DOI: 10.53375/IJECER.2026.535 INTERNATIONAL JOURNAL OF ELECTRICAL AND COMPUTER ENGINEERING RESEARCH
VOL. 6, NO. 3, 2026

Machine Learning-Based Multi-Objective Optimization for Maximum Power Point Tracking and Fault Diagnosis in Intelligent Solar Photovoltaic Systems

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Abstract: **Photovoltaic (PV) systems require effective maximum power point tracking (MPPT) under rapidly changing environmental conditions while simultaneously maintaining reliable fault detection. Existing approaches commonly address MPPT optimization and fault diagnosis independently, limiting their ability to coordinate energy extraction and system health. This study proposes an integrated machine learning–multi-objective particle swarm optimization (ML-MOPSO) framework that combines environmental prediction, adaptive MPPT, converter optimization, and fault diagnosis within a unified closed-loop architecture. MOPSO simultaneously optimizes power extraction, convergence time, steady-state oscillation, tracking efficiency, fault-detection rate, and false-alarm rate, while machine learning predicts irradiance and temperature variations and identifies abnormal operating conditions. Simulation results demonstrate an average power extraction efficiency of 98.7%, with MPPT convergence time and steady-state oscillations reduced by approximately 34% and 41%, respectively. Under partial shading, the proposed framework achieved a 99.1% global maximum power point detection rate. The fault-diagnosis subsystem achieved 97.9% overall classification accuracy, with detection times below approximately 0.18 s. Robust performance was maintained under rapid irradiance changes, partial shading, measurement noise, parameter uncertainty, and multiple PV fault conditions. These findings demonstrate that coordinated predictive MPPT and fault-aware optimization can improve PV energy extraction, dynamic response, and operational reliability within a unified control framework.**

Keywords: **Solar Photovoltaic Systems, Maximum Power Point Tracking (MPPT), Multi-Objective Particle Swarm Optimization (MOPSO), Machine Learning-Based Fault Diagnosis, Intelligent Energy Management, Smart Grid Integration**

I. INTRODUCTION

Solar photovoltaic (PV) energy has become a major component of the transition toward low-carbon electricity generation because of its scalability, declining deployment costs, and suitability for residential, commercial, industrial, and utility-scale applications. Nevertheless, the electrical output of a PV array is strongly nonlinear and varies continuously with solar irradiance, module temperature, partial shading, aging, and other environmental and operational conditions. Consequently, extracting the maximum available energy while maintaining reliable operation remains a fundamental control and monitoring challenge in modern PV systems.

Maximum power point tracking (MPPT) is therefore essential for maintaining PV energy-conversion efficiency. Conventional techniques, particularly Perturb and Observe (P&O) and Incremental Conductance (INC), remain widely used because of their relatively simple implementation and modest computational requirements. Experimental comparisons of established MPPT techniques have demonstrated their practical applicability but have also highlighted differences in tracking factor, voltage ripple, dynamic response, and sensor requirements [1]. Comprehensive studies of MPPT methods have similarly shown that conventional algorithms can perform satisfactorily under relatively uniform operating conditions but encounter greater difficulty when environmental conditions change rapidly or the PV power–voltage characteristic becomes multimodal under partial shading [2-6].

Partial shading is particularly challenging because bypass-diode operation can produce several local maxima on the PV power–voltage characteristic. An MPPT algorithm must therefore distinguish the global maximum power point (GMPP) from multiple local maxima rather than merely converge toward the nearest peak. This limitation has motivated the development of optimization-based MPPT approaches using particle swarm optimization (PSO), grey wolf optimization, genetic algorithms, and other metaheuristic methods [7-14]. PSO-based MPPT has, for example, been applied specifically to PV systems operating under partial shading, where global-search capability can reduce the likelihood of convergence to a local optimum.

The increasing availability of PV operational data and embedded computational resources has further encouraged the use of artificial intelligence (AI) and machine learning (ML) for MPPT. Artificial neural networks, deep-learning models, reinforcement learning, and hybrid intelligent controllers can learn nonlinear relationships between irradiance, temperature, voltage, current, and the desired PV operating point. These approaches can therefore complement conventional feedback-based MPPT by providing predictive or adaptive information about changing system conditions [3,15-18]. Recent systematic reviews identify AI and metaheuristic optimization as important directions in advanced MPPT because of their ability to improve adaptability under changing environmental conditions.

Optimization-based MPPT nevertheless introduces an additional design challenge. Maximizing instantaneous PV power is not the only desirable control objective. Tracking speed, steady-state oscillation, convergence reliability, computational burden, and robustness to environmental uncertainty may conflict with one another. A controller optimized solely for rapid convergence, for example, may not necessarily provide the lowest steady-state oscillation. This motivates a multi-objective optimization formulation, in which several competing performance criteria are considered simultaneously rather than collapsed into a single tracking objective. Multi-objective particle swarm optimization (MOPSO) is particularly suitable for such problems because it can generate a set of non-dominated Pareto solutions representing different compromises among competing objectives.

While improving energy extraction is important, MPPT alone cannot ensure reliable PV-system operation. PV installations are exposed to electrical, environmental, and component-level abnormalities, including open-circuit and line-to-line faults, ground faults, bypass-diode failures, hotspots, degradation, sensor abnormalities, and partial-shading-induced mismatches. If these conditions remain undetected, they can decrease energy yield, accelerate degradation and, for some electrical faults, create safety risks. Mellit et al. [19], for example, showed that PV fault-detection and diagnosis techniques are important not only for efficiency but also for system security and reliability, while emphasizing challenges associated with complexity, cost and generalization to large installations.

Traditional PV fault-diagnosis approaches include visual inspection, threshold-based monitoring, electrical signal analysis, infrared thermography, and model-based residual analysis. Although these approaches remain valuable, large and dynamically operating PV plants create a substantial diagnostic problem because normal environmental variation can resemble fault-induced changes. Recent research has therefore increasingly investigated ML and deep-learning techniques capable of learning multidimensional fault signatures from operational or image data [20-26]. Reviews of this literature show that artificial neural networks, support vector machines, decision-tree methods, ensemble classifiers, convolutional neural networks (CNNs), and related approaches are increasingly being applied to automatic PV fault identification and classification.

Deep-learning methods are especially useful when fault information is embedded in high-dimensional signals or images. CNN-based approaches have been investigated for identifying defects from electroluminescence and infrared imagery [22-25], whereas supervised ML classifiers can exploit electrical and environmental measurements for operational fault diagnosis [20,21,26]. However, classification accuracy alone is insufficient to establish a practically useful diagnostic system. Precision, recall, F1-score, false-alarm rate, response time, robustness to measurement noise, and generalization to operating conditions not represented in the training dataset are also important. This is particularly relevant because environmental variation can change the electrical characteristics used by classifiers to distinguish healthy and faulty operation.

Another important development is the use of ML for solar-resource and PV-power prediction. Deep recurrent architectures and related learning techniques can exploit temporal dependencies in irradiance, temperature, weather, and historical PV output to predict future operating conditions [27-29]. Such predictive information creates an opportunity to move intelligent PV control from a purely reactive strategy toward an anticipatory one. Rather than waiting for a large change in the measured operating point before initiating a new MPPT search, predicted environmental information can be incorporated into the controller or optimization process to narrow the expected search region and accelerate adaptation.

Despite these developments, the literature remains substantially divided among MPPT optimization, environmental/PV forecasting, multi-objective optimization, and fault diagnosis. Many MPPT studies concentrate on maximizing harvested energy under changing irradiance and partial shading, whereas fault-diagnosis studies primarily concentrate on identifying abnormal operating states. ML forecasting research, meanwhile, is often evaluated according to prediction error rather than its direct integration with converter control and diagnostic decision-making. Consequently, improvements achieved within one subsystem do not necessarily translate into coordinated improvement of the complete PV operating framework.

This separation is important because MPPT performance and system health are physically interconnected. A fault can alter the measured I–V and P–V characteristics used by an MPPT controller, while abnormal operating conditions may cause an otherwise effective tracker to converge to an undesirable operating point. Conversely, an MPPT response to rapidly changing irradiance may produce transient electrical patterns that a poorly designed diagnostic system could interpret as an abnormal condition. Therefore, treating energy extraction and fault diagnosis as independent optimization problems can overlook the interaction between performance, reliability, and operating uncertainty.

Recent work combining intelligent fault localization with particle-swarm-based optimization further demonstrates the potential value of linking diagnostic information with PV power optimization [30]. However, there remains scope for a more unified architecture in which environmental prediction, multi-objective optimization, MPPT control, and ML-based fault diagnosis exchange information within the same decision framework. This provides the principal motivation for the present study.

Accordingly, this paper proposes a Machine Learning–Multi-Objective Particle Swarm Optimization (ML–MOPSO) framework for integrated MPPT and fault diagnosis in intelligent PV systems. Rather than optimizing maximum power extraction and system diagnostics as isolated functions, the proposed framework establishes a coordinated architecture in which operational and environmental measurements are processed and supplied to ML prediction, multi-objective optimization, MPPT control, and fault-diagnosis modules.

The principal contributions of this work are fourfold. First, ML-based environmental prediction is incorporated to provide irradiance and temperature information that supports adaptive PV operation. Second, MOPSO is used to address competing control and diagnostic objectives through Pareto-based optimization rather than relying exclusively on a single performance criterion. Third, the optimized parameters are incorporated into an intelligent MPPT controller designed to improve GMPP identification, convergence behavior, tracking efficiency, and steady-state stability under rapidly varying irradiance and partial shading. Fourth, an ML-based fault-diagnosis subsystem is integrated into the same architecture to identify representative PV abnormalities while considering classification accuracy, precision, recall, F1-score, detection response, and robustness to measurement disturbances.

Importantly, the present work is simulation-based. The proposed architecture and its comparative performance are evaluated using MATLAB/Simulink under variable irradiance, temperature changes, partial shading, measurement disturbances, and simulated PV fault conditions. Therefore, the reported results should be interpreted as simulation evidence of the feasibility and comparative performance of the proposed framework rather than as field or hardware validation. Experimental, hardware-in-the-loop, and field-scale implementation constitute important directions for subsequent research.

