ARTIFICIAL INTELLIGENCE BASED CONTROL SYSTEMS FOR ROBOTICS AND RENEWABLE ENERGY APPLICATIONS

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DOI: https://doi.org/10.5281/zenodo.20215699

Keywords
Artificial Intelligence; Control Systems; Electrical Engineering; Intelligent Control; Machine Learning

Article History
Received: 16 April 2026
Accepted: 11 May 2026
Published: 13 May2026

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Abstract
The high development rate and growing complexity of current systems in electrical engineering prompted the incorporation of artificial intelligence-oriented approaches to control mechanisms, which have the potential to manage non-linear dynamics, uncertainties of the system, and changing operating environments in an effective manner. In this manuscript, we present a detailed narrative review of recent progress in AI-based methods of control with a specific emphasis on the implementation of the methods in the context of robotics and renewable energy systems. The review discusses major intelligent control paradigms among them artificial neural networks, fuzzy logic control, reinforcement learning, evolutionary optimization techniques and hybrid intelligent control structure. The literature survey is organized by the main areas of applications including robotic motion and trajectory control, renewable energy conversion systems, microgrid operation, and power electronic applications. Moreover, the paper gives a critical comparison of AI-based controllers against the traditional control methods including Proportional Integral Derivative, Linear Quadratic Regulator, H∞ control highlighting the variations of adaptability, robustness, computational load, and model transparency. Significant constraints associated with data accessibility, operational safety, explain ability as well as real-life use are also considered in more detail. Lastly, the we provide practical implications and the prospective areas of research that can be used to support the concept of creating dependable, effective, and scalable AI-based control solutions. The work is also meant to have a good reference to researchers and practitioners involved in intelligent control application in the field of robotics and renewable energy.

1. Introduction

The increasing complexity of electrical and robotic systems has been motivated to find new control strategies beyond classical Proportional Integral Derivative (PID), state-space or linear-quadratic control approaches. Conventional controllers are effective in familiar well-defined linear environments, but in high uncertainty, severe nonlinearities and changing environments. Conversely, AI-based control methods (neural networks, fuzzy systems, reinforcement learning, etc.) are able to learn using data and adjust to changes over time on-the-fly, increasing their resilience and performance when trained in problematic environments. In fact, Fernandez Mareco et al. [1], discuss the present-day intelligent control technologies, which include fuzzy logic, hybrid neuro-fuzzy controllers, evolutionary optimization, and deep reinforcement learning are some of the most commonly implemented in the context of intelligent control. These AI techniques have proved to be highly useful where AI is deployed in power grid management applications or autonomous robotics. As an example, Mareco states that fuzzy systems and neural nets are popular in controllers in the area of renewable energy and robotics. Likewise, Irigoyen et al. [2], highlight that smart control systems have developed and been put to successful application in industrial automation, renewable generation and service/assistive robotics. Due to this popularity, this review summarizes and compares the latest AI-based methods of control, with particular attention to robotics and renewable energy applications. We spot the trends in algorithms and applications, systematize the literature and provide comparisons between approaches. This study discusses the article, AI in Control Systems for Electrical Engineering that explores the application of intelligent algorithms to enhance the effectiveness of control. We highlight the two key areas of application, robotics, and renewable energy systems, where AI has had an influence. We aim to provide a summary of background notions, overview the literature along with the themes, juxtapose AI and traditional approaches, and address the emerging trends.

The rest of the paper is organized in the following manner:

- Section 2, will give a background on control systems and AI techniques.
- Section 3, examines the recent studies according to themes (robotics control, renewable energy, predictive maintenance, optimization).
- Section 4, contains a comparative analysis of approaches.
- Section 5, talks about Design Guidelines and Lessons learned.
- Section 6, discussion about control summary of representative AI, traditional vs AI-based control studies and Section 7, ends with conclusion.

