Proceedings of the 4th International Conference on Mechatronics and Smart Systems
DOI: 10.54254/2755-2721/2026.34172

AI-Assisted Control of Renewable-Energy Power Converters: Task Mapping, Method Adaptation, and Trustworthy Deployment

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Abstract. High-penetration renewable generation is reshaping the operating envelope of power electronic converters. Photovoltaic, wind, and wave-energy systems are characterized by strong time variation, severe disturbances, and coupled operational constraints, which challenge conventional control strategies based on accurate models and fixed parameter settings. Artificial intelligence can learn nonlinear mappings from operating data and support maximum power point tracking, power prediction, fault diagnosis, parameter tuning, and surrogate-based optimization. However, its real-time capability, stability assurance, and safety verifiability remain insufficient for direct use in high-frequency inner-loop control. This paper reviews recent progress in AI-assisted control and optimization for photovoltaic converters, wind-energy converters, and wave-energy converters. Supervised learning, ensemble learning, reinforcement learning, physics-informed modeling, and surrogate optimization are examined from the perspective of task suitability rather than algorithm listing. Common limitations are further discussed in terms of real-time deployment, stability boundaries, generalization, digital-twin pretraining, and lightweight implementation. The review indicates that AI is currently better suited to slow-layer optimization, state perception, parameter design, and decision support, while traditional control should remain the safety baseline for fast inner loops and protection-critical actions.

Keywords: artificial intelligence, renewable energy, power electronic converter, renewable-energy converter, wind-energy converter

1. Introduction

The central technical challenge in renewable-energy systems is not limited to generation-side intermittency. Through the power-electronic interface, intermittency is transformed into a multi-time-scale control problem. Photovoltaic arrays are affected by irradiance, temperature, and partial shading; wind-energy systems are influenced by turbulent wind speed, mechanical transmission, and converter dynamics; wave-energy converters are governed by stochastic sea states, slowly varying hydrodynamic parameters, and array-level interactions. Consequently, converter control must simultaneously consider energy-conversion efficiency, power quality, thermal safety, device lifetime, grid stability, and fault protection. Conventional PI control, sliding-mode control, model predictive

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DOI: 10.54254/2755-2721/2026.34172

control, and rule-based energy management remain attractive because of their engineering reliability, but their performance often depends on model fidelity, empirical parameter tuning, and predefined trade-offs. Zhao et al. systematically reviewed artificial intelligence applications in power electronics and argued that AI is most valuable when it extends conventional control through data-driven modeling, state recognition, and optimization, rather than when it is treated as a direct replacement for control theory [1].

Therefore, the use of AI in renewable-energy converter control should be discussed according to the time scale and safety level of the control task. Inner current loops, modulation loops, and protection functions require deterministic execution time and verifiable stability, whereas MPPT, power dispatch, fault diagnosis, and parameter tuning can tolerate longer computation cycles and are more suitable for machine learning, online learning, or optimization algorithms. Zhang et al. reviewed online learning for control and diagnostics of power converters and drives, showing that online model updating can mitigate parameter drift and operating-condition changes, but may also introduce training instability, data-quality problems, and real-time blocking risks [2]. Accordingly, this review moves beyond the simple question of whether AI is better than conventional control and clarifies in which layer, under which constraints, and for which engineering objective AI offers a net benefit.

In this paper, AI-assisted renewable-energy converter control is organized into three task classes. The first class concerns efficiency and power-capture optimization, including photovoltaic maximum power point tracking (MPPT), converter efficiency search, and wave-energy power-take-off and converter-level power prediction. The second class concerns state perception and operational safety, including wind-converter fault diagnosis, sea-state estimation, and device-parameter identification. The third class concerns trustworthy engineering deployment, including surrogate modeling, constrained optimization, digital-twin pretraining, and lightweight inference. Rather than listing algorithms in isolation, recent AI-related studies published mainly from 2021 to 2026 are classified by scenario, control layer, AI role, and deployment boundary, while classical predictive-control studies are retained as methodological baselines. Accordingly, the scope is limited to representative photovoltaic, wind, and wave-energy converter interfaces rather than all renewable-energy conversion technologies.

Reinforcement learning has been investigated for topology derivation, parameter design, and control implementation because it can address sequential decision-making and long-term reward optimization. Ye et al. showed that reinforcement learning has cross-layer potential in power electronic converters, yet its engineering adoption remains limited by exploration cost, feasible-region constraints, real-time inference, and stability verification [3]. Based on this observation and the task mapping in Table 1, the contributions of this review are threefold: first, AI methods are mapped to representative photovoltaic, wind, and wave-energy converter-interface tasks; second, the roles of AI are distinguished as direct control, auxiliary control, and offline design support; third, deployment constraints are summarized to motivate a trustworthy framework in which conventional control serves as the safety baseline and AI provides optimization and perception enhancement.

