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- Digital twins
- Artificial intelligence,
- Photovoltaic systems,
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- Gemelos digitales,
- Inteligencia artificial,
- Sistemas fotovoltaicos,
- Monitoreo inteligente,
- Optimización energética

3. Artificial Intelligence and Integrated Optimization in the Energy Sector: Advances in Photovoltaic Systems

Inteligencia Artificial y Optimización Integrada en el Sector Energético: Avances en Sistemas Fotovoltaicos

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1. Introduction

Over the past decades, photovoltaic solar energy has experienced exponential growth, positioning itself as one of the most promising renewable sourcesfor the global energy transition.

However, its large-scale integration faces critical challenges related to operational efficiency, fault prediction, and real time performance optimization.

In this context,digitalization has becomea key factor in improving the management of photovoltaic systems, with digital twins and artificial intelligence (AI) being two of the most significant emerging technologies in the sector.

The implementation of digital twinsin to photovoltaic systems is useful to detect anomalies, degradation of prediction and helps to make decision to optimize the energy generation (Jain, Poon, Singh, Spanos, Sanders and Panda, 2020).

On the other hand, physics-based models are capable to simulate the behavior of photovoltaic systems: they are capable of offering insights into electrical, thermal and optical processes.

The integration of digital twins and physics-based models withartificial intelligence makespossible to enhancethis capability to analyze large volumes of data and detect patters in a more efficient and autonomous way (Mousavi, Mousavi,Mousavi, Tavasoli, Arab, Kucukdemiral, Alfi and Fekih, 2025).

The Internet of Things (IoT) enables real-time data acquisition and communication between sensors,inverters and monitoring platforms.

Architectures based in IoT enhance the capabilities of digital twins by providing continuous streams of environmental and operational data, ensuring a more dynamic and adaptive approach to system management.

By integrating IoT with advanced analytics, photovoltaic plants can achieve higher efficiency and reliability.

2. THE DIGITALIZATION OF PHOTOVOLTAIC SYSTEMS

Digital twins enable the creation of virtual duplicates of physical systems, providing a safe environment for simulation and analysis Ghenai, Husein, Nahlawi, Hamid and Bettayeb (2022).

In the photovoltaic context, digitaltwins enable real time monitoring of the performance of solar panels and inverters. With this, it is possible to perform an early fault detection and optimization of energy production.
Their implementation improves operational efficiency, reduces maintenance costs, and extends the lifespan of equipment.

A comprehensive scheme of the implementation of ML-based and physics-based modeling is described in Figure 1.

2.1.Machine Learning-Based Digital Twins

Data-driven digitaltwins utilize information collected from sensors in the photovoltaic system to train predictive models. Through machine learning techniques and big data analysis, these models can anticipate anomalous behaviors, improve maintenance planning, and adjust systemoperation based on weather conditions and energy demand.

There are variouschallenges to addressduring the development of a digital twin. First, it is necessary to prepare data using routines to determine whether they are contaminated by noise, equipment disconnections, or changes in the baselinebehavior of devices. The correction of contaminated data has been addressed in the state of the art through the implementation of generative adversarial networks and feature extraction using neural networksZhang, Li, Li, Gui, Sun and Gao (2024).

Several studies have investigated the use of data-driven digital twins for monitoring and maintaining photovoltaic plants. For instance, Yalçin, Solà, Stefanidou-Voziki, Domínguez-García and Demirdelen (2023) implemented ML models in MATLAB/Simulink to predict failures and optimize operational efficiency.

Their study leveraged neural networks and computer vision techniques, achieving a fault detection accuracy of 98.3%in identifying anomalies in inverters and panels.

These results highlight the potential of purely data-driven models which enhance reliability and performance of photovoltaic systems.

Yu, Liu, Zhu and Zhan (2024) developed a data-driven digital twin model capableof estimating internalinverter parameters without the need to install additional sensors. Instead of relying on external measurements, the system uses operational data collected directly from the inverter to adjust its model and improve the interpretation of the system'sdynamics.

This approachis particularly usefulin environments where installing additional sensors can be costly or impractical (Yu et al., 2024).

The use of AI in the contextof neural networksand optimization also addresses the management of photovoltaic networksusing ML and computational optimization through cloud computing and fog computing techniques to balance energy load and minimize latency Fan and Li (2023). In their study,an algorithm called Whale Optimization Algorithm (WOA) is implemented.