2. Background

2.1 Control Systems in Electrical Engineering

A control system is developed to control the dynamics behavior of a dynamic process in order to guarantee steady state operation or attain performance attainment of the process. In electrical engineering, control mechanisms are also important in the control of power electronic converters, electric drives, power systems and robotic manipulators. The traditional methods of control can be PID controllers, commonly implemented to do feedback-based stabilization, and state-space methods, such as the Linear Quadratic Regulator (LQR), that seeks to balance the performance of a system in an optimal way. Besides, robust control schemes, such as the $H\infty$ control, and adaptive control schemes, are also designed to address parameter variations and external disturbances. Even though they are effective, such techniques usually depend on precise mathematical model representations of the system dynamics; thus, modeling errors, nonlinearities not modeled, or uncertainty in the values of parameters can severely impact the performance of the controllers. Furthermore, the growing popularity of multivariate systems and high degree of freedom robotic platforms poses additional constraints to the traditional approaches to control design [1, 31].

2.2 Artificial Intelligence Techniques

Artificial Neural Networks (ANNs) are a key AI tool in control. ANNs have the ability to estimate nonlinear dynamics of arbitrary systems and use error feedback to adjust their weight. A neural controller can learn to model or control a system, even where no analytic model of the system exists, through the input-output evidence. ANNs are commonly applied for system identification and adaptive control in complex environments. For instance, a multilayer perceptron can learn a motor's inverse dynamics, enabling model-free control of a manipulator. The downside is that neural controllers require training data and can be "black box" (low interpretability) compared to classical designs.

Fuzzy logic (FL) provides another intelligent control approach by encoding expert knowledge in rule-based form. Fuzzy controllers use membership functions and linguistic rules to handle imprecise inputs and uncertainty. They do not require precise mathematical models; instead, they blend fuzzy IF–THEN rules to make decisions smoothly. For example, a fuzzy controller can robustly regulate a robot joint under noisy sensor inputs. The strengths of fuzzy control include interpretability and tolerance of ambiguity but rules and membership functions are often tuned by hand or heuristic methods, which can be time-consuming.

Evolutionary algorithms (EAs) and swarm intelligence (e.g. genetic algorithms, particle swarm) are widely used for optimizing control parameters. By using population-based search (selection, crossover, mutation), these metaheuristics can efficiently tune controller gains, optimize fuzzy rule bases, or design neural network weights when gradient information is not available [1] [18]. For instance, GA or PSO can find optimal PID gains to minimize control error, or evolve membership functions in a fuzzy controller. EAs offer global search and can escape local minima, but they typically require many function evaluations.

Model Predictive Control (MPC) is a popular advanced control strategy where a dynamic model predicts future behavior and an optimization problem is solved in real time [1]. MPC is effective for multivariable processes with constraints. In intelligent control, MPC is often combined with AI components: e.g. a neural network model may be used inside MPC for nonlinear predictions, or MPC may act as a high-level planner for a reinforcement learner. Overall, MPC brings optimality and constraint-handling to control, though it demands computational resources for online optimization [1].

Reinforcement Learning (RL) is an AI approach in which an agent learns a control policy by interacting with the environment. Unlike supervised learning, RL does not require labeled output data; instead, it maximizes a reward signal over time. RL has shown promise for controlling complex or unknown systems, because it can learn without a prior model. In power systems, safe RL methods have been proposed to handle uncertainty from renewables [9]. Annaswamy notes that adaptive control provides formal stability guarantees in real time, whereas RL can attain near-optimal policies for complex tasks after extensive (often offline) training [15]. Thus, RL controllers can achieve high performance, but they require large datasets and safety precautions (to avoid dangerous exploration) [9] [15] . In robotics, RL enables dynamic behaviors (e.g. locomotion, manipulation) by learning from trial-and-error, though transferring policies from simulation to real robots remains challenging.

Hybrid approaches combine these AI methods to exploit complementary strengths [1]. A common hybrid is neuro-fuzzy, where a neural network tunes a fuzzy inference system. This yields adaptive fuzzy controllers with learned membership and rule weights[17]. Another example is evolutionary-fuzzy, where a GA optimizes fuzzy rules or membership functions. In complex control tasks, such hybridization often improves robustness: e.g. combining ANN learning with fuzzy interpretability or combining MPC with an outer RL loop.