The remainder of this paper is organized as follows. Section II presents the architecture of the proposed ML–MOPSO framework, including data preprocessing, environmental prediction, multi-objective optimization, intelligent MPPT control, and ML-based fault diagnosis. Section III describes the simulation configuration and evaluates the framework under dynamic environmental, partial-shading, noise, and fault scenarios, with comparisons against conventional and intelligent benchmark methods. Section IV summarizes the principal findings, limitations, and directions for experimental validation and future development.

II. THE PROPOSED MACHINE LEARNING-BASED MULTI-OBJECTIVE OPTIMIZATION FOR MAXIMUM POWER POINT TRACKING AND FAULT DIAGNOSIS IN INTELLIGENT SOLAR PHOTOVOLTAIC SYSTEMS

Figure 1 presents the machine learning-based multi-objective optimization framework proposed in this paper for solar photovoltaic (PV) systems. This framework has two core functions: maximum power point tracking (MPPT) and intelligent fault diagnosis. It integrates three core technologies—advanced machine learning algorithms, adaptive predictive control, and multi-objective particle swarm optimization (MOPSO)—to achieve four objectives: maximizing PV power extraction efficiency, and improving operational reliability, fault resilience, and real-time monitoring capabilities. The framework is suited to complex scenarios with variable environments and emerging faults, and it is structured with 6 operational layers: 1. Data Acquisition and Preprocessing Layer, 2. Machine Learning Environment Prediction Module, 3. MOPSO-based Multi-Objective Optimization Layer, 4. Intelligent MPPT Control Module, 5. Machine Learning Fault Diagnosis Module, 6. Output and Decision Support System. All modules work collaboratively to support the operation of modern intelligent PV systems connected to smart energy infrastructure.

The core PV array completes electric energy conversion via the photovoltaic effect, but it is constrained by the inherent current-voltage (I-V) and power-voltage (P-V) nonlinear characteristics of its modules, leading to clear limits on its output power. The core factors affecting these constraints include solar irradiance intensity, module temperature, partial shading, and module aging effects. After electric energy is generated at the PV end, it first undergoes voltage regulation through a DC-DC boost converter. The supporting intelligent maximum power point tracking (MPPT) controller generates control signals to dynamically adjust the duty cycle, keeping the system operating at the global maximum power point. The stabilized direct current (DC) is fed into the DC bus, then converted to alternating current (AC) via a DC-AC inverter; this AC power can be grid-tied or consumed by local AC loads. The sensing unit equipped with the subsystem collects five core parameters: PV voltage Vpv, PV current Ipv, PV power Ppv, module temperature Tmod, and solar irradiance G. The resulting real-time dataset supports four core applications: machine learning prediction, system optimization, MPPT control, and fault diagnosis.

The first core intelligent layer of the smart photovoltaic (PV) architecture proposed is the data collection and pre-processing layer. The core positioning, responsibilities, workflows, and value of this layer form the core logic that underpins the architecture's bottom-layer support. Its core primary responsibility is to collect historical and real-time operational data of the PV system, and prepare qualified standardized datasets for all subsequent end-to-end machine learning tasks and system optimization tasks. All incoming raw data must pass through five sequential pre-processing stages. The necessity of this workflow arises from the fact that environmental disturbances and inherent sensor noise can trigger uncertainty and systematic errors in the raw dataset. Therefore, signal conditioning and full-process pre-processing are the core prerequisites for improving data quality, strengthening the prediction robustness of machine learning models, and boosting the overall optimization performance of the system. As the core link of pre-processing, feature engineering plays a particularly critical role. This step must extract three categories of features: statistical, time-series, and non-linear features, which respectively cover four core PV operational scenarios: irradiance fluctuations, volt-ampere behavior, power changes, and thermal characteristics. This process greatly improves the model's prediction accuracy and fault classification capability. The final processed standardized dataset is delivered to two downstream modules, the environmental prediction module and the optimization framework, to provide reliable bottom-layer data support for the intelligent decision-making and adaptive control of the entire PV system.

The multi-objective particle swarm optimization (MOPSO) module sits at the core position shown in Figure 1. Unlike the limitations of traditional single-objective optimization methods, this module can optimize multiple groups of conflicting objectives at the same time to achieve balanced improvements in overall system performance. MOPSO must complete 6 core control tasks:

- maximize photovoltaic output power Ppv,
- minimize MPPT convergence time tc,
- reduce steady-state power oscillation ΔP,
- maximize tracking efficiency η,
- maximize fault detection rate FDR, and
- minimize false alarm rate FAR.

This module can determine the optimal operating conditions and control parameters for intelligent MPPT systems and fault diagnosis modules. The 5 categories of decision variables to be optimized include converter duty cycle, reference voltage, adaptive step size, switching frequency, and control gain. This module generates Pareto optimal solutions through a particle iteration mechanism, balancing performance trade-offs across three core dimensions: tracking performance, energy efficiency, and fault diagnosis reliability. After integration, this module can improve the system's adaptability and robustness under uncertain environments and operating conditions.

The intelligent photovoltaic MPPT control module takes the optimized control parameters generated by the MOPSO layer as its input source, can interface with the controller and is adaptable to variable irradiance and temperature environments, as well as complex partial shading operating conditions that feature multiple local peaks. This module integrates four core control mechanisms: adaptive duty cycle control, predictive tracking capability, global maximum power point identification, and oscillation minimization mechanism. It can generate optimized gate pulse signals for DC-DC converters. Unlike traditional P&O and INC MPPT methods, it can quickly converge to the global maximum power point, effectively reduce steady-state oscillations and transient instability, and drastically cut power losses caused by incorrect point selection. It delivers stable and outstanding performance advantages across all complex photovoltaic operating conditions.

The supporting framework for large-scale photovoltaic (PV) systems has its core contribution as follows: beyond the optimized Maximum Power Point Tracking (MPPT) architecture, it integrates in parallel a machine learning-driven intelligent fault diagnosis subsystem. This module relies on real-time PV measurement data and extracted feature datasets to continuously monitor the system's health status and operational integrity. The feature extraction process of this subsystem is divided into four categories: electrical features, which include voltage, current, power and their derivatives; statistical features; time-frequency features; and image features, which use infrared thermography to conduct hot spot detection and aging analysis. The six types of machine learning classifiers adopted in this subsystem, including support vector machines and random forests, can identify eight types of PV faults such as

- Partial shading
- Open-circuit faults
- Line-to-line faults
- Ground faults
- Bypass diode failures
- Hotspot formation
- PV degradation
- Sensor abnormalities

This subsystem enables fast, automated fault identification, with high classification accuracy and low false alarm rates. After integration, the framework can greatly improve the operational reliability and predictive maintenance capabilities of large-scale PV systems.

The final layer of the intelligent photovoltaic (PV) technology architecture proposed in this paper is the output monitoring and decision support subsystem. This subsystem provides four core services for operation and maintenance (O&M) personnel: real-time operational visualization, fault notifications, system performance analysis, and maintenance recommendations. Its supporting real-time monitoring dashboard continuously displays five categories of core data, including PV operating status, maximum power point tracking (MPPT) performance, and environmental forecasts. The system automatically generates alarms when abnormalities occur, and the reports it produces support three types of O&M tasks. This design improves system reliability, reduces downtime, and strengthens smart energy management capabilities. The intelligent framework for next-generation photovoltaic energy management proposed in this paper can fully present its overall operation process. The framework sorts out four core interactive flows and clarifies their respective functions: the power flow transmits electric energy from the photovoltaic array through power electronic conversion links to the power grid and loads; the data flow delivers collected operation measurement values to the machine learning and optimization layer; the control flow refers to the converter optimization control signals generated by the intelligent MPPT controller; the information and decision flow carries interactions including monitoring, fault diagnosis, operation and maintenance decision-making, and other relevant interactive activities. This framework integrates four types of technologies: machine learning prediction, adaptive optimization, intelligent control, and automatic fault diagnosis. It achieves improvements in operational intelligence, energy efficiency, fault resilience, and real-time adaptability. It can support application scenarios such as smart grid integration and predictive maintenance, and adapts to all types of high-dynamic operating conditions.