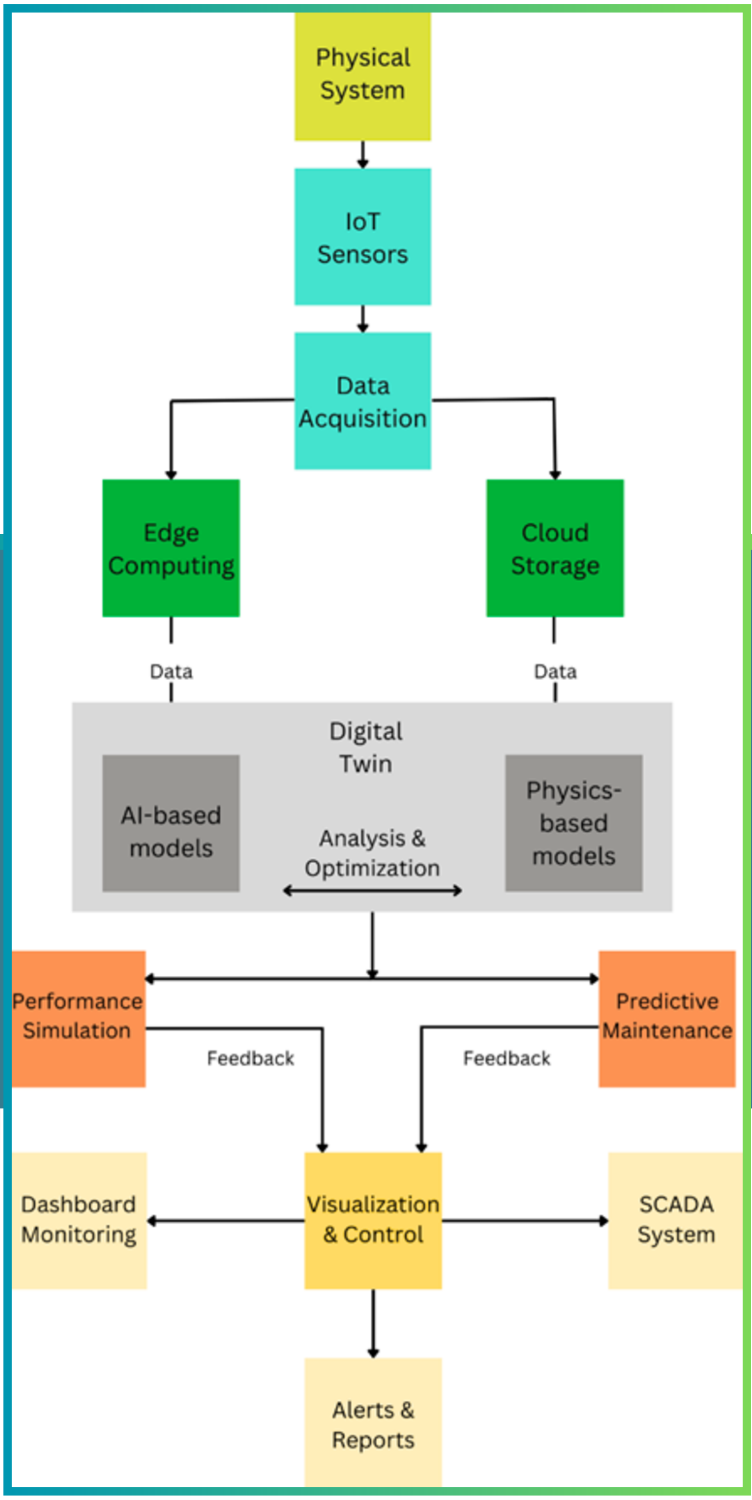


FIGURE 1. DIGITAL TWIN IMPLEMENTATION PIPELINE

The authors compare with algorithms such as Particle Swarm Optimization (PSO) and Teaching - Learning - Based Optimization (TLBO), achieving a 5% improvement in energy efficiency

2.2.PHYSICS-BASED TWINS

This approach is based on the mathematical modeling and physical simulations of photovoltaic systems, achieving a highly accurate representation of electrical and thermal processes.

Unlike data- driven models, physics-based twins do not rely on large volumes of historical data but instead use physical principles to predict system behaviorunder different conditions to simulate solar energy generation scenarios beforeinstalling a photovoltaic plant (Clausen, Ma and Jørgensen, 2022).