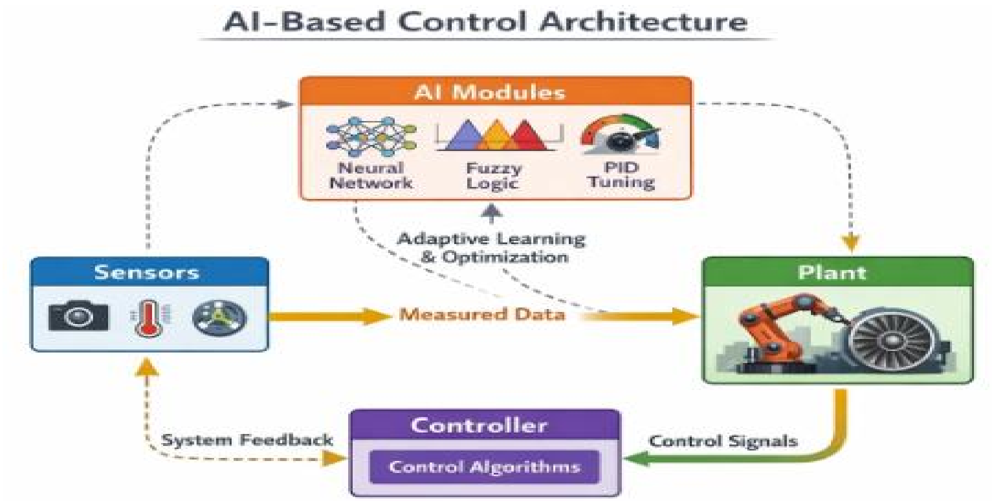

Figure 1: Illustrates a conceptual intelligent control architecture that integrates classical and AI components.

2.3 Review Methodology

The literature review that was chosen as part of the current research takes on a structured narrative review format that would provide the full and objective picture of the recent investigation into AI-based control methods in robotics and renewable energy systems. Regarding the wide coverage of high-quality academic literature, the main scientific databases such as IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Google Scholar were searched thoroughly. The search strategy used different combinations of the keywords that were of relevance including artificial intelligence control, intelligent control systems, robotics control, renewable energy control, machine learning, fuzzy logic, and reinforcement learning. A focus was made on peer-reviewed journal articles, credible review papers, and already established conference proceedings published primarily between 2015 and 2026, with some older studies being selected to define the background views.

First queries of the database provided a big sample of publications, which were narrowed down to a relevancy-based screening procedure. The studies were included when they focused on the design, implementation or evaluation of AI-based control measures in the application in robotics, renewable energy systems, power electronics, and smart grid infrastructures. Articles that only describe theoretical AI advances and offer no real control-system applications, to the point that they are not technical enough, were dismissed also. The last group of chosen literature was arranged thematically according to the areas of both applications like robotic control, renewable and power systems, microgrids and predictive maintenance and methodologies used to achieve the latter like neural networks, fuzzy logic, reinforcement learning, evolutionary optimization and hybrid intelligent methods. After the selection, the identified studies were analyzed using qualitative analysis and common patterns, described benefits, practical constraints, and unaddressed research questions were identified. The comparative assessment was conducted by assessing performance metrics, flexibility, stability, computational and interpretability of AI-engines based controllers against the traditional control methods. This review does not involve quantitative meta-analysis rather, it places more emphasis on engineering-based insights, design, and practical lessons, based on real-world applications that allows one to make a meaningful comparison of control strategies under different operating conditions.

3. Literature Review

3.1 AI for Robotics Control

Robotic systems demand precise and adaptive control for tasks like locomotion, manipulation, and human–robot interaction. AI methods have been increasingly applied in these domains. Neural networks and deep learning enable robots to handle high-dimensional sensor data: for example, Pierson and Gashler note that deep neural networks can form compact representations of raw, multimodal sensor inputs (vision, LIDAR, etc.) and approximate the robot's nonlinear dynamics. Deep networks have been used for end-to-end control policies in mobile robots and quadrotors. Tang et al. [4], surveyed recent successes of deep reinforcement learning (DRL) in robotics and report that tasks like drone racing and quadruped locomotion have been achieved in simulation or real-world trials, However, Tang et al. also caution that many DRL breakthroughs remain in simulated environments, and applying DRL on physical robots poses safety and sample-efficiency challenges. In summary, deep ANN controllers give powerful function approximation for robots but require large training datasets and cautious real-world deployment.

