm
FWA	Evolutionary Fireworks Algorithm
LsSVR	Least Square Support Vector Regression
TLABC	Teaching–Learning-based Artificial Bee Colony
IWA	Invasive Weed Algorithm
ISMA	Improved Slime Mould Algorithm
DOA	Dragonfly Optimization Algorithm
LASSO	Least Absolute Shrinkage and Selection Operator
PR	Polynomial Regression
DL	Deep Learning
EMSFLA	Ensemble Multi-strategy-driven Shuffled Frog Leading Algorithm
ALSM	Attention-based Long-term and Short-term Temporal NN Prediction Model
MRTPP	Multiple Relevant and Target Variables Prediction Pattern
SFLBS	Shuffled Frog-leaping Algorithm
ELM	Extreme Learning Machine
RLHE	Randomized Learning-based Hybrid Ensemble
CCO	Crisscross Optimizer
EO	Equilibrium Optimizer
SSA	Salp Swarm Optimization
MFO	Orthogonal Moth Flame Optimization
THD	Total Harmonic Distortion
VMD	Variational Mode Decomposition
BIPV	Building-integrated PV
RMSE	Root Mean Square Error
ELM	Extreme Learning Machines
SCN	Stochastic Configuration Networks
RVFL	Randomized Vector Functional Links
MAPE	Mean Absolute Percentage Error
SMA	Slime Mould Algortihm
MPO	Marine Predators Optimization
GBO	Gradient-based Optimizer
UMF	Upper Membership Functions
LMF	Lower Membership Functions
FOU	Footprint of Uncertainty

Appendix A

Table A1. Papers included in the final review.

Reference	Title	Year	AI technique	Application
[94]	An innovative hybrid model combining informer and K-Means clustering methods for invisible multisite solar power estimation	2024	MissForest, K-means, Principal Component Analysis (PCA)	Location selection
[95]	Levenberg-Marquardt algorithm-based solar PV energy integrated internet of home energy management system	2024	Levenberg-Marquardt, Bayesian Regularization, Scaled Conjugate Gradient	Energy management
[21]	Enhanced Fault Detection in Photovoltaic Panels Using CNN-Based Classification with PyQt5 Implementation	2024	CNN and VGG16 architecture	Fault detection
[96]	PDeT: A Progressive Deformable Transformer for Photovoltaic Panel Defect Segmentation	2024	Progressive Deformable Transformer (PDeT)	Defect segmentation
[64]	Explainable artificial intelligence of tree-based algorithms for fault detection and diagnosis in grid-connected photovoltaic systems	2024	Extremely Randomized Trees (Extra Trees)	Fault detection and diagnosis
[97]	Research on a Photovoltaic Panel Dust Detection Algorithm Based on 3D Data Generation	2024	YOLOv8 model, SENetV2, AKConv, and DySample	Dust detection
[98]	Non-invasive health status diagnosis of solar PV panel using ensemble classifier	2024	Ensemble Classifier	Health monitoring
[18]	Comparative study of real-time photovoltaic fault diagnosis using artificial intelligence: Fuzzy logic and neural network approaches	2024	FL and ANN	Fault diagnosis
[99]	An adaptive method for real-time photovoltaic power forecasting utilizing mathematics and statistics: Case studies in Australia and Vietnam	2024	Linear regression (LR)	Power forecasting
[32]	An ensemble learning framework for snail trail fault detection and diagnosis in photovoltaic modules	2024	SVM, KNN, and DT	Fault detection and diagnosis
[36]	Novel data-driven health-state architecture for photovoltaic system failure diagnosis	2024	XGBoost, DT, KNN, and Angle-Based Outlier Detection (ABOD)	Fault diagnosis and predictive O&M
[100]	A feature space class balancing strategy-based fault classification method in solar photovoltaic modules	2024	CNN, Feature Space Class Balancing, PatchUp-based Feature Mixing:	Fault classification
[101]	Backpropagation artificial neural network-based maximum power point tracking controller with image encryption inspired solar photovoltaic array reconfiguration	2024	ANN	MPPT
[25]	A novel hybrid intelligent approach for solar photovoltaic power prediction considering UV index and cloud cover	2024	LST and CNN	Power forecasting
[102]	Battery-less uncertainty-based control of a stand-alone PV-electrolyzer system	2024	NN and FL	Power forecasting
