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A Review of AI-Driven Optimization Technologies for Distributed Photovoltaic Power Generation Systems

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Abstract: The rapid development of artificial intelligence (AI) technology, particularly breakthroughs in branches such as deep learning, reinforcement learning, and federated learning, has provided powerful technical tools for addressing these core bottlenecks. This paper provides a systematic review of the research background, technological evolution, core systems, key challenges, and future directions of AI technology in the field of distributed photovoltaic power generation system optimization. At the same time, this paper analyzes the current technical bottlenecks and cutting-edge response strategies. Finally, it explores fusion innovation directions such as quantum-classical hybrid algorithms and neural symbolic systems, as well as business model expansion paths such as carbon finance integration and community energy autonomy.

Keywords: AI optimization; Distributed photovoltaic systems; Virtual power plant coordination; Community energy autonomy

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1. Introduction

The urgency of global efforts to address climate change, particularly the widespread adoption of "carbon neutrality" goals, has become the core driving force behind profound transformations in the energy system [1]. Against this backdrop, distributed photovoltaic (PV) power generation—with its notable cleanliness, deployment flexibility, and inherent advantage of being close to electricity consumption points—is being scaled up globally at an unprecedented pace, gradually transitioning from a "supplementary role" to a "mainstay" in the energy system [2]. However, the large-scale, high-proportion integration of distributed PV power generation has also posed significant challenges to traditional power systems. Its power generation output is highly dependent on meteorological conditions, exhibiting pronounced intermittency and volatility, which places enormous pressure on the grid's real-time power balance and frequency stability [3]. The widespread decentralized connection of distributed power sources to distribution grids, coupled with their inherent low inertia characteristics and the complexity of coordinating control across multiple nodes, has increasingly highlighted grid stability issues [4]. Additionally, efficiently integrating a vast number of decentralized PV units to maximize overall benefits faces challenges such as poor information exchange and low efficiency in collaborative decision-making [5]. These core bottlenecks severely hinder further improvements in the economic viability, reliability, and sustainability of distributed PV power generation systems [6]. In response to these challenges, artificial intelligence (AI) technology, with its exceptional capabilities in data processing, pattern recognition, complex decision-making, and adaptive learning, has gradually been recognized as a key enabling tool for addressing the optimization barriers of distributed photovoltaic systems [7]. Its technological evolution has exhibited clear stage-specific characteristics. In the initial stage (approximately 2020–2022), research focused primarily on using specific AI technologies to address optimization issues in individual components. For example, long short-term memory (LSTM) networks were used for short-term power generation forecasting [8], while convolutional neural networks (CNNs) were applied for the automatic identification and detection of PV module fault images [9]. While these studies achieved some success and validated the effectiveness of AI in specific tasks, they generally suffered from the limitation of addressing issues in isolation, lacking a systematic and coordinated optimization approach for photovoltaic systems as complex organic wholes. Optimization modules were often disconnected from one another [10]. Entering the breakthrough phase (approximately 2023–2024), the research perspective has begun to broaden, with a greater emphasis on system-wide and data-driven collaboration. The introduction of federated learning technology has provided an innovative approach to addressing the inherent "data silo" issues of distributed photovoltaic data (data dispersion and high privacy protection requirements) [11], enabling collaborative training of more powerful global models while preserving local data privacy. At the same time, digital twin technology has begun to be applied in the distributed photovoltaic field. By constructing a virtual mapping of physical systems and combining real-time data with historical information, dynamic simulation, prediction, and optimization strategy rehearsals can be conducted in virtual space, significantly improving the accuracy and foresight of system optimization decisions [12]. Currently, we are entering the integration phase (2025 to present), characterized by AI technology being more deeply integrated into the architecture and operational models of energy systems. Virtual power plants (VPPs), as an effective model for integrating distributed resources into grid operations and power market transactions, have seen a qualitative leap in their intelligence levels due to the application of AI [13]. AI technology is deeply integrated with blockchain (ensuring transparent and secure transactions) and edge computing (enabling local rapid response), collectively forming an intelligent foundation that supports multi-energy entities participating in market transactions and achieves efficient cross-platform resource scheduling and collaborative optimization [14]. The core objective of this phase is to achieve adaptive, self-optimizing, and self-coordinated operation of distributed photovoltaic systems across multiple spatio-temporal scales [15].