Fuzzy logic has also been applied in robotic control, especially where linguistic rules or uncertainty handling are beneficial. For instance, Autsou et al. [5] review the use of fuzzy logic in collaborative (cobot) robot control and conclude that fuzzy rules can improve adaptability in human–robot interaction. They note that combining fuzzy inference with machine learning or evolutionary algorithms can further enhance robustness. Zahedi and Zahedi [17] similarly discuss neuro-fuzzy systems in robotics; they explain that a fuzzy controller encodes human-like "if-then" rules, while a neural network can learn to adjust those rules from experience. This neuro-fuzzy approach leverages the interpretability of fuzzy logic with the learning ability of neural nets. On the other hand, pure fuzzy controllers rely on hand-designed rules, so they may not scale well to very high-dimensional robot states.

Reinforcement learning in robotics has shown notable progress. DRL algorithms like DQN and PPO have enabled robots to learn complex skills. Tang et al. [4] report several real-world robotic DRL successes: for example, a quadruped robot learned to walk dynamically, and a simulated drone learned obstacle courses. These successes highlight RL's ability to handle nonlinearity and high dimensionality. However, safe exploration is a critical limitation: selecting random actions during learning can damage hardware. Adaptive control theory provides stability guarantees, whereas RL prioritizes performance via trial and error define by Annaswamy [15]. Thus, while RL has great potential (indeed, Soler et al. [16] demonstrate RL controlling a wind turbine surpassing PID control), in robotics one must often combine RL with safety layers or simulation pre-training. Many jobs employ hybrid AI controllers in robotics. For example, fuzzy-neural PID controllers are designed for mobile robot tracking, where a neural network tunes the PID gains online under varying loads. Others use GA or PSO to optimize fuzzy rule sets for robot manipulators. Comparative studies generally find that hybrid neuro-fuzzy or neuro-PID controllers yield smoother tracking and better disturbance rejection than pure PID or pure fuzzy controllers. Table 2 (below) summarizes key AI control approaches: neural networks excel in capturing nonlinearities and learning from data, fuzzy logic excels at handling ambiguity with simple rules, and RL excels at sequential decision-making, while each method has trade-offs in data needs, interpretability, and stability.

Table 1: *Summarizes representative literature in robotics control*

Strengths	AI methods often yield better handling of nonlinearity and disturbances. Deep RL can solve tasks without explicit models, and ML predictors improve trajectory planning. Fuzzy logic adds robustness in uncertain environments.
Limitations	AI controllers may require extensive training data or simulation. Sample inefficiency (especially in

RL) and lack of stability guarantees are drawbacks annualreviews.org Training overhead and black-box nature raise safety/validation issues.

3.2 AI for Renewable Energy and Power Systems

Renewable energy systems (solar, wind, microgrids, etc.) pose control challenges due to intermittent generation and complex grid interactions. AI techniques have been applied for generation control, grid support, and forecasting. Forecasting is a critical step: machine learning models like RNNs and deep networks can predict solar irradiance or wind power with higher accuracy than linear models[20]. For power electronics, model predictive control (MPC) is common, and recent reviews show MPC handles multi-constraint optimization well in grid-tied inverters[14] [19]. Neural network–based MPC or ANN observers are also investigated for fast adaptation.

Wind turbines and solar plants use AI for optimal operation. Dardabi et al. design an ANN-based direct power control (DPC) for a doubly fed induction generator; their ANN controller greatly reduces current ripples and maintains near-unity power factor under variable conditions [6]. Similarly, reinforcement learning has been applied: Soler et al. [16] use a double deep Q-learning agent to adjust wind turbine rotor speed, yaw, and pitch in turbulent wind, achieving higher annual energy capture than a PID controller. These results illustrate RL's adaptability in nonstationary renewable environments.

