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Article

AI-Based Hybrid Control for Renewable Energy Systems: A Review

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Abstract: Efficient control strategies are needed for renewable energy systems due to the nonlinear nature of their dynamics, their intermittent characteristics, parameter uncertainties, as well as grid connection limitations and the need for real-time implementation. Recently, hybrid control structures where traditional real-time control principles combine with artificial intelligence adaptation, tuning or decision support are being used more often to address these issues. This paper presents a systematic review of the recent literature concerning the use of hybrid controls in renewable energy systems. In particular, it will focus on solar energy, wind energy, microgrids, as well as hybrid renewable configurations, providing both a theoretical framework and practical examples. The methodology applied to review scientific articles of both AI-tuned PID controllers, which will include literature about the following groups of controllers: artificial intelligent neural networks, fuzzy and neuro-fuzzy approaches, adaptive PID and predictive-control schemes that highlight their workflow, performance enhancement, robustness considerations, computational complexity, practicality of application/controller family and usage modes, as well as other issues. The analysis of scientific works presented so far shows three main tendencies in the research: researchers mostly rely on computer simulation results to present their findings; comparisons of controller types fail to provide methodological consistency; and their failure to address practical problems of complexity, tuning, and embedded implementation. In conclusion, this systematic review will indicate what methodological and practical aspects are missing in the literature and provide some suggestions on how to improve future research on intelligent hybrid control schemes to achieve more manageable solutions.
Keywords: Renewable energy systems; AI-based hybrid control; intelligent control; PID tuning; neural networks; fuzzy logic control; neuro-fuzzy control; robust control; model predictive control; photovoltaic systems; wind energy systems; microgrids

1. Introduction

As renewable energy systems continue to gain importance in modern electricity generation, active control of photovoltaic plants, wind energy systems, micro-grids, and hybrid renewable configurations is becoming a vital engineering problem [1],[2]. Unlike with conventional generation systems, the operation of renewable energy plants is subject to various environmental changes, therefore affected by nonlinear dynamics, intermittency, parameter uncertainty, requirements of interconnection with grid, and constraints on real-time operation [3]–[6].

Such issues manifest differently depending on the application. For photovoltaic plants, the control system must ensure successful maximum power point tracking in response to changes in irradiance level, temperature, and partial shading [3],[4],[7]. For wind energy systems, this challenge becomes complicated further by randomness of wind, nonlinear dynamics of turbines, and changes in operation targets within different speed ranges [3]–[12]. Micro-grids have to provide control systems which ensure voltage regulation, power quality, and coordinated work of the generators with storage facilities and consumers.

Due to such challenges, fixed or strictly nominal control systems are often incapable of providing reliable outcomes within a wide range of operation [13],[2]. Hence, there is a growing interest in AI-based hybrid control systems able to solve this problem as this technology does not eliminate the classical control but adjusts and enhances it by acting on already established and trusted control systems such as PID, fuzzy logic, robust control, and model predictive control [12],[13][1],[2].The latest literature manifests this trend through the introduction of adaptive neuro-fuzzy MPPT/photovoltaic systems' AI-based hybrid control, intelligent cooperative control/microgrids, and hybrid renewable energy systems' AI-based hybrid control [5]–[10]. Despite the growing volume of work being produced on various studies, there is still a lack of unification of literature on different controller types, renewable energy area of applications, and application target objectives [9], [8], [5]. In most cases, there is no possibility of being able to compare the various forms of controllers in the literature as all the studies are application-oriented and, hence, fail to make meaningful comparisons.

Within the existing review literature, there is a tendency of focusing too much on specific subfields (e.g., MPPT photovoltaic even), such as wind turbine control and microgrid control, while other renewable energy application areas have failed to produce significant literature for adequate comparisons. In this review, therefore, the gap left from other forms of literature is filled. The aim of this paper, therefore, is not only to organize the available literature in this field, but also to identify gaps in methodology and the most promising research areas for the future. The paper is organized in sections as follows: in Section 2, a description of the scope, classification approach and search strategy of the review is given; Section 3 outlines the challenges faced in renewable energy; Section 4 reviews past works; Section 5 presents AI-based hybrid systems; and Section 6 provides the application-related review in terms of technology.

2. Review Scope and Methodology

2.1 Scope of the Review

This review will highlight studies that deal with the control for renewable energy system using either artificial intelligence-based control system or hybrid intelligent control approaches. The emphasis is not placed on the renewable energy technologies in general, but only on some work related to controls, which applies artificial intelligence to improve tracking performance, stability of operations, robustness, as well as real-time decision support. The areas of applications that are used in this review include photovoltaic system, wind-energy system, microgrid, and hybrid renewable system configuration, since they were the most relevant subjects in the studied literature [3]–[12], [7], [1], [2].

The families of controllers reviewed in this work are PID and AI-tuned PID, neural networks-based control, fuzzy and neuro-fuzzy control, robust control, model predictive control based approaches, and other hybrid intelligent method frameworks [12], [7], [1], [13], [2]. In contrast, studies dealing with forecasting, fault detection, predictive maintenance, general planning, and energy management will be excluded from this review unless control is still the main technical input. The focus of this review will therefore be on the design of control systems and evaluation in relation to control.

The studies to be included in this work have been selected using the following three criteria. Firstly, the study has to be about renewable energy control problem as opposed to renewable energy. Secondly, it has to involve the use of at least one of the following families of controllers discussed in this paper. Thirdly, the study should belong to one of the chosen application areas: photovoltaic energy systems, wind energy, microgrids, and hybrid renewable configuration in order for it to pass this review. Priority has been given to recent publications in peer-reviewed journals during the selection process.

2.2 Literature Search and Selection Procedure

Academic databases and publishing schemes were used to collect the information reviewed in this article, and the reference lists of pertinent documents were examined to gather additional related research. The selection criteria chose studies published between 2019 and 2026 with special focus on recent journal articles that are peer reviewed. The search terms were intended to connect research topics of renewable-energy applications with control and AI topics, including but not limited to, intelligent control for photovoltaic systems, hybrid control applied to renewable systems, microgrid control using AI, neural networks for renewable energy control, fuzzy control applied to wind energy systems, and model predictive control with AI employed in renewable applications.

The screening process took place in three stages. In stage one, the titles and abstracts were assessed for keys and thus unsuitable studies were eliminated. Stage two involved the detailed reading of the pertinent papers' full texts. Stage three required the remaining papers to be checked once again to ensure both method and application relevance. Duplicate papers, studies which were outside the realm of renewable energy control, and research focused mainly on prediction, predictive maintenance, diagnosis, or any broad forms of energy planning were all eliminated from the research database.A paper was included only if it fulfilled three conditions: it dealt with a control issue in renewable energy, it involved on or more controller types mentioned herein, and it was directed mainly toward one of the application areas outlined. After screening and verification of relevance, the final paper selection yielded 45 documents which were subsequently analyzed in this research. These studies represent the foundation of comparative discussions in the following sections of this article. Figure 1 shows the selection and screening process adopted in this review and provides step-by-step coverage from initial search and record collection to screening, relevance checking, and the file classification according to controller and application field.

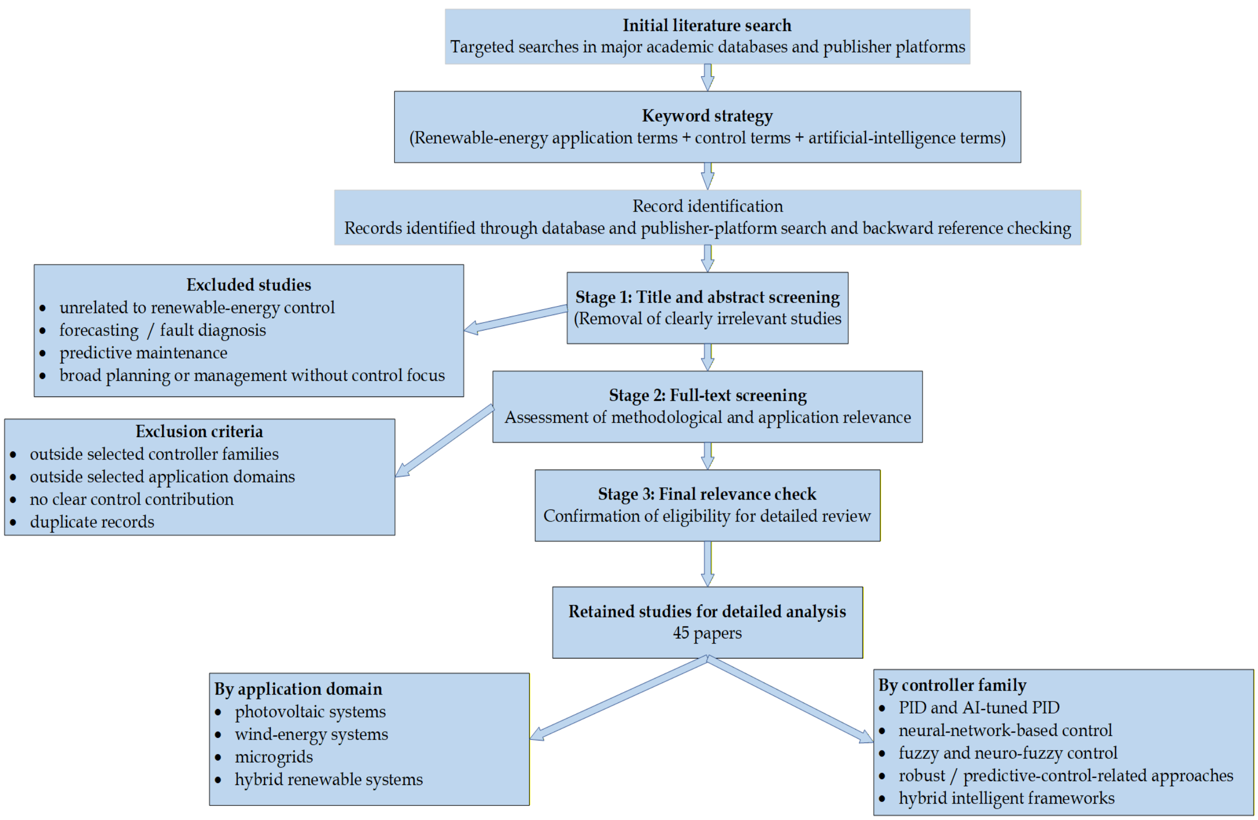

Figure 1. Literature search, screening, and classification workflow used in this review.

