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EXPERT SYSTEM FOR CONTROLLING OPERATING MODES OF SOLAR PANELS WITH NEURAL NETWORK-BASED OPTIMALITY ASSESSMENT OF DECISIONS

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The rapid growth of solar energy utilization necessitates increasing the efficiency of control systems for photovoltaic installations operating under conditions of variable solar irradiance, temperature fluctuations, and component degradation. Modern photovoltaic systems are characterized by nonlinear behavior, stochastic external influences, and dynamic load conditions. Under such circumstances, traditional Maximum Power Point Tracking (MPPT) algorithms, which are typically based on fixed logic and local optimization procedures, do not always ensure optimal system performance, especially in transient and rapidly changing environments.

Existing approaches to photovoltaic system control primarily rely on classical MPPT techniques, rule-based logic, or monitoring-oriented analytical modules. While these methods provide stability and acceptable efficiency under steady-state conditions, they are often limited in adaptability and do not adequately account for complex interdependencies between environmental and electrical parameters. In particular, conventional solutions lack mechanisms for self-learning, dynamic optimality evaluation, and real-time corre ction of control actions, which significantly reduces their effectiveness under uncertainty and nonstationary operating conditions.

A promising direction for overcoming these limitations is the development of cyber-physical control systems that integrate expert knowledge with adaptive data-driven models. In such systems, an expert subsystem generates control decisions based on formalized rules and domain knowledge, while a neural network module evaluates the quality of these decisions and performs their correction based on learned patterns. This hybrid approach enables combining interpretability and structural clarity of expert systems with the adaptability and approximation capabilities of artificial neural networks.

The use of neural networks allows modeling nonlinear relationships between system parameters, approximating complex objective functions, and adapting to changing operating conditions. At the same time, expert systems provide a transparent and logically structured mechanism for initial decision formation, ensuring reliability and compliance with operational constraints. The integration of these components creates conditions for building intelligent control systems capable of maintaining high efficiency, stability, and robustness of photovoltaic installations.

Therefore, the development of an expert system for controlling operating modes of solar panels with neural network-based optimality assessment of decisions represents a modern and relevant scientific and practical task. Such systems have significant potential for improving energy efficiency, reducing losses, and enhancing the adaptability of renewable energy sources within modern cyber-physical infrastructures.

Keywords: photovoltaic systems, expert systems, neural networks, control systems, MPPT, cyber-physical systems, optimality assessment, solar energy.

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Introduction

The current stage of renewable energy development is characterized by a rapid increase in the deployment of photovoltaic systems, the growing complexity of their architectures, and rising requirements for energy efficiency, stability, and adaptability. Solar power plants operate under conditions of significant uncertainty caused by fluctuations in solar irradiance, temperature variations, degradation of photovoltaic modules, and dynamic changes in load profiles. Under such conditions, effective control of operating modes becomes a critical factor in ensuring maximum energy extraction and reliable system performance.

Traditional approaches to controlling photovoltaic systems are primarily based on classical Maximum Power Point Tracking (MPPT) algorithms, including perturb and observe and incremental conductance methods. These approaches are relatively simple to implement and provide acceptable performance in steady-state conditions. However, in dynamic environments with rapidly changing external factors, such methods often exhibit oscillations around the maximum power point, delayed response to disturbances, and limited ability to account for complex nonlinear dependencies between system parameters [1].

Modern commercial solutions for solar energy management are mainly focused on monitoring, visualization, and maintaining operational stability. Analytical modules, when present, typically perform auxiliary functions and are not directly integrated into the decision-making loop. As a result, such systems lack mechanisms for adaptive control, self-learning, and real-time evaluation of decision optimality, which significantly limits their effectiveness in conditions of uncertainty and nonstationary operation.

A promising direction for improving control efficiency is the use of cyber-physical systems that integrate physical processes of energy generation with intelligent data processing and decision-making algorithms. Within this paradigm, expert systems enable the formalization of domain knowledge in the form of production rules and provide a structured and interpretable mechanism for generating control actions. At the same time, expert systems are inherently limited by the static nature of their rule base and difficulties in representing complex nonlinear relationships.

To overcome these limitations, it is advisable to combine expert approaches with methods of artificial intelligence, particularly artificial neural networks. Neural networks are capable of approximating nonlinear dependencies, processing multidimensional data, and adapting to changing operating conditions based on accumulated experience. Their integration into the control loop makes it possible to evaluate the optimality of decisions generated by the expert system and to perform their correction in real time.

The combination of expert knowledge representation and neural network-based adaptive evaluation creates a foundation for developing intelligent control systems for photovoltaic installations. Such systems can ensure higher accuracy in maintaining optimal operating modes, reduce energy losses, and improve responsiveness to external disturbances.

The relevance of this work is justified by a requirement of increasing efficiency of controlling solar panels in the everchanging environment, increasing requirements for energy efficiency and limitations of traditional MPPT methods. Integration of expert systems and neural models opens vast possibilities for creating adaptive solutions, capable of accounting for complex parameter interoperations and ensure optimized operations in real-time.

The aim of this work is to develop an expert system for controlling operating modes of solar panels with neural network-based optimality assessment of decisions [2].

The object of study is the process of energy generation and control in photovoltaic systems.

The subject of the study is methods, models, and software-hardware tools for expert-neural control of photovoltaic installations.

The scientific novelty lies in the integration of a rule-based expert system with a neural network module for adaptive evaluation and correction of control decisions under uncertainty.

The practical significance of the obtained results consists in the possibility of applying the proposed approach in intelligent control systems for solar power plants to improve energy efficiency, reduce losses, and enhance system adaptability.

Analysis of Existing Methods for Controlling Photovoltaic Systems

Modern approaches to controlling photovoltaic systems are increasingly oriented toward adaptive, data-driven, and intelligent decision-making mechanisms. The rapid growth of solar energy integration into power systems is accompanied by an increase in the variability of operating conditions, structural complexity of energy infrastructures, and the need for continuous optimization of energy conversion processes. Photovoltaic installations operate under stochastic external influences, including fluctuations in solar irradiance, temperature changes, and dynamic load behavior. Under such conditions, conventional static control methods become insufficient, creating a demand for intelligent systems capable of real-time adaptation and optimal decision-making[3].

The evolution of control technologies in photovoltaic systems reflects a transition from deterministic algorithms to hybrid and intelligent approaches. Classical control methods, particularly MPPT algorithms, were designed to maximize instantaneous power extraction under relatively stable conditions. However, modern energy environments require systems that are capable not only of tracking optimal points but also of predicting, adapting, and correcting their behavior dynamically. This has led to the development of approaches based on expert systems, artificial intelligence, and hybrid computational models [4].

