A Review of Methodologies for AI-Based Control and Power Quality Enhancement in Solar–Wind Hybrid Energy Systems

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Abstract:

With rising penetration of renewable energy into modern power grids, hybrid systems need efficient control and power quality management. Among various alternatives, AI-based control methods have proved to be promising means for control optimization to keep grid stability and improving power quality in solar–wind hybrid energy systems. This review serves to synthesize more recent developments with AI-based methods for converter control, energy management, and harmonic mitigation. Conventional methods such as PWM and SVPWM are considered, as well as more advanced ML and RL frameworks that allow adaptive decision-making when considering variations in environmental conditions. Special emphasis is given to how MATLAB/Simulink is applied in modeling, simulation, and validation of hybrid systems and optimization techniques such as genetic algorithms and deep learning models from an MPPT and converter efficiency perspective. The paper then reviews performance evaluation criteria which include efficiency, total harmonic distortion (THD), reliability, and cost-effectiveness. The findings of this study suggest that AI-based hybrid energy systems can operate with greater efficiency and improve grid code compliance while reducing GHG emissions in a significant way, thus paving a sustainable way for smart grids of the future.

Keywords: *Solar–wind hybrid system, Grid integration, Inverter control, Artificial intelligence, Total harmonic distortion, Reactive power compensation*

I. INTRODUCTION

The integration of renewable resources in present-day power systems has witnessed significant growth worldwide, becoming essential to cope with the rising global energy needs, with the idea of lessening the dependence on fossil fuels and environmental hazard. Solar–wind hybrid energy systems have recently been considered favorable because of their somewhat complementary generation profiles, thereby allowing better reliability and resource utilization, as compared to standalone sources [1]. Adversely, the intermittent and stochastic nature of solar irradiation and wind speed operating on various timescales result in many challenges to grid stability, thus contributing to voltage fluctuations, harmonic distortion, and frequency deviations, which are detrimental to power quality [2]. Classical control approaches may indeed provide suitable control under steady conditions but they tend to be inadequate in adapting to nonlinear conditions and dynamically changing operating environments Usually employing AI-base strategies, such as machine learning, deep learning, and reinforcement learning, to embrace data-drive adaptive control would render operation more efficient with robust power quality management and sustainability enhancement of hybrid systems [3].Figure 1 shows Inverter Control Cycle.

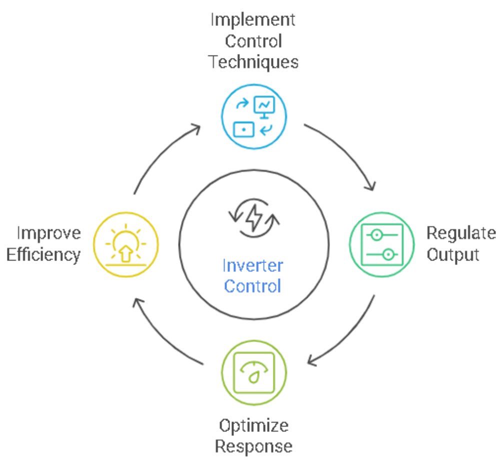

Figure 1: Inverter Control Cycle [4]

a) Overview of Solar–Wind Hybrid Energy Systems

The solar–wind hybrid energy system essentially comprises the photovoltaic panels, wind turbines, power electronic converters, storage, and a control system to enable coordinated operation. Depending on the application, these systems can be configured as grid-connected ones that export excess energy to the utility grid, or they can be off-grid ones that provide energy to isolated loads with relatively higher reliance on storage [4]. Despite their advantages, SWHES often face critical quality-of-power-related issues, such as harmonic distortions caused by converters and voltage fluctuations due to the intermittent nature of the resources. Also, frequency instability arises with the variation in load and generation [5].