Their work focuses on the physical simulation of real conditions such as shadow incidence, sun position, and reflections to optimize the installation of solar panels.

The study demonstrates that modelingbased on graphicsengines improves the accuracy of energy planningstudies. The authors highlightthe need for combining these models with advanced physical simulations to improve energy modeling accuracy.

Incorporating the system's physical equations is crucial for accurately simulating the conversion of direct current (DC) to alternating current (AC) in the inverter.

In Yu et al. (2024), the authors introduce a temporal synchronization filter that aligns the simulation with real measurements, reducing discrepancies between theoretical and observed responses.

This strategy improves simulation accuracywithout relying solelyon empirical models.

Digital twinscombined with physics-based models have been developed for fault detection and diagnosis in urban solar systems (Kaitouni, Abdelmoula, Es-sakali, Mghazli, Er-retby, Zoubir, Man- souri, Ahachad and Brigui, 2024). Here, the authors modeled five Building-Applied PV (BAPV) systems using tools such as Rhinoceros for 3D modeling and Python for data processing

2.2.1.Tuning Physics-Based Digital Twins Using ML

Combining physicalmodels with machinelearning (ML) techniques enhances the accuracy and adaptability of digital twins.

By leveraging real measured data, ML-based tuning allows continuous adjustment of simulation parameters, leading to improved fault prediction and system performance

This hybrid approach is also featured in the Digital-PV platform, where physical models are combined with neural networks to enhance fault detection and autonomous monitoring of solar plants(Kolahi, Esmailifar, Sizkouhiand Aghaei,2024).

In this study, the authorsadvance process digitization by not only considering electrical variables from installed equipment but also using drones to monitor solar plants. Their research demonstrates the applications of neural networks for image segmentation and contaminant detection on solar panels using AirSim and Unreal Engine to conduct virtual maintenance and fault analysis tests.

As expected, a model tends to differ from real device behavior, and this discrepancy betweenthe model and real-world monitoring data must be minimized.

These solutions integrate an ML-based tuning mechanism that allows the model to be continuously updated as new operational data is collected, dynamically adjusting the inverter parameters over time (Yu et al., 2024). This is crucial for degradation monitoring since it can adapt the model without requiring manual recalibrations.

Various approaches have been reportedto refine physicalmodels using obtained data to enhance prediction accuracy.

One study implemented a hybrid approach combining a convolutional neural network (CNN) with a bidirectional long short-term memory (BiLSTM) network (CNN-BiLSTM, Convolutional Neural Network with Bidirectional Long Short-Term Memory) to improve energy prediction. This approach resulted in greater stability and accuracy in energy forecasting. Zhang et al. (2024).

Hybrid optimization approaches positively impact data-driven decision-making in digital twin environments.

Small and medium- sized enterprises often face resource constraints in adopting advanced technologies.

The study by Lee, Chua, Liu, Moon and Lopez (2025) introduces a simulation-optimization framework for decision making using multiple criteria, known as Simulation-Optimization with Multi-Criteria Decision-Making (SOMCDM).

Ultimately, the relevance of digital twins and their implementation, along with artificial intelligence integration, lies in model interpretability.

The combination of physics-based solutions with data-driven optimization can reduce the need for additional sensors in some cases. Toachieve this, researchers have opted to implement a temporal synchronization filter to align the frequency of simulated models, correcting errorsin synchronization betweenmeasured data and digitalmodel outputs (Yu et al., 2024).

The model'sparameters were optimized using a Grey Wolf Optimization (GWO) algorithm to improve the dynamic representation accuracy of grid-connected inverters.

Managing and predicting the performance of a photovoltaic system is crucial for diagnostic purposes,providing substantial value toall monitoring interfaces while also supportingdecision-making.

Additionally, a fault detection system not only provides diagnostics from monitoring data but also servesas a tool to optimizeprocesses, schedule maintenance, and anticipate contingencies.