Microgrid and smart grid control also benefit from AI. In a hierarchical microgrid, Bahabri et al. embed neural networks at multiple control layers: a neural MPPT controller, a battery management NN, and an intelligent energy management system. Their ANN-driven system improved power tracking by ~12% and reduced voltage deviations compared to conventional controllers [8]. On a broader scale, Ahmadi et al. [11] surveyed AI systems in smart grid stability and reliability; the systematic consideration of ML, deep learning, and RL to address fault detection and real-time energy management are considered. They emphasize hybrid AI models (mixing the use of neural nets and optimization) to solve the variability of renewables. In summary, AI techniques have been reported to improve grid resilience, minimize cost, and optimization of distributed generation within renewable-rich grids [11,19].

Renewable control has also been applied to the use of fuzzy logic. According to Suganthi et al. [7], the fuzzy controllers have been extensively employed in the field of maximum-power-point tracking (MPPT) in PV systems and the smoothing of power flow under uncertainty. Neuro-fuzzy adaptive and neuro-fuzzy MPPT controllers have the ability to perform better than fixed-gain schemes in irradiance variations. Fuzzy rules also adjust inverters or voltage regulators, which is uncertainly loaded. Nonetheless, the development of fuzzy rules to suit large systems can be tedious to do without an expert or hybrid optimization. To conclude, AI in renewables has provided better predictions, control of adaptive generation, and astute grid management [20,11]. The shortcomings are that it requires large amounts of data (to train ANNs or train RL) and difficulty in ensuring safety and stability in actual grids [9, 1].

4. Comparative Analysis

Control methods that are based on AI have different trade-offs. Neural network controllers can estimate very nonlinear dynamics, and can learn between data, and thus are useful in robotics and power-electronics control. They tend to be however, very demanding in terms of in terms of training data and are not transparent. In comparison, fuzzy logic controllers are easily tuned intuitively to rule-based design and easily cope with uncertainties, but are challenging to optimally tune in high-dimensional space. Reinforcement learning controllers are able to learn sequential control policies without an explicit model, and able to change policies to changing environments in real systems, but require careful reward shaping and heavy exploration, which is a safety concern in real systems [15, 9]. The evolutionary algorithms (GA, PSO, etc.) are better at offering global optimization of controller parameters with more significant computational costs and not guaranteeing convergence in real-time. Table 2, provides a comparison between these AI methods in terms of common control applications, strong and weak. To take a particular example, according to Alhamrouni et al. [18], ANNs are most effective in identifying nonlinearities in power systems, fuzzy logic is quite effective in dealing with uncertainty and a metaheuristic optimization introduces fresh efficiencies in tuning the controllers.