The retained studies were identified through targeted database and publisher-platform searches, followed by backward reference checking. Screening was performed in three stages: title and abstract screening, full-text assessment, and final relevance confirmation. Studies were retained only when control was the main technical contribution and the work matched the selected controller families and application domains. A total of 45 papers were finally retained and classified by controller family and application domain.

2.3 Classification Framework

This systematic discussion focuses on an examination of the selected literature from two different viewpoints: first, the control methods employed and the second the application domains which were studied [12], [7], [1], [2]. The control methods will be classified into controller categories, including PID methods, Neural Networks (NN), Fuzzy Logic Control (FLC), Robust Control (RC) and Moris–Controller based approaches and Hybrid Control Systems. This classification provides an insight into methodological similarities and dissimilarities among different applications of renewable energy [3]-[12], [7], [1], [13].

The second classification based on application includes photovoltaic devices, wind energy devices, microgrids, and hybrid renewable systems. This classification is important because a specific control method may perform differently for each application; for instance, for photovoltaic maximum power point tracking, wind abundant turbine pitch and power control, converter regulation, and microgrid frequency and voltage management [12], [7], [1], [2].

Finally, the later sections will analyze the PV literature through five major criteria: tracking performance, robustness to operational uncertainty, computation complexity, ease of implementation, and ability to work in real time.

In the photovoltaic control studies, the first criterion is related to speed of mppt control and oscillation reduction; the second, shading and the third, controller complexity [3], [4], [7], [8], [1]. In microgrid control studies, power quality, voltage regulation, converter interaction, and dynamic characteristics are used [6], [9], [10], [2].

In the wind energy generation studies, the criteria are defined as the ability of control system stability, predictive capabilities, and operational performance in variable wind conditions [5], [11], [12], [14].

3. Control Challenges in Renewable Energy Systems

The operation of renewable energy is based on nonlinear dynamics of the plant, environmental variations, the converter connection, and certain limitations imposed on the implementation. Each renewable energy type faces its own set of difficulties, however, they are similar in essence. Controlling systems have to perform well, while the plant is changing because environment changes, variations in the load, and so on [3]–[7], [15]–[17], [2].

3.1 Nonlinearity and Parameter Uncertainty

One important limitation to the control of renewable energy is the non-linearities of the systems. For example, photovoltaic technology has non-linear current-voltage characteristics (I-V) and power-voltage characteristics (P-V) that are functions of irradiation and temperature. Furthermore, the presence of partial shading may mean that there are different local maximum points rather than one optimum operating point [3], [4], [8], [7], [1]. The wind energy sector also experiences non-linearities due to aerodynamics, rotor dynamics, pitch angle effects, and changing operational requirements [5], [11], [12], [18]. In microgrids and hybrid renewable systems, the non-linearities problem grows more complicated because the controlled system consists of interconnected generation sources, storage units, converters, and loads [6], [9], [10], [16], [17], [2]. Therefore, many researchers have begun using adaptive or hybrid approaches to allow for system variations [19]–[21].

3.2 Intermittency and Environmental Variability

A second major problem is intermittency, because renewable resources are dependent directly on the environment so that control is affected greatly by weather conditions. For example, in photovoltaic systems, irradiance, temperature, and shading continuously change the operating point and in this situation it is difficult to achieve fast and exact MPPT [3], [4], [7], [22]. The same situation occurs in wind energy systems, where weather impacts not only on power extraction but also on structural loading [5], [12], [18]. In microgrids and hybrid renewable systems, the situation is even more complicated because there are a number of different resources with variable power generation and consumption [6], [9], [10], [16], [19], [2].

3.3 Grid Integration, Voltage Stability, and Power Quality

The use of grid-connected operation creates further layers of control challenges. Power electronic converters are usually used to interface renewable energy systems to their respective local networks, microgrid, or utility grid, and this gives rise to the need for considerations such as voltage support, harmonic mitigation, reactive power control, power sharing, and frequency response [15], [16], [17], [24],[2]. In photovoltaic systems, controllers need to maintain stable inverter and dc-link behavior while ensuring effective power extraction [4],[1],[25]. For microgrids, coordination of converters and the need for local power quality become important [6],[9],[10],[15],[24],[26]. Wind energy systems also have challenges with respect to grid interacting operations, since there is a need to maintain stable output power under changing wind conditions [5],[11],[12],[18].

3.4 Real-Time Implementation and Computational Burden

The next challenge pertains to implementation. Generally speaking, renewable-energy controllers are executed in real-time through the use of embedded processors, converter hardware and/or digital control platforms. This puts limits on the sensing requirements, training efforts, algorithm complexity and computational costs. Even though intelligent methods may enhance flexibility and effectiveness, they can also add an implementation burden [3], [34]. This issue is commonly observed in both photovoltaic and wind applications as the most powerful method may not be the simplest to implement [15]. Therefore, real-time applicability needs to be viewed as a primary criterion when making comparisons instead of being relegated to a secondary category. In combination, such difficulties provide insight regarding the increasing popularity of hybrid forms of AI-based control over renewable energies and positions the basis for the baseline strategies presented in the next section.

4. Conventional and Baseline Control Approaches

It is helpful to first lay out some groundwork concerning the fundamental control strategies that are still practiced with regard to renewable energy before proceeding with a comprehensive discussion of AI hybrid control approaches. These strategies are of particular significance, since a considerable amount of the practical renewable energy control is still developed using conventional control type, PI, PID, PR (proportional-resonant), robust, adaptive and predictive control [3],[5],[7],[8],[9],[10],[11]. Furthermore, a significant portion of the recent literature on AI does not replace conventional control strategies but instead enhances them through tuning, adaptation or hybridization [6],[7],[9],[10],[13],[17],[30].

4.1 PI and PID Control in Renewable Energy Systems

Due to their simplicity, low implementation costs, and light computational load, PI and PID controllers are still in popular use. Their applications can be noticed particularly in voltage and frequency stabilization and regulation of converters, as well as in control loops [17], [20], [30], [31]. In microgrid research, PID control is typically adopted as a reference to compare fuzzy control, ANN, or neuro-fuzzy methods [9], [10]. In wind energy applications, PID is still relevant in conjunction with anti-windup or optimization schemes through new approaches of online PID tuning based on GA [14].

Conventional MPPT approaches, including Perturb and Observe, Hill Climbing, and Incremental Conductance in photovoltaic systems follow the same logic as they are all low-cost methods although they are inadequate under certain circumstances [3], [4], [7], [22].

4.2 Robust, Adaptive, and Predictive Baseline Methods

Aside from utilizing PI and PID control methods, research works on renewable energy indicate that there is a typical baseline of classical control strategies based on the principles of robust, adaptive and predictive control systems. In this context, robust probably refers to a robust strategy that lies between classical control methods and the intelligent strategies of control. Robust control is aimed at preserving the acceptable performance properties under different disturbances, uncertainties, variations of parameters and constraints in operation. This is extremely relevant for wind energy systems, where robustness becomes the dominant design requirement thus it is essential in case of disturbances. Adaptive control is even more relevant for photovoltaic systems and microgrid systems as fixed gains of control systems usually work effectively only in a few cases of local operation points. Model predictive control seems to be constructed in such a way that it can integrate system dynamics into its operation. This method provides system dynamics and predictive models as well as operation constraints.

4.3 Main Limitations of Conventional Standalone Approaches

There is no doubt that conventional and baseline approaches have provided their share of benefits in practice yet the scientific literature under review points to persistent shortcomings in regards to major renewable energy applications. In the case of photovoltaic systems, conventional MPPT techniques exhibit tendencies to oscillate about the operating point, respond to rapid changes of irradiance with delays, and become inefficient under partial shading conditions [3], [4], [7], [8], [22]. Microgrid control is characterized by a different problem because fixed gain approaches are often unable to perform well in cases when distributed generation sources, energy storage systems, and variable loads are interactively performing [9], [10], [17], [31], [32]. Wind energy control has comparable issues– not only does one have to deal with the nonlinearities of the process but there are disturbances and variable operational zones that make nominal control hard to maintain in practice [5], [11], [12], [18].

Another obstacle is the existence of a tradeoff between simplicity and versatility. Classic PI, PID, and MPPT controls have the advantage of simplicity both in terms of implementation and interpretation but they often become limited in performance when there is uncertainty or sudden changes in operation. More sophisticated baseline methods (such as robust control or MPC), on the other hand, offer more flexibility but require significant modeling and computing effort compared to simple PI/PID/MPPT controls [3], [5], [6], [9], [11], [13], [17], [19], [21]. This tradeoff is one of the reasons why the current line of research has increasingly looked at hybrid methods which combine conventional control scheme with one of the AI-driven (fuzzy control, optimization-based control, or neural networks) methods to achieve desired results.

5. AI-Based Hybrid Control Strategies

Recent developments in renewable energy control indicate an obvious transition toward hybrid approaches which use structured control in collaboration with AI, fuzzy logic, optimization, or predictive technology rather than just sticking to pure conventional systems. Most often, the motivation behind the hybrid approach is not to discontinue the use of conventional control methods altogether, but rather aim at greater flexibility for adaptive control in the event of having to deal with nonlinear situations, uncertainty, and changing operating conditions. This trend exists in photovoltaic systems, wind energy systems, and micro grids, although the form of hybridization may differ in every case [3]–[14]. The main classification of AI-based hybrid control methods is shown in Figure 2 and is included for discussion in this paper.