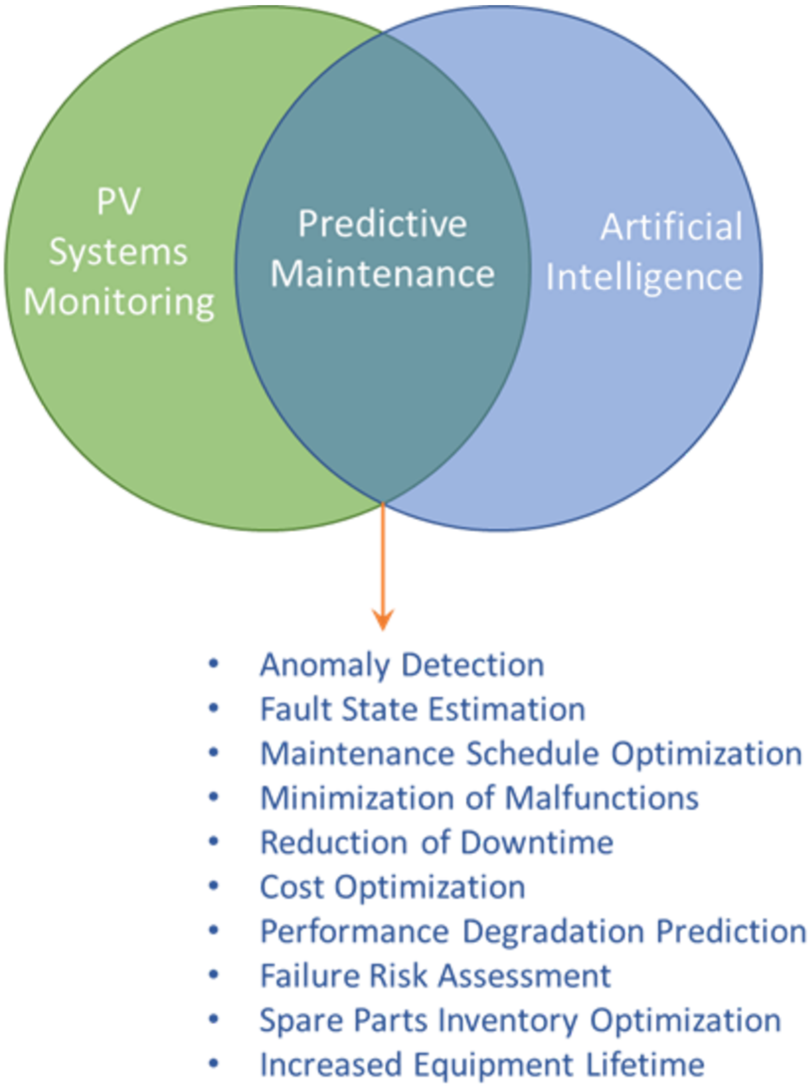


Figure 2. Importance of Predictive Maintenance in the Context of Photovoltaic Systems

A machine learning-based approach that optimizesphysical models using ML is presented in Cao, Zhang and Yi (2023), where the authors implement an algorithm called Bat Optimization Algorithm (BOA) to improve fault prediction efficiency.

Furthermore, the study incorporates an intrusion detection system to prevent cyberattacks on photovoltaic microgrids, validated on a 33-bus test system

The interconnectivity of so-called smart grids has made data- driven solutions integral to security challenges. Machine learning has been employedto enhance photovoltaic system security through hybrid digital twins that prevent false data injection attacks and propose mitigation strategies.

These strategies utilize automatic anomaly classification techniques to assessthe impact of attacks on energy production and introduce a detection framework based on deep neural networks (Shen, Xu, Li, Shi and Gao, 2023).

3. ARTIFICIAL INTELLIGENCE AND PV SYSTEMS

Artificial intelligence has revolutionized the photovoltaic industry by enabling more efficient and automated solar plant management.

Through advanced data analysis algorithms, AI can identify energy generation patterns, optimize system operation, and reduce downtime through predictive maintenance. Its integration with digital twins further amplifies these capabilities, providing a holistic approach to solar asset management.

The integration of monitoring technologies and artificial intelligence enables the automation of anomaly and fault detection (Fig. 2).

3.1.Detection

Fault detection in photovoltaic systemsis a key area in optimizing the performance and reliability of these systems,where artificial intelligence has enabled significant progress. These advancements have introduced approaches based on physical models, signal analysis, and machine learning to identifyanomalous and faulty

states in photovoltaic systems (Ding, Wu, Li and Zhang, 2024). Fault detection is essential for searching the causes and consequences to help designing strategies to ensure that a photovoltaic system remains operational.