[22]	Radiometric Infrared Thermography of Solar Photovoltaic Systems: An Explainable Predictive Maintenance Approach for Remote Aerial Diagnostic Monitoring	2024	CNN	Fault detection and diagnosis
[103]	Multi-step photovoltaic power forecasting using transformer and recurrent neural networks	2024	Transformer networks and LSTM	Power forecasting
[82]	Examining nonlinear effects of socioecological drivers on urban solar energy development in China using machine learning and high-dimensional data	2024	SVM—Recursive Feature Elimination, RF, DT, XGBoost	Nonlinear effects examination

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[83]	Two-Stage Neural Network Optimization for Robust Solar Photovoltaic Forecasting	2024	NNs and RF	Power forecasting
[104]	SkyGPT: Probabilistic ultra-short-term solar forecasting using synthetic sky images from physics-constrained VideoGPT	2024	GAI	Sky forecasting
[105]	Implementation of optimized extreme learning machine-based energy storage scheme for grid connected photovoltaic system	2024	Arithmetic Optimized Algorithm (AOA) based Extreme Learning Machine (ELM)	Power forecasting
[106]	A Life-Long Learning XAI Metaheuristic-Based Type-2 Fuzzy System for Solar Radiation Modeling	2024	XAI Metaheuristic	Solar radiation forecasting
[107]	Analyzing grid connected shaded photovoltaic systems with steady state stability and crow search MPPT control	2024	Crow Search Algorithm (CSA)	MPPT
[108]	Super-evolutionary mechanism and Nelder-Mead simplex enhanced salp swarm algorithm for photovoltaic model parameter estimation	2024	Super-Evolutionary Nelder-Mead Salp Swarm Algorithm (SENMSSA) and Nelder-Mead simplex method	Parameter estimation
[109]	Novel applications of various neural network models for prediction of photovoltaic system power under outdoor condition of mountainous region	2024	NN	Power forecasting
[110]	Developing a Deep Learning and Reliable Optimization Techniques for Solar Photovoltaic Power Prediction	2024	CNN and LSTM	Power forecasting
[111]	A new dust detection method for photovoltaic panel surface based on Pytorch and its economic benefit analysis	2024	Adam algorithm	Dust detection
[112]	Short-term photovoltaic prediction based on CNN-GRU optimized by improved similar day extraction, decomposition noise reduction and SSA optimization	2024	Convolution Neural Network-Gate Recurrent Unit (CNN-GRU) and Sparrow Search Algorithm	Power forecasting
[113]	A Coronavirus Optimization (CVO) algorithm to harvest maximum power from PV systems under partial and complex partial shading conditions	2024	Coronavirus Optimization (CVO) algorithm	MPPT
[114]	Improved YOLOv8-GD deep learning model for defect detection in electroluminescence images of solar photovoltaic modules	2024	YOLOv8-GD.	Fault detection
[115]	Multi-objective based Hybrid Artificial Intelligence Controlled Parallel Inverter in Islanded and Grid Connected Operations	2024	adaptive neuro-fuzzy hybrid controller (ANFHC)	Inverters
[116]	Explainable Deep Learning Model for Grid-Connected Photovoltaic System Performance Assessment for Improving System Reliability	2024	feedforward neural network (FFNN)	Performance assessment
[117]	Photovoltaic Panel Defect Detection via Multiscale Siamese Convolutional Fusion Network With Information Bottleneck Theory	2024	multiscale Siamese convolutional neural network (MsSCNN)	Fault detection
[10]	Wavelet and Signal Analyzer Based High-Frequency Ripple Extraction in the Context of MPPT Algorithm in Solar PV Systems	2024	ANN and P&O	MPPT
[55]	Enhancing One-Day-Ahead Probabilistic Solar Power Forecast With a Hybrid Transformer-LUBE Model and Missing Data Imputation	2024	XGBoost	Power forecasting

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[118]	Energy Community Management Based on Artificial Intelligence for the Implementation of Renewable Energy Systems in Smart Homes	2024	Multi-agent deep reinforcement learning, Markov Decision Process, ANN	Peer-to-peer (P2P) markets