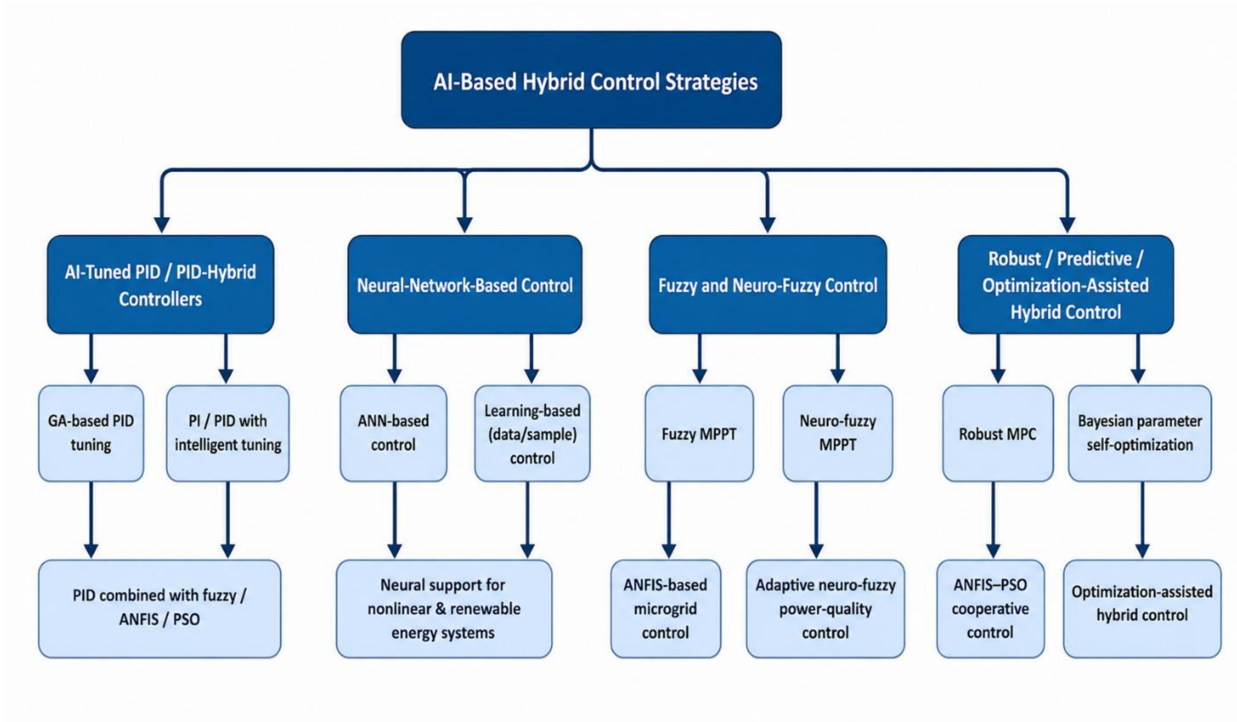

Figure 2. Taxonomy of AI-based hybrid control strategies for renewable energy systems.

5.1 AI-Tuned PID and PID-Hybrid Controllers

One of the most common directions in the literature is the enhancement of PID-type controllers through AI- or optimization-based tuning. This remains attractive because PID structures are simple, familiar, and relatively easy to implement, while intelligent tuning can improve performance under variable operating conditions. In wind-energy applications, for example, online genetic-algorithm-based PID tuning has been used to improve settling time, overshoot, and steady-state behavior relative to fixed PID designs [14]. In microgrid studies, PID often appears as a baseline against which fuzzy, neural, or neuro-fuzzy methods are compared, especially in voltage- and energy-management tasks [10]. More explicitly hybrid designs follow the same logic.In DFIG-based wind-control systems, PI regulation has been combined with ANFIS, fuzzy logic, and PSO to improve dynamic response, reduce harmonic distortion, and enhance performance under changing wind conditions [11].

These studies suggest that AI-tuned PID and PI-hybrid structures remain attractive because they preserve interpretability and low implementation burden while improving adaptability. Their main strength is practical continuity with established control design. Their limitation, however, is that performance remains tied to the underlying PID structure, so these methods may still be insufficient in strongly nonlinear or heavily coupled operating conditions [11], [14].

5.2 Neural-Network-Based Control

Neural-network-based control is another significant area in the literature. Its main benefit is the capability to model non-linear relationships when analytical models are complex and hard to formulate [27], [28], [33]–[35]. In renewable-energy applications, it works well when the controller should meet aggressive changeable environmental parameters, uncertain plant behaviour or numerous interactive variables [27], [29], [30]. In microgrid research, neural-network-based control was compared to PID and fuzzy logic applications in the tasks of voltage and energy management with the results indicating higher capabilities under changing operational conditions [10], [28], [29], [31], [36]. In photovoltaic systems, neural-network-based applications were applied in grid-based PV control, inverter-related control, converter control, and PV-battery energy-management systems [27], [30], [33], [34].

In wind-energy systems, learning-based techniques appeared in the intelligent pitch-angle application particularly where turbine non-linear nature and wind variation degrade the effectiveness of fixed controllers [11], [12]. It can be observed that neural-network-based control is interesting when a need for adaptation is more important than the presence of simpler controller design. Additionally, many publications do not provide deep discussion of the training complications, transparency and limitations of use in real applications. Therefore, the control improvement dose not always guarantee real-world applicability [10], [12], [27], [29].

5.3 Fuzzy and Neuro-Fuzzy Control

Hybrid approaches involving fuzzy and neuro-fuzzy controls are important intelligent tools for the renewable energy sector. The attractiveness of these techniques stems from their features that allow rule-based reasoning and tolerate uncertainty, as well as the element of learning introduced by neuro-fuzzy structure [9], [22], [32], [37]. This approach can be specifically noted in support of photovoltaic systems. The use of adaptive neuro-fuzzy technique in developing maximum power point tracking (MPPT) mechanisms for photovoltaic systems is also recognized in cases where these systems are interconnected to microgrid [3]. Furthermore, neuro-fuzzy controllers have been developed for photovoltaic systems under partial shading conditions thus improving tracking procedures in extreme cases [4], [38].

MPPT techniques that employ the use of fuzzy logic nowadays are confirmed to have advantages in real time insignificantly reducing oscillations, overshoot level, and reaction time when compared to the traditional techniques [8]. Positive outcomes of fuzzy logic-related methods and fuzzy logic/application procedures in regarding MPPT and different solutions for converters are recorded in different studies [22], [37], [39]. The newest review of the MPPT literature demonstrates the growth of the research field since the traditional techniques are incapable of coping with partial shading conditions and changing environmental circumstances [7].

Similar developments are observed in the field of microgrids. The implementation of adaptive neuro-fuzzy techniques aimed at better power quality in multiple microgrids is reported in studies exploring the comparison between fuzzy controllers and traditional controls [9]. Various publications report how fuzzy logic methodologies can be employed in the development of effective algorithms in power quality improvement, frequency setting, and hybrid control of converters [15], [32]. A good example of successful representation of the hybrid logic using fuzzy techniques is presented in studies about cooperative control of hybrid AC/DC microgrid via the use of ANFIS combined with PSO [6].

Overall, fuzzy logic and neuro-fuzzy logic approaches play the most significant role in the processes of controlling nonlinear, multidimensional systems that have to be tuned using models where parameters remain unchanged. The main advantage of fuzzy logic and neuro-fuzzy logic approaches is their ability to provide solutions that combine adaptability and interpretability. This advantage, however, is offset by difficulties associated with the formulation of rules and tuning and scalability issues in the case of a system with higher complexity [6], [9], [15], [32].

5.4 Robust, Predictive, and Optimization-Assisted Hybrid Approaches

Another essential field of hybrid artificial intelligence control merges optimization techniques with robust and predictive controls as well as adaptive intelligent methodologies. This is of utmost importance in the field of wind energy since wind is associated with stochastic behavior, turbines present nonlinear properties, and there are numerous variations regarding the way that the system operates [5], [18], [40]. In this field, model predictive control that incorporates self-optimizing Bayesian parameterization is suggested to ensure a steady generation of output power while the wind conditions change. A similar procedure is applied in wind energy studies where the intelligent control of the pitch angle is recommended to overcome the drawbacks of traditional approaches due to unpredictability and nonlinear character of the processes [11], [12].

Optimization-based hybrid control systems are also rather popular among the wind, solar energy systems and microgrids. To illustrate, the WIND microgrid utilizes cooperative control by means of ANFIS-PSO based converter to ensure salt-free voltage behavior, voltage tracking, and response to certain changes [6]. Also, the PSO method is applied in the wind energy sector based on hybridization with PI control, ANFIS, and fuzzy control methods [11]. The results of research show that optimization is rarely used by itself and rather acts as a supervisory and tuning mechanism in the control systems. Given the effectiveness of such systems, there are concerns regarding the complexity of modeling and computational workload when it comes to real-time applications.

5.5 General Observations

A few overarching conclusions can be drawn from the studies surveyed thus far. To begin with, hybrid control in renewable-energy systems encompasses a particular architecture. In some instances, hybrid control may be used to refer to PID with genetic optimization as a method; while for others it may mean fuzzy control combined with neural learning; on the other hand, there are also cases when one refers to model-based control with optimization [5], [6], [11], [14].

However, the backbone of hybrid control laying under the various methods named above is not a common structure, but one common objective: to ensure flexible control over the particular system without losing the advantages of conventional control methods. To continue, it should be noted that hybrid control methods are developed as a reaction to weaknesses of traditional control methods. Thus, in photovoltaic systems, hybrid methods are mainly motivated by disadvantages of MPPT under changing conditions of radiation light intensity [3], [4], [7], [8]. In case of microgrids, the need for hybrid control appears in order to solve the problem of voltage support and electricity quality; as for wind-generation systems, the motivation behind hybrid control methods is due to the requirement of tackling the issue of fluctuating electrical resources [5], [11], [12], [14] . Finally, it is important to make the comment about the fact that an improvement in efficiency of administration of hybrid control processes is always given; however, the weakness of comparison of studies between themselves is presented as well. Such methods have different benchmark and input values that prevent an objective assumption concerning the effectiveness of administrative measures. Therefore, one should consider the need for reasonable approaches when evaluating the efficiency of studies widely.

6. Application-Based Review

To classify the literature according to controller family is valuable but does not convey a complete picture of how AI-based hybrid methods are being employed in reality. There exists the need for an application-based viewpoint because the same controller family may serve varying purposes based on the utilized field whether in regard to photovoltaic systems; wind-energy systems, microgrids or other hybrid renewable configurations. The literature has covered the aforementioned four domains consistently [3]–[14]. Figure 3 shows the main renewable energy application domains as covered in the literature reviewed.