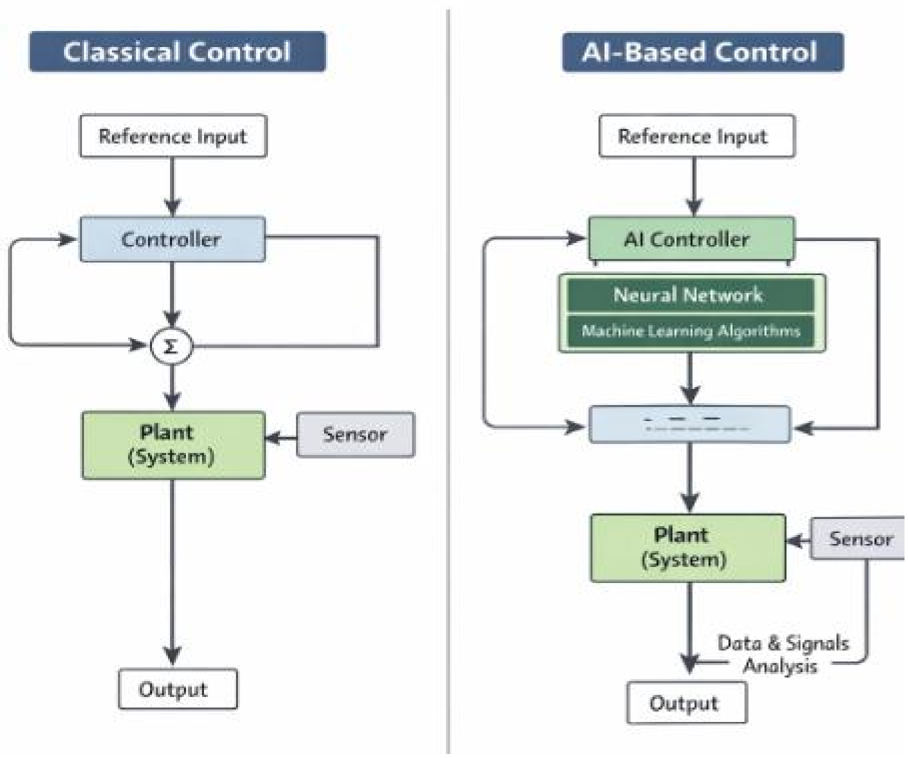

Figure 2: Illustrates a conceptual control loop comparing a classical PID controller and an AI-based controller

For example, an induction motor speed control: a traditional PID would base its response on feedback error to change its voltage, whereas an AI based controller may rely on an ANN to learn the nonlinear dynamics of the motor. ANN controller simulation experiments (Scheidler et al. 2020 [1]) demonstrate that ANN controller minimized the overshoot and settling time is improved over a fixed PID.

5. Practical Design Guidelines and Lessons Learned

The analysis of literature provided allows identifying a number of practical guidelines and lessons to be followed in order to design and deploy AI-based control systems successfully in robotics and renewable energy. The guidelines to be used are based on assisting engineers and researchers to choose appropriate control strategies considering the complexity of performance, safety, and complexity of implementation.

5.1. Selection of Control Strategy

System characteristics, as well as the requirements of operations, should determine the selection of traditional and AI-based controllers. Classical controllers like PID, LQR or H∞ still have their use in well-modeled, linear, and low-dimensional systems where the interpretability and stability is of paramount importance. On the other hand, AI-based controllers are better adapted to dynamical systems that have pronounced nonlinearities, parameter uncertainty and time-varying dynamics, like robotic manipulators, autonomous mobile robots and renewable energy generation units.

Controllers based on neural networks are suggested when the available data exist in sufficient numbers in operational or simulation form, and when the system dynamics are hard to describe analytically. Fuzzy logic controllers are especially useful in situations that are characterized by uncertainty, noisy measurements, or the presence of expert knowledge which is represented by linguistic rules. Reinforcement learning is best applied to complex problems of sequential decision making but can be used with caution in safety critical systems.

5.2. Hybrid Control as a Practical Compromise

A significant revelation that has come to mind after the analyzed research is that hybrid control structures often provide better performance than those that are entirely based on artificial intelligence or conventional control systems. Introducing AI-based approaches into the existing control constructions, these architectures combine the freedom, adaptability, and learning of smart approaches with maintaining the stability, transparency, and predictability of traditional controllers. As an example, neural networks or fuzzy logic systems could be used to control the parameters in PID in real-time, but the underlying PID architecture can still be used to give a well-understood and reliable system behavior. Similarly, AI-based models may also be integrated in model predictive control methods to improve predictability of a system without impairing constraints management.

Industrial robotics and power system applications are especially well suited to hybrid control approaches because operational safety and reliability are especially important in this context. In addition, these methods enable the progressive and viable implementation of AI technologies through the introduction of intelligent elements into the already existing control infrastructures to eliminate the necessity of the total reconstruction of the system.

5.3. Data Availability and Training Considerations

The quality and access to data is determinative in designing and performance of AI-based control systems. The neural network-based controllers and observers used as supervised learning techniques rely on carefully selected datasets to cover the entire set of operating conditions of the system. When used in the context of the renewable energy applications, these datasets are usually based on the past operational records along with the information related to the environment and weather. Conversely, it is often used in robotic controls where it is based on high-fidelity simulation platforms to create enough training data before the control is implemented in the real world.