[119]	Photovoltaic power forecasting: A dual-attention gated recurrent unit framework incorporating weather clustering and transfer learning strategy	2024	dual-attention gated recurrent units (DAGRU)	Power forecasting
[120]	Forecasting meteorological impacts on the environmental sustainability of a large-scale solar plant via artificial intelligence-based life cycle assessment	2024	ANN	Life Cycle Assessment (LCA)
[121]	An efficient power extraction using artificial intelligence based machine learning model for SPV array reconfiguration in solar industries	2024	Fuzzy Expert System (FES)	PV arrays configurations
[81]	Energy management of buildings with energy storage and solar photovoltaic: A diversity in experience approach for deep reinforcement learning agents	2024	Deep reinforcement learning (DRL), K-means Clustering, Proportional Selection Method (PSM), Random Selection Method (RSM)	Energy management
[122]	Quadratic interpolation and a new local search approach to improve particle swarm optimization: Solar photovoltaic parameter estimation	2024	Particle Swarm Optimization (PSO)	Parameter estimation
[123]	SEiPV-Net: An Efficient Deep Learning Framework for Autonomous Multi-Defect Segmentation in Electroluminescence Images of Solar Photovoltaic Modules	2023	encoder-decoder networks, Dense and Successive Features (DSF), Hierarchical Feature Precision and Extraction (HFPE), Contextual Characteristics Extraction and Attribute Fusion (CCEAF), attention mechanisms, loss functions	Defects detection
[124]	Accurate and generalizable photovoltaic panel segmentation using deep learning for imbalanced datasets	2023	Deep learning (GenPV)	PV panel segmentation
[125]	Moth flame optimization for the maximum power point tracking scheme of photovoltaic system under partial shading conditions	2023	Moth Flame Optimization (MFO)	MPPT
[126]	Open-Circuit Fault Diagnosis for Three-Phase Inverter in Photovoltaic Solar Pumping System Using Neural Network and Neuro-Fuzzy Techniques	2023	NNs and neuro-fuzzy networks	Inverter fault detection
[127]	Application of Artificial Intelligence Algorithms in Multilayer Perceptron and Elman Networks to Predict Photovoltaic Power Plant Generation	2023	MLP (Multilayer Perceptron) and Elman networks	Power forecasting
[128]	A solar radiation intelligent forecasting framework based on feature selection and multivariable fuzzy time series	2023	two-stage feature selection (TSFS), improved chaotic multi-objective dragonfly algorithm (ICMODA), seasonal multivariable fuzzy time series (SMFTS), and outlier-robust extreme learning machine (ORELM)	Solar radiation prediction

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[129]	Deep learning based model predictive control of active filter inverter as interface for photovoltaic generation	2023	one-dimensional convolutional neural network (1D-CNN) based model predictive control (MPC)	Inverters
[130]	A novel global MPPT technique to enhance maximum power from PV systems under variable atmospheric conditions	2023	modified fluid search optimization (MFSO) and adaptive neural-fuzzy inference system (ANFIS)	MPPT
[15]	New Hybrid MPPT Technique Including Artificial Intelligence and Traditional Techniques for Extracting the Global Maximum Power from Partially Shaded PV Systems	2023	ANN, Variable Step P&O, and FL Controller (FLC)	MPPT
[44]	A new two-axis solar tracker based on the online optimization method: Experimental investigation and neural network modeling	2023	genetic algorithm (GA), PSO, Artificial Bee Colony (ABC), teaching learning based optimization (TLBO), and ANN	Solar tracker
[131]	Assessing the impact of soiling on photovoltaic efficiency using supervised learning techniques	2023	LR, RF, DT, Multilayer Perceptron and LSTM	Soiling
[53]	Driving training-based optimization (DTBO) for global maximum power point tracking for a photovoltaic system under partial shading condition	2023	driving training-based optimization (DTBO)	MPPT