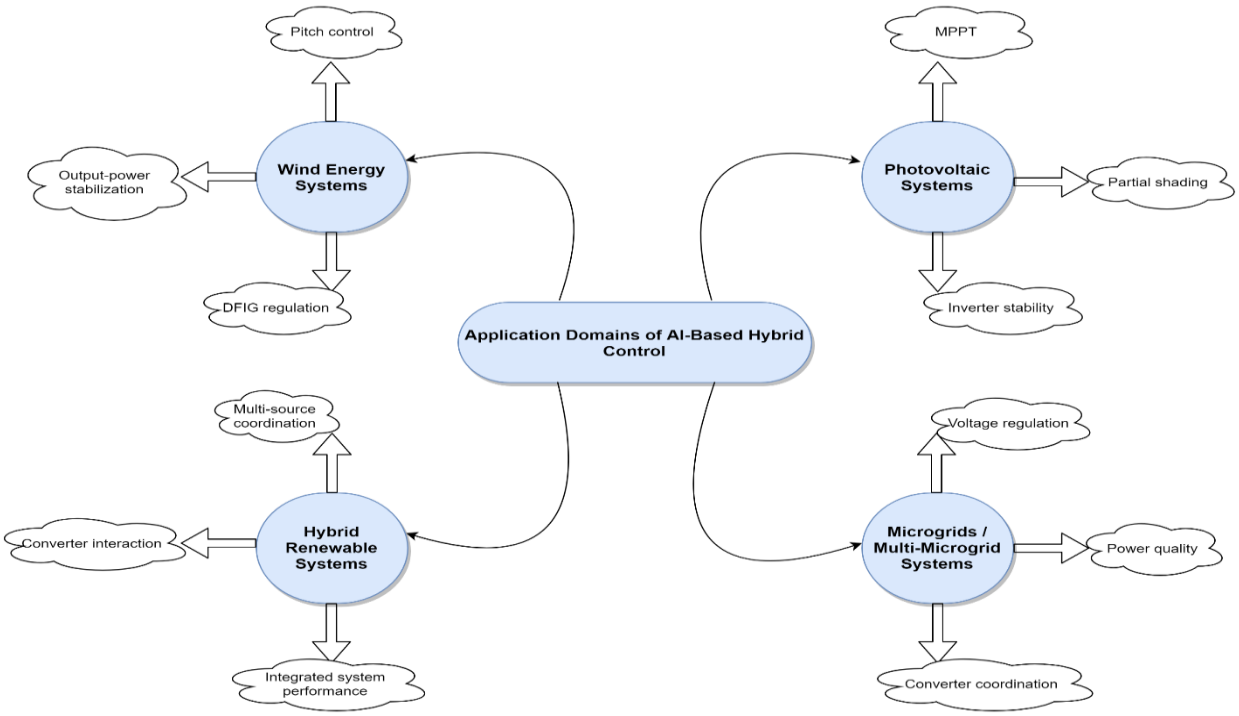

Figure 3. Application domains of AI-based hybrid control in renewable energy systems.

6.1 Photovoltaic Systems

The photovoltaic (PV) systems are one of the popular applications in this field of research. The maximum power point tracking is the most important function in PV systems when there is the variation in irradiance, change in temperature, and partial shading of the module [3], [4], [7], [8], [38]. These factors make PV control a suitable area for the intelligent and hybrid approach, as an intelligent controller has to react quickly to the changes without inducing large oscillations around the operating point [3], [4], [7], [8], [39].

Fuzzy and neuro-fuzzy controllers are the most widely used approaches in PV applications. Adaptive neuro-fuzzy feedback linearization is one of the techniques applied in MPPT for microgrid connected PV systems [3]. Neuro-fuzzy control technique in grid-connected PV systems has been used for partial shading with the main aim of moving toward the global maximum power point rather than settling at the local operating point [4]. In the case of fuzzy logic only applications, the objective is likely to be the same: quicker response time, lower steady-state oscillation, and improved tracking performance in comparison to the conventional MPPT methods [8].

The use of PV systems in various studies seems to be more evident when comparing the conventional MPPT with the intelligent/almost hybrid systems [7], [41]. This is due to the problem that the classical MPPT systems cannot perform effectively whenever the environmental parameters change rapidly or partial shading generate several local maxima [7]. Such arguments illustrate quite well the reason why the control of renewable energies has gradually transformed from constant algorithms to adaptive methods in those areas where classical algorithms could not operate accurately.

6.2 Wind Energy Systems

Wind energy generation techniques are among another major class of the studies presented in the reviewed work. With PV power generation techniques, the focus is primarily on MPPT, with wind-power generation techniques covering several goals. Included in the list of goals are the controlling of the pitch angle, the control on the generator side, stabilization of the output power, and ensuring of the safety of operation amid varying wind conditions. In the reviewed work, the achieved results suggest greater emphasis on reliability, forecasting, and adjusting techniques as wind energy generation systems operate within a range of speeds and operate under the influence of stochastic changes. Several opportunities arise in the reviewed literature on the wind energy generation sector.

Use of both robust and predictive techniques has been noted as the only avenue to enhance performance in dynamic situation, as in the case of robust model predictive control that incorporated Bayes parameter self-tuning in the wind turbine industry area [5]. Other combined approaches accounted for conventional and intelligent approaches together, such as integral control along with ANFIS, fuzzy logic, and PSO that have been used in wind turbine DFIG installations in order to enhance dynamic performance in variable winds [11].

The reviewed literature on intelligent pitch angle control signify the same indication, with the point that there is great need for incorporation of various learning-based techniques instead of solely relying on conventional controllers that are incapable of addressing nonlinear characteristics of wind turbine systems [12]. Research works in adaptive robust pitch control also prove this point, since they indicate the need for load reduction [18].

Therefore, in as much as the two classes of applications contain numerous commonalities, the greatest difference relates to the specific aim of the control systems. PV studies mainly concentrate on evaluating hybrid systems, with measurements being taken mainly on the accuracy of MPPT and speed tracking. The control systems for wind energy must incorporate various aspects, including dynamic performance, stability, reliability, and general safe operation during varying wind conditions of operation. The above reasons prove that wind energy remains a critical application area for hybrid control systems that rely on relativity, predictive tools, and optimization techniques [5].

6.3 Microgrids and Multi-Microgrid Systems

Microgrids provide a rather complicated application realm in the literature reported to date. The control problem to be solved in microgrids encompasses not simply one renewable energy source, but rather the management of several components and systems such as distributed generation units, storage systems, converters, loads, voltage regulation, and power quality criteria. This has caused many studies on microgrid systems to employ hybrid and intelligent control systems, in contrast to purely fixed parameter based controllers, which is the case for studies in earlier sections [6], [9], [10], [15], [17], [24], [26], [28], [29], [42]–[44].

Microgrid studies reported herein can be classified into categories based upon particular control applications required. One major type of study involves converter and interlinking control. Within this application area, hybrid AC/DC microgrids are often operating with the cooperative control approach to solving their control problems and using ANFIS-PSO methods to improve dynamic performance and tracking control objectives [6], [26], [36]. Another group of papers examines power quality issues and supports voltage regulation. In this area, adaptive neuro-fuzzy control has been proposed for multiple, low- or no-emission microgrid clusters and compared to the control provided by the existing techniques [9].

Other studies in the literature have examined issues associated with inverter control, D-FACTS support, and the application of ANN control for microgrids [15], [24], [28], [35]. Still another category of studies has compared various types of control systems such as PID, ANN, and fuzzy logic for local microgrid control, stability, and energy management [10], [31]. Overall, compared with solar PV systems, microgrid studies have focused less on one dominant control objective and tended to involve multiple requirements such as voltage support, harmonic reduction, source-load coordination, local system reliability, and frequency regulation.

6.4 Hybrid Renewable Energy Systems

The literature reviewed indicates that hybrid renewable systems represent cases in which multiple energy sources, and sometimes storage units, operate together.

In such systems, there are numerous control problems to solve, since the controller must often manage the interplay of different generation units, power converters, energy storage devices, and loads under different operating scenarios [2], [3], [6], [10], [11], [16], [20], [45]. It seems that hybrid renewable systems initially appear as one of the most obvious areas for hybrid intelligent control application.

This is partially because such systems involve multiple interacting subsystems, and because the tuning of existing control schemes with fixed parameters becomes more complicated with the increasing diversity of the entire facility [2], [16], [20], [42]. In the context of the photovoltaics-microgrid, hybrid control provides MPPT and multiple sources integration support [3], [4], [33]. In hybrid AC/DC microgrids, it allows converter coordination and instantaneous response [6], [26]. In wind hybrid intelligent applications, it supports generator-side performance improvement under changing operating conditions [11].

The presence of these patterns indicates that hybrid (renewable) systems should provide an environment in which the usage of hybrid control can be pretty easily justified. Overall, the reviewed studies show that there are some preferences in the application of hybrid intelligent control technology in renewable energy area. It is clear that the solution for photovoltaic systems is mainly associated with MPPT orientation, for wind turbine systems, it is based on robust regulation and adaptable turbine control, for microgrid systems, it includes coordination/power quality control, and finally, for hybrid renewable systems, it covers concerted control of different energy sources [1], [2], [7], [12].

In order to relate the application discussions with the evidential findings based on the literature review, Table 1 categorizes selected papers in one consistent format based on application domain, control goal, family of controller, artificial intelligence (AI) or hybrid technique, major contribution, and limitation. This method of organization is relevant because the reviewed papers vary widely on their system model, operational settings, depth validation, and performance metrics. The results in one consistent format allow one to differentiate between reported performance gains, methodological advancements, and operational limitations. The results reveal the state of maturity of the various group of literature reviewed, with photovoltaic studies emphasizing maximum power point tracking (MPPT), wind energy on robust and adaptive control, microgrid studies on coordination and power quality, and hybrid renewable energy systems on multiple source integration. As thus, Table 1 not only summarizes each of the papers reviewed; rather, it serves as the basis for the cross-domain comparisons and the gaps between previous researches discussed in subsequent sections.

Table 1. Representative application-based summary of selected reviewed studies.