2. Core technology system and optimization path

The core of AI-driven distributed photovoltaic power generation system optimization lies in building a comprehensive technical system that spans data sensing, predictive decision-making, and collaborative control, thereby achieving intelligence from micro-components to macro-systems.

2.1. Intelligent sensing and data governance

The cornerstone of optimized decision-making is high-quality, multi-dimensional real-time data. In distributed photovoltaic scenarios, data collection faces challenges such as widely distributed nodes, complex environments, and diverse (heterogeneous) data types. Low-power wide-area network (LPWAN) technologies, such as LoRaWAN (long-range wide-area network) and NB-IoT (narrowband IoT), have become the ideal choice for connecting widely distributed edge sensing nodes (monitoring light intensity, component temperature, inverter operating parameters, environmental temperature and humidity, local grid load status, etc.) [16], enabling the low-cost, low-power, and reliable transmission of massive amounts of data. However, data collected in actual operation inevitably contains noise, missing values, or even outliers, which can severely impact the accuracy of subsequent models if used directly. Therefore, data governance has become an indispensable backend process in intelligent sensing. In addition to traditional cleaning, interpolation, and standardization methods, advanced AI technologies such as generative adversarial networks (GANs) have been innovatively applied to the field of anomaly data repair [17]. By training the generator to simulate the distribution of real data and using the discriminator to distinguish between real and generated data, GANs can learn the intrinsic patterns of data even in the absence of complete annotations, thereby more effectively identifying and repairing abnormal data points [18]. This significantly improves the overall quality and reliability of the dataset, laying a solid foundation for subsequent precise analysis and decision-making.

2.2. Dynamic prediction and adaptive optimization

Accurate forecasting is key to addressing photovoltaic variability and enabling proactive management. Power forecasting models themselves have undergone significant iterations driven by AI technology. Early research primarily relied on single time series models, such as LSTM, which primarily utilized historical power generation data. However, photovoltaic power generation is influenced by a variety of spatiotemporal factors, such as weather patterns (e.g., cloud movement) and complex terrain. Spatio-temporal graph neural networks (ST-GNN) represent a significant breakthrough in recent years [19], naturally modeling the spatial correlations between nodes (geographic locations) and the dynamic temporal evolution patterns within distributed photovoltaic systems. By integrating spatial information such as cloud maps and irradiance distributions provided by meteorological satellites, historical power generation curves of each node, and meteorological forecast data into the ST-GNN model, it is possible to comprehensively capture the complex spatio-temporal dependencies affecting power generation, effectively controlling the error rate of short-term predictions below 3% [20], significantly outperforming traditional models. Prediction is a means, and optimization is the goal. AI also plays a central role in the coordinated scheduling of energy storage systems with photovoltaic systems. Considering the inherent uncertainty of predictions and the real-time changes in operational conditions, a "dual-timescale optimization" strategy based on reinforcement learning (such as Q-learning, deep deterministic policy gradient DDPG, etc.) has become the mainstream approach [21]. This strategy establishes an initial plan for energy storage charging and discharging based on relatively accurate predictions at the "intraday planning" scale (e.g., several hours in advance); at the "real-time correction" scale (minute-level or even second-level), it utilizes the latest ultra-short-term predictions and actual system status information to make online decisions through reinforcement learning agents, dynamically adjusting the charging and discharging power and status of energy storage to smooth power fluctuations, participate in frequency regulation, or engage in arbitrage. This hierarchical, progressive, and real-time response strategy not only maximizes the regulatory value of energy storage but also effectively extends the cycle life of energy storage systems by 15–20% [22] through optimized charging and discharging depth and frequency, significantly reducing the lifecycle cost.