b) Conventional Control Strategies

Regulation of solar–wind hybrid energy systems with conventional control laws—particularly PI and PID methods—is ensured due to their ease of implementation [6]-[7]. These controllers have been traditionally implemented in grid-connected converters for current/voltage regulation, with further enhancements in response time achieved by employing heuristic optimization methods like particle swarm optimization (PSO) and grey wolf optimization (GWO) under varying operating conditions [8]- [9]. Thereafter, the fuzzy logic controllers emerged, encoding heuristic rules for addressing system uncertainties and nonlinearities better than classical PI/PID, with hybrid Fuzzy–PI methods performing better in voltage regulation and harmonic reduction [10]-[11]. Incidentally, all these controllers with their merits stand crippled in the face of intermittency and nonlinearities, leading to instabilities, increased total harmonic distortion (THD), and poor frequency regulation in a weak or islanded grid [12]-[13]. Therefore, adaptive and metaheuristics-tuned ones provide good robustness; however, their inherent assumptions of linearization plus fixed parameters stand as a stumbling block for scaling, and this sets the scenario for the AI-based control approaches [14].

II. Optimization and Reliability in Source-Side Microgrid Control

In the advancing world of hybrid renewable energy systems (HRES), researchers are deliberating new approaches to improve efficiency, reliability, and sustainability. One set of people came up with a PV-PMSG wind system that directly links solar panels to the grid and employs multiloop nonlinear control. While this ensured some stability, the complexity of design also brought about other major hurdles [15]. Another team integrated a qZSI-based STATCOM with PV systems to enhance power quality, and it brought down harmonic distortion to the extent of marvel; yet the exact tuning of parameters was difficult [16].

Using a different approach, the researchers dealt with a two-area thermal system with renewable sources, having the ICA-tuned cascade controller handling the frequency deviations. The system got highly reactive and considered stability, demanding very accurate tuning of the ICA [17]. Machine learning now came onto the scene, with some researchers modeling and optimizing HRES with an aim toward better prediction and storage management; however, scale and variety of data were considered the stumbling points so far [18].

Other distances adopted included an adaptive hybrid fuzzy FOPID controller coupled with a virtual oscillator-based inverter to reduce battery stress and increase stability, but its complex tuning rendered practical deployment problematic [19]. Some were uttering cost-effective solutions by designing Wind-PV-BESS-FC-Electrolyzer systems with minimized converters for storage coordination towards uninterrupted power; however, controls management remains a big hurdle [20].

On the optimization back, microcontroller-based dynamic decision algorithms for solar-wind systems gave very strong economic returns at partial penetration and underperformed at full penetration [21]. Similarly, the hybrid forecasts of long term and short term for MPC for PV-battery building systems improved battery safety and operational efficiency, but the increase in model complexity and limited field testing reduced the areas of application [22]. Comprehensive reviews situate HRES as promising in improving reliability and reducing emissions but with cautionary notes on the difficulty of configuration optimization and uncertainty control [9]. Prescient MPCs for HPES along with CHP and BESS yielded 12% primary energy savings and 70% computational speedups at best but remain hindered by controller complexity as well as reliance on exact modeling [23].

The required enhancement of system reliability, efficiency, and sustainability through innovative solutions enhances the developing field of hybrid microgrids. Codec-free and prediction-based deep reinforcement learning control methods with Double Dueling Deep Q-Networks were employed for optimizing power flows while profiting from the market, minimizing carbon emissions, limiting peak loads, and maintaining battery health, thus marking a significant leap toward decarbonization and cost efficiency, along with operational resilience [24]. At the same time, power scheduling problems are relaxed from MINLP to MILP, enabling storage management and power exchange to occur in one-minute intervals online with drastic cuts to computation time [25].

Numerous adaptive algorithms take fuel utilization, load mismatch, power quality, battery degradation, and renewable unpredictability as inputs to enhance system reliability and energy storage behavior [26]. Fuzzy Markov models have been used to accommodate subsystem failure and repair uncertainties within the wind, PV, battery, and converters to provide a more realistic microgrid reliability assessment when these systems operate under uncertain conditions [14]. Probabilistic reliability modeling further shows that component degradation is accelerated by intermittent renewables, which, in turn, reduce system availability [27]. Seasonal variation of renewable availability and environmental factors is demonstrated to have an appreciable impact on component failure rates and system reliability in a coastal microgrid environment integrating wind, tidal, and solar energy [28].