Ref	Year	Application domain	Control objective	Control approach / AI technique	Main contribution	Main limitation
[3]	2020	Photovoltaic system in microgrid	Maximum power point tracking	Adaptive neuro-fuzzy feedback linearization	Improved MPPT performance by combining adaptive control with neuro-fuzzy modeling in a microgrid-connected PV system	Limited to PV MPPT application and mainly simulation-based validation
[4]	2024	Grid-connected photovoltaic system	GMPPT /MPPT under partial shading	Neuro-fuzzy control with gravity search algorithm	Improved tracking speed and output performance under uniform and	Application-specific and evaluated mainly in simulation

					partial shading conditions	
[5]	2023	Wind turbine system	Output-power stabilization under varying wind speeds	Robust MPC with Bayesian parameter self-optimization	Improved wind-turbine performance through robust predictive control with adaptive parameter tuning	Higher model and optimization complexity; focused on wind systems
[6]	2023	Hybrid AC/DC smart microgrid	Converter coordination, voltage regulation, and MPPT	ANFIS-PSO-assisted cooperative control with PR controller	Combined intelligent tuning and converter control to improve voltage profile and tracking behavior in a smart microgrid	Structurally complex and mainly simulation-based
[8]	2023	Commercial photovoltaic system	Maximum power point tracking	Fuzzy logic control	Real-time validation showed reduced oscillation and improved response compared with incremental conductance	Limited to PV MPPT and a single application setting
[9]	2022	Multi-microgrid clusters	Power-quality improvement	Adaptive neuro-fuzzy control strategy	Improved power-quality indices compared with conventional PI and fuzzy controllers	Focused mainly on PQ metrics and simulation evaluation
[11]	2025	Wind energy system (DFIG-based)	Dynamic regulation and performance improvement	Hybrid PI–ANFIS–fuzzy–PSO control	Enhanced dynamic response and operating performance under changing	Complex hybrid structure and wind-specific focus

					wind conditions	
[14]	2025	Wind power generation system	Online PID parameter optimization	Genetic-algorithm-based PID tuning	Improved PID behavior through online gain optimization for wind-power control	Narrow controller focus and application-specific scope

While Table 1 summarizes representative studies at the individual-study level, Table 2 provides a broader comparison across application domains. This second comparison is useful because photovoltaic systems, wind-energy systems, microgrids, and hybrid renewable systems do not share the same dominant control objectives or technical challenges. Therefore, Table 2 compares these domains in terms of their main control objectives, frequently used controller families, reported benefits, and recurring challenges.

Table 2. Cross-domain comparison of AI-based hybrid control applications in renewable-energy systems.

Application domain	Dominant control objectives	Frequently used controller families	Key reported benefits	Recurring challenges
Photovoltaic systems	Maximum power point tracking, shading response, inverter-side stability	Fuzzy, neuro-fuzzy, ANN-assisted, hybrid MPPT methods	Faster tracking, reduced oscillation, better behavior under dynamic irradiance and partial shading	Partial shading, multiple local maxima, environmental variability
Wind energy systems	Pitch-angle control, generator-side control, output-power stabilization, dynamic regulation	Robust MPC, AI-tuned PID, PI–ANFIS–PSO hybrids, intelligent pitch control	Better robustness, improved dynamic response, stronger handling of variable wind conditions	Turbulence, nonlinear turbine behavior, changing operating regions
Microgrids / multi-microgrid systems	Voltage regulation, power quality, converter coordination, source-load balancing	ANN, fuzzy, neuro-fuzzy, cooperative hybrid control	Better coordination, improved voltage behavior, stronger power-quality performance	Multi-objective operation, networked complexity, converter interaction
Hybrid renewable systems	Multi-source coordination, converter interaction, integrated system performance	Hybrid intelligent frameworks, optimization-assisted methods, fuzzy/neuro-fuzzy hybrids	Improved flexibility, better coordination among sources and converters, broader adaptability	Increased structural complexity, more difficult tuning, system-level interaction effects

7. Comparative Analysis and Discussion

The existing literature suggests that AI-based hybrid control has emerged via different domains, rather than through one approach alone. Some researchers modify conventional controllers with intelligent tuning, while other researchers devise fuzzy and neuro-fuzzy theories to cope with nonlinearity and uncertainty, and in some instances, researchers merge robust and/or predictive control with adaptation based on optimization. Since each of these strategies is employed for distinct types of renewable energy settings, it is usually impossible to carry out direct one-to-one comparisons. However, a number of important rules can be determined based on this literature [3]–[14]. Figure

4 depicts the comparison framework utilized in this review, which includes the basic elements considered for evaluating the utilized strategies of AI hybrid control.

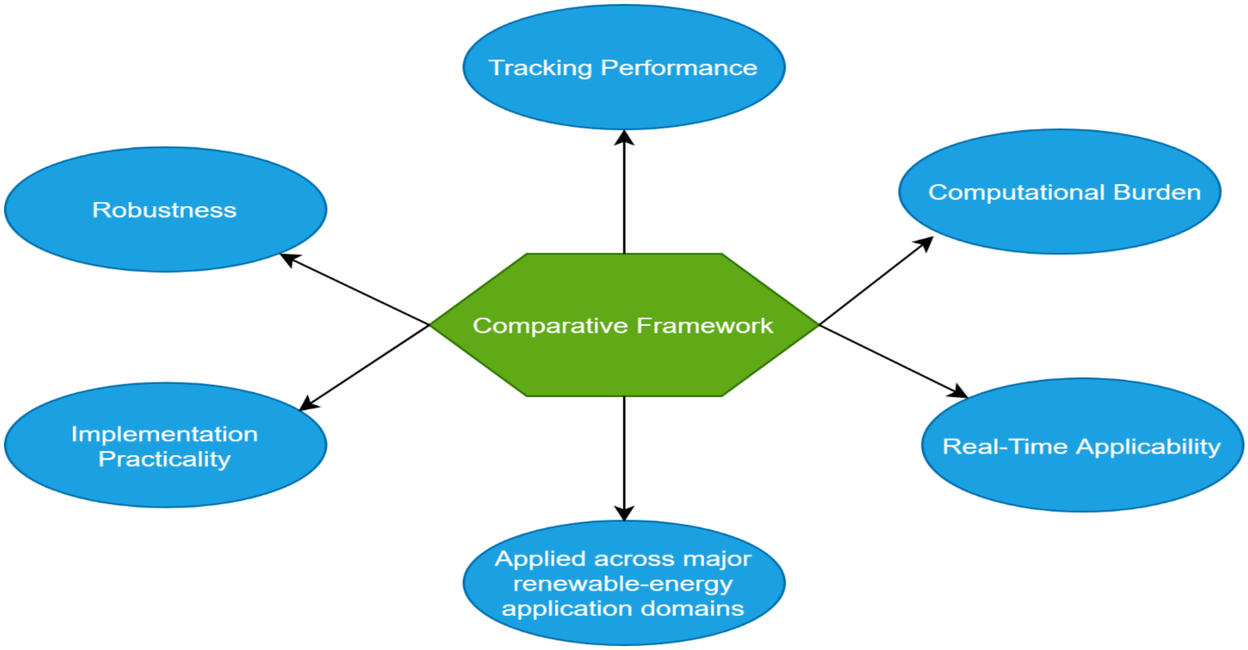

Figure 4. Comparative framework used in this review for evaluating AI-based hybrid control approaches in renewable energy systems.

7.1 Comparison by Controller Family

PID methods with the integration of AI are still appealing as they maintain the effectiveness and comprehensibility of PID controllers while providing the advantage of adjustment through optimization. The biggest benefit of PID methods is practicality in use. They are simple to use, tune, and implement as compared to many learning methods, which have become more relevant in renewable energy where the open engineering of processes is necessary [14], [20], [22], [30], [31]. However, the effectiveness of PID-based techniques largely depends on the quality of tuning. Though the intelligent optimization makes the mentioned methods more flexible, PID-based systems still hold the limited flexibility in case of severe non-linearity, operating variations, or coupling [10], [11], [14], [18].

Neural control systems provide a better opportunity to adapt to non-linear behavior and the uncertain regime of operations. It is necessary in renewable energy systems where analytical models cannot be used or where a lot of interconnected variables are influencing control actions [27]–[29], [33], [34]. The main advantage of neural methods is the ability to approximate possible outcomes and adapt to conditions. But this benefit is ensured at a higher risk of reliance on proper design of training, structure of models, data quality, and implementation [27]–[29], [33], [34], [36]. This is why neural control appears to provide a high promise in simulation, but it does not always demonstrate the practical advantage over simpler hybrid methods. In fuzzy logic and neuro-fuzzy systems, one of the most utilized compromises is attained in the reviewed literature.In microgrid applications, the topology of the system is connected with voltage regulation in addition to converter coordination and power quality improvement [6]. One of the most interesting advantages is the combining of uncertainty acceptance and comprehensibility at the same moment.

However, this advantage can diminish when a system expands and complexity grows since tasks, such as membership function design, rule base creation, training, and optimization, can become challenging to fulfill [3]. Hybrid techniques based on predictive, optimization-supported and robust controllers show remarkably strong performance if the focus of the application lies on disturbance rejection and dynamic stability, as can be demonstrated in the field of wind energy, where robust model predictive control (MPC), Bayesian parameter optimization, and hybrid PI-ANFIS-PSO control strategies are utilized for ensuring dynamic stability in uncertain wind conditions. The reason hybrid techniques based on predictive, optimization-supported, and robust controllers are attractive is that they address uncertainties, constraints, and variations in the operating region more efficiently than conventional controller techniques with fixed parameters. However, hybrid techniques based on predictive, optimization-supported, and robust controllers have certain disadvantages, such as higher modeling and computational costs, along with the fact that they apply various assumptions that limit the performance of conventional techniques. The key advantages, drawbacks, and application characteristics of controller approaches dealt with in this paper can be found in Table 3.

Table 3. Comparative summary of the main AI-based hybrid controller families in renewable-energy systems.