Table 1. Task mapping and deployment boundaries of AI methods in renewable-energy converters

Scenario	Task	AI method	Function	Deployment risk
PV	MPPT; dispatch	Learning/search	Tracking	Shading; delay
Wind	Diagnosis; state	Ensemble/online	Warning	False/missed alarms
Wave	Prediction; power-take-off (PTO)	NN surrogates	Fast support	Sparse data; drift

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Table 1. (continued)

Cross-scenario	Design; twins	Physics surrogates	Deployment	Fallback; constraints

2. Intelligent control of photovoltaic converters

2.1. Maximum power point tracking and efficiency optimization

The typical objective of photovoltaic converter control is to maintain high energy-capture efficiency under varying irradiance, temperature, and load conditions. Conventional perturb-and-observe and incremental-conductance methods are simple and easy to implement, but they may suffer from steady-state oscillation, incorrect tracking, and slow convergence under rapid irradiance variation or partial shading. AI methods improve this task mainly in two ways: they provide nonlinear estimation of the maximum power point, and they accelerate dynamic operating-point search. Milasi proposed an emotion-inspired controller that integrates MPPT and power-factor correction in a three-phase grid-connected photovoltaic converter, indicating that intelligent control concepts can support both energy capture and power-quality improvement [4]. However, such approaches still require more extensive validation under hardware control cycles, grid disturbances, and controller-parameter sensitivity.

For photovoltaic water pumping and hybrid energy systems, Sumathi and Selvarajan used machine learning to examine how hybrid converter configurations affect system efficiency, demonstrating that data-driven models can rapidly screen converter structures and operating regions [5]. Mishra et al. developed an energy-management and converter-control scheme for a grid-interfaced photovoltaic water-pumping system with energy storage, showing that energy storage improves the dynamic matching between photovoltaic generation and load demand [6]. Liu et al. further combined machine learning with particle swarm optimization for a solar-to-hydrogen system with energy storage, indicating that AI can extend from converter control to cross-energy-carrier coordination [7]. These studies suggest that the key value of AI in photovoltaic applications is not only higher single-point MPPT accuracy but also joint modeling of irradiance variation, converter state, storage constraints, and load demand. The limitation is equally clear: many results are still based on simulation or limited experimental conditions, and robustness under extreme shading, device aging, and sensor noise remains insufficiently established.

2.2. Grid interaction and multi-port energy management

As photovoltaic systems evolve from single generation units into photovoltaic-storage-charging-load systems, converter control expands from single-port power conversion to multi-port coordination. Tiwari and Singh investigated a photovoltaic-battery system with parallel converters for charging stations and distributed loads under anomalous grid conditions, integrating grid abnormality, storage support, and load-supply reliability into one architecture [8]. The control difficulty in such systems is not merely local converter efficiency, but rather the dynamic coordination among multi-port power sharing, dc-bus voltage stability, and grid-current quality.

Similar multi-port ideas are also found in high-frequency isolated converter studies. Liao et al. proposed machine-learning-based feedforward power-flow control for multi-active-bridge converters, using learned models to replace complex analytical mapping from power commands to control variables [9]. Lin et al. developed the STAR method for one-stop optimization of dual-active-bridge converters across diverse operating points, emphasizing robustness under different

DOI: 10.54254/2755-2721/2026.34172

voltages, loads, and power-flow directions [10]. Although these studies are not all directly focused on photovoltaic inverters, they provide useful implications for renewable-energy systems with storage, dc buses, and multi-port energy routing. Learning-based feedforward or optimization strategies should still be supervised by voltage, current, and thermal constraints to prevent infeasible control actions under out-of-distribution conditions.

3. State perception in wind-energy converters

3.1. Data-driven fault diagnosis

Wind-energy converters operate for long periods under strong disturbances, wide temperature ranges, and high mechanical stress. Fault diagnosis is therefore a prerequisite for reliable control. Conventional threshold-based, frequency-domain, and physics-model-based diagnosis methods are interpretable, yet they are less adaptive to nonlinear coupled faults and unknown operating conditions. Dhibi et al. proposed a reduced neural-network ensemble approach for fault detection and diagnosis of wind-energy converter systems, improving classification efficiency and diagnostic accuracy through dimensionality reduction and ensemble learning [11]. The contribution of this work is that AI is moved beyond prediction and into operational safety, where the control system can receive early information about degradation and faults.

However, two additional steps are required before diagnostic results can become part of a real control loop. First, the model must provide reliable confidence or uncertainty information; otherwise, false alarms may cause unnecessary derating, while missed alarms may enlarge fault consequences. Second, diagnostic outputs must be connected to fault-tolerant control, power limitation, and protection strategies rather than remaining offline accuracy indicators. Behara and Saha reviewed AI techniques for the design and optimization of power electronic converters in doubly fed induction generator systems and observed that AI applications in wind energy have extended from fault recognition to parameter optimization, state estimation, and control support [12]. Future intelligent wind-converter control should therefore focus on the consistency between diagnostic models and operational decisions, not only on isolated model accuracy.