Classical MPPT methods, such as Perturb and Observe and Incremental Conductance, remain widely used due to their simplicity and ease of implementation. These methods operate by iteratively adjusting the operating point of the photovoltaic panel to maximize output power. While effective in steady-state conditions, they exhibit several critical limitations. In rapidly changing environments, these algorithms tend to oscillate around the maximum power point, leading to energy losses. Additionally, they demonstrate slow response times to abrupt changes in irradiance and temperature, which reduces overall system efficiency. Their inability to account for complex nonlinear interactions between system parameters further limits their applicability in modern adaptive control systems.

Expert systems represent the next stage in the development of control methodologies. These systems rely on formalized knowledge represented in the form of production rules and logical inference mechanisms. By encoding domain expertise, expert systems enable structured and interpretable decision-making. They can incorporate multiple criteria, including efficiency, stability, and safety constraints, and are capable of handling discrete operating conditions more effectively than classical algorithms. However, their primary limitation lies in the static nature of their knowledge base. The process of defining and updating rules is labor-intensive and does not scale well with increasing system complexity. Furthermore, expert systems struggle to model continuous nonlinear relationships and lack mechanisms for autonomous learning and adaptation.

Artificial neural networks introduce a fundamentally different paradigm by enabling data-driven modeling and approximation of complex nonlinear dependencies. Neural network-based approaches can learn from historical data, identify hidden patterns, and generalize across a wide range of operating conditions [5]. In photovoltaic systems, neural networks have been applied for power prediction, optimal control, and anomaly detection. Their ability to adapt to changing environments makes them suitable for dynamic control tasks. However, these methods also exhibit significant drawbacks. They require large volumes of high-quality training data, are computationally intensive, and often function as black-box models, limiting interpretability. The lack of transparency complicates validation and reduces trust in critical applications.

Hybrid approaches attempt to combine the strengths of multiple methodologies. In particular, the integration of expert systems with neural networks has been proposed as a means of achieving both interpretability and adaptability. In such systems, expert rules provide an initial decision framework, while neural networks evaluate and refine these decisions based on learned patterns. This approach improves performance in dynamic environments and reduces reliance on manual rule updates [6]. Nevertheless, hybrid systems introduce additional complexity in terms of architecture, synchronization, and parameter tuning. Ensuring stable interaction between components remains a nontrivial task.

To provide a structured comparison of the analyzed approaches, Table 1 summarizes their characteristics according to key system criteria.

Table 1.

Comparative analysis of photovoltaic control methods

Paper	Method	Adaptability	Complexity	Reliability	Interpretability	Main limitations
[4-5]	Classical MPPT	Low	Low	Medium	High	Oscillations, slow response, limited adaptability
[6-9]	Expert systems	Medium	Medium	Medium	High	Static knowledge base, no self-learning
[10-15]	Neural networks	High	High	Medium	Low	Data dependency, black-box behavior
[16-22]	Hybrid approaches	High	High	High	Medium	Architectural complexity, integration issues

The comparison indicates that no single method fully satisfies the requirements of modern photovoltaic control systems. Classical methods are efficient but lack adaptability. Expert systems provide interpretability but are limited by static knowledge. Neural networks offer adaptability but introduce complexity and reduce transparency. Hybrid systems improve performance but require careful design to avoid instability.

To further illustrate the performance differences between these approaches, efficiency characteristics under dynamic conditions can be represented using comparative charts.