An innovative method in this area is the work by Amaral, Pires and Pires (2021), which develops an image processing algorithm based on Principal Component Analysis (PCA) for fault detection in photovoltaic tracking systems. They identified anomalies without additional sensors. This ensures a reliable system without increasing instrumentation data.

The work of Bouyeddou, Harrou, Taghezouit, Sun and Arab (2022) introduces a fault detection framework using advanced semi-supervised data mining techniques combined with statistical monitoring through a triple exponentially weighted moving average filter (TEWMA). Their methodology gives greater weight to the most recent data to computethe moving average.

The TEWMA approach provided effective results in the early detection of anomalies in a 9.54 kW photovoltaic plant, surpassing traditional techniques both in sensitivity and accuracy.

Hybrid methods have proven to be effective in detecting and classifying faults in grid connected photovoltaic systems. Alrifaey et al. (2022) proposes a combination of Wavelet Packet Transform (WPT) and a deep learning model based on Stacked Autoencoders with Long Short-Term Memory (LSTM-SAE).

This model is further integrated with the Equilibrium Optimizer Algorithm (EOA), which enhances fault classification in 250 kW photovoltaic systems.

On the other hand, Yao, Kang, Zhou, Abusorrah and Al-Turki (2021) presents a data-driven method for fault detection in photovoltaic plants, using regression models based on decision trees. Evaluations carried out in a 6.95 MW plant demonstrate the ability of the model to detect direct and indirect faults with high accuracy.

A novel approach based on clustering models and deep neural networks was proposed by Zulfauzi, Dahlan, Sintuyaand Setthapun (2023). In this study, a hybrid model was implemented that combines the K-Means clustering algorithm to classify operational data based on irradiance and temperature with a Long Short-Term Memory (LSTM) neuralnetwork to detectanomalies in the current output of photovoltaic modules.

The model's performance was compared to conventional artificial neural networks (ANN) using error metrics such as MAE, MSE, and RMSE, demonstrating that the LSTM-based method achieves higher accuracy in anomaly detection. Additionally, this strategy led to reduced costs and predictive maintenance time and was validated in an LSSPV plant in Malaysia.

These approaches have been complemented by optimized models to improve anomaly detection. Kapucu, Ozcan and Akbulut (2021) employs Ensemble Learning techniques to combine multiple ML models using Bagging and Boosting techniques, significantly improv- ing fault detection without requiring additional sensors in the system.

Machine learning has been crucialin designing fault detectors due to its ability to identify patternsnot visible with classical techniques. In Kellil, Bouchakour, Khelifa, Menasria and Bourouis (2023), a methodology based on Deep Learning (DL) is introduced for fault detection using infrared images of photovoltaic modules.

Their model, based on Convolutional Neural Networks (CNN), achieved a 99.91% accuracyin binary classification of photovoltaic modules, using two labels for training: normal or faulty state.

The work of Bouyeddou et al. (2022) introduces a fault detection

TABLE 1. COMPARISON OF APPROACHES FOR FAULT DETECTION IN PHOTOVOLTAIC SYSTEMS

REF	APPROACH	MAIN METRICS
Kellil, Bouchakour, Khelifa, Menasria and Bourouis (2023)	Deep Learningwith infrared images	99.91% accuracy in binary classification
Zulfauzi et al. (2023) Ding, Chen, Jiang, Yang, Chen, Zhang, Gao and Cui (2024)	K-Means and LSTM I-V modelingwith classification algorithms	Relative error reduction comparedto ANN 99.4% accuracy,0.17s computation time
Belhachat et al. (2024)	Review and evaluationof fault detection tech- niques	Comparative evaluation of over 50 approaches

NOTE: THE STUDIES HAVE BEEN SUMMARIZED FOR PRESENTATION PURPOSES, BUT THE CONTENT OF THE CORRESPONDING RESEARCH IS MORE EXTENSIVE.

approach in grid-connected photovoltaic systems based on data mining and advanced statistical monitoring. A hybrid methodology is proposed that combineslatent variable regression (PCR and PLS) with the Triple Exponentially Weighted Moving Average (TEWMA) monitoring scheme, achieving high sensitivity to small changes in operational data.

After validating with a 9.54 kW photovoltaic plant, it was demonstrated that the PLS-TEWMA method outperforms traditional approaches in early fault detection, reducing the false positive rate and improving the model's adaptability to non-Gaussian distributions. This study shows the importance of semi-supervised methods in monitoring and maintaining PV systems, which enables optimized diagnostics without the need for extensivemanual labeling.