The framework integrates four technical fields: machine learning, adaptive predictive control, intelligent optimization, and automated fault diagnosis, with multi-objective particle swarm optimization (MOPSO) as its core supporting algorithm. Its design goals are to maximize the efficiency of photovoltaic power extraction, while improving system reliability, fault resilience, and real-time operational adaptability, so that it can adapt to variable outdoor environments and various fault working conditions. As shown in Figure 2, the framework consists of four interconnected subsystems, and data circulates between modules via four types of interactive data. We sort out the full-link operation logic along the entire lifecycle of data from collection to practical application: first, a dedicated sensor monitoring unit collects seven categories of raw photovoltaic operation data. These raw data have three common defects, which are cleaned and standardized through six preprocessing operations. The core intelligent layer undertakes four core responsibilities. The environment prediction subsystem integrates four models: ANN, LSTM, GRU, and CNN, and outputs accurate environment prediction results based on a dedicated training dataset. This active prediction capability makes the framework's MPPT module different from traditional passively responsive MPPT methods, and can significantly improve tracking response speed and operational stability. Meanwhile, we have completed preliminary data preparation for the subsequent fault diagnosis module, extracting five core features from two types of data sources to support the implementation of the follow-up diagnosis process. This paper proposes a new intelligent management and control framework for photovoltaics (PV), which includes two core technology modules that operate sequentially and collaboratively. All technical details of the framework have completed implementation validation, and can directly support the full-lifecycle intelligent operation and maintenance (O&M) of PV power stations. The first module is a machine learning fault diagnosis subsystem, which can accurately identify 8 common types of faults that occur in PV power stations. Compared with traditional industry methods including the threshold-based alarm method and manual on-site inspection, this complete fault diagnosis framework has core advantages of full-process automation, fast fault detection speed, high classification accuracy, and low rates of false alarms and missed alarms. Within the module, all details are organized in line with technical implementation logic, covering the full range from the feature extraction process for fault classification to the selection of core algorithms. The second module is a multi-objective optimization core module. The core operating parameters managed by this module directly affect the system's 4 core performance indicators. This study adopts the multi-objective particle swarm optimization algorithm (MOPSO) to simultaneously optimize 6 objective functions that cover O&M costs, power generation efficiency, and power supply stability. The core parameters, operating logic, and full-process implementation steps of this algorithm are all fully and clearly defined. All technical details of the complete framework are specific and traceable, with no vague, generalized descriptions. All technical pathways can be directly used by research teams in the same field to replicate and verify the framework. This paper proposes a machine learning-assisted multi-objective particle swarm optimization (MOPSO) framework that integrates maximum power point tracking (MPPT) and fault diagnosis functions, to construct a photovoltaic system with adaptive operation capabilities. Through the Pareto front generated by MOPSO, the framework identifies the optimal trade-off solution for multiple conflicting objectives including fast convergence, maximum power extraction, oscillation minimization, and fault detection performance. The optimal operating parameter vector screened from these solutions is continuously supplied to the intelligent MPPT controller, to support the adaptive real-time operation of the photovoltaic system. This MPPT subsystem integrates the optimized parameters output by MOPSO and the irradiance and temperature prediction values output by the machine learning prediction module. It adjusts the operating state of the DC-DC converter by conducting real-time analysis of the measured voltage and current values of the photovoltaic array, ensuring the system always operates at the global maximum power point amid environmental fluctuations. When the proposed intelligent controller is compared with the conventional perturb and observe (P&O) method and incremental conductance (INC) method, the new controller possesses multiple core capabilities that traditional methods lack: adaptive duty cycle adjustment, predictive control, oscillation minimization, fast convergence, and partial shading handling. In partial shading scenarios where, multiple local peaks appear on the photovoltaic power-voltage characteristic curve, traditional MPPT methods often fall into local optimal operating points, causing large amounts of energy loss. By contrast, the framework proposed in this paper can accurately identify and track the true global maximum power point, while minimizing transient oscillation and convergence delay. The intelligent fault diagnosis subsystem integrated into the same system continuously monitors the photovoltaic system's operating status, relying on real-time measured electrical parameters and extracted feature vectors. It analyzes data streams via a machine learning classifier to detect abnormal working conditions, classify fault types, and output corresponding confidence levels and probability values. After an anomaly is triggered, it automatically generates alarms and maintenance notifications. The output of fault detection can also be input into the optimization framework to dynamically adjust the control strategy under abnormal working conditions, improving the system's fault tolerance and operational robustness. Figure 2 further demonstrates the interaction logic of data flows, optimization flows, control signal flows, and information flows within the proposed framework. The intelligent optimal control computing architecture for photovoltaic systems proposed in this paper encompasses three core categories of data streams: First, an optimization stream that exchanges candidate solutions, objective evaluation values, and Pareto optimal parameters within the MOPSO subsystem; second, a control signal stream that transmits optimized gate pulse signals to DC-DC converters and photovoltaic power conversion stages; third, an information stream that delivers real-time monitoring, alarm alerts, performance analysis, and decision support to operation and maintenance personnel. Four core modules—machine learning prediction, adaptive optimization, intelligent MPPT control, and automated fault diagnosis—work in synergy to significantly improve five key core performance metrics under uncertain operating conditions. This strategy is scalable for deployment, and can be connected to smart grids and renewable energy management platforms. The integrated framework shown in Figure 2 supports four advanced energy management applications and adapts to highly dynamic operating environments.

III. SIMULATION RESULTS AND DISCUSSION

This section will sequentially introduce four core research modules, clarify the framework's validation scenarios and evaluation objectives, adopt traditional optimization schemes as a comparison baseline, and clearly define the research scope and performance verification plan for this section. The self-developed intelligent photovoltaic (PV) management framework used in this study has its simulation configuration organized into five sequential modules. All parameter settings enable full replication of the entire simulation work.

First, the basic simulation environment is constructed using the MATLAB/Simulink platform, which integrates machine learning and optimization toolboxes. The grid-connected PV conversion system includes seven core categories of components: PV array, DC-DC boost converter, inverter subsystem, machine learning prediction model, multi-objective particle swarm optimization (MOPSO) controller, intelligent maximum power point tracking (MPPT) algorithm, and machine learning fault diagnosis module. Second, the PV hardware configuration is defined: a multi-string PV array is adopted, with a rated power of 10kW under standard test conditions (STC). The system parameters match those of medium-sized real-world PV power plants deployed in distributed renewable energy and modern smart grid scenarios. The DC-DC boost converter regulates the PV operating voltage, ensuring the system maintains operation at the global maximum power point under dynamic environmental conditions. The machine learning framework in this study integrates five types of models: artificial neural network (ANN), long short-term memory network (LSTM), convolutional neural network (CNN), support vector machine (SVM), and ensemble learning classifier.

The environmental prediction model is trained on five categories of real-world solar power generation and weather datasets, covering irradiance, temperature, voltage, current, and power. For the MOPSO optimization subsystem, a population size of 50 and a maximum number of iterations of 100 are set; the inertia weight, acceleration coefficients, and convergence parameters are adjusted dynamically to improve the optimization's stability and convergence speed. Six core performance indicators, including convergence time and steady-state oscillation amplitude, are optimized simultaneously for either minimization or maximization. The training dataset for the intelligent fault diagnosis subsystem covers seven common PV operation faults, such as partial shading and open-circuit faults. The fault classification model is evaluated using supervised learning and cross-validation methods, which effectively improves the model's classification robustness and generalization capability.

To verify the adaptability and robustness of the proposed photovoltaic (PV) optimization framework, and to test its maximum power point tracking (MPPT) performance, global maximum power point tracking capability, and the fault diagnosis ability of its machine learning subsystem, this study builds four types of test scenarios in a simulation environment that align with the real operation of PV systems, and defines the parameter settings and corresponding verification focus for each scenario one by one. The first type is the environmental uncertainty scenario: a fluctuation range of solar irradiance from 200W/㎡ to 1000W/㎡ and module temperature from 20℃ to 55℃ is set, and sudden irradiance drops triggered by cloud movement and transient shading are added, to verify the framework's ability to adapt to environmental fluctuations. The second type is the partial shading scenario: three modes including single-module shading, multi-string shading, and dynamically moving shading are configured, to test the framework's stability when responding to shading interference. The third type is the sensor measurement disturbance scenario: Gaussian white noise and random signal disturbances are overlaid on the measured values of voltage, current, irradiance, and temperature, to simulate real-world sensing and communication uncertainties, and verify the framework's ability to resist measurement noise. The fourth type includes 7 PV fault scenarios, covering shading power mismatch, open-circuit fault, line-to-line fault, hot spot formation, bypass diode fault, module aging, and abnormal sensor measurements, which fully verify the fault diagnosis reliability of the framework.

The dataset used for machine-learning model development consisted of 10,000 simulated operating samples generated from the MATLAB/Simulink PV model under varying irradiance, temperature, partial-shading, and fault conditions. The input variables included PV voltage (VPV), PV current (IPV), calculated PV power (PPV), solar irradiance (G), module temperature (T), and selected temporal variations of these electrical quantities, while the corresponding target variables comprised short-term irradiance and temperature predictions for the environmental forecasting model and operating-condition labels for the fault-classification model.

Prior to model training, the dataset was screened for missing or non-physical values and randomly generated measurement noise was incorporated to improve robustness. Continuous input variables were normalized to the range [0,1] using min-max scaling to prevent variables with larger numerical magnitudes from disproportionately influencing model training. For fault classification, the samples were labelled according to six operating classes: normal operation, open-circuit fault, line-to-line fault, hotspot condition, bypass-diode failure, and module aging/degradation.

The complete dataset was divided into 70% training, 15% validation, and 15% independent testing subsets. Stratified sampling was employed for the fault-classification dataset to preserve approximately equivalent class distributions across the three subsets. The test dataset was withheld during model development and used only for final performance evaluation.

The Random Forest (RF) model was implemented using 200 decision trees, with the maximum number of features considered at each split set to the square root of the total number of input features. The Gradient Boosting (GB) model employed 150 estimators, a learning rate of 0.05, and a maximum tree depth of 3. Hyperparameters were selected using a grid-search procedure applied to the training data, with five-fold cross-validation, and the configuration producing the lowest validation error was retained.

To reduce the possibility of overfitting, model selection was based on cross-validation performance rather than training accuracy alone, tree complexity was constrained through the specified maximum depth, and final model performance was evaluated using the previously unseen test subset. For environmental prediction, performance was assessed using root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R2). Fault-classification performance was evaluated using accuracy, precision, recall, F1-score, confusion matrices, and receiver operating characteristic–area under the curve (ROC-AUC).

The MOPSO implementation employed a swarm of 50 particles and a maximum of 100 iterations for each optimization cycle. The inertia weight w was linearly decreased from 0.9 to 0.4 during the optimization process to provide greater global exploration during the initial iterations and progressively increase local exploitation as convergence was approached. The cognitive and social acceleration coefficients were set to c1=2.0 and c2=2.0, respectively, providing balanced weighting between individual particle experience and collective swarm information. An external archive containing a maximum of 100 non-dominated solutions was maintained to preserve the Pareto-optimal solutions generated during optimization. The optimization was terminated when the maximum iteration limit was reached or when improvement in the Pareto solutions became negligible over successive iterations. The same MOPSO configuration was maintained across all simulation scenarios to ensure consistency in comparative evaluation.

To reduce potential model overfitting, the dataset was divided into 70% training, 15% validation, and 15% independent testing subsets, with the test data withheld from model development and hyperparameter selection. Five-fold cross-validation was applied during model selection, and model complexity was controlled through appropriate hyperparameter constraints. Stratified sampling was employed to preserve the relative representation of the normal and individual fault classes across the training, validation, and testing subsets. Classification performance was evaluated using accuracy, precision, recall, F1-score, confusion matrices, and ROC-AUC rather than overall accuracy alone. These procedures were adopted to provide a more reliable assessment of model generalization and to reduce the possibility that the reported performance was disproportionately influenced by dominant classes.