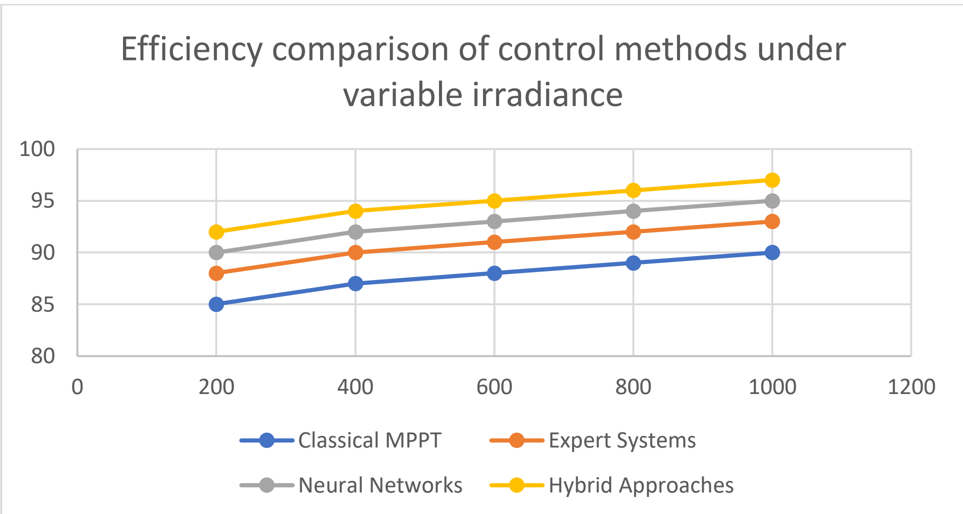

Fig. 1. Efficiency comparison of control methods under variable irradiance

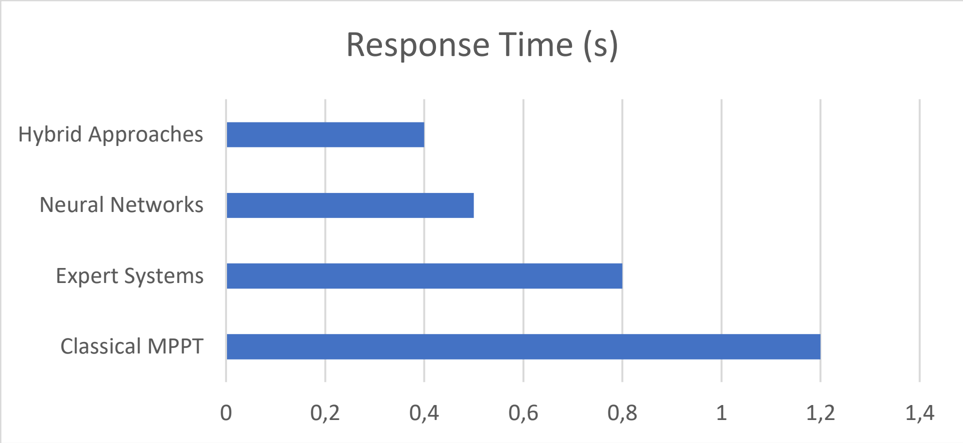

Fig. 2. Response time to step changes in irradiance

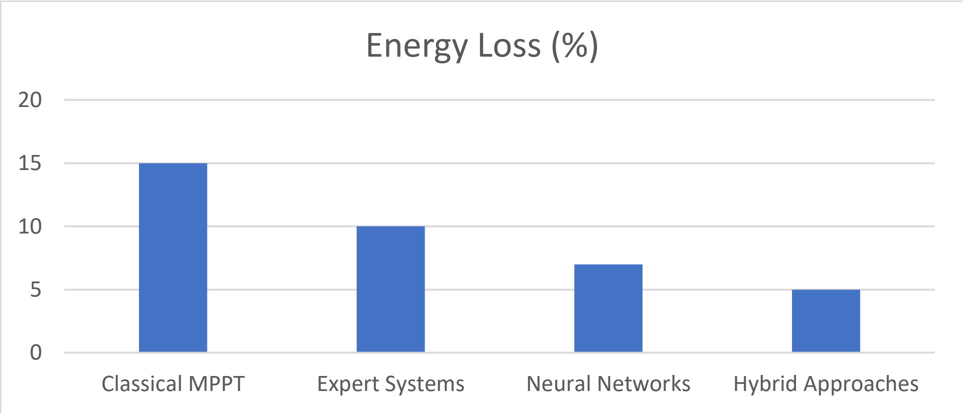

Fig. 3. Energy loss comparison across control strategies

Analysis of these characteristics demonstrates that while hybrid approaches outperform classical methods in terms of efficiency and adaptability, they still face limitations related to stability, computational cost, and integration complexity.

A critical review of existing solutions reveals several systemic shortcomings. First, most methods do not provide a unified mechanism for combining interpretability with adaptive learning. Second, the majority of approaches either rely heavily on predefined models or require extensive retraining, which limits real-time applicability[7]. Third, many systems lack a formalized mechanism for evaluating the optimality of control decisions, focusing instead on local optimization objectives.

These limitations lead to a fundamental contradiction: achieving high adaptability often reduces interpretability and increases complexity, while maintaining simplicity and transparency limits performance under dynamic conditions. This trade-off remains unresolved in existing methodologies.

Therefore, the problem addressed in this work is the development of an integrated control approach that combines the structured decision-making capabilities of expert systems with the adaptive evaluation and correction mechanisms of neural networks. The objective is to create a system that ensures high efficiency, stability, and adaptability while maintaining interpretability and manageable computational complexity.

The proposed approach aims to eliminate the identified shortcomings by introducing a neural network-based optimality assessment module into the expert control loop. This enables continuous evaluation and correction of control decisions, ensuring adaptive behaviour in dynamically changing environments while preserving the logical transparency of the expert system.

Extensive descriptions of the methodology of synthesis and system operation

Information technologies in the domain of cyber-physical energy systems are undergoing a paradigm shift toward deeper integration between physical processes, data-driven analytics, and adaptive control mechanisms. This evolution is particularly critical in photovoltaic energy generation, where the inherent variability of environmental conditions–such as solar irradiance, temperature fluctuations, and atmospheric interference–demands a sophisticated approach to system management [8]. The proposed method addresses these challenges by introducing a hybrid expert–neural control loop, designed to continuously adapt to uncertainty while preserving the deterministic integrity of the system. This hybrid approach bridges the gap between traditional rule-based systems, which excel in interpretability but lack adaptability, and purely data-driven models, which offer flexibility but often struggle with transparency and domain-specific constraints.

The methodological foundation of the proposed approach is rooted in a structured decomposition of the control process into sequential yet interdependent stages. Each stage is responsible for a distinct transformation of information, beginning with raw sensor data acquisition and culminating in the generation and refinement of control actions. This modular architecture ensures not only traceability of decisions but also the ability to incrementally refine individual subsystems without compromising the overall system stability [9]. By isolating functional components, the method facilitates targeted improvements, such as enhancing noise suppression algorithms or refining rule-based inference mechanisms, without necessitating a complete redesign of the system.

At the initial stage, the method emphasizes the structured acquisition of input data within the cyber-physical framework. Sensor measurements, collected in real time, undergo rigorous preprocessing to mitigate the impact of environmental noise and sensor inaccuracies. This preprocessing includes normalization to standardize data ranges, temporal alignment to synchronize measurements across distributed sensors, and advanced filtering techniques to suppress high-frequency noise [10]. Given the stochastic nature of solar irradiance and ambient temperature, adaptive filtering methods, such as Kalman filters or wavelet transforms, are employed to stabilize input signals. Additionally, validation checks are implemented to detect and eliminate anomalous readings, which may arise from sensor malfunctions, communication delays, or external interference. The result is a consistent and reliable state vector that accurately represents the current operating conditions of the photovoltaic system, forming the basis for subsequent decision-making processes.

The second stage focuses on transforming preprocessed data into symbolic representations suitable for expert system processing. Continuous variables, such as irradiance levels or temperature readings, are mapped into linguistic categories through discretization or fuzzy membership functions. This transformation enables the application of rule-based reasoning mechanisms, which operate on qualitative descriptors rather than raw numerical values. The design of membership functions is informed by empirical data distributions and domain expertise, ensuring that the symbolic representation captures essential system dynamics while reducing computational complexity. For instance, solar irradiance may be categorized into linguistic terms such as "low," "moderate," or "high," allowing the expert system to reason about system states in a more intuitive and interpretable manner [11].

At the third stage, the expert system performs inference based on the current symbolic state. The knowledge base, structured as a set of production rules, encodes domain-specific relationships between environmental conditions, system states, and optimal control actions. These rules are derived from a combination of empirical observations, theoretical models, and expert insights, ensuring that the system operates within safe and efficient boundaries. The inference mechanism evaluates rule conditions in parallel, constructing a conflict set of applicable rules. Conflict resolution strategies, such as priority-based selection or rule specificity, are then applied to determine the most appropriate control action. These strategies may also incorporate historical performance data, allowing the system to favor rules that have consistently yielded positive outcomes under similar conditions.

The output of the expert system is an initial control action that defines the operating mode of the photovoltaic converter. While this action is derived from deterministic logic and reflects accumulated domain expertise, it is not assumed to be globally optimal under all conditions. Recognizing the limitations of static rule-based systems, the method introduces an additional evaluation layer to assess and refine the proposed decision [12]. This layer leverages neural network-based models to evaluate the potential performance of the control action, ensuring that the system remains adaptive and responsive to dynamic environmental changes.