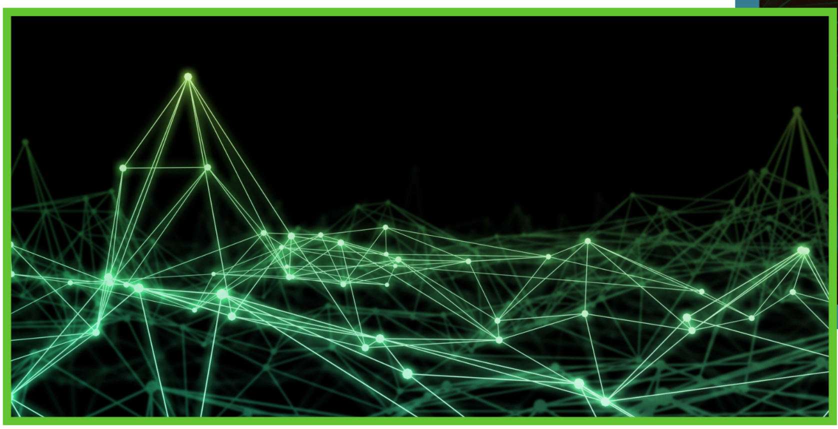
In Table 1 a list of the main approaches to detect faults in photo- voltaic systems is presented, along with their methodologies and performance metrics.

3.1.Diagnosis

Fault diagnosis in photovoltaic systems has evolved with the use of artificial intelligence, enabling automated anomaly detection through real-time data analysis. Techniques such as signal processing and computervision allow the identification of irregularities in solar panelsor inverters beforethey impact energy production.

The use of artificial intelligence has improvedthe fault diagnosis of photovoltaic systems by enabling an automated anomaly detection in real-time data. Signal processing and computer vision help to identify irregularities in solar panels or inverters before they have an impact in the energy production.

In this context, various approaches have been proposed to improve diagnostic accuracy. In Chokr, Chatti, Charki, Lemenand and Hammoud (2023), a methodology based on the extraction and reduction of operational data features is presented. This approach employs machinelearning models such as SupportVector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN), achieving an 8-12% improvement in diagnostic accuracycompared to models without feature reduction.



On the other hand, Montes-Romero, Heinzle, Livera, Theocharides, Makrides, Sutterlueti, Ransome and Georghiou (2024) proposes an innovative data-driven architecture to assess the health status of photovoltaic systems. Their methodology combinesdata quality assurance routines, digital twins, and artificial intelligence algorithms for fault identification and classification.

The results show errors below 2% in digital twin predictions and an accuracy greater than 90% in detecting faults with magnitude greater than 8%, enabling advanced and automated supervision of large-scale solar plants.

In addition to data-driven analysis, some studies have explored model-based approaches. Chi, Wei, Shen and He (2024)introduces a method for detecting hidden cracks in photovoltaic modules by evaluating parameters of equivalent circuit models.

This approach characterizes fault effects such as hot spots, potential- induced degradation (PID), and aging, assessing variations in photo-generated current (Iph) and series and shunt resistances.

A neural networktrained using backpropagation was implemented, achieving high accuracy in identifying and assessing the sever- ity of cracks, providing a solid foundation for predictive maintenance.

Similarly, Ding, Chen, Jiang, Yang, Chen, Zhang, Gao and Cui (2024) proposesa fault diagnosis method based on the conversion of current-voltage (I–V) curves of photovoltaic arrays. Using models such as the Double Diode Model (DDM) and the Reverse Bias Model (RBM), I–V curves are simulated under various operating conditions.

Among the evaluated classification models, the Variable Prediction Model (VPM) achieved the highest accuracy (99.4%) with a computation time of only 0.17s. This method significantly improves fault detection without the need for additional sensors, relying solely on electrical data.

From the perspective of advanced machine learning, Kapucu and Cubukcu (2021) introduces a fault diagnosis method based on Ensemble Learning for photovoltaic systems.

Their methodology optimizes hyperparameters of multiple machine learning models and combines them using Bagging and Boosting techniques, achieving improved generalization and efficient fault detection without the need for additional sensors. This makes the model robust for implementation in real-time monitoring systems.