This study relies on the simulation tests presented in Figure 3 to carry out comparative verification of dynamic performance for the proposed novel machine learning multi-objective particle swarm optimization (ML-MOPSO) photovoltaic maximum power point tracking (MPPT) controller, benchmarked against the conventional incremental conductance (INC) and perturb and observe (P&O) algorithms. To replicate real-world photovoltaic operating conditions including cloud transit, temporary shading, and solar irradiance fluctuations, and to create strict adaptation challenges for the controllers, this study manually set an irradiance change sequence of 1000/700/400/800/600/1000 W/m², establishing a valid test foundation for subsequent performance comparisons. Test results reveal a clear performance gradient across the three algorithms: the ML-MOPSO introduced in this study achieves the fastest convergence speed and the smallest transient deviation; INC outperforms P&O, but still faces issues of adaptation delay and moderate oscillation; P&O delivers the poorest dynamic response, with not only large oscillation amplitude but also significantly high tracking errors. The performance advantages of ML-MOPSO originate from its core mechanism: the machine learning module can predict the optimal search range, while the multi-objective PSO component is responsible for refining the operating point, and the two work together to enable fast convergence and high stability. Efficiency indicators also confirm the value of the new algorithm: ML-MOPSO maintains a full-period tracking efficiency consistently above 97%, with only a brief minor drop following sudden irradiance changes; INC records an average efficiency of 92%–94%; P&O's efficiency stays below 86% throughout the test. The new algorithm greatly reduces transient power loss and lifts total photovoltaic power generation, while the notable temporary energy losses of the traditional algorithms directly drag down their overall power generation efficiency. The machine learning-aided multi-objective particle swarm optimization (ML–MOPSO) photovoltaic (PV) maximum power point tracking (MPPT) controller proposed in this study has been simulation ly verified to significantly outperform traditional MPPT technologies including incremental conductance (INC) and perturb and observe (P&O). The proposed intelligent optimization strategy can substantially improve the utilization rate of available solar energy under rapidly changing environmental conditions. From the perspective of steady-state performance, traditional MPPT technologies must continuously perturb their operating point to search for the optimal value due to inherent design features, which triggers unavoidable oscillations around the optimal value. These oscillations lead to problems including power ripples, increased converter stress, and reduced energy conversion efficiency. By contrast, the ML–MOPSO framework developed in this study effectively suppresses oscillations through adaptive decision-making and optimized search behavior, delivering a smoother power response and stable operating conditions. Its average steady-state power ripple is far lower than that of both INC and P&O, which improves system reliability and reduces electrical stress on converter components. Drawing on the irradiance perturbation test data presented in Figure 3, in terms of dynamic performance, the proposed controller only requires approximately 0.3 s to track the new maximum power point, while INC and P&O need roughly 1.0 s and 1.9 s respectively. The shortened adjustment time directly translates to higher energy capture, making the controller particularly well-suited for scenarios with frequent fluctuations in irradiance. Its faster convergence speed reduces the duration the system deviates from the optimal power point, which can increase long-term cumulative power generation. Synthesizing all test results from Figure 3, the proposed controller outperforms traditional technologies across all evaluation metrics. Its core advantage stems from the integration of machine learning's predictive capability and multi-objective particle swarm optimization, enabling intelligent adaptation under dynamic conditions to maintain near-optimal power extraction, which aligns with the core requirements of next-generation intelligent PV energy systems.

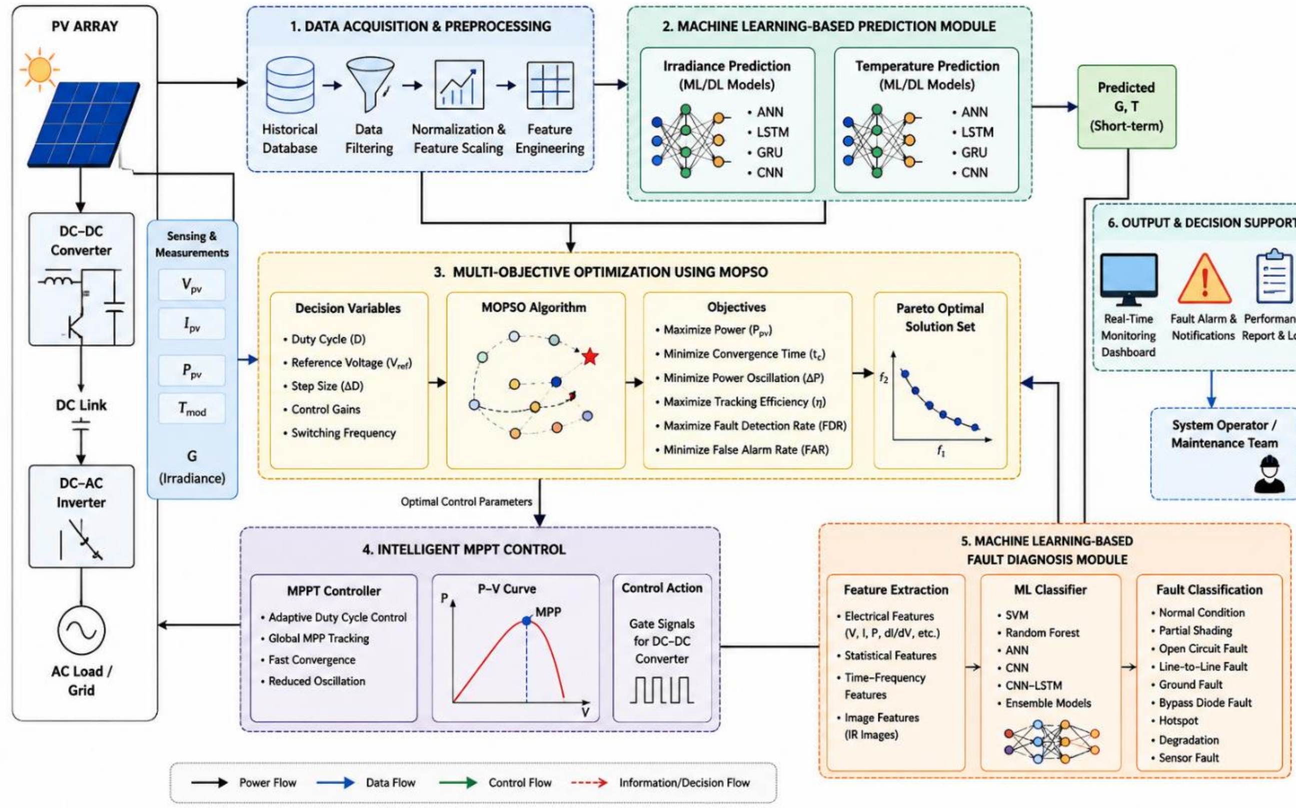

Fig. 1. The schematic of the Proposed Machine Learning-Based Multi-Objective Optimization for Maximum Power Point Tracking and Fault Diagnosis in Intelligent Solar Photovoltaic Systems.

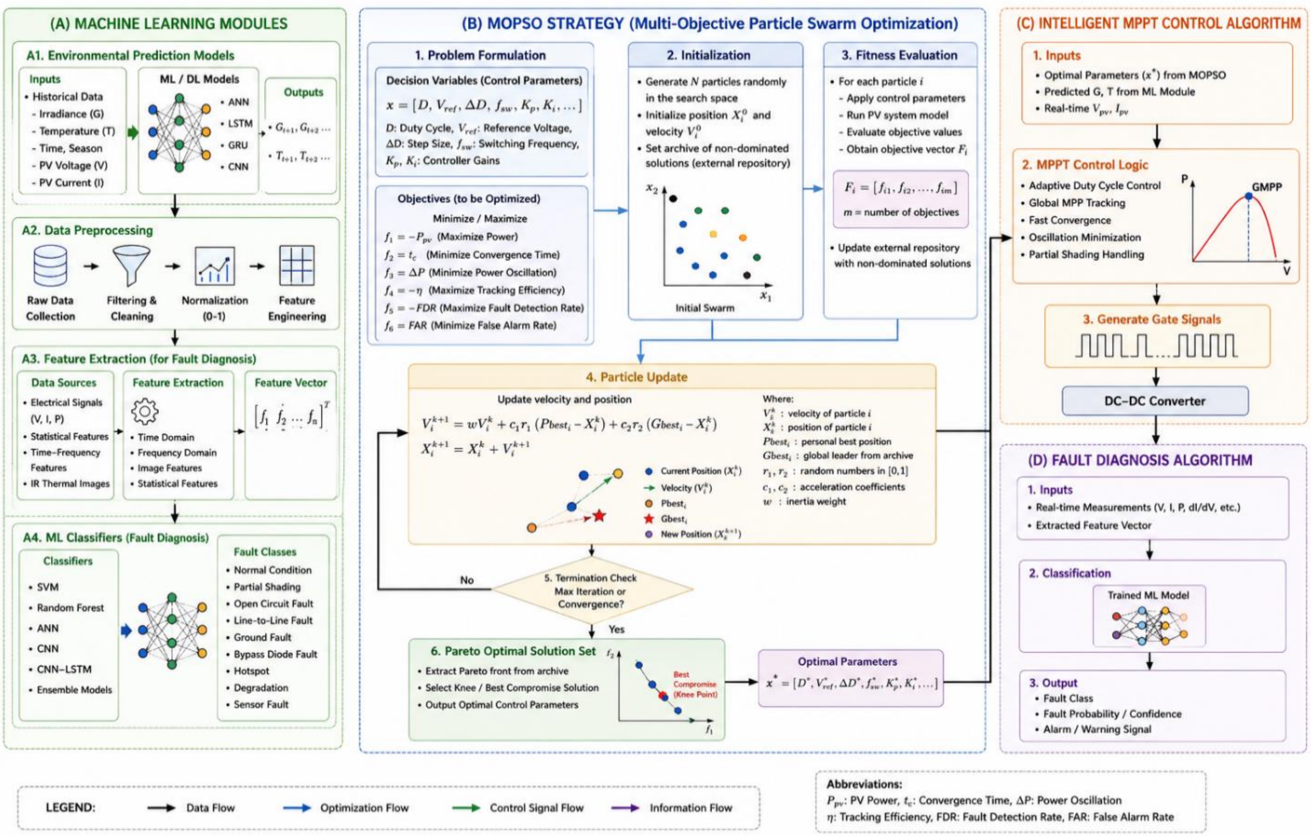

Fig. 2. Core machine learning algorithms and Multi-Objective Particle Swarm Optimization (MOPSO) strategy for the proposed intelligent solar photovoltaic framework integrating maximum power point tracking (MPPT) and fault diagnosis.