Monte Carlo simulations have been applied to hybrid AC microgrids experiencing high solar and wind penetration, stressing the seasonal variations of irradiance and wind speed [29]. It has been demonstrated that the optimal battery storage, combined with Markov-type modeling of failure, can reduce the Loss of Power Supply Probability (LPSP) by more than 40% [30]. Solar-wind hybrid AC microgrids under stochastic weather conditions, through adaptive inverter control, successfully correlate wind-solar fluctuations in favor of voltage stability and system adequacy [31]. On the other hand, hybrid reliability assessment frameworks using deterministic load flow and probabilistic renewable variability models had success in tracking down failure propagation at the distribution level [32].

Table 1: Optimization and Reliability in Source-Side Microgrid Control

Ref	Technique Used	Dataset/Case Used	Key Findings	Results	Limitations
[14]	Multi-objective controllers, MPPT (electrical parameters), Sliding Mode & Backstepping	Hybrid PV-Wind-PMSG system	Direct PV-grid connection without DC/DC converter; nonlinear control ensures stability	Stable operation of hybrid system	Complexity in controller design; intermittency of renewables
[15]	qZSI-based STATCOM, AFF-SOGI, Fuzzy Logic optimized PI controller	Smart grid 3P4W distribution	Improved power quality and reactive compensation	THD reduced from 25.5% → 1.3%	Complex system, sensitive to controller tuning
[16]	ICA-tuned $(1+TD)^3$-TID cascade regulator	Two-area thermal system with RES	Addresses frequency deviations in LFC	Achieved lowest performance index (0.091), faster response	Requires precise ICA tuning; added complexity
[17]	ML models: regression, neural networks, ensemble	Historical solar & wind datasets	Predicts HRES performance, optimizes storage	Improved prediction accuracy & real-time optimization	Handling variability, model scalability
[18]	Hybrid adaptive fuzzy multistage FOPID; nVdPO-based VOC	Hybrid microgrid under varying solar/load	Improved DC bus management; battery life extension	Validated via OPAL-RT with reduced stress on BESS	Complex design, requires advanced tuning
[19]	Hybrid Wind-PV-BESS-FC-Electrolyzer with lead compensator-integrator	MATLAB/Simulink hybrid model	Eliminated PV converter; hydrogen generation via electrolyzer	Improved efficiency, steady-state stability	Control coordination complexity
[20]	Intelligent EMS with dynamic decision algorithm (microcontroller-based)	Solar-Wind hybrid for residential unit	Optimized renewable penetration scenarios	Positive NPV, high IRR at 20–50% penetration	Negative NPV, long payback at 100% penetration
[21]	Hybrid prediction + MPC	Real office building (Japan)	Enhances battery safety, CHP operation, and off-grid optimization	81.6% safety, 36.4% CHP, 69% off-grid improvement	Complex prediction design, limited validation
. [22]	Review of HRES (configuration, storage, sizing, control)	Literature review	HRES lowers emissions, improves reliability, lowers costs	Comprehensive evaluation framework for designers	Configuration selection, managing uncertainties