The fourth stage involves the neural network-based evaluation of the generated control action. The neural model receives as input both the system state and the proposed control action, forming an augmented feature vector that captures the relationship between control decisions and their resulting performance metrics. The neural network operates as a regression model, estimating key performance indicators such as energy efficiency, system stability, and response time [13]. This evaluation provides a probabilistic assessment of the control action's effectiveness, complementing the deterministic output of the expert system.

Training of the neural network is performed offline using historical operational data, which includes recorded system states, applied control actions, and corresponding performance indicators. Feature scaling and dimensionality reduction techniques, such as principal component analysis or autoencoders, may be applied to improve model convergence and generalization. The training process is guided by a multi-objective loss function that balances energy efficiency, stability, and response time, ensuring that the model aligns with the system's operational goals [14]. To enhance robustness, the training procedure incorporates cross-validation and regularization techniques, such as dropout or L2 regularization, which prevent overfitting and improve generalization to unseen data.

The model is periodically retrained to account for long-term changes in system behavior, such as component degradation, seasonal variations, or shifts in operational patterns. This continuous learning capability enables the system to adapt to evolving conditions without requiring manual reconfiguration of the knowledge base. By integrating new data into the training process, the neural model remains aligned with the current state of the system, ensuring that its evaluations remain accurate and relevant over time.

At the fifth stage, the evaluation output is compared against predefined performance thresholds, which represent acceptable levels of efficiency, stability, and responsiveness. If the estimated performance of the control action falls within these bounds, the action is accepted and transmitted to the actuator layer for execution. However, if the evaluation indicates suboptimal performance, a correction mechanism is activated [15]. This mechanism adjusts the control parameters iteratively or selects alternative rules from the knowledge base, generating a revised control action that better aligns with the system's objectives.

The correction process is guided by feedback from the neural model, effectively forming a closed-loop optimization system. Unlike traditional iterative optimization methods, which rely on exhaustive search or gradient-based techniques, the proposed approach leverages learned representations to accelerate convergence. This results in faster adaptation to changing conditions and reduced computational overhead during real-time operation, making the system more efficient and responsive in dynamic environments.

The sixth stage addresses the temporal dynamics of the photovoltaic system, which are inherently time-dependent and influenced by transient behaviors. To capture these dynamics, the method incorporates a sliding time window for state analysis, allowing the system to identify short-term trends and transient patterns that may not be evident from instantaneous measurements [16]. Temporal features, such as the rate of change of irradiance or temperature gradients, are included in the input vector to enhance the predictive accuracy of both the expert system and the neural model. This temporal awareness enables the system to anticipate changes in environmental conditions and proactively adjust control actions to maintain optimal performance.

Additionally, the method accounts for delayed effects and system inertia by integrating state history into the decision-making process. This is achieved either through feature augmentation, where historical data is explicitly included in the input vector, or by employing recurrent structures, such as long short-term memory (LSTM) networks, in the neural component [17]. The choice between these approaches depends on computational constraints and the required level of accuracy, with recurrent structures offering superior performance in capturing long-term dependencies at the cost of increased computational complexity.

The seventh stage extends the control framework to incorporate system-level coordination and resource management. In practical deployments, photovoltaic systems often operate as part of larger energy networks, which may include energy storage systems, load demand centers, and grid interfaces. The method integrates constraints related to energy storage capacity, load demand profiles, and grid stability into the decision-making process. These constraints are enforced through additional rules in the expert system and modified evaluation criteria in the neural model, ensuring that control actions align with broader operational objectives. For example, during periods of high energy demand, the system may prioritize grid stability over maximum energy extraction, adjusting control actions to balance supply and demand.

The method also includes robust mechanisms for fault detection and resilience. Continuous monitoring of system behavior allows for the early detection of deviations from expected performance, triggering diagnostic procedures to identify and mitigate potential faults. The expert system contains predefined rules for handling common fault scenarios, such as sensor failures or communication disruptions, while the neural component assists in detecting subtle anomalies that may not be captured by these rules. This dual-layer approach enhances system reliability, reduces downtime, and ensures safe operation even in the presence of unforeseen disturbances [18].

An important aspect of the methodology is its focus on interpretability, which is critical in safety-critical energy applications. While neural networks provide adaptive capabilities, their internal representations are often opaque, making it difficult for operators to understand the rationale behind control decisions. To address this, the method incorporates an explanation module that traces the contribution of individual rules and input features to the final decision. This module generates human-readable explanations, highlighting the key factors that influenced the control action and enabling operators to validate system behavior. By providing transparency into the decision-making process, the method fosters trust and facilitates the adoption of adaptive control strategies in real-world applications.

The final stage of the method involves performance monitoring and feedback integration. Key performance indicators, such as energy yield, system efficiency, and fault detection rates, are continuously evaluated, and the results are used to update both the knowledge base and the neural model. Rule effectiveness is assessed based on historical outcomes, allowing for the pruning of obsolete or ineffective rules and the reinforcement of those that consistently yield positive results. Similarly, the neural model is updated with new operational data, ensuring that it remains aligned with the evolving dynamics of the system. This feedback loop enables the system to continuously improve its performance, adapting to changes in environmental conditions, operational requirements, and technological advancements [19].

The overall methodological framework can be summarized as a hierarchical control loop consisting of data acquisition, symbolic transformation, rule-based inference, neural evaluation, decision correction, and feedback adaptation. This structure strikes a balance between interpretability and adaptability, addressing the limitations of existing systems while providing a foundation for further advancements in intelligent energy management. By combining deterministic reasoning with data-driven evaluation, the method achieves improved efficiency, robustness, and scalability, making it suitable for deployment across a wide range of photovoltaic installations.

The proposed method distinguishes itself through the explicit integration of expert knowledge and machine learning within a unified control architecture. Unlike purely data-driven approaches, which may struggle to enforce domain-specific constraints, or traditional expert systems, which lack adaptability, the hybrid approach retains the strengths of both paradigms. It ensures safe and efficient operation under all conditions while continuously adapting to new challenges and opportunities. This dual capability is particularly valuable in the context of photovoltaic energy systems, where environmental variability and operational complexity demand a flexible yet reliable control strategy.

The scalability of the method is further ensured through its modular design, which allows each component to be independently developed, tested, and optimized. This modularity facilitates deployment across diverse photovoltaic installations, from small-scale residential systems to large utility-grade solar farms. The method is also compatible with distributed implementations, where local controllers operate autonomously while sharing aggregated data for global model updates. This distributed architecture enhances system resilience, enabling robust operation even in the face of localized failures or communication disruptions.