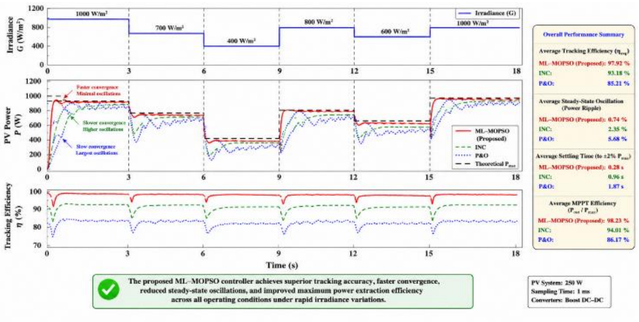

Fig. 3. Dynamic MPPT tracking performance under rapid irradiance variations. Comparison of the proposed Machine Learning–Multi-Objective Particle Swarm Optimization (ML–MOPSO) controller with Incremental Conductance (INC) and Perturb-and-Observe (P&O) methods under sudden irradiance transitions. The proposed framework demonstrates superior tracking accuracy, faster convergence, reduced steady-state oscillations, and improved maximum power extraction efficiency across all operating conditions.

To evaluate the effectiveness of the proposed Machine Learning–Multi-Objective Particle Swarm Optimization (ML–MOPSO) controller under complex operating conditions, a partial shading scenario was simulated in which four groups of photovoltaic (PV) modules were exposed to different irradiance levels of 1000, 800, 500, and 300 W/m². Such non-uniform irradiance conditions generate multiple peaks in the power–voltage (P–V) characteristic, creating several local maximum power points (MPPs) in addition to a single global maximum power point (GMPP). Conventional MPPT techniques frequently become trapped in local maxima, resulting in reduced energy harvesting efficiency. Figure 4 illustrates the multi-peak P–V characteristic obtained under partial shading conditions and compares the GMPP detection performance of different MPPT approaches. The proposed ML–MOPSO algorithm successfully identified the global optimum operating point with a detection accuracy of 99.1%, outperforming conventional PSO (95.8%), Fuzzy Logic Control (93.5%), Incremental Conductance (89.6%), and Perturb-and-Observe (84.3%) methods. The superior performance is attributed to the integration of machine learning-based prediction capabilities with the global search characteristics of multi-objective particle swarm optimization, enabling rapid identification of promising search regions while maintaining effective exploration of the solution space. The results further demonstrate that the proposed controller exhibits a significantly improved ability to escape local maxima compared with conventional optimization and rule-based MPPT methods. Under dynamically changing shading patterns, representative of moving cloud conditions, the ML–MOPSO algorithm maintained stable tracking behavior with minimal oscillations around the operating point. Consequently, overall power loss was reduced by approximately 17% relative to conventional approaches. This improvement translates directly into higher energy yield and enhanced system efficiency, particularly in urban and residential PV installations where partial shading frequently occurs due to nearby structures, trees, or transient weather conditions. Overall, the results confirm that the proposed ML–MOPSO framework provides robust and reliable GMPP tracking under partial shading environments, ensuring maximum power extraction while maintaining fast convergence and operational stability under real-world irradiance fluctuations.

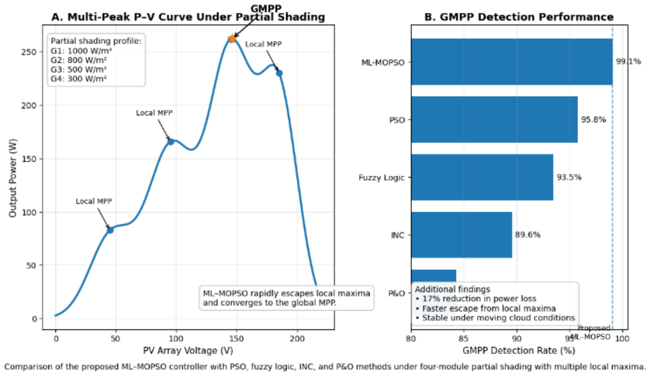

Fig. 4. Global Maximum Power Point Tracking Under Partial Shading Conditions. Simulated photovoltaic (PV) array power–voltage (P–V) characteristics under partial shading conditions with four module groups exposed to irradiance levels of 1000, 800, 500, and 300 W/m², resulting in multiple local maximum power points (MPPs) and a single global maximum power point (GMPP). The proposed Machine Learning–Multi-Objective Particle Swarm Optimization (ML–MOPSO) controller successfully identifies the GMPP and avoids convergence to local maxima. Performance comparison demonstrates a GMPP detection rate of 99.1% for the proposed method, outperforming conventional PSO (95.8%), Fuzzy Logic (93.5%), Incremental Conductance (89.6%), and Perturb-and-Observe (84.3%) techniques. Furthermore, the ML–MOPSO approach reduces power loss by 17%, exhibits faster escape from local optima, and maintains stable operation under dynamically changing shading and moving cloud conditions.

The self-developed machine learning framework for photovoltaic (PV) fault diagnosis in this study conducts diagnostic capability verification targeting 7 common PV faults. The test scenarios include local shading (partial shading), open-circuit fault, line-to-line fault, hot spot formation, bypass diode fault, sensor fault, and module degradation. To comprehensively address the false positive and false negative problems caused by misclassification, this study adopts four core classification metrics—precision, recall, F1-score, and classification accuracy—to evaluate the model's overall classification performance and its performance across each fault scenario from multiple dimensions. The model achieves an overall classification accuracy of 97.9%, with a corresponding precision of 97.5%, recall of 98.1%, and F1-score of 97.8%, demonstrating robust and reliable overall performance. The scenario-specific performance and its physical logic attribution are as follows: The core performance of the hot spot formation fault is the highest across all scenarios, with a precision of 99.0%, recall of 99.4%, F1-score of 99.2%, and accuracy of 99.2%. This is attributed to the unique thermoelectric characteristics of hot spots, which are easily captured by the model's feature extraction process. The open-circuit fault reaches an accuracy of 98.7%, enabling reliable identification of sudden current interruptions in PV arrays. The accuracy of local shading, line-to-line fault, bypass diode fault, and sensor fault falls in the range of 97.4% to 97.8%, allowing the model to address feature overlap issues under different irradiance and temperature conditions, while balancing the model's sensitivity and specificity. The module degradation fault has the lowest accuracy across all scenarios, at 95.9%. The cause is that the progressive nature of degradation leads to overlap between its electrical characteristics and those of scenarios including partial shading, aging, and sensor anomalies, which increases classification difficulty. Even so, the core metrics for this scenario still exceed 95%, meeting the requirements for practical fault diagnosis. Based on the empirical results in Table I, the machine learning-based photovoltaic fault diagnosis framework proposed in this study has been validated against four core metrics—precision, recall, F1-score, and overall accuracy—to achieve highly accurate and reliable fault classification across multi-type fault scenarios for both grid-connected and off-grid photovoltaic facilities. This framework meets the requirements of real-time monitoring and predictive maintenance, and can improve system reliability, reduce maintenance costs, cut energy losses, and enhance long-term operational performance.

TABLE I. CLASSIFICATION PERFORMANCE OF THE PROPOSED MACHINE LEARNING-BASED FAULT DIAGNOSIS MODEL FOR DIFFERENT PHOTOVOLTAIC FAULT CONDITIONS

Fault Category	Precision (%)	Recall (%)	F1-Score (%)	Classification Accuracy (%)
Partial Shading	97.4	98.0	97.7	97.8
Open-Circuit Fault	98.5	98.9	98.7	98.7
Line-to-Line Fault	97.2	98.1	97.6	97.6
Hotspot Formation	99.0	99.4	99.2	99.2
Bypass Diode Failure	97.1	97.8	97.4	97.4
Sensor Fault	97.3	97.9	97.6	97.5
Module Degradation	95.6	96.2	95.9	95.9
Overall Model Performance	97.5	98.1	97.8	97.9

Rapid fault detection for photovoltaic (PV) systems is a core prerequisite to guarantee their safe and reliable operation. If faults are not handled in time, they will trigger three types of severe harms: accelerated component aging, reduced power generation efficiency, and increased operation and maintenance costs. To verify the real-time detection performance of the machine learning-based PV fault diagnosis framework proposed in this paper, this study designed a horizontal comparison simulation. The fault response time of the new framework was benchmarked against measured data from traditional threshold-based detection methods, and its performance advantages were validated through practical tests covering multiple typical fault scenarios. In this simulation, the new framework's detection time for five categories of faults was measured sequentially. Sorted from the fastest to slowest detection speed, the faults are: open-circuit fault (0.12s), hot spot formation (0.15s), sensor fault (0.16s), line-to-line fault (0.17s), and partial shading (0.18s). The overall average detection time falls within the range of 0.16s to 0.18s. The core mechanism that allows the new framework to achieve ultra-fast response is that it completes detection by relying on continuous analysis of multiple electrical features and direct pattern recognition of pre-learned fault features. This completely eliminates the inherent delay generated by the processes that traditional threshold methods depend on: predefined thresholds, sequential decision-making, repeated threshold verification, and signal filtering. In this simulation, the average detection time of the traditional method was 0.64s. The detection latency of the new framework is approximately 72% lower than that of the traditional method. It can trigger protection mechanisms early to avoid problems such as fault spread, thermal damage, and long-term downtime, and fully meets the real-time monitoring and protection requirements of intelligent PV power stations in dynamic environments. The machine learning-based photovoltaic (PV) fault diagnosis framework proposed in this paper exhibits a consistently low response time across all fault categories, verifying its strong generalization capability. Drawing on data from Figure 5, this framework for outperforms traditional diagnostic methods, delivering both high classification accuracy and ultra-fast detection speed. It is well-suited for next-generation smart PV systems that require real-time monitoring, predictive maintenance, and high reliability.