In reinforcement learning-based controllers, the need to explore extensively creates further difficulties, especially when it is time to apply their use to a physical system where safety and reliability are considerations. Consequently, one of the widely used practices is to perform preliminary training in simulated settings, and then transfer learning or limited fine-tuning on actual hardware data. Further, it is necessary to incorporate physical constraints, operational boundaries, and safety conscious mechanisms into the learning process to reduce the chances of instability or unsafe system behavior during the training and implementation stages.

5.4. Safety, Stability, and Explain ability

A major lesson learned during the research of the literature is that the implementation of AI-controlled measures should be regarded with a thorough approach to safety and stability limitations. Unlike classical control methods, a large number of learning-based controllers do not make explicit or provable statements about stability. Therefore, safety mechanisms, including constraint-handling layers, supervisory control schemes or fallback controllers, are of special concern to safety-critical applications, such as robotics and power system operation.

Explain ability can also be regarded as a crucial aspect of practical AI-driven control solution adoption. The neural network and deep reinforcement learning algorithm usually have high performance, but their black-box nature may make it difficult to achieve transparency and decrease the confidence of engineers and system operators. In this respect, fuzzy logic controllers and hybrid neuro-fuzzy structures provide a convenient trade-off between a better interpretability and an acceptable control performance. These are particularly appropriate when transparency, traceability and human comprehension are mandatory requirements.

5.5. Computational and Implementation Constraints

Machine learning-based control methodologies can bring about more computational overhead through training functions, optimization functions, and real-time inference functions. In cases of control applications which have very strict real-time requirements, then special attention should be paid to the evaluation whether the computational hardware available can be confidently capable of providing such a high stiff requirement. The introduction of the lightweight learning models, the offline training, or the hierarchical control architectures can be used as the strategies to reduce a computational load significantly. The implementation of simplified AI models or AI-assisted parameter tuning of classical controllers is faster and more consistently successful than the entirely learning-based implementation of control loops particularly in applications with power electronics, fast dynamic responses, and application-specific complexity.

5.6. Lessons for Future Deployments

The analyzed sources suggest that AI-based control has a high potential, but its practical application has not been performed as much. Future applications ought to be focused on experimental confirmation, standardized performance measures and publication of training processes and parameters. It is essential to collaboratively work on the control engineers and AI researchers to make the learning-based controllers as reliable as the real-world systems.

Altogether, the literature indicates that AI can be regarded as an empowering instrument instead of an alternative to classical control theory. The most likely development of a reliable and efficient performance in robotics and renewable energy systems is careful design of hybrid and application-specific solution.

6. Discussion

The literature reviewed proves that AI could greatly be used to improve electrical engineering control systems. It is common in studies to find better accuracy, disturbance rejection, and energy efficiency to the integration of AI elements in controllers [1, 6]. In robotics, the AI controllers allow the more autonomous and flexible behavior, which can be helpful in such tasks as dynamic locomotion and human-robot cooperation. AI can be used in renewable systems to enhance the extraction of maximum power, grid stability, and demand forecasting. Thematic analysis indicates that fuzzy-logic and neural methodologies are particularly advanced, and deep learning and RL are the new frontiers [1, 4].

Although these advances have happened, there are still challenges. The other problem is that there is a disparity between simulation and the actual implementation. Most RL and learning-based control algorithms have only been proven to be valid in simulated or laboratory environments [4, 1]. According to Mareco, the majority of AI-control research is mostly based on simulations, and few studies test their controllers in practice and report on hyperparameters [1] Safety is another issue: traditional controllers have stability guarantees, and new ML-based controllers have little to no guarantees. In systems where safety is needed (e.g., power grids or industrial robots), it is necessary to make sure the system operates safely; this drives the development of safe RL algorithms that limit exploration [9].

Computational complexity and data requirements is also an obstacle. Deep network training or training RL agents might be large data and computation intensive in which case those data and time might not be available in any engineering environment. Further, intelligent controllers do not have a common standard in terms of evaluation.