Finally, Kellil, Aissat and Mellit (2023) proposes a diagnostic system based on Deep Learning using infrared images of photovoltaic modules.

A Convolutional Neural Networks (CNN)model based on VGG-16 is implemented for automatic fault identification, achieving an accuracyof 99.91% in binary detection(normal/faulty) and 99.80% in faulttype classification.

This model was validated in a test facility in northern Algeria, demonstrating its effectiveness in real-world environments.

Table 2 summarizes the main approaches used for faultdiagnosis in photovoltaic systems, comparing their methodologies and performance metrics. These advancements have optimized predictive maintenance processes, reduced operational costs,and improved the reliability of photovoltaic systems, establishing artificial intelligence and physical modeling as essential tools for the efficient management of solar photovoltaic energy.

TABLE 2. COMPARISON OF APPROACHES FOR FAULT DIAGNOSIS IN PHOTOVOLTAIC SYSTEMS

REF	APPROACH	MAIN METRICS
Chokr et al. (2023)	ML for feature reduction	Diagnosis improvement of 8-12%
Montes-Romero et al. (2024)	Data-driven architecture	Accuracy >90%, error <2%
Chi et al. (2024)	Equivalent circuit model	Accurate crack detection
Ding, Chen,Jiang, Yang, Chen, Zhang, Gao and Cui (2024)	I-V conversion	99.4% accuracywith VPM
Kapucu and Cubukcu (2021)	Ensemble Learning for diagnosis	Generalization improvement with Boosting
Kellil, Aissat and Mellit (2023)	Deep Learning with IR images	99.91% accuracy in binary detection

NOTE: THE STUDIES HAVE BEEN SUMMARIZED FOR PRESENTATION PURPOSES, BUT THE CONTENT OF THE CORRESPONDING RESEARCH IS MORE EXTENSIVE.

4 Trends and Prospects

The digitalization of photovoltaic systems is advancing rapidly, driven by the convergence of artificial intelligence, digital twins, and real- time data analytics. Several key trends are shaping the future of this field:

1. Edge Computing and 5G Networks:
The increasing demand for real-time energy optimization has led to the adoption of edge computing in photovoltaic monitoring. By processing data closer to the source,these systems reduce latency and enable faster fault detection. Coupled with 5G networks, this approach allowsseamless communication between smart grids, inverters, and predictive models improving grid stability and energy forecasting.

2.Quantum Computing for Solar Optimization:
The complexity of large-scale energy distribution models is pushing researchers toward quantum-inspired algorithms for solar optimization. Quantum computinghas the potential to significantly accelerate optimization tasks, such as maxi- mum power point tracking (MPPT) and predictive maintenance scheduling, outperforming classical computing in handling high- dimensional data.

3.Hybrid AI Models and Physics-Informed Learning:
The integration of physics-informed neural networks (PINNs) is a promising approach to bridge the gap betweenpurely data- driven models and physics-based simulations. This trend enhances the accuracyof digital twins by embeddingfundamental physics into AI-driven optimization, reducing the dependency on large historical datasets while maintaining interpretability.

4.AI-Driven Autonomous Energy Systems:
Future solar plants are expected to move toward fully autonomous management, where AI-driven digitaltwins not only predict failures but also make real-timeoperational adjustments to maximize efficiency.