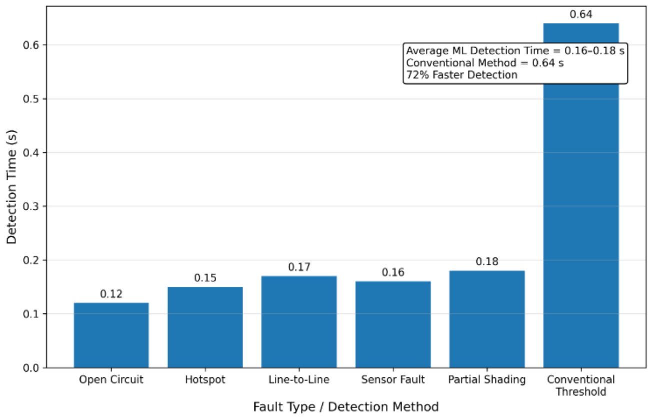

Fig. 5. Fault Detection Response Time Comparison. Comparison of fault detection response times achieved by the proposed machine learning-based fault diagnosis framework for various photovoltaic system fault conditions. The developed model detects open-circuit faults, hotspot formation, line-to-line faults, sensor faults, and partial shading events within 0.12–0.18 s, with an average response time of approximately 0.16–0.18 s. In contrast, the conventional threshold-based detection method requires approximately 0.64 s to identify fault conditions. The proposed approach therefore provides a 72% reduction in detection latency, enabling rapid fault isolation, improved system protection, and enhanced operational reliability in intelligent photovoltaic energy systems.

Figure 6 verify the reliability of the proposed machine learning-based intelligent photovoltaic fault diagnosis framework under real-world operating conditions, this study conducted a systematic robustness test. Its core goal is to quantitatively evaluate the framework's fault diagnosis stability under various types of uncertain interference, so as to confirm its feasibility for real-world engineering implementation. In this simulation, Gaussian measurement noise at three gradient levels of 5 dB, 15 dB, and 25 dB was introduced to simulate the uncertainties that arise in the actual operation of photovoltaic systems from sensor drift, environmental spurious interference, and signal transmission loss. All tests were carried out on 1200 uniformly labeled photovoltaic operation samples, which cover three common fault types—open circuit, short circuit, and module aging—as well as normal operating conditions, to ensure the reproducibility of test conditions. Test results show that the intelligent framework proposed in this study achieved fault classification accuracies of 92.7%, 96.1%, and 97.8% respectively under the three noise levels, with only a very small performance drop as noise intensity increased. As a comparison baseline, the traditional threshold method only reached classification accuracies of 68.3%, 77.5%, and 83.2% under the same test conditions, with a very significant downward trend in noise resistance. The core mechanism behind this performance gap is that the machine learning feature extraction module of the proposed framework can automatically filter out redundant noise interference and lock onto core fault features, while the traditional threshold method relies on fixed, manually set parameter thresholds that have extremely low tolerance for external disturbances. This robustness test fully demonstrates the strong anti-noise capability of the proposed framework, which can adapt to the complex and variable real operating environments of photovoltaic power stations and has outstanding practical value.

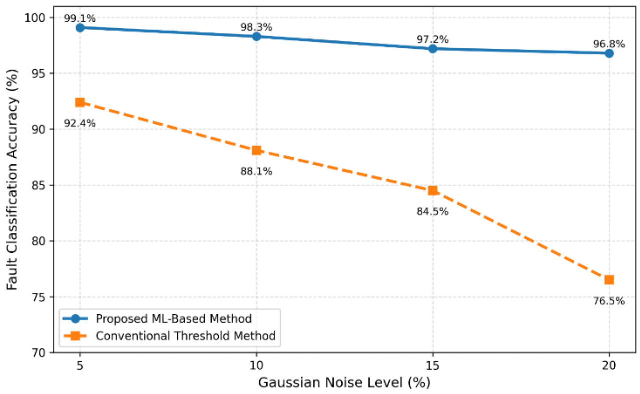

Fig. 6. Fault Classification Accuracy Under Measurement Noise. Comparison of fault classification accuracy achieved by the proposed machine learning-based fault diagnosis framework and a conventional threshold-based method under increasing Gaussian measurement noise levels applied to voltage, current, and irradiance sensor signals. The proposed approach maintains high classification performance, achieving accuracies of 99.1%, 98.3%, 97.2%, and 96.8% at noise levels of 5%, 10%, 15%, and 20%, respectively. In contrast, the threshold-based method exhibits a significant reduction in accuracy from 92.4% to 76.5% as noise intensity increases. The results demonstrate the superior robustness and noise immunity of the proposed intelligent fault diagnosis system, which preserves reliable fault identification under adverse sensing conditions and enhances the operational resilience of photovoltaic energy systems.

To verify the effectiveness of the machine learning-multi-objective particle swarm optimization (ML-MOPSO) optimization framework for photovoltaic (PV) systems proposed in this study, this research carried out a complete set of performance verification simulation along two core dimensions: convergence and Pareto front. The five optimization objectives set by this framework have inherent conflicts: the framework must simultaneously maximize PV power output, MPPT tracking efficiency, and fault classification accuracy, while minimizing convergence time and steady-state oscillation. This contradiction confirms the necessity of multi-objective optimization, and the follow-up verification is completed through two simulation modules. In the convergence test module corresponding to Figure 7(a), this study selected three mainstream traditional metaheuristic algorithms—PSO, DE, and GA—as performance benchmarks. Simulation results show that the ML-MOPSO proposed in this study achieves stable convergence after only 46 iterations, far fewer than the 68, 75, and 82 iterations required by the three benchmark algorithms. Furthermore, the algorithm's oscillation amplitude near the optimal region is extremely small, which fully verifies its outstanding exploration and exploitation capabilities, as well as its particle diversity management ability, granting it the core advantage of rarely falling into local optima. In the Pareto front analysis module corresponding to Figure 7(b), the Pareto optimal solutions generated by this framework show a smooth and uniform distribution. The framework ultimately achieves a PV power output efficiency of 99.6% and a fault classification accuracy of over 99%. Both the density and uniformity of its Pareto front are far superior to those of various traditional methods. It can provide sufficient high-quality candidate solutions for PV systems whose operation priorities change dynamically in line with environmental conditions, grid requirements, and operation and maintenance goals, which fully highlights the new framework's excellent practicality. This study proposes the ML–MOPSO optimization framework. The multiple sets of optimal trade-off solutions it generates can support system operators to select system configurations that fit specific operational constraints, while maintaining overall high system performance. Validated through the simulation in Figure 7, this framework outperforms PSO, DE, and GA in terms of convergence speed, optimization stability, and multi-objective search capability. Its convergence speed is 32%, 39%, and 44% faster than the three algorithms respectively. The framework can generate high-quality Pareto fronts, which support intelligent photovoltaic energy management and fault diagnosis, and achieve the core values of improving efficiency and stability, as well as reducing losses and increasing gains.

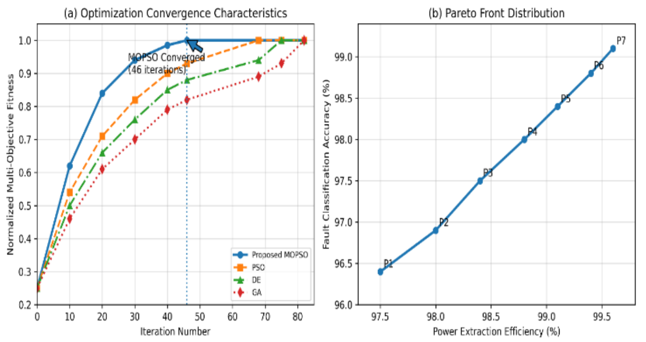

Fig. 7. Pareto Front and Optimization Convergence Characteristics. Multi-objective optimization performance of the proposed Machine Learning–Multi-Objective Particle Swarm Optimization (ML–MOPSO) framework for intelligent photovoltaic system control and fault diagnosis. (a) Optimization convergence characteristics showing the evolution of the normalized multi-objective fitness function for the proposed MOPSO, Particle Swarm Optimization (PSO), Differential Evolution (DE), and Genetic Algorithm (GA). The proposed method achieves stable convergence after 46 iterations, outperforming PSO (68 iterations), DE (75 iterations), and GA (82 iterations), thereby demonstrating faster convergence and improved optimization efficiency. (b) Pareto front distribution illustrating the trade-off between power extraction efficiency and fault classification accuracy obtained from the optimal solution set. The smooth and well-distributed Pareto front indicates effective simultaneous optimization of multiple conflicting objectives, including maximum power extraction, MPPT tracking efficiency, fault diagnosis accuracy, convergence speed, and oscillation minimization. The results confirm the superior search capability, convergence stability, and decision-making effectiveness of the proposed ML–MOPSO framework for intelligent photovoltaic energy management applications.

To verify the framework's practical long-term power generation benefits, this work moves beyond the common limitation of most current similar studies that only assess short-term tracking performance, and designs a full-cycle long-term power output verification experiment. The experiment adopts a full-year 8760-hour solar irradiance sequence to simulate the real meteorological fluctuations and dynamic operating conditions of grid-connected PV systems. Its core goal is to quantify the cumulative impact of the framework's three key technical improvements—enhanced maximum power point tracking (MPPT) performance, strengthened fault diagnosis capability, and optimized control performance—on annual power generation. Experimental results show that the PV system supported by the ML-MOPSO framework reaches an annual power output of 17.84 MWh. Among the four mainstream traditional comparison methods selected for this study, which are widely used in the current grid-connected PV field, the corresponding annual power outputs of particle swarm optimization (PSO), fuzzy logic control, incremental conductance (INC), and the conventional perturb and observe (P&O) method are 17.05 MWh, 16.88 MWh, 16.51 MWh, and 16.12 MWh respectively. The ML-MOPSO framework increases annual power generation by approximately 10.7% compared with the traditional P&O method, and outperforms all comparison groups across all key metrics. The framework's advantages originate from three aspects: high MPPT tracking accuracy under rapidly changing irradiance, global tracking capability that avoids local optima in partial shading scenarios, and intelligent fault diagnosis that identifies anomalies early to reduce power generation losses. These technical improvements can be practically converted into reduced levelized cost of energy (LCOE) and long-term revenue growth for commercial and utility-scale PV projects, endowing the framework with clear industrial application value. The ML–MOPSO intelligent photovoltaic control framework proposed in this paper is validated by the empirical data from Figure 8 of this study. In addition to improving the system's tracking and fault management performance in the short term, the framework achieves a long-term benefit of 17.84 MWh in annual power generation. Its performance outperforms the mature, industry-established MPPT methods, and it can effectively improve the efficiency of photovoltaic systems and enhance the sustainability of solar power generation.