In conclusion, the developed methodology provides a comprehensive and adaptive framework for the control of photovoltaic systems within a cyber-physical context. By integrating deterministic reasoning with data-driven evaluation, it achieves a harmonious balance between efficiency, robustness, and interpretability. This framework not only addresses the limitations of existing systems but also forms a solid foundation for future advancements in intelligent energy management, paving the way for more sustainable and resilient energy infrastructures.

Experimental Evaluation of the Expert–Neural Control Method

The evaluation of the proposed expert–neural control methodology for photovoltaic systems demands a rigorous and structured experimental framework that accurately reflects real-world operational conditions. Such a framework must not only incorporate stochastic environmental variations but also enable a comparative analysis against established baseline control strategies. Unlike purely analytical validation, which relies on theoretical models and simulations, experimental assessment provides empirical evidence of system behavior under dynamic and often unpredictable conditions [20]. This includes the nonlinear interactions between environmental inputs, control actions, and the resulting energy output, all of which are critical for validating the effectiveness and robustness of the proposed methodology.

The experimental methodology is meticulously constructed around a series of controlled simulation scenarios, derived from a high-fidelity mathematical model of the photovoltaic subsystem. These scenarios are designed to replicate both stationary and transient operating conditions, ensuring that the performance of the control system is thoroughly evaluated across a representative spectrum of environmental states. The evaluation process is centered on three primary performance dimensions: energy efficiency, which measures the system's ability to maximize power extraction; dynamic responsiveness, which assesses the system's capacity to adapt to rapid changes in environmental conditions; and stability of operation, which evaluates the consistency and reliability of the system's performance over time.

At the initial stage of experimentation, a comprehensive baseline dataset is generated using a classical Maximum Power Point Tracking (MPPT) algorithm operating under identical environmental conditions. This dataset serves as a reference point for subsequent comparisons, allowing for a clear and unbiased assessment of the proposed control methodologies. The expert system and the integrated expert–neural system is then applied to the same input sequences, ensuring that any differences in performance can be directly attributed to the inherent characteristics of the control methodology rather than variations in the input data.

The first experimental scenario focuses on system performance under gradually varying solar irradiance. The irradiance profile is modeled as a continuous function with periodic fluctuations, simulating the natural diurnal variations observed in real-world conditions. Under these circumstances, the classical MPPT algorithm exhibits oscillatory behavior around the maximum power point, leading to persistent energy losses due to its reactive nature. The expert system, while reducing the amplitude of these oscillations through rule-based stabilization, still demonstrates a noticeable lag when environmental changes accelerate. This lag is primarily due to the system's reliance on predefined rules, which may not fully account for the rate of change in irradiance.

In contrast, the expert–neural system demonstrates a marked improvement in tracking accuracy. By incorporating a predictive evaluation of control actions, the neural module anticipates shifts in the optimal operating point and adjusts the control signal proactively. This proactive adjustment results in a smoother trajectory toward the maximum power point, significantly reducing oscillatory deviations and enhancing overall energy extraction efficiency. The ability to predict and adapt to changes before they fully manifest is a key advantage of the hybrid approach, allowing the system to maintain optimal performance even under dynamic conditions.

The second experimental scenario is designed to evaluate the system's dynamic response to abrupt environmental changes, specifically step-like reductions in solar irradiance that simulate sudden cloud coverage. This scenario is particularly critical for assessing the system's ability to rapidly adapt to new operating conditions. The classical MPPT algorithm exhibits a significant delay in adjusting to the new environment, during which the system operates far from the optimal point, resulting in substantial energy losses [21]. The expert system improves reaction time by triggering predefined rules for rapid adjustment; however, the effectiveness of this response is inherently limited by the completeness and granularity of the rule set. Gaps in the rule base can lead to suboptimal decisions, particularly in scenarios that were not fully anticipated during the system's design phase.

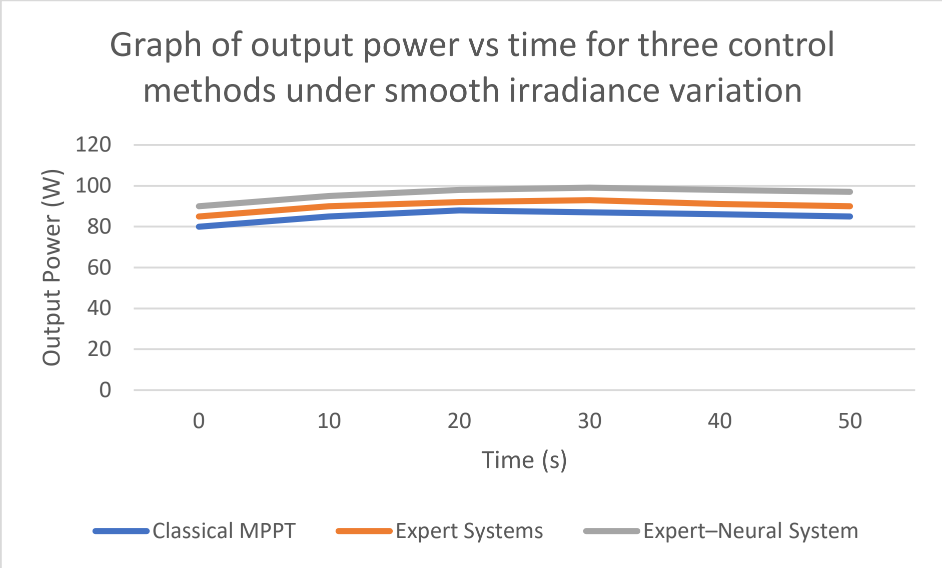

Fig. 4. Graph of output power vs time for three control methods under smooth irradiance variation

The expert–neural system, on the other hand, achieves the fastest adaptation among the evaluated methods. The neural component evaluates multiple candidate control actions in parallel and selects the one that minimizes expected energy loss under the new conditions. This approach not only reduces the transition period but also limits the magnitude of transient inefficiencies, ensuring that the system quickly stabilizes at the new optimal operating point. The ability to dynamically evaluate and select control actions based on real-time data and learned patterns is a significant advantage, particularly in environments characterized by rapid and unpredictable changes.