[23]	DRL-based control schemes (prediction-based & prediction-free) with Double Dueling DQN (D3QN)	Hybrid microgrid simulations under uncertainty	Optimizes power flows while balancing profits, carbon goals, peak mitigation, and battery degradation	Enhanced decarbonization, cost efficiency, and operational resilience	Relies on accurate system modeling; scalability under extreme uncertainty not fully tested
[24]	MINLP → MILP conversion using McCormick's relaxation, DIPPS with rolling predictive window	Prosumers with storage and external power exchange	Real-time power scheduling optimization feasible	Solves in ~0.92s vs 38.27s (97.6% faster)	Limited to short predictive horizon; may struggle with larger-scale grids
[25]	Adaptive multi-objective optimization framework	Real-time energy system with ESS	Dynamically balances fuel usage, power quality, battery degradation, and renewable use	Improved reliability and ESS charging optimization	Computational cost increases under high variability
[26]	Fuzzy Markov model for subsystem availability	Wind–PV–Battery–Converter hybrid microgrid	Estimates availability/unavailability with fuzzy uncertainty	Provides nuanced reliability assessment	Complexity in parameter estimation
[27]	Probabilistic reliability with weather-dependent failure rates	Coastal hybrid microgrids	Links intermittency to accelerated component degradation	Improved planning/operation insights	Requires extensive environmental data
[28]	Reliability evaluation considering temperature and intermittency	Coastal microgrid with wind, tidal, and PV	Shows resource variability strongly impacts reliability	Demonstrated influence of temperature and renewable fluctuations	Location-specific; generalization limited
[29]	Probabilistic reliability + Monte Carlo simulations	Hybrid AC microgrids (solar + wind)	Seasonal solar/wind variations create major challenges	Robust planning needed for reliability	High computational load for large systems
[30]	Markov-based failure modeling	Hybrid systems with varying storage	Optimal storage reduces LPSP by >40%	Enhanced supply adequacy	Model sensitive to storage assumptions
[31]	Stochastic weather modeling with adaptive inverter control	Solar–wind hybrid AC microgrids	Identifies voltage instability from correlated fluctuations	Adaptive inverter stabilizes system	Requires advanced inverter tech, not widely deployed
[32]	Hybrid reliability framework (deterministic load flow + probabilistic variability)	Distribution-level solar–wind hybrid microgrids	Captures failure propagation more accurately	Better failure prediction than traditional methods	High data/compute requirements

III. AI-BASED POWER QUALITY ENHANCEMENT TECHNIQUES

Power quality improvement in a solar–wind hybrid energy system (SWHES) focuses on harmonic problems and voltage/frequency fluctuations, along with reactive power imbalances. Harmonics are inhibiting filters dealing traditionally with passive and active power filters parameters however, with AI-based controllers, the filters are found to be more adaptive through helping in dynamically tuning inverter switching patterns and predicting harmonic content under variable renewable generation [33]-[34]. Voltage and frequency oscillations stabilization remains critical in islanded and grid-connected modes; hence, the RL and adaptive neural-type controllers were used to control DC-link voltage, suppress transient oscillations, and provide frequency support when there is a fast change of load or resource [35]. For reactive power compensation, classical capacitor banks and static VAR compensators are now supplemented by AI-based control of grid-tied converters, which yields optimal reactive support and minimizes THD in real-time [36]. Moreover, intelligent hybrid schemes combining fuzzy logic and optimization algorithms (PSO, GA) display better performance in dynamic voltage regulation and improved LVRT performances [37]. Another promising domain of AI applications in SWHES is fault detection and classification; that is, machine learning models using SVM, RF, and CNN allow identification from patterns extracted out of current, voltage, and harmonic signatures of short-circuits, open-switch faults, and converter malfunctions [38]- [39]. Compared with rule-based approaches, AI-based fault detection is faster, has a higher detection rate under noisy data, and is more resistant to nonlinearities, making it necessary for ensuring the reliability-assured operational continuity of the hybrid renewable systems [40].

IV. COMPARATIVE ANALYSIS OF AI VS. CONVENTIONAL CONTROL

Comparative studies in solar–wind hybrid energy systems based on conventional and AI-based control strategies have revealed notable performance gaps in major metrics. Traditionally, PI/PID and fuzzy controllers only provide satisfactory regulation at steady-state conditions but fail to maintain low total harmonic distortion (THD) and fast response during intermittency and nonlinear dynamics [41]-[42]. In contrast, AI-driven approaches such as reinforcement learning (RL), neural networks (NN), and hybrid optimization-based controllers ensure low THD (<5%), fast transient recovery, and high reliability amid stochastic solar–wind variations [43]-[44]. Case studies on grid-connected PV–wind plants further demonstrate the efficacy of AI-empowered control algorithms in cutting THD up to 40% and stabilizing frequency over classical loops [45]. Further, adaptive ML models operate to re-tune parameters interactively in accomplishing more efficiency and less energy loss, whereas their traditional counterparts demand offline tuning and manual calibration [46]. Moreover, scalability contracts in favor of AI approaches because the data-driven controller ensures its robustness in the microgrid scenario and in large-scale hybrid networks, while the conventional design suffers when exposed to high penetration levels or weak-grid scenarios [47]. Hence, the benchmarking results univocally pronounce AI methodologies preeminent regarding adaptability, efficacy, and long-sustainability, thus catapulting them as the key enablers for next-generation hybrid renewable systems. Figure 2shows Comparative analysis of AI vs. Conventional control.