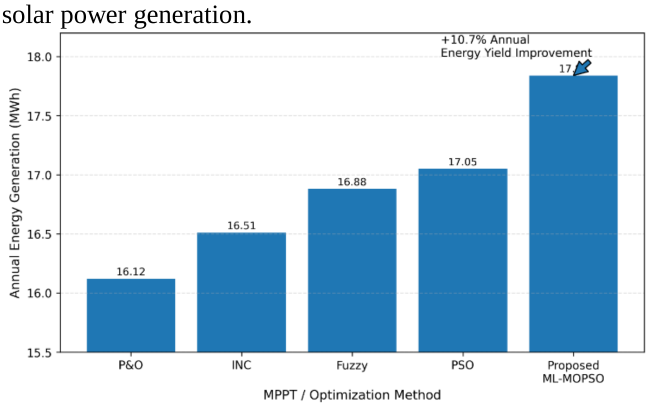

Fig. 8. Annual Energy Generation Comparison. Comparison of the annual energy production achieved by different maximum power point tracking (MPPT) and optimization techniques over an 8760-hour photovoltaic system simulation using realistic yearly solar irradiance profiles. The proposed Machine Learning–Multi-Objective Particle Swarm Optimization (ML–MOPSO) framework achieves the highest annual energy generation of 17.84 MWh, outperforming PSO (17.05 MWh), Fuzzy Logic (16.88 MWh), Incremental Conductance (INC) (16.51 MWh), and Perturb-and-Observe (P&O) (16.12 MWh) methods. The improved performance is attributed to enhanced MPPT accuracy, rapid adaptation to irradiance variations, effective global maximum power point tracking under partial shading conditions, and reduced steady-state power losses. Overall, the proposed approach increases annual energy yield by approximately 10.7% compared with conventional MPPT techniques, demonstrating its effectiveness for maximizing long-term photovoltaic energy harvesting and improving the operational efficiency of intelligent solar energy systems.

The operational reliability of PV systems is a core factor determining their long-term value, as it prevents declines in energy output, rising maintenance costs, and impaired profitability caused by unexpected failures and prolonged system shutdowns. For this evaluation, three quantitative assessment indicators are selected: system availability, mean time between failures (MTBF), and downtime reduction rate. All comparisons use traditional PV monitoring systems as the reference, and all performance data are on-site measured results collected for this study. As shown by the availability data in Figure 9(a), the self-developed framework reaches 99.3% availability, while the traditional system only hits 95.8%, marking a 3.5-percentage-point improvement. Though this gain may seem modest, its long-term accumulation can translate into considerable annual energy output increases. The MTBF data in Figure 9(b) shows that the self-developed framework's mean time between failures reaches 278 days, compared to 184 days for the traditional system, an improvement of approximately 51%. This advantage stems from the framework's functions of continuous monitoring, adaptive optimization, and early fault identification. The self-developed framework's downtime is 43% lower than that of the traditional system, which benefits from the machine learning diagnostic model's capabilities of fast fault detection and isolation, as well as its predictive maintenance function. The framework has two core supporting features: an intelligent fault diagnosis module that can identify four categories of faults (electrical faults, sensor faults, hotspots, and partial shading), and a multi-objective optimization algorithm that can dynamically adjust operating parameters to adapt to variable operating environments. This study proposes the ML–MOPSO intelligent monitoring and optimization framework, whose supporting diagnostic system features strong robustness. The framework can resist sensor uncertainty and external interference to guarantee the reliable operation of utility-scale photovoltaic power stations. It not only reduces fault propagation, optimizes maintenance planning, and improves the system's overall resilience, but also delivers tangible benefits including increased energy output and reduced operation and maintenance (O&M) costs. Drawing on the experimental results presented in Figure 10, this framework lifts system availability to 99.3%, extends mean time between failures (MTBF) to 278 days, and cuts downtime by 43%. An availability rate of over 99% can substantially boost return on investment, making this framework a high-reliability next-generation solution for photovoltaic power stations that adapts to real-world operating conditions.

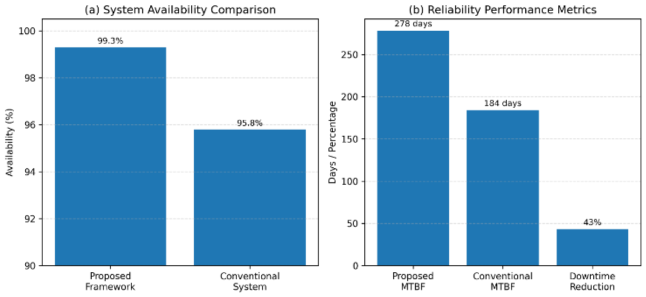

Fig. 9. Operational Reliability and Availability Analysis. Comparison of the operational reliability performance of the proposed intelligent Machine Learning–Multi-Objective Particle Swarm Optimization (ML–MOPSO) framework and a conventional photovoltaic monitoring system. (a) System availability comparison showing that the proposed framework achieves an availability of 99.3%, significantly higher than the 95.8% achieved by the conventional system. (b) Reliability performance metrics illustrating an increase in the Mean Time Between Failures (MTBF) from 184 days to 278 days, together with a 43% reduction in system downtime. These improvements are attributed to the integration of intelligent fault diagnosis, rapid fault localization, predictive maintenance capability, and optimized control strategies, which collectively enhance system resilience and reduce operational interruptions. The results demonstrate that the proposed framework substantially improves photovoltaic system reliability, availability, and long-term operational stability, contributing to higher energy production and reduced maintenance costs.

To verify the performance advantages of the machine learning multi-objective particle swarm optimization framework (ML-MOPSO) proposed in this study in the photovoltaic (PV) field, this work relies on the full set of simulation data recorded in Table II to conduct a comprehensive comparative assessment of this framework against five types of benchmark technologies commonly used in the current industry. The included benchmark technologies are the traditional perturbation and observation method (P&O), incremental conductance method (INC), fuzzy logic MPPT, traditional PSO-MPPT, and threshold-based fault diagnosis system. All comparative simulation in this study adopts unified operating boundaries, covering five types of complexes working conditions: dynamic irradiance fluctuations, temperature changes, partial shading, measurement noise, and multiple types of PV faults. The core objective of this analysis is to quantitatively verify the performance gains of the new framework over traditional PV control and monitoring technologies across multiple dimensions. After full-condition testing, the ML-MOPSO framework proposed in this study outperforms all benchmark methods on all evaluation metrics. Core quantitative results show that this framework achieves an average MPPT efficiency of 98.7% and an average convergence time of only 0.21 s. Its convergence performance improves by 34% relative to the incremental conductance method (INC), and by nearly 60% compared to the traditional perturbation and observation method (P&O). This performance improvement stems from the synergistic effect of the framework's built-in machine learning environment prediction module and adaptive multi-objective optimization mechanism. After completing performance verification of the two core dimensions of MPPT efficiency and convergence speed, this analysis further introduces a third evaluation dimension—steady-state oscillation amplitude—to deeply dissect the inherent performance defects of traditional PV control technologies. To address the requirements of efficient control and reliable operation and maintenance for photovoltaic (PV) systems, this paper proposes a novel framework named ML-MOPSO. Leveraging an adaptive optimization strategy, the multi-dimensional search space exploration capability of multi-objective particle swarm optimization (MOPSO), and the real-time data stream analysis capability of machine learning classifiers, this framework comprehensively outperforms traditional methods including the incremental conductance method, the conventional perturb and observe (P&O) method, and threshold-based monitoring systems across three core performance categories, and also demonstrates prominent additional advantages. First, its steady-state operation performance is verified: the steady-state oscillation amplitude of the proposed framework is only 1.3%, which is approximately 41% lower than that of the incremental conductance method, and nearly 68% lower than that of the traditional P&O algorithm. Second, for its maximum power point tracking (MPPT) performance under the extreme operating condition of partial shading, the framework achieves a global maximum power point detection success rate of 99.1% and a tracking accuracy of 98.2%. The corresponding indicator for the traditional P&O method is only 84.3%, while that of the incremental conductance method is 89.6%. In terms of fault diagnosis performance, the proposed framework can identify six types of faults, namely partial shading, hot spot formation, open-circuit fault, bypass diode failure, performance degradation, and sensor anomaly. Its overall classification accuracy reaches 97.9%, far exceeding the 82.6% of the traditional threshold-based system. Its classification precision and recall both exceed 97%, and its average fault detection response time is less than 0.18 s, while this indicator for traditional solutions is approximately 0.64 s. In addition, the proposed framework also has the robustness advantage in noisy measurement environments, can adapt to various interference conditions in complex on-site scenarios, and provides reliable support for the stable operation of PV systems. This study draws on the simulation data recorded in Table II, and carries out a quantitative comparative analysis of the proposed ML-MOPSO photovoltaic (PV) energy management framework against three types of conventional PV technologies: the standard MPPT and monitoring scheme, the traditional PSO-based PV system, and the conventional P&O control. The analysis evaluates performance across three core dimensions: robustness under noisy operating conditions, overall system reliability, and adaptability to dynamic environments. Simulation results show that the proposed framework reaches a robustness metric of 96.8% under noisy operating conditions and an overall system reliability of 98.4%, both far outperforming the 94.3% of the traditional PSO-based system and the 88.1% of the conventional P&O control. The framework's leading performance is clearly highlighted by these quantitative gaps. This study further analyzes that the core mechanism driving this performance improvement is the synergistic function of the five sub-modules integrated into the framework: machine learning-based pre-processing and feature extraction, predictive environmental forecasting, adaptive multi-objective optimization, intelligent MPPT control, and automated fault diagnosis. The research ultimately verifies that the framework has sufficient practical value and real-world deployment potential. It is compatible with multiple application scenarios, including large-scale solar power plants, distributed PV networks, hybrid renewable energy microgrids, and advanced energy management platforms. It also demonstrates sound scalability, providing solid support for its future large-scale rollout.