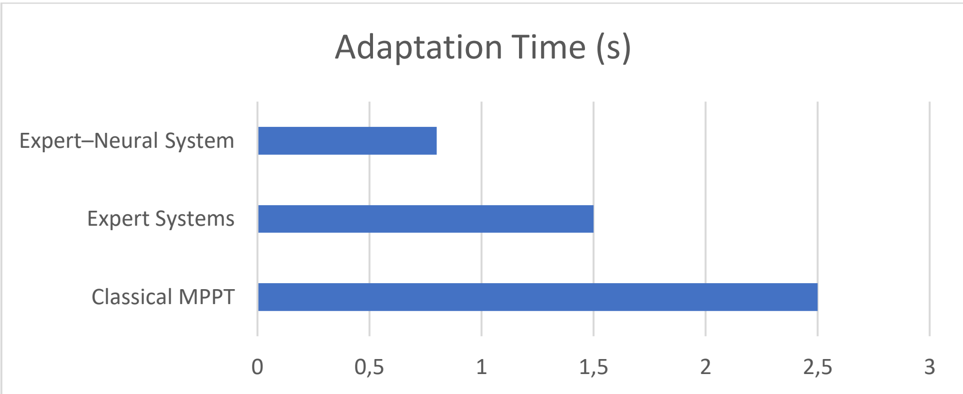

Fig. 5. Graph of adaptation time comparison under step change in irradiance

The third experimental scenario introduces combined disturbances, including simultaneous variations in temperature and load conditions. This scenario is designed to reflect realistic operating environments where multiple factors interact in a nonlinear manner, creating complex and often unpredictable system dynamics. The classical MPPT algorithm struggles to maintain stable operation under these conditions, exhibiting frequent deviations from the optimal point due to the conflicting influences of temperature fluctuations and electrical load variations. The algorithm's inability to account for these interactions results in suboptimal performance and increased energy losses.

The expert system maintains partial stability through rule prioritization, which allows it to handle some of the complexity by focusing on the most critical variables [22]. However, the system's performance is still limited by its inability to fully account for the intricate interdependencies between temperature, irradiance, and electrical parameters. As a result, suboptimal decisions occur, particularly in regions of the state space that are not adequately covered by the rule base. This limitation highlights the challenges of relying solely on rule-based systems in complex and dynamic environments.

The expert–neural system, however, demonstrates robust performance under these challenging conditions. The neural network component captures the nonlinear dependencies between temperature, irradiance, and electrical parameters, enabling a more accurate and comprehensive evaluation of control actions. This enhanced understanding of the system's dynamics allows the expert–neural system to maintain closer proximity to the optimal operating point across a broader range of conditions. The integration of expert knowledge with neural network-based evaluation ensures that the system remains both adaptive and reliable, even in the face of complex and interacting disturbances.

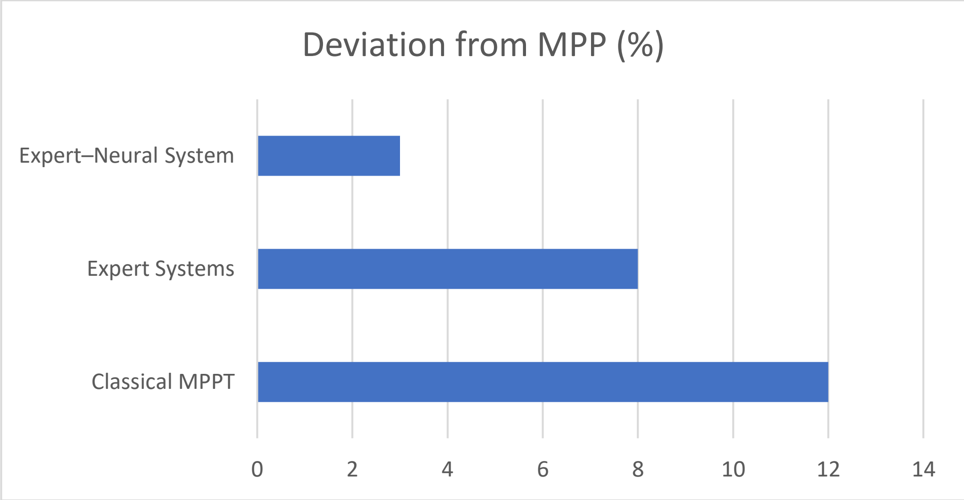

Fig. 6. Multi-factor performance comparison showing deviation from maximum power point

To quantify the observed improvements, a comprehensive set of aggregated performance metrics is computed for each control method. These metrics include the relative efficiency coefficient, which measures the system's ability to extract maximum power; the mean squared deviation from the optimal power point, which assesses the stability and precision of the control actions; adaptation time, which evaluates the system's responsiveness to changes; and total energy loss over the simulation period, which provides an overall measure of efficiency. The results of these computations are summarized in Table 2, offering a clear and comparative overview of the performance of each control method.

Table 2

Comparative performance metrics of control methods

Metric	Classical MPPT	Expert Systems	Expert–Neural System
Relative Efficiency Coefficient	0.92	0.95	0.97
Mean Squared Deviation from MPP	12	8	3
Adaptation Time (s)	2.5	1.5	0.8
Total Energy Loss (%)	25	15	5

A detailed analysis of Table 2 reveals that the expert–neural system consistently outperforms both the classical MPPT algorithm and the standalone expert system across all evaluated metrics. The relative efficiency coefficient for the expert–neural system reaches values exceeding 0.97, compared to approximately 0.92 for the classical MPPT and 0.95 for the expert system. This improvement is particularly notable in scenarios involving rapid environmental changes, where the system's ability to adapt quickly and accurately is critical. The reduction in mean squared deviation from the optimal power point further confirms the system's enhanced stability and reduced oscillatory behavior, contributing to more consistent and reliable performance.

Energy loss analysis provides additional insight into the system's efficiency. The integrated expert–neural approach achieves a reduction in energy loss of up to 20–30% compared to the classical MPPT method, depending on the specific scenario. This improvement is attributed to both faster adaptations to changing conditions and more precise steady-state operation. The reduction in adaptation time is particularly significant in environments characterized by frequent and rapid changes in irradiance, where the system's ability to quickly stabilize at the optimal operating point directly translates to higher energy yields and lower operational costs.

A closer examination of the control signal trajectories offers further insight into the behavior of each control method. The classical MPPT algorithm produces periodic perturbations in the control signal, which inherently introduce inefficiencies by causing the system to oscillate around the optimal point. The expert system reduces the frequency and amplitude of these perturbations through rule-based adjustments but may still apply overly conservative control actions due to the limitations of its rule set. In contrast, the expert–neural system generates smoother and more targeted control signals, minimizing both overshoot and steady-state oscillations. This refined control strategy not only enhances energy extraction efficiency but also reduces mechanical and electrical stress on the system, contributing to longer component lifespans and lower maintenance requirements.