[68]	A Hybrid Ensemble Model for Solar Irradiance Forecasting: Advancing Digital Models for Smart Island Realization	2023	XGBoost, light gradient boosting machine, categorical boosting, RF, and hybrid tree-based ensemble learning model (HYTREM)	Solar radiation forecasting
[31]	Cloud Computing and Machine Learning-based Electrical Fault Detection in the PV System	2023	SVM, Naive Bayes, KNN, DT and RF	Fault detection
[132]	Extracting accurate parameters of photovoltaic cell models via elite learning adaptive differential evolution	2023	Elite Learning Adaptive Differential Evolution (ELADE)	Parameter estimation
[51]	Optimizing Large-Scale PV Systems with Machine Learning: A Neuro-Fuzzy MPPT Control for PSCs with Uncertainties	2023	neuro fuzzy network (NFN)	MPPT
[77]	Novel extreme seeking control framework with ordered excitation and nonlinear function based PSO: Method and application	2023	nonlinear function (NF) based PSO	MPPT
[41]	A robust MPPT approach based on first-order sliding mode for triple-junction photovoltaic power system supplying electric vehicle	2023	sliding mode control (SMC), P&O, PSO, flower pollination (FPA) and the cuckoo search algorithm (CSA)	MPPT
[62]	Efficient fault diagnosis approach for solar photovoltaic array using a convolutional neural network in combination of generative adversarial network under small dataset	2023	Wasserstein generative adversarial network (WGAN) and CNN	Fault detection and diagnosis
[133]	Energy Efficiency Improvement in Photovoltaic Installation Using a Twin-Axis Solar Tracking Mechanism with LDR Sensors Compared with Neuro-Fuzzy Adaptive Inference Structure	2023	Neuro fuzzy inference method	MPPT
[134]	A RERNN-SGO Technique for Improved Quasi-Z-Source Cascaded Multilevel Inverter Topology for Interfacing Three Phase Grid-Tie Photovoltaic System	2023	recalling-enhanced recurrent neural network (RERNN) and Shell Game Optimization (SGO)	MPPT
[37]	Energy forecasting of the building-integrated photovoltaic façade using hybrid LSTM	2023	RF and LSTM	Power forecasting

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[135]	Design and implementation of a new adaptive MPPT controller for solar PV systems	2023	model reference adaptive control (MRAC)	MPPT
[13]	Real-time hardware-in-loop based open circuit fault diagnosis and fault tolerant control approach for cascaded multilevel inverter using artificial neural network	2023	ANN	Inverter fault detection
[29]	Short-Term Power Prediction by Using Least Square Support Vector Machine With Variational Mode Decomposition in a Photovoltaic System	2023	fuzzy C-means (FCM), whale optimization algorithm (WOA), Least squares support vector machine (LSSVM), and improved sparrow search algorithm (ISSA)	Power forecasting
[136]	Intelligent maximum power point tracking for coastal photovoltaic system concerning the corrosion and aging of modules	2023	deep neural network (DNN)	MPPT
[137]	A Short-Term Power Prediction Method Based on Temporal Convolutional Network in Virtual Power Plant Photovoltaic System	2023	efficient channel attention module (ECANet), and temporal convolutional network (TCN)	Power forecasting
[138]	Performance Analysis of Classification and Detection for PV Panel Motion Blur Images Based on Deblurring and Deep Learning Techniques	2023	visual geometry group-16 (VGG-16), VGG-19, residual neural network-18 (RESNET-18), RESNET-50, RESNET-101, and CNN	Snow detection
[34]	Combining data envelopment analysis and Random Forest for selecting optimal locations of solar PV plants	2023	RF	Location selection
[139]	Variable boundary reinforcement learning for maximum power point tracking of photovoltaic grid-connected systems	2023	variable boundary reinforcement learning	MPPT
[140]	A Novel Nonisolated Quasi Z-Source Multilevel Inverter for Solar Photovoltaic Energy System Using Robust Technique: An ICSA–RPNN Technique	2023	chameleon swarm algorithm (ICSA) and recurrent perceptron neural network (RPNN)	Inverters