Controller family	Main value	Main limitation	Typical use and implementation profile
AI-tuned PID / PID-hybrid	Simple, familiar, and easy to implement; improves adaptability compared with fixed-gain PID.	Performance still depends strongly on tuning quality and may be limited under severe nonlinearity.	Wind control, microgrids, and converter regulation; low to moderate computation; generally suitable for real-time use.
Neural-network-based control	Strong nonlinear approximation capability and useful adaptability under interacting variables.	Sensitive to training data, model structure, and validation quality; lower interpretability.	Microgrids, wind systems, and nonlinear renewable applications; moderate to high computation; real-time use depends on implementation.
Fuzzy and neuro-fuzzy control	Handles uncertainty well and keeps a relatively interpretable rule-based structure.	Membership-function design, rule-base construction, and scaling can become difficult.	PV MPPT, microgrids, and power-quality control; moderate computation; generally feasible for real-time use.
Robust / predictive / optimization-assisted hybrid control	Strong disturbance handling, improved dynamic stability, and explicit treatment of constraints and uncertainty.	Requires higher modeling effort, greater design complexity, and higher computational cost.	Wind systems, hybrid AC/DC microgrids, and advanced converter control; high computation; moderate real-time suitability.
Hybrid intelligent frameworks	Flexible structure that can combine advantages of several methods in complex renewable systems.	Can be difficult to tune, validate, and compare fairly; implementation may be demanding.	Hybrid renewable systems, DFIG wind systems, and multi-objective microgrid control; moderate to high computation; moderate real-time suitability.

7.2 Comparison by Performance Criteria

Performance is the evaluation aspect that appears most often across the studies reviewed herein, although its meaning often changes by application area (e.g., photovoltaic, wind-energy, microgrid applications). In the case of photovoltaic systems, performance is generally expressed through MPPT speed, oscillation reduction, accuracy of tracking and behavior in partial shading [1], [3], [4], [7], [8], [22]. For wind-energy systems, it more closely relates to output-power regulation, pitch angle behavior, and dynamic response in varied wind situations [5], [11], [12], [14], [18]. For microgrids, performance relies on assessing voltage stability, converter coordination, and power quality improvements, for example, rather than on just one tracking variable only [6], [9], [10], [28], [31]. Thus, the concept of enhanced performance does not mean the same thing for every application area under the renewable-energy sector. Robustness is another evaluation aspect that is discussed in conjunction with the use of hybrid control.

Classical fixed-structure control types generally perform well at nominal operating points.

However, most renewable-energy systems are utilized at various environmental or electrical conditions. Studies in the section have indicated that hybrid control is applied when a fixed-tuning method seems inadequate [17], [18], [19], [21], [23]. In the case of photovoltaic systems, this occurs generally due to partial shading or environmental variations such as irradiance [3], [4], [7], [22], [38], [41]. Wind-energy systems face problems regarding turbulence, speed variations and unknown aerodynamic behavior in many instances [5], [12], [18]. In the case of microgrid-related applications, robustness is challenged because of entire system interactions, that is, its constituents, storage, and loads [2], [6], [9], [10], [17], [32]. Therefore, robustness is established as an important reason for hybrid control adoption.

The other comparison criterion concerns computational burden and practicality of implementation. Clearly, several studies deal with improved regulation or disturbance rejection and tracking performance; however, only a few address issues related to hardware, training cost, input and output requirements for sensors.

Nevertheless, this is a key limitation since a good controller may turn out to be impractical even in simulation for the cases of real-world situations concerning the use of renewable energy systems [27]–[29].

7.3 Recurring Limitations in the Literature

A common limitation that emerges from all studies surveyed in this review is heavy reliance on simulation-based validation. Simulation plays an important role in the design of the controllers but, in many cases, it serves as the only validation approach.

This makes it hard to assess whether the performance gains observed in a given study would be sustained in the presence of hardware limitations, noisy measurements, delays in communication, and nonlinearities in converters or computational limitations [3], [6], [9], [11], [27], and [29]. Another limitation is the lack of a broad cross-family benchmarking effort. Although several studies compare the proposed approach to a limited number of conventional methods, fewer evaluate many families of control against each other.

This is a critical issue in the light of the fact that the control performance on renewable energy systems can depend largely on the application area, disturbance patterns, operating point, and performance measure defined for each specific case.

Without additional benchmarking, it is impossible to know whether the improvement seen is due to the proposed techniques or only attributed to the scenario being investigated [1], [2], [5], [7], [10], and [12]. Another limitation has to do with the deployment-oriented discussions offered in many publications.

While these documents may do a good job of presenting new control techniques, they are often very weak in explaining how to implement these techniques [27]–[29].

8. Research Gaps and Future Directions

From the literature reviewed, it can be concluded that whilst marked progress has been achieved on the use of AI techniques to generate hybrid control for renewable energy systems, there remains a considerable number of research gaps that exist. The research gaps identified by the literature under review should not be regarded as indicating lack of development within the research area in general. On the contrary, they reflect some inconsistencies in development between different control techniques, application areas, and forms of validating the research [1], [2], [7], [12], [13]. There is a sizeable amount of suggested control techniques, but not so much in terms of comparing different concepts, realism in implementation, and standards for assessing the implementation of various systems [2], [3]–[14]. Figure 5 provides an overview of the main research gaps that come from the literature reviewed in this study, including suggestions for future research directions.

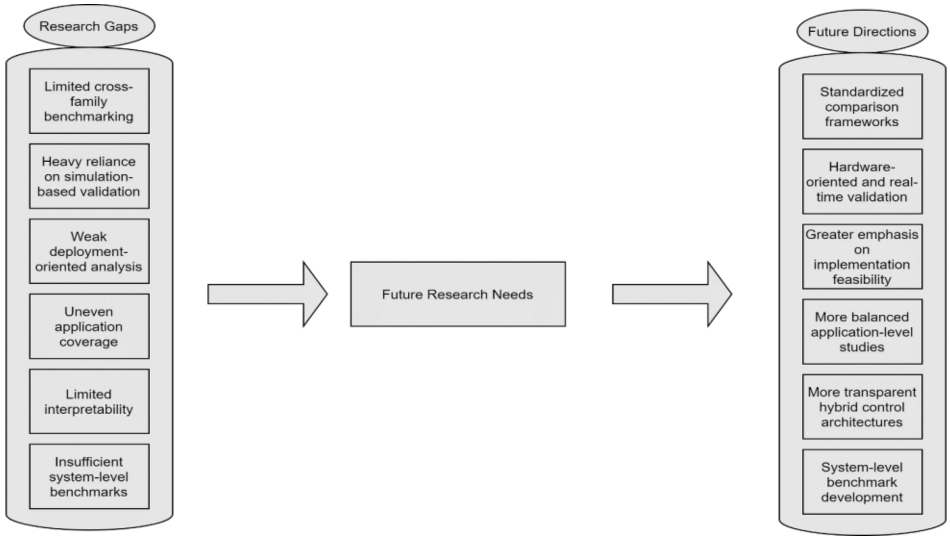

Figure 5. Conceptual map of the main research gaps and future directions in AI-based hybrid control for renewable energy systems.

8.1 Main Research Gaps

An essential drawback of the presented literature is the insufficient implementation of systematic cross-family references. There are a lot of papers, which make comparisons between proposed controllers and one or two common standards, but very few papers test PID-based controllers, neural networks or fuzzy logic controllers, robust and predictive hybrid controllers within the same renewable energy system and prescribed conditions. Therefore, sometimes it is hard to see whether the enhancement is a result of the implementation of a more efficient control scheme or just some lucky testing conditions [1], [2], [5], [7], [10], [12].

Validation procedural issues. A great number of papers show wonderful results in terms of validation, however, validation methods for photovoltaic, wind or microgrid applications have been mostly limited to MATLAB/Simulink or closely related software tools. Simulation is very helpful at the initial state of development of the controller but cannot represent in a full measure the sensor noise, communication time delay, constraints on embedded implementation, non-idealities of the converter, and others [3], [6], [9], [11], [27], [29]. Further gap lies in deployment-oriented analysis. A great number of authors describe their hybrid algorithms only as a way of achieving better performance, omitting such important issues as controller complexity, data requirements for development, tuning necessities, and real-time feasibility of their system.

There are many important issues in renewable-energy control since a controller that is accurate/robust in theory is not necessarily practical. The practical implementation of a controller involves computational cost, sampling-time feasibility, availability of measurements, tuning efforts, and compatibility with embedded converter-control hardware. To clarify this issue of implementation, Figure 6 below summarizes the validation maturity vs. deployment readiness of the studies reviewed in this chapter in main application areas. As shown in the figure, the most common method of validation available in the literature is simulation, while field implementation, hardware-in-the-loop measurement, and experimental real-time implementation are not mentioned. Thus, it can be concluded that algorithms have been progressed at a relatively higher rate than the actual implementations of these algorithms. Therefore, more attention should be given in future research to prove the controller performance under operating constraints such as measurement noise, sampling limits, nonlinear characteristics of the converter, delays in communication, and the limitations on the hardware resources.

Application domain	Simulation	Hardware-in-the-loop (HIL)	Experimental / real-time validation	Field deployment
PV systems MPPT, fuzzy/ neuro-fuzzy	High	Limited	Some	Rare
Wind systems robust MPC, AI-tuned PID	High	Limited	Limited	Rare
Microgrids ANN, fuzzy, ANFIS-PSO	High	Limited	Limited	Rare
Hybrid RES multi-source coordination	High	Rare	Rare	Rare

The qualitative levels indicate the relative presence of each validation type in the retained literature, based on the evidence matrix of the reviewed studies.

Figure 6. Evidence maturity and deployment-readiness map of AI-based hybrid control studies in renewable-energy systems.

The reviewed literature also shows an imbalance across application areas. Photovoltaic control, particularly MPPT, is strongly represented, while other domains are less evenly developed. Wind-energy studies are substantial, but many of them are concentrated around pitch control, power regulation, and DFIG-based systems [5], [11], [12], [18]. Microgrid studies are diverse, but they often differ greatly in structure, objective, and evaluation criteria, which makes direct comparison difficult [15], [17], [26], [32], [42]. This uneven coverage means that some controller families may appear stronger partly because they have been tested more often in mature and well-defined application settings [2], [3]–[7].