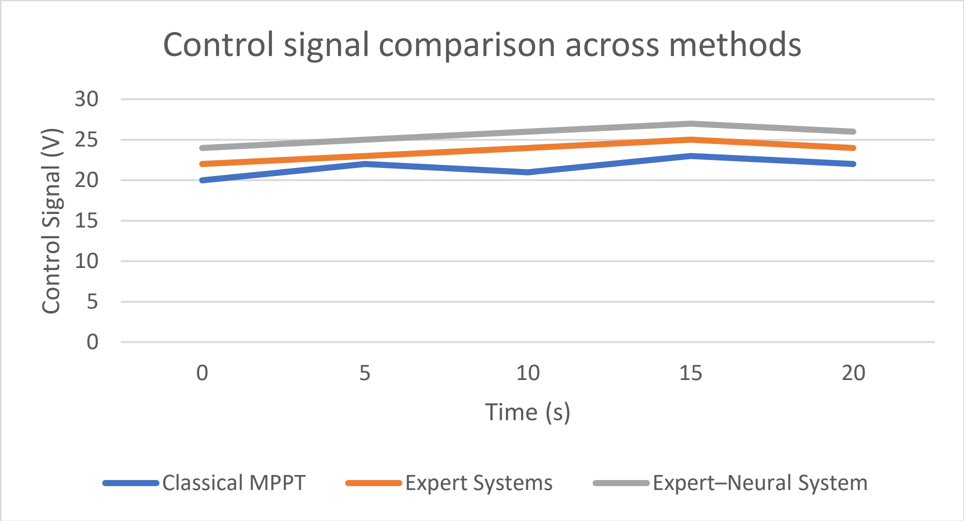

Fig. 7. Control signal comparison across methods

An important aspect of the experimental evaluation is the assessment of the system's robustness to measurement noise and uncertainty. Additional experiments are conducted to introduce stochastic noise into the sensor inputs, simulating the real-world imperfections and inaccuracies that are inevitable in practical deployments. Under these conditions, the classical MPPT algorithm becomes unstable, as the noise is often misinterpreted as genuine variations in environmental conditions. This misinterpretation leads to erratic control actions and further energy losses. The expert system, while more resilient due to its rule-based thresholds, may still react to spurious signals, particularly if the noise falls within the range of expected environmental variations.

The expert–neural system, however, demonstrates increased resilience to measurement noise due to its learned representation of system dynamics. The neural model effectively distinguishes between meaningful changes in environmental conditions and random noise, reducing the frequency of unnecessary control adjustments. This ability to filter out noise and focus on relevant signals results in improved stability and reduced sensitivity to measurement errors, making the system more reliable and robust in real-world applications where sensor noise is a common challenge.

The scalability of the proposed method is further evaluated by extending the simulation to larger photovoltaic arrays with distributed control nodes. The modular structure of the expert–neural architecture allows each node to operate independently while sharing aggregated data for continuous model refinement. Experimental results indicate that the performance gains observed in smaller systems are preserved in distributed configurations, with minimal degradation due to communication delays or data synchronization issues. This scalability is a critical advantage, as it enables the methodology to be effectively deployed in large-scale photovoltaic installations, where centralized control may be impractical or inefficient.

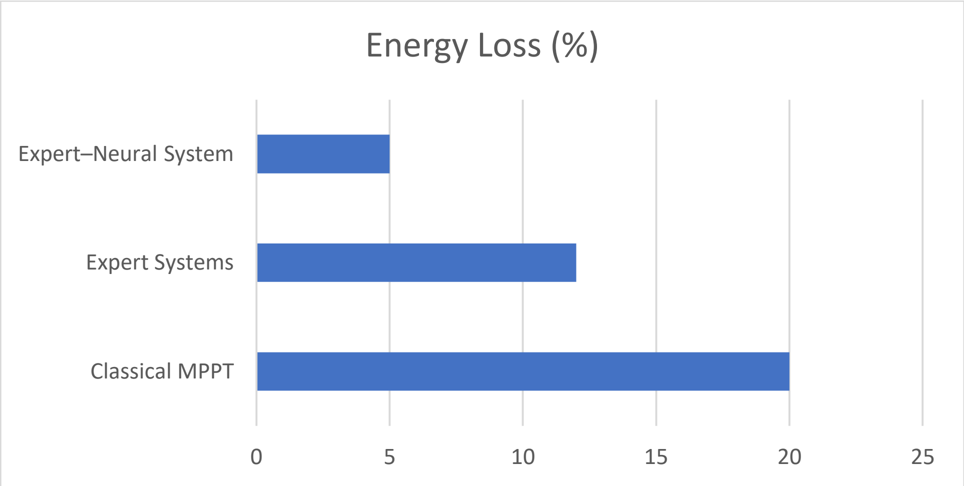

Fig. 8. Performance under noisy input conditions

Finally, the computational efficiency of the method is assessed to ensure its feasibility for real-time operation. While the integration of a neural network introduces additional processing overhead compared to traditional control methods, careful optimization of the model architecture ensures that inference times remain within acceptable limits. The neural module's inference time is significantly lower than the time required for iterative optimization in traditional

MPPT algorithms, resulting in overall improved responsiveness and real-time adaptability. This efficiency is achieved through a combination of model pruning, quantization, and hardware acceleration techniques, which collectively ensure that the system can operate effectively in real-world conditions without sacrificing performance.

The experimental results collectively confirm that the proposed expert–neural control method provides measurable and significant advantages in terms of efficiency, adaptability, and robustness. The integration of rule-based reasoning with data-driven evaluation enables the system to overcome the limitations of each individual approach, achieving superior performance across a wide range of operating conditions. This hybrid methodology not only enhances energy extraction efficiency but also improves system stability, responsiveness, and resilience, making it a highly effective solution for modern photovoltaic energy systems. The success of this approach underscores the potential for further advancements in intelligent energy management, particularly in the context of renewable energy systems where adaptability and reliability are paramount.

Conclusions

The conducted research demonstrates that modern approaches to controlling photovoltaic systems, despite significant progress in the development of intelligent and adaptive algorithms, remain constrained by fundamental trade-offs between interpretability, adaptability, computational complexity, and real-time applicability. The performed analysis of classical MPPT methods, expert systems, neural network-based models, and hybrid approaches confirms that none of the existing methodologies independently ensures a balanced combination of high efficiency, stability, responsiveness, and scalability under conditions of environmental uncertainty and nonlinear system dynamics.