[23]	Hybrid Convolutional Neural Network-Multilayer Perceptron Model for Solar Radiation Prediction	2023	CNN and multi-layer perceptron (MLP)	Solar radiation forecasting
[141]	Boosted backtracking search optimization with information exchange for photovoltaic system evaluation	2023	backtracking search optimization algorithm (BSA) and TLBO	Parameter estimation
[52]	Maximum power point tracking technique based on variable step size with sliding mode controller in photovoltaic system	2023	Grey wolf optimizer (GWO)	MPPT
[142]	Experimental Modeling of a New Multi-Degree-of-Freedom Fuzzy Controller Based Maximum Power Point Tracking from a Photovoltaic System	2022	multi-degree-of-freedom FLC	MPPT
[143]	Optimized RNN-oriented power quality enhancement and THD reduction for micro grid integration of PV system with MLI: Crow Search-based Harris Hawks Optimization concept	2022	Optimized Recurrent NN, CSA and Harris Hawks Optimization (HHO)	Grid integration
[60]	Photovoltaic System Parameter Estimation Using Marine Predators Optimization Algorithm Based on Multilayer Perceptron	2022	GWO and marine predators optimization algorithms and multilayer perceptron	Parameter estimation
[144]	Geospatial assessment of rooftop solar photovoltaic potential using multi-source remote sensing data	2022	CNN and MLP	Geospatial assessment

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[145]	A Novel Approach to Achieve MPPT for Photovoltaic System Based SCADA	2022	CSA and ABC	MPPT
[78]	Photovoltaic Energy Production Forecasting through Machine Learning Methods: A Scottish Solar Farm Case Study	2022	LR, kNN, DT, XGBoost, Light Gradient Boosting (LGBM), MLP, Elman NN and LSTM	Power forecasting
[146]	Optimal Design of an Artificial Intelligence Controller for Solar-Battery Integrated UPQC in Three Phase Distribution Networks	2022	soccer league algorithm and ANN	unified power quality conditioner (UPQC)
[49]	Deep Reinforcement Learning for the Optimal Angle Control of Tracking Bifacial Photovoltaic Systems	2022	DRL	Angle control
[56]	An Integrated Missing-Data Tolerant Model for Probabilistic PV Power Generation Forecasting	2022	recursive LSTM	Power forecasting
[147]	Generation of Maximum Power in Grid Connected PV System Based MPPT Control Using Hybrid Elephant Herding Optimization Algorithm	2022	Elephant Herding Optimization (EHO) and ANN	MPPT
[66]	Solar radiation forecasting with deep learning techniques integrating geostationary satellite images	2022	3D-CNN and ConvLSTM	Solar radiation forecasting
[148]	Information sharing search boosted whale optimizer with Nelder-Mead simplex for parameter estimation of photovoltaic models	2022	WOA	Parameter estimation
[149]	Prediction of photovoltaic power output based on similar day analysis using RBF neural network with adaptive black widow optimization algorithm and K-means clustering	2022	radial basis function NNs, adaptive black widow optimization algorithm (ABWO), similar day analysis (SDA) and K-means clustering	Power forecasting
[150]	Neural Network Controlled Solar PV Battery Powered Unified Power Quality Conditioner for Grid Connected Operation	2022	ANN	Power quality
[151]	Extremal Nelder–Mead colony predation algorithm for parameter estimation of solar photovoltaic models	2022	enhanced colony predation algorithm (ECPA)	Parameter estimation
[152]	A Novel Hybrid MPPT Technique Based on Harris Hawk Optimization (HHO) and Perturb and Observer (P&O) under Partial and Complex Partial Shading Conditions	2022	HHO	MPPT and shading
[153]	Parameter estimation of static solar photovoltaic models using Laplacian Nelder-Mead hunger games search	2022	Laplacian Nelder-Mead hunger games search (LNMHGS)	Parameter estimation
[154]	Application of Temporal Fusion Transformer for Day-Ahead PV Power Forecasting	2022	Temporal Fusion Transformer (TFT)	Power forecasting