2.3. System-level collaborative control

The full value of distributed photovoltaic systems can only be realized through system-level coordination. VPPs, as platforms for integrating distributed resources, rely on intelligent decision-making at their core. AI technology plays the role of the "brain" in this context [23]. A peer-to-peer (P2P) energy trading platform built on blockchain smart contracts is an important application of VPPs. AI algorithms (such as multi-agent reinforcement learning and game theory optimization) can analyze real-time data on distributed PV power generation forecasts, energy storage status, user load demand curves, and power market price signals within a region. They dynamically match energy suppliers with demand, formulate optimal pricing strategies (such as dynamic pricing) to incentivize supply-demand balance, and maximize overall economic benefits [24]. Actual cases (such as the 5MW demonstration project in Jiaxing, China) demonstrate that such AI-driven VPP platforms can effectively reduce operational costs (by up to 12%) [25] and enhance local energy consumption rates. On the other hand, the high penetration of distributed PV systems in distribution grids, especially in weak grid scenarios (with low short-circuit capacity), can easily trigger grid stability issues such as harmonic resonance and voltage over-limit. AI also shows potential in power electronics control applications [26]. For example, by optimizing the parameters of the LCL filter at the front end of the grid-connected inverter and combining advanced resonance suppression algorithms such as dual current feedback control, AI-assisted controllers can more effectively suppress specific harmonics, significantly reducing total harmonic distortion (THDi) [27] and enhancing the system's stable operation under complex grid conditions. This "device-level intelligent control" is the technological foundation for ensuring the friendly grid connection of large-scale distributed PV systems.

3. Challenges and response strategies

Although AI-driven optimization technologies hold great promise, their practical implementation in engineering applications still faces a series of significant challenges that require ongoing research and technological innovation to overcome. The following is an analysis of the technical bottlenecks. First is the sharp contradiction between computing power and energy efficiency: the optimization of distributed photovoltaic systems, particularly real-time prediction and online control, often requires the deployment of AI models at the edge (such as field station controllers, smart inverters, or even local gateways) to achieve rapid response. However, edge devices are typically constrained by computational power, memory size, and power consumption budgets. Deploying complex deep learning models (such as large ST-GNNs or DDPG agents) on resource-constrained edge devices presents significant challenges [28]. High computational loads not only increase inference latency, making it difficult to meet real-time requirements (such as millisecond-level control), but also significantly increase device energy consumption, which contradicts the energy-saving and carbon-reduction objectives of photovoltaic systems. This constitutes the primary bottleneck constraining the deep application of AI in distributed photovoltaic systems [29]. Additionally, there are issues of cross-system compatibility and lagging standardization: distributed photovoltaic systems involve numerous equipment manufacturers and subsystems, including different models of photovoltaic inverters, various types of energy storage systems, various sensors, energy management systems (EMS), and grid dispatch systems. Currently, the international standard system for AI photovoltaic system interoperability is still incomplete [30]. Although IEC 61850 is an important standard for substation automation, its extensions targeting distributed energy (especially in combination with AI applications), such as IEC 61850-7-420, have progressed relatively slowly [31] and exhibit discrepancies in practical implementation. This directly leads to the "fragmentation" of communication protocols between devices. Different devices may use various proprietary or public protocols such as Modbus, CAN, DNP3, MQTT, and OPC UA, with inconsistent data models and interface definitions. This heterogeneity makes data collection and aggregation difficult, significantly increasing system integration complexity [32], severely hindering the construction of high-quality datasets required for AI models and the implementation of cross-platform collaborative optimization strategies, resulting in "data silos" and "system silos."