3.2. Online adaptation and control support

Wind-energy systems are strongly time-varying. Wind-speed fluctuation, pitch action, dc-bus disturbance, and grid-voltage variation jointly affect converter-control performance. Online learning provides a possible solution by continuously updating state models, fault boundaries, or control parameters during operation. Compared with offline-trained models, online models adapt more quickly to parameter drift, but they also introduce greater risk: the training data may be contaminated by transients, model updating may consume control resources, and incorrect updating may amplify control errors. Hence, online learning is better positioned in slow-layer diagnostics, state estimation, and controller-parameter recommendation than in high-frequency current-control loops.

From an engineering perspective, AI support for wind-energy converters should follow a hierarchical architecture. The lower layer should still rely on mature vector control, model predictive control, or robust control to guarantee basic stability; the middle layer can use learning models to estimate health state, thermal risk, and fault type; and the upper layer can translate state information into derating, dispatch, and maintenance decisions. Bahrami and Khashroum reviewed machine-learning techniques for power electronics control and optimization and concluded that ML has

DOI: 10.54254/2755-2721/2026.34172

potential in complex operating-condition recognition, parameter optimization, and anomaly detection, but should be coordinated with deterministic control strategies [13]. Such a hybrid structure better matches the safety requirements of wind-energy systems, where converter faults may lead to costly shutdowns and grid-side disturbances.

4. AI-assisted prediction and optimization of wave-energy converters

4.1. Power prediction and sea-state estimation

Compared with photovoltaic and wind-energy systems, wave-energy converters are subject to stronger low-frequency stochastic excitation and device-sea-state coupling. Their control performance depends on the estimation of wave height, wave period, phase, device motion, and the power-take-off variables that determine generator-side loading and converter-level decision support. Conventional hydrodynamic models can be accurate but are computationally expensive, which limits their direct use in real-time control. Wang et al. proposed a machine-learning-based electric-power prediction method for a two-body hinge-barge wave-energy converter, establishing a mapping from wave height, wave period, and load variables to electrical power and thereby reducing the computational burden of complex numerical models [14]. The advantage of this approach lies in fast approximation of nonlinear dynamics, while its reliability depends strongly on the coverage of the training data.

Sea-state estimation is another key step in wave-energy control. Shifat et al. developed a machine-learning approach for real-time sea-state estimation for wave-energy converter control, connecting wave-parameter identification with controller selection [15]. This is closer to a control loop than simple power prediction because the controller can adjust damping, stiffness, generator load, or converter-side power commands according to the estimated sea state. Nevertheless, out-of-distribution conditions are more severe in marine environments than in many land-based renewable systems. Extreme waves, sensor loss, and long-term device drift may all cause accumulated model error. AI in wave-energy systems should therefore be used mainly as a fast surrogate and sea-state recognition module, while physics-based constraints should be retained for verification.

4.2. Array layout and energy-capture optimization

The optimization target of wave-energy systems includes not only a single device but also array layout, device spacing, seawall reflection, and investment return. Natarajan and Cho used artificial neural networks for the techno-economic optimization of a wave-energy converter array in front of a vertical seawall, showing that surrogate models can reduce the computational cost of layout search and jointly incorporate energy capture and economic metrics [16]. Although this task is not a switching-level converter-control problem, it reflects a distinctive advantage of AI in wave-energy applications: unlike high-frequency converter control, array optimization is a slow-time-scale problem and therefore permits more complex surrogate models and global search procedures.

Whether array-optimization results can be transferred to engineering practice depends on three conditions. First, the training data must cover sufficiently diverse sea states and array configurations. Second, the surrogate model must preserve the dominant mechanisms of hydrodynamic interaction, seawall reflection, and device constraints. Third, the objective function should consider energy production, maintenance cost, extreme-sea-state risk, and grid-connection conditions simultaneously. If only average power is maximized, the optimized solution may be economically or operationally fragile. AI-based wave-energy optimization should therefore follow a workflow of

DOI: 10.54254/2755-2721/2026.34172

physics simulation for sample generation, surrogate modeling for rapid evaluation, and engineering constraints for final verification.