[155]	Modified honey badger algorithm based global MPPT for triple-junction solar photovoltaic system under partial shading condition and global optimization	2022	Honey Badger Algorithm (HBA) and Dimensional Learning Hunting (DLH)	MPPT and shading
[156]	A population diversity-controlled differential evolution for parameter estimation of solar photovoltaic models	2022	differential evolution (DE)	Parameter estimation
[63]	An efficient fault classification method in solar photovoltaic modules using transfer learning and multi-scale convolutional neural network	2022	CNN	Fault detection and classification
[157]	Modified search and rescue optimization algorithm for identifying the optimal parameters of high efficiency triple-junction solar cell/module	2022	Search and Rescue optimization algorithm (SAR)	Parameter estimation

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[158]	Quantum Nelder-Mead Hunger Games Search for optimizing photovoltaic solar cells	2022	Hunger Games Search (HGS)	Parameter estimation
[67]	Forecasting intra-hour solar photovoltaic energy by assembling wavelet based time-frequency analysis with deep learning neural networks	2022	feedforward NN	Solar radiation forecasting
[159]	Hardware-In-the-Loop Validation of Direct MPPT Based Cuckoo Search Optimization for Partially Shaded Photovoltaic System	2022	CSO	MPPT and shading
[160]	Constraint estimation in three-diode solar photovoltaic model using Gaussian and Cauchy mutation-based hunger games search optimizer and enhanced Newton–Raphson method	2022	HGS	Parameter estimation
[61]	Improved gradient-based optimizer for parameters extraction of photovoltaic models	2022	Gradient-based optimizer (GBO)	Parameter estimation
[161]	Short-Term Forecasting of Energy Production for a Photovoltaic System Using a NARX-CVM Hybrid Model	2022	nonlinear autoregressive with exogenous inputs (NARX)	Power forecasting
[162]	Power Generation Prediction of Building-Integrated Photovoltaic System with Colored Modules Using Machine Learning	2022	NN	Power forecasting
[163]	Adaptive slime mould algorithm for optimal design of photovoltaic models	2022	adaptive slime mould algorithm (ASMA)	Parameter estimation
[35]	Tree-based machine learning models for photovoltaic output power forecasting that consider photovoltaic panel soiling	2022	RF, extra trees (ET) and gradient boosting (GB)	Power forecasting and soiling
[58]	Solar photo voltaic module parameter extraction using a novel Hybrid Chimp-Sine Cosine Algorithm	2022	hybrid Chimp-Sine cosine algorithm (HCSCA)	Parameter estimation
[164]	Analyzing the performance of photovoltaic systems using support vector machine classifier	2022	SVM	Monitoring
[12]	A Novel Hybrid Method Based on Fireworks Algorithm and Artificial Neural Network for Photovoltaic System Fault Diagnosis	2022	ANN and Evolutionary Fireworks Algorithm (FWA)	Fault detection
[165]	Data driven approach to forecast the next day aggregate production of scattered small rooftop solar photovoltaic systems without meteorological parameters	2022	least square support vector regression (LsSVR)	Power forecasting
[166]	A powerful meta-heuristic search algorithm for solving global optimization and real-world solar photovoltaic parameter estimation problems	2022	teaching-learning-based artificial bee colony (TLABC)	Parameter estimation
[167]	Modeling of solar photovoltaic power using a two-stage forecasting system with operation and weather parameters	2022	ANN	Power forecasting
[39]	Artificial Intelligence Applications in Estimating Invisible Solar Power Generation	2022	KNN	Power forecasting
[79]	Hourly Forecasting of Solar Photovoltaic Power in Pakistan Using Recurrent Neural Networks	2022	LSTM and bidirectional LSTM	Power forecasting
[27]	Comparison of deep learning and regression-based MPPT algorithms in PV systems	2022	LSTM	MPPT
[168]	Large-scale photovoltaic system in green building: MPPT control based on deep neural network and dynamic time-window	2022	DNN	MPPT