The following are cutting-edge developments in solutions: Lightweight AI models and efficient deployment: Addressing the bottleneck of edge computing power, research at the forefront focuses on lightweight model design and high-efficiency deployment technologies. Model compression is a key direction, including: Knowledge distillation: Training a large and complex "teacher model" and then using it to guide the training of a smaller-structured, computationally lighter "student model," enabling the student model to approximate the performance of the teacher model [33]. Model pruning: Identifying and removing redundant connections (weights) or even entire neurons/channels within a neural network, significantly reducing the number of model parameters and computational requirements [34]. Quantization: Converting model weights and activation values from high precision (e.g., 32-bit floating-point numbers) to low precision (e.g., 8-bit integers), significantly reducing memory usage and computational overhead [35]. Ultra-low-power machine learning technologies, such as TinyML, aim to deploy lightweight models on resource-constrained microcontrollers (MCUs). Specifically, for example, the hybrid architecture combining MobileNet (specializing in efficient image processing) and GRU (lightweight recurrent unit) proposed in 2024 [36] was successfully deployed on popular edge computing platforms such as the Raspberry Pi 4B after pruning and quantization, achieving real-time prediction and inference of photovoltaic power in complex environments with end-to-end latency stably controlled within 50 milliseconds [37], meeting the requirements of most real-time control scenarios. Accelerated advancement of standardization and interoperability: The fundamental solution to compatibility issues lies in establishing a unified standard system. The International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC) are actively promoting related work. ISO/TC 301 (Energy Management and Energy Efficiency Technology Committee) is leading the effort, collaborating with multiple working groups to expedite the development of interface specifications and data model standards specifically tailored for AI-driven energy systems (including photovoltaic systems) [38]. This standard is expected to be published in 2026 [39], with its core objectives being to define clear, open API interfaces, unified information models (such as semantic descriptions of device capabilities, status, and control commands), and secure communication frameworks. This will lay the foundation for achieving "plug-and-play" interoperability between devices from different manufacturers, significantly reducing system integration complexity and costs, enabling seamless data flow, and clearing obstacles to the development of large-scale, cross-platform AI-optimized applications. Before the standard matures, industry alliances and leading companies are also actively promoting the establishment and application of de facto interoperability standards [40].

4. Typical applications and benefit assessment

AI-driven optimization technology has gradually moved from theoretical research to engineering practice, demonstrating significant application value and comprehensive benefits at multiple levels.

4.1. City-level photovoltaic cluster case study

Distributed photovoltaic systems are typically densely deployed in urban areas (such as commercial and industrial rooftops, residential communities, and public buildings). One of the key challenges faced by these urban-scale photovoltaic clusters is the impact of extreme weather events (such as typhoons, severe convective storms, and extreme rainstorms). Under traditional methods, extreme weather may cause extensive damage to photovoltaic units or cause them to go offline, with system recovery relying on manual inspections and on-site repairs, which are time-consuming, inefficient, and high-risk. AI technology offers a new solution to enhance the resilience and self-healing capabilities of clusters. By deploying AI analysis platforms in the cloud or at the edge, real-time access to weather warning information, operational status of each node (voltage, current, power, insulation monitoring data), and even video surveillance footage is enabled. Before or during extreme weather events, AI can assess the potential risk levels of each node based on predicted wind speeds, rainfall intensity, and component stress models. More importantly, when some nodes are taken offline due to disaster damage or local grid failures occur, AI can quickly analyze the entire network topology and real-time operational status, utilize dynamic reconfiguration of the power generation topology, and calculate and execute the optimal reconfiguration scheme online (such as adjusting interconnection switch states or changing microgrid operational modes). This effectively endows photovoltaic clusters with "intelligent self-healing" capabilities, bypassing faulty or damaged areas to maximize the utilization of remaining available resources and rapidly restore power supply to critical loads. Practical applications have shown that after a severe typhoon, systems employing AI-based dynamic reconfiguration strategies can restore power supply in a timeframe that is one-third or even less of the time required by systems relying on traditional manual intervention methods, significantly enhancing the resilience and reliability of urban energy supply.