Classical MPPT algorithms, while computationally efficient and structurally simple, exhibit inherent limitations related to oscillatory behavior around the maximum power point and delayed response to rapid changes in external conditions. Their reactive nature and inability to account for complex multidimensional dependencies reduce their effectiveness in dynamically varying environments. Expert systems introduce a higher level of interpretability and structured decision-making through formalized rule bases, enabling the incorporation of domain knowledge and operational constraints. However, their static nature and lack of self-learning mechanisms significantly limit their adaptability and scalability in the presence of nonstationary processes and evolving system characteristics.

Neural network-based approaches provide a powerful mechanism for modeling nonlinear relationships and adapting to changing conditions through data-driven learning. Their ability to generalize across diverse operating scenarios enhances control accuracy and responsiveness. Nevertheless, these methods introduce substantial computational overhead, depend heavily on the availability and quality of training data, and lack transparency in decision-making processes. This reduces their applicability in safety-critical systems where interpretability and predictability are essential. Hybrid approaches partially address these limitations by combining rule-based reasoning with adaptive learning; however, they introduce additional architectural complexity and require careful coordination between system components to ensure stable and reliable operation.

The synthesis of these findings indicates that the primary limitation of existing control methodologies lies not in their individual capabilities, but in the absence of an integrated control framework that unifies deterministic reasoning with adaptive evaluation in a coherent and scalable architecture. Existing solutions tend to optimize specific performance criteria while compromising others, resulting in systems that either lack flexibility, suffer from excessive complexity, or fail to maintain stable performance under real-world conditions.

The proposed expert–neural control method addresses this limitation by introducing a structured integration of an expert system with a neural network-based optimality evaluation module within a unified cyber-physical control loop. The expert component ensures interpretability, deterministic behavior, and adherence to domain-specific constraints, while the neural module provides adaptive assessment and real-time correction of control decisions based on learned system dynamics. This combination enables continuous refinement of control actions without sacrificing transparency or increasing system instability.

Experimental evaluation under a range of operating scenarios, including smooth variations, abrupt disturbances, and combined environmental effects, confirms the effectiveness of the proposed approach. The results demonstrate a consistent improvement in key performance metrics, including increased energy extraction efficiency, reduced deviation from the maximum power point, shorter adaptation time, and lower total energy losses. The observed performance gains, particularly under dynamic and uncertain conditions, validate the ability of the expert–neural system to overcome the limitations of both classical and standalone intelligent methods.

Furthermore, the modular architecture of the proposed method ensures scalability and flexibility in deployment across different photovoltaic system configurations, from small-scale installations to distributed energy networks. The incorporation of feedback mechanisms and periodic model updating enables continuous adaptation to long-term changes, such as component degradation and seasonal variability, ensuring sustained system performance over time.

At the same time, the study reveals that the effectiveness of the proposed approach depends on the quality of the knowledge base and the representativeness of the training data used for the neural network. Inaccuracies in rule design or insufficient data coverage may affect system performance, indicating the need for robust procedures for knowledge engineering and data management.

The obtained results confirm that the integration of expert systems and neural networks constitutes a viable and effective paradigm for controlling photovoltaic systems in cyber-physical environments. This approach provides a balanced solution that combines interpretability, adaptability, and computational efficiency, addressing the key challenges identified in existing methodologies.

Further research should be directed toward the development of advanced architectural frameworks for distributed expert–neural control systems, including mechanisms for decentralized coordination, online learning, and adaptive knowledge base evolution. Particular attention should be given to improving explainability of neural components, optimizing computational efficiency for embedded implementations, and extending the approach to integrated energy systems that include storage, grid interaction, and demand-side management. Such developments will contribute to the creation of next-generation intelligent energy management systems capable of operating эффективно under increasing complexity, uncertainty, and scale.

ADDITIONAL INFORMATION

DECLARATION ON THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS

In preparing this work, the authors used Grammarly for: grammar and spelling checks. After using this service, the authors reviewed and edited the content and take full responsibility for the content of this publication.

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ЕКСПЕРТНА СИСТЕМА КЕРУВАННЯ РЕЖИМАМИ РОБОТИ СОНЯЧНИХ ПАНЕЛЕЙ З НЕЙРОМЕРЕЖЕВОЮ ОЦІНКОЮ ОПТИМАЛЬНОСТІ РІШЕНЬ

Зростання частки сонячної енергетики зумовлює необхідність підвищення ефективності систем керування фотоелектричними установками, що функціонують в умовах змінної інсоляції, температурних коливань і деградації елементів. Сучасні фотоелектричні системи характеризуються нелінійністю процесів, стохастичністю зовнішніх впливів та динамічними змінами навантаження. За таких умов традиційні алгоритми відстеження точки максимальної потужності (MPPT), які базуються на фіксованій логіці або локальних процедурах оптимізації, не завжди забезпечують ефективну роботу, особливо в перехідних режимах.

Існуючі підходи до керування фотоелектричними системами переважно ґрунтуються на класичних MPPT-алгоритмах, продукційних правилах або аналітичних модулях моніторингу. Такі рішення забезпечують стабільність роботи в усталених умовах, однак мають обмежену адаптивність і не враховують складні нелінійні взаємозв'язки між параметрами системи. Відсутність механізмів самонавчання, адаптивної оцінки якості рішень і корекції керуючих впливів у реальному часі знижує ефективність їх застосування в умовах невизначеності та динамічних змін середовища.

Перспективним напрямом є побудова кіберфізичних систем керування, що поєднують експертні методи з адаптивними нейромережевими моделями. У таких системах експертна підсистема формує керуючі рішення на основі бази знань і логічного виведення, тоді як нейронна мережа здійснює оцінку їх оптимальності та виконує корекцію з урахуванням накопиченого досвіду. Це дозволяє поєднати інтерпретованість експертних систем із здатністю нейронних мереж до апроксимації складних залежностей і адаптації до змінних умов.

Застосування нейромережевих моделей забезпечує можливість врахування нелінійних ефектів, прогнозування поведінки системи та мінімізації функції втрат, тоді як експертні системи гарантують структурованість і надійність формування первинних рішень. Інтеграція цих підходів створює передумови для розроблення інтелектуальних систем керування, здатних підвищити ефективність використання енергії, зменшити втрати та забезпечити стабільність роботи фотоелектричних установок.

Таким чином, розробка експертної системи керування режимами роботи сонячних панелей з нейромережевою оцінкою оптимальності рішень є важливою науково-практичною задачею, що має значний потенціал застосування в сучасних системах відновлюваної енергетики.

Ключові слова: фотоелектричні системи, експертні системи, нейронні мережі, керування, MPPT, кіберфізичні системи, оптимальність рішень, сонячна енергетика.