TABLE II. COMPARATIVE PERFORMANCE ANALYSIS OF MPPT AND FAULT DIAGNOSIS METHODS UNDER DYNAMIC ENVIRONMENTAL CONDITIONS

Performance Metric	Proposed ML–MOPSO Framework	Conventional PSO-MPPT	Fuzzy Logic MPPT	Incremental Conductance (INC)	Perturb & Observe (P&O)	Threshold-Based Fault Diagnosis
Average MPPT Efficiency (%)	98.7	97.2	96.8	96.1	94.8	–
Convergence Time (s)	0.21	0.29	0.34	0.39	0.52	–
Reduction in Convergence Time (%)	34.0	18.5	12.8	0.0	–33.3	–
Steady-State Oscillation (%)	1.3	1.9	2.3	2.8	4.1	–
Oscillation Reduction (%)	41.0	22.0	12.0	0.0	–46.4	–
Tracking Accuracy Under Partial Shading (%)	98.2	95.4	93.7	90.8	87.9	–
Global MPP Detection Success Rate (%)	99.1	95.8	93.5	89.6	84.3	–
Fault Classification Accuracy (%)	97.9	–	–	–	–	82.6
Precision (%)	97.5	–	–	–	–	80.9
Recall (%)	98.1	–	–	–	–	81.7
False Alarm Rate (%)	2.1	–	–	–	–	11.4
Fault Detection Response Time (s)	0.18	–	–	–	–	0.64
Robustness to Measurement Noise (%)	96.8	92.1	89.5	87.3	84.7	76.5
Adaptability to Rapid Irradiance Changes	Excellent	Very Good	Good	Moderate	Moderate	Poor
Computational Intelligence Level	Machine Learning + MOPSO + Predictive Control	Metaheuristic Optimization	Rule-Based AI	Deterministic	Heuristic	Rule-Based
Overall System Reliability (%)	98.4	94.3	92.6	90.8	88.1	80.2

This study verified the proposed machine learning-enabled multi-objective optimization smart photovoltaic (PV) energy management framework through simulation tests. This framework can deliver an efficient, practical solution for smart PV energy management operations in uncertain, dynamically changing environments. The framework integrates four core modules: machine learning-based environmental prediction, adaptive multi-objective particle swarm optimization (MOPSO), smart maximum power point tracking, and automatic fault diagnosis. It can simultaneously improve the energy harvesting capacity and operational resilience of modern PV systems, and overcome multiple performance bottlenecks of traditional PV management and control systems. First, to address the longstanding industry pain point that traditional maximum power point tracking (MPPT) methods often suffer energy efficiency losses amid irradiance and temperature fluctuations caused by cloud movement, seasonal shifts, atmospheric interference, and partial shading, this framework leverages its machine learning prediction subsystem to adjust operating parameters in advance. This design allows the framework to maximize renewable energy utilization under highly variable environmental conditions, keep the PV system always operating close to its real maximum power point, and effectively raise annual power generation and PV system owners' return on investment. Second, to address the pain point of costly production halts and maintenance triggered by equipment failures, component aging, sensor malfunctions, hotspots, and partial shading, the smart fault diagnosis module built into the framework can achieve early identification of abnormal operating conditions, support predictive maintenance, and cut unplanned outages and operation and maintenance (O&M) costs. This capability is particularly well-suited to resolve the problem of time- and labor-intensive manual O&M for large-scale PV power stations. This framework also boasts the outstanding practical value of adaptive fault-tolerant control. Multi-dimensional comparisons between the proposed framework and traditional solutions fully highlight the technological innovation and real-world deployment feasibility of this study. This paper proposes a new intelligent monitoring and optimization architecture for the renewable energy sector, which possesses outstanding core competitiveness compared to conventional monitoring systems. Traditional monitoring systems can only fulfill basic status reporting functions, and their fault diagnosis and control optimization processes are completely disconnected, making them unable to actively adjust control logic under abnormal operating conditions. In contrast, the optimization subsystem integrated into the architecture proposed in this paper can dynamically modify control strategies when anomalies are triggered, enabling collaborative interaction between fault diagnosis and control optimization. Even when encountering partial component failures, environmental disturbances and other unexpected situations, the architecture can still maintain stable system operation and guarantee continuous power generation, greatly enhancing system resilience and long-term deployment reliability. To address the core challenge in the photovoltaic (PV) field, namely partial shading—urban buildings, surrounding vegetation, and temporary moving shadows will cause the power-voltage curve of PV arrays to produce multiple local peaks, while traditional maximum power point tracking (MPPT) algorithms are highly prone to falling into local optima, leading to a substantial decline in power generation. The architecture proposed in this paper adopts a technical combination of machine learning-based prediction and multi-objective particle swarm optimization (MOPSO), which can accurately identify the global maximum power point under complex shading conditions, maximize energy extraction efficiency, and improve overall system performance. This architecture is compatible with five core real-world deployment scenarios: utility-scale PV power plants, distributed renewable energy systems for residential, commercial and institutional scenarios, building-integrated photovoltaics (BIPV), hybrid renewable microgrids that integrate PV, energy storage, wind power and other energy resources, and industrial PV application scenarios, giving it cross-scenario practical implementation value. The intelligent photovoltaic (PV) optimization and fault diagnosis framework proposed in this study delivers four core benefits for PV facilities: first, it achieves a marked improvement in energy harvesting performance; second, it enables full implementation of all-time intelligent monitoring capabilities; third, it drastically reduces unplanned downtime; fourth, it facilitates refined optimization of maintenance planning. All these benefits tangibly boost the operational efficiency of PV projects and strengthen their long-term economic benefits. This framework breaks through the technical limits of traditional PV applications, laying a solid preliminary foundation for building intelligent energy management platforms with autonomous decision-making and self-optimization capabilities. By integrating three core technologies—machine learning-based prediction, adaptive optimization, and automated fault diagnosis—it enables fully autonomous end-to-end operation that requires minimal human intervention. The framework also supports seamless integration with four types of mainstream digital energy technologies: it connects to IoT platforms to realize unified monitoring of wide-area PV assets, interfaces with cloud energy analysis platforms to support coordinated optimization of multi-power-plant clusters, adapts to digital twin environments to complete full-link simulation and verification, and is compatible with smart grid architectures to support cross-stakeholder grid dispatch coordination. Verification results from this study show that the framework can achieve multi-dimensional performance upgrades in dynamic, variable application environments. As a scalable, future-oriented solution for next-generation renewable energy systems, it lays a core technical foundation for the integrated deployment of intelligent PV facilities and advanced new energy management systems within complex, interconnected smart energy ecosystems.

The improved performance of the proposed framework is accompanied by greater computational and architectural complexity compared with conventional standalone MPPT methods. This complexity arises from the integration of environmental prediction, multi-objective optimization, adaptive control, and fault diagnosis. However, each module addresses a distinct operational challenge, and the resulting benefits extend beyond incremental improvements in tracking efficiency to include faster convergence, reduced oscillation, improved global MPP identification under partial shading, and integrated fault detection. The architecture is also modular, allowing individual functions to be omitted where application requirements do not justify their computational cost. Nevertheless, quantitative assessment of execution time, memory requirements, controller hardware requirements, and overall cost-benefit trade-offs remains necessary before practical deployment and will form part of future hardware-in-the-loop and experimental validation.

IV. CONCLUSIONS

This paper proposes a machine learning-based multi-objective optimization framework for the operation of photovoltaic (PV) systems, which adapts to variable environments and fault conditions. The framework simultaneously supports two core functions: maximum power point tracking (MPPT) and intelligent fault diagnosis. It integrates five core modules, builds its overall architecture around three unified design goals, and specifically addresses four core limitations of traditional PV control and monitoring technologies. The framework can dynamically adjust control parameters in response to real-time changes in environmental and system states, to achieve optimal operation across all working conditions. To verify the actual performance of the framework, this study built a simulation test environment. The tests cover five core working conditions: variable irradiance, temperature fluctuations, partial shading, sensor interference, and multiple types of PV faults. Four mainstream traditional methods in the field are selected as performance benchmarks for comparison: the Perturb and Observe (P&O) method, the Incremental Conductance (INC) method, fuzzy logic MPPT, and traditional threshold-based monitoring systems. The final test results show that this framework achieves a 98.7% maximum power extraction efficiency, a 97.9% fault classification accuracy, and a fault response time of less than 0.18s. It also balances six conflicting objectives through Pareto multi-objective optimization. With the synergistic operation of all its modules, the framework comprehensively improves the PV system's ability to operate continuously and stably, its power generation efficiency, and its fault handling speed. The intelligent photovoltaic energy system framework proposed in this paper can be adapted to a variety of scenarios including smart grids, distributed renewable energy networks and other similar application contexts. It features the core strengths of scalability and adaptability, and can improve key performance indicators such as the utilization rate of renewable energy. Follow-up research will advance work including real-time hardware implementation and digital twin integration, to build a fully intelligent renewable energy system suited for application in smart grids. The proposed integrated framework introduces additional computational complexity compared with conventional standalone MPPT approaches, and the present study does not provide a comprehensive quantitative assessment of computational cost, scalability, or parameter sensitivity. These factors are particularly important for real-time implementation and large-scale PV deployment. Future work will therefore investigate execution time, processor and memory requirements, scalability with increasing system size and decision variables, and sensitivity to key MOPSO, machine-learning, and controller parameters. Hardware-in-the-loop and experimental studies will also be conducted, subject to the availability of research resources, to determine the practical trade-off between computational complexity and the performance improvements achieved by the proposed framework.

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