5. Trustworthy deployment and engineering constraints

5.1. Real-time performance, stability, and safety boundaries

A central deployment challenge is to define the conditions under which AI outputs can be safely embedded into power-electronic control loops. Inner converter-control cycles often operate from microseconds to milliseconds; the controller must not only approximate the optimal decision but also guarantee deterministic execution time, stability, and constraint feasibility. Model predictive control has long been an important method for power-electronic systems. Vazquez et al. summarized its advances in converters and drives and emphasized its ability to explicitly handle constraints while maintaining dynamic performance [17]. The classical work by Kouro et al. on finite-control-set MPC further illustrates why conventional predictive control entered engineering practice: its cost function, switching set, and stability boundary are relatively explicit [18]. By contrast, the internal decision mechanism of neural or reinforcement-learning controllers is harder to verify, which is the main barrier to their direct replacement of inner-loop controllers.

AI methods require explicit safety boundaries, including deterministic execution time, voltage and current limits, thermal constraints, switching-stress limits, and fallback logic, before being embedded in engineering control systems. A more robust pathway is to place AI in outer-layer optimization or feedforward compensation, while the conventional closed loop enforces stability constraints. Tang et al. proposed an AI-aided online real-time efficiency optimization method for power electronic converters, combining automated experimentation with intelligent search to identify efficient control strategies [19]. Even in this case, AI outputs should be filtered through voltage, current, temperature, and switching-stress constraints. Chen et al. also pointed out in their review of reinforcement-learning control for power electronic converters that safe exploration, sample efficiency, and stability proof still restrict practical adoption [20]. Therefore, the more rigorous statement is not that AI replaces conventional control, but that AI enhances conventional control under constraint supervision.

5.2. Generalization, digital twins, and lightweight implementation

Generalization is the second key constraint in AI-assisted renewable-energy converter control. Many learning models perform well near the training distribution but degrade under extreme weather, device aging, sensor bias, or topology changes. Li et al. proposed a data-light physics-informed modeling method for the modulation optimization of dual-active-bridge converters, aiming to reduce data requirements and improve reliability through physical constraints [21]. Mahajan et al. used probabilistic learning and stochastic surrogate modeling for converter-parameter design, incorporating temperature and uncertainty information in addition to efficiency prediction [22]. These studies suggest that future AI control should not pursue purely data-driven black boxes, but should integrate physical knowledge, probabilistic uncertainty, and constrained optimization.

Digital twins and design automation provide a practical engineering route. Dragicevic et al. earlier proposed AI-aided reliability design for power electronic systems, linking design parameters with reliability metrics [23]. Tian et al. developed automated extraction of MOSFET datasheet information for converter design automation, indicating that AI can build richer design databases from device data, design documents, and simulation results [24]. Li et al. further proposed AI-based

DOI: 10.54254/2755-2721/2026.34172

design for converter circuit parameters, reflecting the trend of moving AI from the control stage to the design stage [25]. A trustworthy deployment pathway is therefore to generate high-quality data by digital twins and automated design in the offline stage, use lightweight models for fast estimation and optimization suggestions online, and enforce final execution through conventional control and hard constraints.

6. Conclusions and perspectives

This paper reviewed AI-assisted control and optimization methods for photovoltaic, wind-energy, and wave-energy converter systems from a task-oriented perspective. Overall, AI contributes to renewable-energy converter control in four aspects. First, nonlinear mapping and search optimization improve MPPT, efficiency search, and multi-port power allocation. Second, data-driven diagnosis and online learning enhance state perception and operational support in wind-energy converters. Third, power prediction, sea-state estimation, and surrogate modeling reduce computational cost in wave-energy power-take-off control, converter-level support, and array optimization. Fourth, digital twins, physics-informed modeling, and lightweight inference improve engineering adaptability under complex operating conditions.

At the same time, the boundary of AI must be recognized. For microsecond-level control, grid protection, and fault-critical actions, current AI models cannot fully replace conventional control methods with explicit stability and constraint structures. A more reasonable technical route is a hybrid control framework: conventional control provides the stability baseline, while AI undertakes state estimation, parameter tuning, efficiency optimization, and fault warning. This position avoids overstatement while preserving the real engineering value of AI under high renewable-energy penetration.

Future research may advance in three directions. First, unified evaluation metrics should be established so that tracking efficiency, dynamic response, total harmonic distortion (THD), temperature rise, computation delay, false-alarm rate, and constraint-violation rate are assessed in one framework rather than through isolated prediction accuracy. Second, physics-informed learning, probabilistic surrogate modeling, and safe reinforcement learning should be developed so that AI outputs include uncertainty estimation and feasibility judgement. Third, hardware-in-the-loop testing, edge computing, and digital-twin validation should be strengthened to demonstrate that models remain stable under real control cycles, communication delay, and abnormal operating conditions.

In the long term, AI will not simply replace power-electronics control theory; rather, it will change the design workflow of control systems. Conventional methods will remain responsible for stability, verifiability, and protection logic, while AI will learn complex mappings, recognize operating states, and search large design spaces. Only when these two types of methods form an interpretable, verifiable, and deployable collaborative structure can AI-assisted control of renewable-energy converters move from reported performance improvement to large-scale engineering application.

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