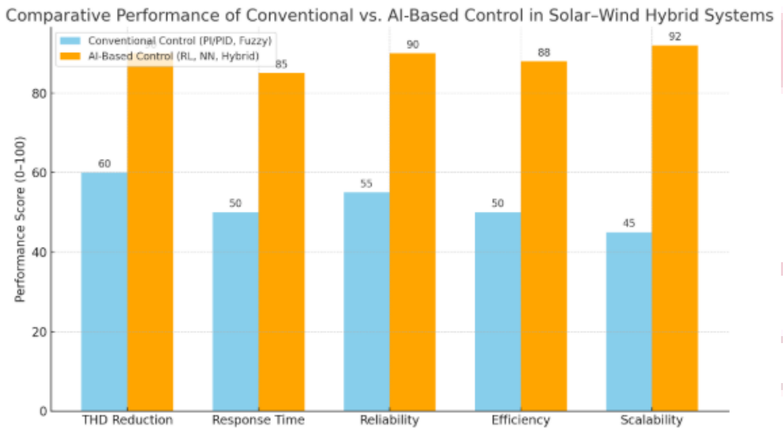

Figure 2: Comparative analysis of AI vs. Conventional control [43], [44], [45], [46], [47]

V. CHALLENGES AND LIMITATIONS

Data requirements and generalization of the model: - AI controllers require large, diverse, and high-quality datasets to perform robustly. However, collecting these datasets is difficult for hybrid energy systems due to resource variability, operation constraints, and regional differences, making it hard to generalize the model into unraveled operational conditions.

Real-time deployment on embedded/edge devices: - The majority of AI models are the most computationally intensive algorithms in training and inference, making their deployment on low-power embedded processors or edge devices rather challenging. Therefore, the real-time software advancement from real-time control to fast convergence and reliable decision making under a severe constraint of hardware resources is a major bottleneck in practice.

Cybersecurity and reliability concerns: - Since AI hybrid system controllers rely heavily on communication networks, they can suffer cyberattacks, data manipulations, and denial-of-service attacks. Performance and reliability are also affected by changes in renewable generation levels, presenting a challenge of instability if AI algorithms are not properly fortified.

Economic and implementation challenges: - AI-based interventions into hybrid systems require capital-intensive investments in advanced sensors, processors, and communication infrastructures. Also, technical expertise, regulatory compliance, and integration with classic power systems form economic and operational challenges detrimental to rapid dispersion.

VI. CONCLUSION

This review emphasizes the pivotal role of AI-based methodologies in advancing control strategies and improving power quality in grid-integrated solar–wind hybrid energy systems. While traditional converter control approaches such as PWM and SVPWM remain effective under steady conditions, they are constrained by the intermittency and nonlinear dynamics inherent to renewable energy sources. In contrast, AI-driven solutions including deep reinforcement learning, machine learning-based forecasting, and hybrid optimization algorithms demonstrate superior adaptability and data-driven decision-making, thereby enhancing efficiency, reliability, and resilience. This review also highlight the integration of advanced converter topologies, MPPT algorithms, and predictive controllers as critical enablers for reducing harmonic distortion, ensuring robust voltage regulation, and optimizing energy dispatch. Overall, this review concludes that AI-based control frameworks represent a transformative pathway toward achieving cleaner, smarter, and more reliable renewable energy integration into modern power grids.

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