[169]	Fuzzy State-Dependent Riccati Equation (FSDRE) Control of the Reverse Osmosis Desalination System With Photovoltaic Power Supply	2022	invasive weed algorithm (IWA)	MPPT

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[26]	AI-Empowered Recommender System for Renewable Energy Harvesting in Smart Grid System	2022	LSTM	Power forecasting
[38]	Fuzzy Based MPPT and Solar Power Forecasting Using Artificial Intelligence	2022	KNN	MPPT
[170]	Dynamic Model and Intelligent Maximum Power Point Tracking Approach for Large-Scale Building-Integrated Photovoltaic System	2021	DE)	MPPT
[24]	GeoAI for detection of solar photovoltaic installations in the Netherlands	2021	CNN (TernausNet)	PV systems detection
[59]	An evolutionary Nelder–Mead slime mould algorithm with random learning for efficient design of photovoltaic models	2021	improved slime mould algorithm (ISMA)	Parameter estimation
[171]	A Dragonfly Optimization Algorithm for Extracting Maximum Power of Grid-Interfaced PV Systems	2021	dragonfly optimization algorithm (DOA)	MPPT
[30]	Small-Scale Solar Photovoltaic Power Prediction for Residential Load in Saudi Arabia Using Machine Learning	2021	least absolute shrinkage and selection operator (LASSO), RF, LR, polynomial regression (PR), XGBoost, SVM, and deep learning (DL)	Power forecasting
[172]	Deep-Learning-Based Probabilistic Estimation of Solar PV Soiling Loss	2021	backbone networks	Soiling
[173]	Random reselection particle swarm optimization for optimal design of solar photovoltaic modules	2021	PSO and cuckoo search	Parameter estimation
[174]	Development of Artificial Intelligence Techniques for Solar PV Power Forecasting for Dehradun Region of India	2021	MLP, ridge regression, DT, RF, SVM and KNN	Powe forecasting
[80]	CNN-based deep learning technique for improved H7 TLI with grid-connected photovoltaic systems	2021	CNN	Inverters
[175]	Predicting diurnal outdoor performance and degradation of organic photovoltaics via machine learning; relating degradation to outdoor stress conditions	2021	ANNs	Power forecasting and degradation
[176]	Evaluation of constraint in photovoltaic cells using ensemble multi-strategy shuffled frog leading algorithms	2021	ensemble multi strategy-driven shuffled frog leading algorithm (EMSFLA)	Parameter estimation
[40]	Design and Evaluation of Fuzzy Adaptive Particle Swarm Optimization Based Maximum Power Point Tracking on Photovoltaic System Under Partial Shading Conditions	2021	fuzzy adaptive PSO and conventional PSO	MPPT
[14]	Implementation of solar energy in smart cities using an integration of artificial neural network, photovoltaic system and classical Delphi methods	2021	ANN	Power forecasting
[43]	Optimal Parameter Estimation of Solar PV Panel Based on Hybrid Particle Swarm and Grey Wolf Optimization Algorithms	2021	PSO and GWO	Parameter estimation
[54]	Day-ahead hourly photovoltaic power forecasting using attention-based CNN-LSTM neural network embedded with multiple relevant and target variables prediction pattern	2021	attention-based long-term and short-term temporal neural network prediction model (ALSM), CNN, LSTM, and attention mechanism under the multiple relevant and target variables prediction pattern (MRTPP)	Power forecasting

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[20]	A Novel Hybrid Maximum Power Point Tracking Controller Based on Artificial Intelligence for Solar Photovoltaic System Under Variable Environmental Conditions	2021	FL	MPPT
[65]	Proposed ANFIS Based Approach for Fault Tracking, Detection, Clearing and Rearrangement for Photovoltaic System	2021	ANFIS	Fault detection
[177]	Real-time implementation of MPPT for renewable energy systems based on Artificial intelligence	2021	fuzzy NN	MPPT
[178]	Modeling Renewable Energy Systems by a Self-Evolving Nonlinear Consequent Part Recurrent Type-2 Fuzzy System for Power Prediction	2021	fuzzy NN	Modeling