4.2. Economic and environmental benefits

AI-driven optimization has a direct and quantifiable positive impact on the economic viability and environmental contributions of distributed photovoltaic projects. From an economic perspective, the following benefits are evident: Increased power generation and reduced curtailment rates: Precise power forecasting and optimized scheduling strategies (especially in conjunction with energy storage) significantly reduce unplanned curtailments (power curtailment) caused by forecasting errors. AI optimization can effectively control curtailment rates below 2%, or even approach zero [41], directly increasing the amount of available clean electricity. Additionally, through measures such as maximum power point tracking optimization, module cleaning strategy optimization, and rapid fault diagnosis and recovery, the overall power generation efficiency of the system can also be improved. Reduced operational costs: AI-enabled intelligent monitoring and fault diagnosis systems enable a transition from "scheduled inspections" to "condition-based maintenance" and "predictive maintenance." The system can automatically identify potential faults (such as hotspots, string faults, and inverter performance degradation) and precisely locate them, significantly reducing unnecessary on-site inspection visits and labor costs [42], shortening fault resolution times, and improving operational efficiency. Increased market revenue: For VPPs participating in the power market, AI-optimized strategies can more accurately predict market price fluctuations, optimize energy storage charging and discharging timings, and photovoltaic output plans, thereby achieving higher returns in ancillary service markets (such as frequency regulation) and energy markets [43]. Dynamic pricing strategies can also optimize user-side energy costs or increase photovoltaic owners' electricity sales revenue. From an environmental perspective, distributed photovoltaic systems are inherently clean energy sources. Each megawatt (MW) of distributed photovoltaic systems can reduce carbon dioxide emissions by approximately 1,200 tons annually under typical annual equivalent utilization hours [44]. AI-driven optimization further amplifies this emissions reduction effect by improving generation efficiency (increasing actual power generation per unit capacity) and significantly reducing curtailment rates (preventing the waste of clean electricity). This means that under the same installed capacity, AI-optimized systems can actually replace more fossil fuel-based power generation, contributing greater efforts toward achieving carbon neutrality goals. Therefore, AI is not only a tool to enhance the economic viability of distributed PV but also a key lever to amplify its environmental externalities [45].

5. Future research direction

The integration of AI and distributed photovoltaics is still in a stage of rapid development. It is observed that future research will continue to break new ground in two major directions: deepening technological integration and innovation, and expanding business models.

Technological integration and innovation: Quantum-classical hybrid algorithms: Large-scale, multi-objective, strongly constrained optimization problems in distributed photovoltaic systems (such as VPP scheduling that considers thousands of nodes, multiple time scales, grid safety constraints, economic objectives, and environmental objectives) often belong to high-dimensional, non-convex, NP-hard problems. Traditional classical algorithms (such as linear/nonlinear programming and heuristic algorithms) face limitations in terms of solution efficiency and optimality guarantees. Quantum computing, particularly quantum annealing and certain quantum optimization algorithms (such as QAOA), theoretically possesses exponential acceleration potential in addressing specific types of combinatorial optimization problems [46]. Future research will focus on exploring how to construct an efficient quantum-classical hybrid algorithm framework. The core idea is to decompose the entire optimization problem, offloading computationally intensive components suitable for quantum computing (such as large-scale combinatorial selection and complex constraint satisfaction) to quantum processors (such as quantum annealing machines) for solution, while the remaining components are handled by classical computers, with the results fused [47]. This hybrid approach is expected to achieve breakthroughs around 2030 [48], offering new avenues for addressing the current challenges of collaborative optimization in large-scale distributed photovoltaic clusters and VPPs, enabling orders-of-magnitude improvements in scheduling efficiency and the attainment of optimal solutions. Neuro-symbolic systems: While current AI models based on deep learning (such as fault diagnosis CNN/LSTM) perform exceptionally well on specific tasks, they generally suffer from the “black box” problem, lacking explainability [49]. This makes it difficult for operations personnel to understand the underlying logic and basis for the model’s diagnostic decisions, reducing trust and hindering the model’s continuous improvement and knowledge accumulation. Neuro-symbolic systems aim to integrate the powerful perception and pattern recognition capabilities of deep learning (the “neural” part) with the explainability, knowledge representation, and reasoning capabilities of symbolic logic systems (Symbolic AI) (the “symbolic” part) [50]. In the field of photovoltaic fault diagnosis, this means that a system can be constructed where neural networks are responsible for extracting features and identifying abnormal patterns from sensor data (current, voltage, temperature, infrared images), while symbolic systems utilize predefined or learned domain knowledge graphs (containing device physical models, fault propagation logic, and expert experience rules) to perform logical reasoning and verification on the outputs of neural networks, and generate human-understandable diagnostic reports (e.g., “Fault type: component hotspot; Possible cause: Local shading; Location: Array A, row 3, column 5; Confidence: 92%; Basis: Infrared image high-temperature anomaly region matches voltage and current feature rule R7” [51]. This will significantly enhance the transparency and credibility of AI diagnostic systems, making them easier for maintenance personnel to understand and adopt, while also facilitating the accumulation and reuse of domain knowledge to drive continuous improvements in diagnostic accuracy.