8.2 Future Directions

To ensure that there is a controlled framework, it would be highly beneficial in future research to have an agreed-upon standard against which different families of controllers can be compared. This standard should include different renewable energy applications, disturbance types, operating conditions of the controller under different performance criteria. This way, one would know if the hybrid intelligent controller is universally applicable or limited in scope [1], [2], [7], [12], [43]. There should be more validation in terms of hardware and real-time functioning as outlined in the studies, focusing on embedded implementation, converter level, hardware in loop simulations, etc.

This is especially important in the area of intelligent and optimization-based paradigms since one cannot determine the utility of the reported results only based on simulation data [27]–[29].

Another vision for the future would be to make a trade-off between performance and explainability. Hybrid control strategies can be complex, particularly with the addition of neural networks or optimization layers, which could become a barrier to a practical application of the new technology if the decision-making is not sufficiently clear and understandable for engineering design, tuning, and troubleshooting reasons. The hybrid strategy that combines the adaptability and transparency of the controller is likely to be very much helpful in the area of renewable energy applications [10], [11], [13], [14], [32]. There is also another research direction that needs to be addressed, namely integrating robustness with intelligent adaptation more directly as it is seen in the studies conducted in the area of wind energy systems and microgrids [5], [6], [11], [12], [17]–[19], [21].

Finally, a more comprehensive approach and integrated renewable energy frameworks should be developed in future research initiatives to provide a more realistic evaluation of hybrid intelligent control, given that hybrid renewable energy systems and microgrids consist of many interactions, converters, energy storage devices, and energy consumption units. In conclusion, all the research gaps mentioned above, together with their characteristics and possible extensions of this study, have been summarized in Table 4.

Table 4. Main research gaps and future directions in AI-based hybrid control for renewable-energy systems.

Research gap	Why it matters	Affected domains	Suggested future direction
Limited cross-family benchmarking	Makes fair comparison difficult and may overstate method-specific gains	All domains	Standardized evaluation frameworks across controller families
Heavy reliance on simulation-based validation	Leaves uncertainty about hardware feasibility and real-world robustness	PV, wind, microgrids, hybrid systems	More hardware-in-the-loop, embedded, and experimental validation
Weak deployment-oriented analysis	High-performing methods may still be impractical to implement	All domains	Greater focus on sensing needs, complexity, computation, and controller integration
Uneven application coverage	Some methods appear stronger partly because they are studied more often in mature domains	Especially PV vs. other domains	More balanced studies across wind, microgrids, and hybrid renewable systems
Limited emphasis on interpretability	Complex intelligent methods may be difficult to tune, trust, and deploy	Neural and optimization-heavy methods	Development of more transparent hybrid control architectures
Insufficient integrated system benchmarks	Single-device studies may not reflect realistic renewable operation	Hybrid systems, microgrids	More system-level benchmark cases with interacting sources, storage, and loads

9. Conclusion

The current study evaluates the advancements in the field of artificial intelligence (AI)-based hybrid controls for systems that employ renewable energies, particularly focusing on photovoltaic, wind energy, microgrid, and combinations of renewable energy systems. Research in AI-based hybrid control suggests that its increased popularity can be attributed to the limitations of conventional individual control systems when faced with nonlinearity, intermittency, uncertainties, the need to integrate with grid systems, as well as varying operations [3]–[14].

When viewed from the perspective of the different families of controllers, it can be argued that AI-based hybrid controls are considered as a collection of related design approaches, rather than as a single approach.

The traditional PID-type systems, however, are still relevant since AI methods can improve them through intelligent tuning and optimization without losing simplicity and effectiveness. While the neural network-based methods allow more flexibility, they require more training and practical implementation. Fuzzy and neuro-fuzzy controllers represent a useful approach in that they involve some adaptive capabilities while being relatively simple and understandable. AI predictive methods, as well as the methods based on optimization, are mainly focused on disturbance rejection, dynamic stability, and variations in the operating region when they are applied [3]–[14].

In terms of applications, the research works conducted on photovoltaic systems effectively deal with implementation of intelligent and hybrid MPPT due to changes in irradiation and partial shading, whereas the wind energy systems studies principally consider robust and adjustable turbine management including pitch control, power management, and dynamic response.Microgrid and hybrid renewable-energy research emphasizes more on issues related to voltage regulation, power quality, control of converters, interaction of storage devices, and multi-source operation. These aspects highlight that the efficacy of a given family of controllers is not only dependent on the algorithmic format that is employed, but also on the specific application domain, objective of control, as well as the constraints in operation.

The analysis has also revealed some persistent limitations. A number of studies still depend largely on simulation-based validation while comparative studies across different families of controller designs remain rather limited. Furthermore, implementation-related issues such as complexity of the controller, sensing requirements, computation burden, and real-time applications are still not discussed adequately. Therefore, it is necessary to move towards standardized framework for comparison, more emphasis on hardware-based validation, better assessment of robustness and stability, as well as more pragmatic systems for validation in the fields of microgrid and hybrid renewable systems.

One of the major implications of this analysis is that no controller family can be considered to the best across all applications in renewable energy. The choice of controller has to be made on the basis of various parameters such as dynamics of the plant, level of uncertainty, measurements available, computational resources, as well as the degree of interpretability required. In certain practical situations, simpler hybrid approach may be preferred over an elaborate one, even if the latter performs better in the simulation environment. To sum up, AI-based hybrid controller design is one of the important avenues in renewable energy control research. Not only does it improve regulation and tracking performance but it has also found application in expanding the operating range of renewable energy systems under uncertain and variable conditions.

Appendix A. **Evidence Matrix of Retained Studies**

Appendix A provides a compact evidence matrix for the 45 studies retained in this review. The appendix supplements the main comparative discussion by listing, for each study, the application domain, control objective, controller family, AI or hybrid technique, validation type, principal contribution, and main limitation. To preserve consistency with the application-based discussion in Section 6, the retained studies are grouped into four subsections: photovoltaic systems, wind energy systems, microgrids and multi-microgrid systems, and hybrid renewable energy system.

9.1 A.1 Photovoltaic Systems

9.2 Tables A1a and A1b summarize the retained studies related primarily to photovoltaic-system control, especially MPPT, inverter-side regulation, and PV-integrated control settings.

Table A1a. Evidence matrix of retained studies in photovoltaic systems (Part I)

Ref.	Year	Domain	Control objective	Controller family	AI / hybrid technique	Validation type	Main contribution	Main limitation
[1]	2024	Photovoltaic inverter systems	Inverter control and intelligent optimization	Review / hybrid intelligent control	Review of PV inverter control and intelligent optimization methods	Review	Broad review of intelligent optimization and control directions for PV inverter systems	Review-based evidence; not a single directly comparable benchmark

[3]	2020	PV system in microgrid	MPPT	Fuzzy / neuro-fuzzy	Adaptive neuro-fuzzy feedback linearization	Simulation	Improved MPPT by combining adaptive control with neuro-fuzzy modeling	Limited to PV MPPT and mainly simulation-based
[4]	2024	Grid-connected PV system	GMPPT / MPPT under partial shading	Fuzzy / neuro-fuzzy	Neuro-fuzzy control with gravity search algorithm	Simulation	Improved tracking speed and output performance under uniform and partial shading	Application-specific and mainly simulation-based
[7]	2023	Solar PV systems	MPPT under uniform and partial shading	Review / MPPT methods	Review of conventional and emerging MPPT algorithms	Review	Consolidated MPPT methods and clarified strengths/weaknesses under shading	Review-based evidence rather than one directly tested controller
[8]	2023	Commercial PV system	MPPT	Fuzzy control	Fuzzy-logic MPPT control	Real-time experimental	Real-time validation showed reduced oscillation and improved response	Limited to PV MPPT and a single application setting
[22]	2023	Stand-alone PV system	Robust MPPT	Robust / adaptive control	Adaptive self-adjusting fractional-order PID	Simulation	Improved MPPT robustness under changing conditions	Narrow focus on MPPT and controller tuning
[25]	2023	Solar-PV inverter / power system interface	Stability and intelligent MPPT-linked inverter behavior	AI-assisted conventional / intelligent MPPT	Intelligent MPPT control of DC-link capacitor voltage	Simulation	Linked PV inverter stability with intelligent MPPT-oriented control	More specific to inverter/DC-link context than broad PV control

Table A1b. Evidence matrix of retained studies in photovoltaic systems (Part II)

Ref.	**Year**	**Domain**	**Control objective**	**Controller family**	**AI / hybrid technique**	**Validation type**	**Main contribution**	**Main limitation**
[30]	2023	Grid-connected PV system	Controller comparison for PV regulation	Conventional vs neural comparison	PI vs ANN control comparison	Comparative simulation	Compared classical and neural control for grid-connected PV behavior	Comparative scope narrower than broader hybrid-controller synthesis

[33]	2025	Grid-integrated PV with battery management	PV control and battery-management coordination	Neural-network-based control	Reinforcement neural network-based PV control and BMS	Simulation	Used learning-based control for grid-integrated PV and battery management	More complex architecture and implementation demands
[34]	2024	PV systems with DC/DC converters	MPPT across converter types	Neural-network-based control	RBF neural-network-based MPPT	Simulation	Compared converter types under RBF-NN-based MPPT	Converter-specific scope and simulation-oriented validation
[37]	2019	Photovoltaic system	MPPT	Fuzzy / neural hybrid	Fuzzy neural network MPPT	Simulation	Applied fuzzy-neural reasoning to PV MPPT	Older study and mainly focused on one PV control task
[38]	2025	Photovoltaic systems	Global MPPT	AI-based control	Artificial-intelligence-based global MPPT	Simulation / comparative	Addressed global MPPT under difficult PV operating conditions	Focused mainly on MPPT rather than wider PV control architecture
[39]	2025	Grid-connected PV systems	AI-enhanced MPPT	Fuzzy / optimization hybrid	ANFIS-PSO optimization for MPPT	Simulation	Combined ANFIS and PSO to improve MPPT accuracy and adaptability	Increased algorithmic complexity
[41]	2025	Photovoltaic panels	MPPT algorithm comparison	Comparative control study	Classical vs AI algorithm comparison	Comparative study	Compared classical and AI MPPT algorithms for PV optimization	Comparison-oriented study rather than one unified controller design

A.2 Wind Energy Systems

Table A2 summarizes the retained studies related primarily to wind-energy-system control, including pitch-angle regulation, turbine robustness, generator-side control, and output-power stabilization.