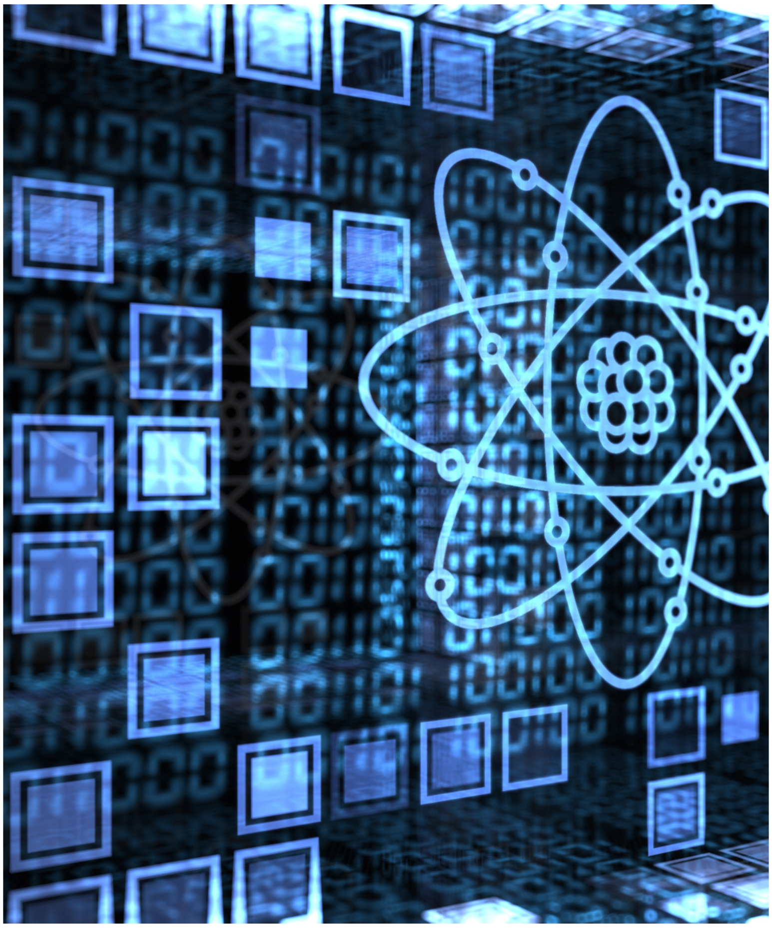
The use of reinforcement learning for adaptive controland multi-agent AI architectures for decentralized energy management are active areas of research.

2.Cybersecurity Challenges in Smart Photovoltaic Systems:

As photovoltaic infrastructures become increasingly interconnected, the risk of cybersecurity threats grows. False data injection attacks, malware, and system vulnerabilities could im- pact grid stability and energy distribution.

Research is focusing on blockchain-based securitymechanisms and AI-powered anomaly detection to protect solar plants from potential cyber threats.

These trends highlight the evolving role of AI and digital twins in shaping the next generation of smart, efficient, and resilient photovoltaic systems. By integrating cutting-edge technologies, solar energy can achieve unprecedented levels of efficiency, autonomy, and security



CONCLUSIONS

Integrating digitaltwins with artificial intelligence has improvedthe management of photovoltaic systems by enabling real-time monitoring and early anomalies prediction.

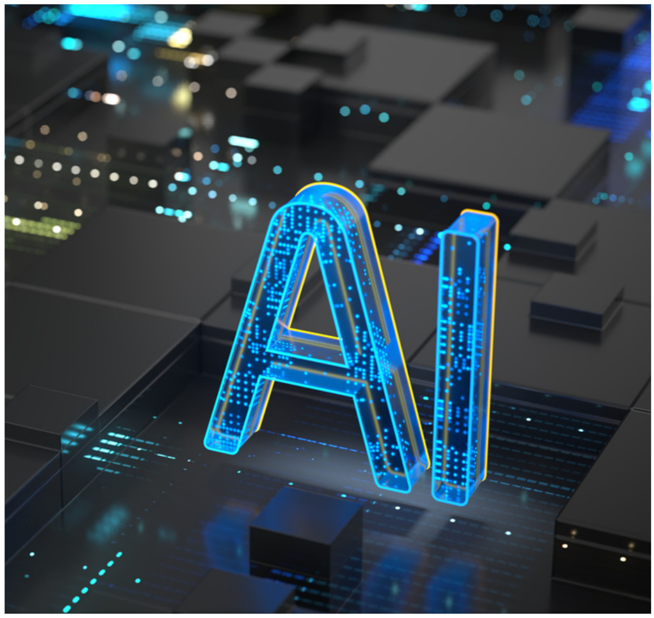
Combining physics-based models with machine learning an enhanced fault detection can be achieved, which reduces maintenance costs.

However, some challenges still must be addressed. It is necessary to further investigate ways to improvescalability, real-time data integration, and computational efficiency to fully take advantage of the potential of these technologies in large-scale solarfarms.

Additionally, it is necessary to standardize frameworks and interoperability between AI-driven and physics-based models.

In future works it is necessary to focus on integrating edge computing, quantum optimization, and AI-driven automation to enhance digital twin performance. It is also important to ensure robust cybersecurity protocols for interconnected photovoltaic infrastructures.

Those advancements will allow us to achieve energy sustainability and seamless integration of solar power into the global energy grid with more autonomous, intelligent, and resilient solar energy systems.



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