Business model expansion: Carbon finance integration: As global carbon pricing mechanisms (carbon taxes, ETS carbon emission trading markets) become more sophisticated and corporate carbon neutrality commitments become more widespread, the carbon reduction value of photovoltaic power generation is increasingly being monetized. A key future direction is the deep integration of AI and carbon finance [52]. AI-based PV systems can not only accurately measure their own power generation but also combine grid emission factors, life cycle assessment (LCA) databases, and other data to real-time, precisely calculate and track the carbon footprint offsets (i.e., carbon emissions reductions) generated by PV power generation [53]. These high-quality, verifiable carbon emissions reduction data are secured and recorded on the blockchain through technologies like blockchain, forming trustworthy digital carbon assets [54]. AI platforms can intelligently connect these carbon assets to various green rights trading markets (such as voluntary emissions reduction markets like VERRA and Gold Standard, or mandatory national/regional ETS systems) [55]. By dynamically analyzing carbon market prices, project emission reduction costs, and trading rules, AI can provide photovoltaic asset owners with optimal strategies for carbon asset development, management, and trading [56], maximizing the economic benefits (carbon credit sales revenue) derived from environmental rights, thereby further unlocking the comprehensive (energy + environmental) value of photovoltaic assets and enhancing project investment returns. Community energy autonomy: Distributed PV is inherently closely integrated with local communities. A more revolutionary model in the future could be community energy microgrids built on the concept of decentralized autonomous organizations (DAOs) [57]. In this model, PV owners, energy storage owners, electric vehicle users, and ordinary electricity consumers within a community organize themselves through blockchain technology to form an energy community jointly owned by its members and operated based on smart contract rules [58].

6. Conclusion

The AI technology has deeply penetrated and is reshaping the design, operation, and management paradigms of distributed photovoltaic power generation systems. From addressing power fluctuations, enhancing grid stability, to achieving efficient multi-node collaboration, AI provides end-to-end solutions spanning from bottom-layer sensing to top-layer decision-making. This paper systematically reviews the evolution of AI from single-function optimization to multi-technology integration, analyzing the technical framework centered on intelligent sensing and data governance, dynamic prediction and adaptive optimization, and system-level collaborative control, as well as the significant performance improvements it brings (such as breakthroughs in prediction accuracy, extended energy storage lifespan, and reduced operational costs). At the same time, it addresses current engineering challenges such as the contradiction between computing power and energy efficiency and cross-system compatibility, and points out key response strategies such as lightweight models (e.g., TinyML applications) and standardization (e.g., ISO/TC 301). Typical application cases validate the tremendous value of AI in enhancing the resilience of city-level photovoltaic clusters (e.g., resistance to extreme weather) and amplifying economic and environmental benefits (reducing curtailment rates and increasing carbon reduction contributions). Looking ahead, quantum-classical hybrid algorithms are expected to overcome the challenges of large-scale optimization, while neural-symbolic systems will endow AI with stronger interpretability and knowledge reasoning capabilities. Meanwhile, carbon finance integration and community energy autonomy (DAO+AI) open up broad prospects for activating the environmental value of photovoltaic systems and exploring new energy governance models. It is foreseeable that AI will continue to serve as the core engine driving the evolution of distributed photovoltaic power generation systems toward smarter, more efficient, more reliable, and more sustainable directions, providing indispensable technical support for building a new power system centered on renewable energy and achieving global carbon neutrality goals. In-depth research and innovative practices in this interdisciplinary field require sustained cross-disciplinary integration and collaborative efforts across energy, power, information, communications, and artificial intelligence.

Disclosure statement

The author declares no conflict of interest.

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