Table A2. Evidence matrix of retained studies in wind energy systems

Ref.	Year	Domain	Control objective	Controller family	AI / hybrid technique	Validation type	Main contribution	Main limitation
[5]	2023	Wind turbine system	Output-power stabilization under varying wind speeds	Robust / predictive	Robust MPC with Bayesian parameter self-optimization	Simulation	Improved wind-turbine performance through robust predictive control with adaptive parameter tuning	Higher model and optimization complexity; focused on wind systems
[11]	2025	DFIG-based wind energy system	Dynamic regulation and performance improvement	PID-hybrid / hybrid intelligent	PI-ANFIS-fuzzy-PSO control	Simulation	Enhanced dynamic response and operating performance under changing wind conditions	Complex hybrid structure and wind-specific focus
[12]	2025	Wind energy systems	Intelligent pitch-angle control	Review / intelligent control survey	Review of intelligent pitch-control frameworks	Review	Clarified main intelligent-control directions in wind pitch regulation	Review-based evidence rather than one directly comparable control benchmark
[14]	2025	Wind power generation system	Online PID parameter optimization	AI-tuned PID	Genetic-algorithm-based PID tuning	Simulation / implementation-oriented	Improved PID behavior through online gain optimization	Narrow controller focus and application-specific scope
[18]	2021	Variable-speed wind turbine	Adaptive robust pitch control with load mitigation	Robust / adaptive control	Optimal adaptive robust pitch-control formulation	Simulation	Improved load mitigation and uncertainty handling in wind control	Focused on pitch-control problem rather than broader system coordination
[40]	2024	DFIG-based	Fault-tolerant	Robust / intelligent control	Self-tuning fractional integral	Simulation	Combined adaptation and	More specialized fault-

		wind turbine	control under faults		sliding-mode control		robustness for DFIG fault-tolerant control	tolerant setting than general wind-control benchmark

A.3 Microgrids and Multi-Microgrid Systems

Tables A3a–A3c summarize the retained studies related primarily to microgrid and multi-microgrid control. These studies mainly address voltage regulation, power quality, converter coordination, frequency support, and energy-management-related control in networked renewable-energy environments.

Table A3a. Evidence matrix of retained studies in microgrids and multi-microgrid systems (Part I)

Ref.	Year	Domain	Control objective	Controller family	AI / hybrid technique	Validation type	Main contribution	Main limitation
[6]	2023	Hybrid AC/DC smart microgrid	Converter coordination, voltage regulation, and MPPT	Hybrid intelligent control	ANFIS-PSO-assisted cooperative control with PR controller	Simulation	Combined intelligent tuning and converter control to improve voltage profile and tracking behavior	Structurally complex and mainly simulation-based
[9]	2022	Multi-microgrid clusters	Power-quality improvement	Fuzzy / neuro-fuzzy	Adaptive neuro-fuzzy control strategy	Simulation	Improved power-quality indices relative to PI and fuzzy controllers	Focused mainly on power-quality metrics and simulation evaluation
[10]	2022	Microgrids	Energy management and voltage control	AI-assisted conventional control	ANN, PID, and fuzzy logic controllers	Comparative simulation	Compared ANN-, PID-, and fuzzy-based approaches for microgrid energy-management and voltage-control tasks	Broader management/control scope; less focused on a single benchmark
[15]	2019	Microgrid with PV	Power-quality improvement	Intelligent conventional / hybrid control	Intelligent controller with	Simulation	Improved microgrid power quality for	Older study and narrower application-

		integration			multilevel inverter		PV integration	specific benchmark
[17]	2022	Microgrid with high renewable penetration	Frequency regulation / virtual inertia control	Robust / optimal control	Robust optimal virtual inertia control	Simulation	Improved microgrid frequency response under high renewable penetration	Focused on frequency regulation and inertia emulation only
[19]	2025	Hybrid microgrid	Load-frequency control	Fuzzy / robust control	Type-3 fuzzy logic control	Simulation	Strengthened load-frequency regulation under stochastic variation	Focused mainly on frequency-control problem

Table A3b. Evidence matrix of retained studies in microgrids and multi-microgrid systems (Part II)

Ref.	Year	Domain	Control objective	Controller family	AI / hybrid technique	Validation type	Main contribution	Main limitation
[21]	2026	Power systems / microgrid LFC context	Robust load-frequency control under renewable disturbances	Adaptive / predictive control	Adaptive MPC / AMPC	Simulation	Improved load-frequency control under uncertainty and renewable disturbances	Narrow to frequency-control benchmark; limited broader deployment discussion
[23]	2026	Sustainable islanded microgrid	Event-triggered load-frequency control	Robust / optimization-assisted control	Adaptive optimizer-based event-triggered LFC	Simulation	Reduced control burden while improving islanded microgrid frequency regulation	Optimization-heavy and scenario-specific
[24]	2020	Isolated microgrid	Power-quality enhancement	Adaptive intelligent control	Adaptive D-FACTS with optimized PID/ASFC structure	Simulation	Improved microgrid power quality and dynamic voltage performance	Mainly simulation-based and device-specific
[26]	2024	Hybrid three-terminal	Power-quality	Conventional / structured	Control-oriented improvem	Simulation	Improved power quality in	More system-specific and less

		AC/DC microgrid	improvem ent	advanced control	ent of hybrid AC/DC microgrid PQ		hybrid AC/DC microgrid operation	focused on AI depth
[28]	202 1	DC microgrid	DC/DC converter voltage control	Neural-network-based control	ANN-based voltage control of DC/DC converter	Experimen tal / conference study	Applied ANN-based regulation to DC microgrid converter control	Narrow converter-level scope
[29]	202 1	DC microgrid	Sensorless microgrid control	AI-based control	Artificial-intelligenc e-based sensorless control	Simulation / experiment al	Reduced sensing dependenc e through AI-based microgrid control	Specialized sensorless setting rather than broad controller comparison
[31]	202 3	Microgrid voltage stabilizati on	Voltage control	Neural / PID-hybrid	PID neural network with PEO-GA optimizati on	Simulation	Improved voltage stabilizati on using optimized PID neural network weights	Optimization/trai ning burden and limited generality

Table A3c. Evidence matrix of retained studies in microgrids and multi-microgrid systems (Part III)

Ref .	Yea r	Domain	Control objective	Controll er family	AI / hybrid technique	Validatio n type	Main contribution	Main limitation
[32]	202 5	Microgrid	Frequency adjustment	Fuzzy / robust control	Fuzzy-robust joint controller design	Simulatio n	Improved frequency regulation with combined fuzzy and robust logic	Focused primarily on one microgrid control objective
[35]	202 4	DC microgrid with renewable integration	Energy manageme nt and nonlinear control	Neural-network-based control	Neural-network energy-management-based nonlinear control	Simulatio n	Addressed nonlinear DC microgrid control with renewable integration	More complex architecture and implementation demands
[36]	202 4	Power converters for microgrid-	Droop control	Neural-network-	Neural-network-based droop	Simulatio n	Proposed intelligent droop control for	Converter/contr ol-layer focus rather than full

		related operation		based control	control strategy		converter operation	system benchmark
[42]	2024	Adaptive microgrid optimization	Adaptive microgrid control	Hybrid intelligent control	Rule-based plus deep-learning hybrid control	Simulation	Combined rule-based control with deep learning for adaptive microgrid optimization	Complexity and interpretability challenges
[43]	2025	Microgrid systems	Energy management	Review / bio-inspired intelligent control survey	Comprehensive review toward bio-inspired approaches	Review	Synthesized resilience- and sustainability-oriented microgrid energy-management directions	Review-based evidence; less centered on one comparable controller benchmark
[44]	2024	Microgrid systems	Power stability and control	Hybrid / multi-paradigm control	Multi-paradigm modelling and control	Simulation / case study	Addressed microgrid power stability through integrated modelling and control	Broad systems scope with less emphasis on one sharply defined controller family

A.4 Hybrid Renewable Energy Systems

Table A4 summarizes the retained studies related primarily to hybrid renewable-energy systems or broader multi-source renewable configurations. These studies emphasize source interaction, integrated performance, hybrid architectures, and system-level coordination across multiple renewable components.

Table A4. Evidence matrix of retained studies in hybrid renewable energy systems

Ref.	Year	Domain	Control objective	Controller family	AI / hybrid technique	Validation type	Main contribution	Main limitation
[2]	2023	Renewable-power-system integration	Intelligent integration and performance evaluation	Review / intelligent techniques	Review of intelligent techniques for renewables integration	Review	Provided broad implementation-oriented perspective on intelligent renewable integration	Review-based evidence; not a single directly comparable benchmark
[13]	2023	Renewable and energy-storage-integrated power systems	Advanced controller review	Review / advanced control survey	Fractional-order control review	Review	Summarized fractional-order control techniques across renewable and storage-	Review-oriented and not limited to AI-hybrid control only

							integrated systems	
[16]	2025	PV/wind smart grid	Power quality enhancement	Neural / intelligent hybrid control	Inverter control with ANN techniques	Simulation	Improved smart-grid power quality using AI-supported inverter control	Broader smart-grid framing and system-specific setup
[20]	2024	Interconnected power system with integrated renewables	Automatic generation control	Fuzzy / PID-hybrid	Robust fuzzy-PID technique	Simulation	Improved AGC performance with renewable-source integration	Focused on AGC benchmark rather than broader hybrid-system coordination
[27]	2025	Grid-connected PV-battery system with V2G/G2V	Predictive energy and converter control	Neural / predictive hybrid	Neural-network-based MPC	Simulation	Combined MPC and neural-network ideas for PV-battery-grid operation	Higher implementation and computational complexity
[45]	2025	Hybrid renewable microgrids	Design and flexibility of hybrid renewable systems	Review / hybrid renewable systems survey	Comprehensive review of hybrid renewable microgrids	Review	Synthesized design parameters, optimization, and flexibility issues in hybrid renewable microgrids	Review-based evidence; broader systems scope than control-only benchmark

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