[179]	Effective Segmentation Approach for Solar Photovoltaic Panels in Uneven Illuminated Color Infrared Images	2021	k-means clustering	Segmentation
[17]	Promising MPPT Methods Combining Metaheuristic, Fuzzy-Logic and ANN Techniques for Grid-Connected Photovoltaic	2021	FL, PSO, and ANN	MPPT
[180]	Neural Network Approach for Global Solar Irradiance Prediction at Extremely Short-Time-Intervals Using Particle Swarm Optimization Algorithm	2021	PSO and NN	Solar radiation prediction
[181]	Evolutionary shuffled frog leaping with memory pool for parameter optimization	2021	shuffled frog-leaping algorithm (SFLBS)	Parameter estimation
[182]	Novel AI Based Energy Management System for Smart Grid With RES Integration	2021	GWO	Energy management
[183]	Artificial Intelligence Method for the Forecast and Separation of Total and HVAC Loads With Application to Energy Management of Smart and NZE Homes	2021	LSTM	Power forecasting
[11]	Adaptive maximum power point tracking using neural networks for a photovoltaic systems according grid	2021	ANN	MPPT
[184]	Robust configuration and intelligent MPPT control for building integrated photovoltaic system based on extreme learning machine	2021	extreme learning machine (ELM)	MPPT
[42]	Parameter Identification of Photovoltaic Cell Model Based on Enhanced Particle Swarm Optimization	2021	enhanced PSO	Parameter estimation
[16]	Analysis of a Traditional and a Fuzzy Logic Enhanced Perturb and Observe Algorithm for the MPPT of a Photovoltaic System	2021	FL	MPPT
[57]	Randomised learning-based hybrid ensemble model for probabilistic forecasting of PV power generation	2020	randomized learning-based hybrid ensemble (RLHE) model	Power forecasting
[28]	Hybrid deep learning for power generation forecasting in active solar trackers	2020	LSTM	Power forecasting
[185]	Horizontal and vertical crossover of Harris hawk optimizer with Nelder-Mead simplex for parameter estimation of photovoltaic models	2020	HHO and Crisscross Optimizer (CCO)	Parameter estimation
[186]	Solar photovoltaic parameter estimation using an improved equilibrium optimizer	2020	Equilibrium Optimizer (EO)	Parameter estimation
[187]	Orthogonally adapted Harris hawks optimization for parameter estimation of photovoltaic models	2020	HHO	Parameter estimation
[19]	Artificial intelligent controller-based power quality improvement for microgrid integration of photovoltaic system using new cascade multilevel inverter	2020	FL	MPPT

Table A1. *Cont.*

Reference	Title	Year	AI technique	Application
[33]	Data Description Technique-Based Islanding Classification for Single-Phase Grid-Connected Photovoltaic System	2020	SVM	Islanding detection
[188]	A particle swarm optimisation-trained feedforward neural network for predicting the maximum power point of a photovoltaic array	2020	ANN and PSO	MPPT
[189]	Photovoltaic power forecast using empirical models and artificial intelligence approaches for water pumping systems	2020	FFNN and ANFIS	Power forecasting
[190]	Multiple scenarios multi-objective salp swarm optimization for sizing of standalone photovoltaic system	2020	Salp Swarm Optimization (SSA)	Sizing
[191]	Orthogonal Nelder-Mead moth flame method for parameters identification of photovoltaic modules	2020	orthogonal moth flame optimization (MFO)	Parameter estimation
[192]	Forecast uncertainty-based performance degradation diagnosis of solar PV systems	2020	ensemble method based on the dropout technique	Degradation diagnosis
[193]	Optimal Sizing of Standalone Photovoltaic System Using Improved Performance Model and Optimization Algorithm	2020	DE multi-objective optimization	Sizing
[194]	Characterization of a polycrystalline photovoltaic cell using artificial neural networks	2020	ANN	Parameter estimation
[195]	Implementation of ANFIS-mptc for 20 kwp spv power generation and comparison with FLMPPT under dissimilar conditions	2020	ANFIS	MPPT

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