Various studies have diverse measures and test conditions and it is hard to compare them directly. As propose, benchmark and best practice development is an essential next step in the future [1, 18].

Last, there has to be interdisciplinary integration. The future research directions warranting the consideration are the integration of AI and domain knowledge (e.g. hybrid learning and physical models), incorporating the online learning into the controllers, and interpretability. Indicatively, integrating ANNs and fuzzy rules would provide powerful but explainable controllers [17]. The field of combining AI with MPC or distributed control designs is an emerging field in renewable grids [19, 11]. The remaining gaps in research are standardizing experiments, scaling AI to very large systems, and enhancing reliability in uncertainty [1,18].

Table 2: *Summary of Representative AI Control Studies*

Study	Application	AI Technique	Key Findings
Rakhmatillaev et al., 2025	Robotics (General)	Review (fuzzy, NN, ML)	Identifies strengths/weaknesses of classical vs intelligent controllers.
Autsou et al., 2025	Collaborative Robots	Fuzzy Logic, Hybrid ML	Fuzzy controllers improve robot adaptability; hybrid fuzzy-ML yields best performance.
Ahmadi et al., 2025	Industrial Processes	Systematic Mapping (ML, fuzzy, GA, DRL)	AI control improves adaptability; common methods include fuzzy, ANN, MPC, DRL.
Razak et al., 2025	Renewable Energy	ML, DL (ANN, SVM, RL, GNN)	AI enables forecasting, optimization, predictive control; trend toward interpretable models.
Ojuekaiye, 2025	Renewable/Predictive Maintenance	ML, DL, RL	AI-driven predictive maintenance reduces downtime; uses sensor data for RUL estimation.
Dev et al., 2021	Industrial/Process Control	ANN (RNN, LSTM)	ML can model nonlinear dynamics and improve stability; focus on RNN/LSTM for predictive control.
Rudas et al., 1996	Robotics (Manipulator)	ANN + Fuzzy	Early neuro-fuzzy control design; emphasizes hardware support and AI for complex tasks.
Jiang et al., 2016	Discrete-Time Control	FLC, NN (review)	Surveys design methods for discrete-time fuzzy and NN controllers; emphasizes robustness strategies.
Meryn & Chu, 2024	Theoretical/Comparative	PID vs Fuzzy (review)	Fuzzy is better for nonlinear uncertainty, PID for linear tasks; hybrid PID-FLC-NN have adaptability.

Comparative Table 3: Traditional vs AI-Based

Aspect	Traditional Control	AI-Based Control
Model requirement	Requires accurate system model (LQR, PID)	Data-driven learning (model-free RL, NN models)
Adaptability	Fixed gains or limited adaptation (MRAC)	Continuous learning and online adaptation (RL, neuro-adaptive)

Performance in Nonlinear/Uncertain Systems	Limited robustness; needs conservative design	Better handling of nonlinearities and disturbances (fuzzy, NN)
Computational Complexity	Low (PID simple algebra, state-space solution)	Higher (training, optimization loops)
Explain ability	High (clear formulas)	Low for NN/RL (black box); moderate for fuzzy
Tuning	Manual or heuristic (Ziegler-Nichols, LQR tuning)	Automated via optimization (GA, PSO)

7. Conclusion

This work has examined the increasing presence of AI in modern-day control systems, specifically in the use of robotics and renewable energy sectors. This article suggests that neural networks, fuzzy logic, reinforcement learning, and evolutionary optimization are all AI-based controllers that can enhance the performance of the control, particularly in adaptability, disturbance rejection, and robustness, compared to the traditional methods of control. These advantages can be best seen in systems that are nonlinear in nature, that have parametric uncertainty and time-varying operating conditions. Although such benefits are present, the review also highlights some crucial drawbacks that are linked with AI-based control strategies. The current literature is limited to simulation-based tests whereas real world application is frequently restricted by safety factors, large data demands and lack of formal stability guarantees. These problems still restrict the direct application of fully data driven control solutions in safety critical applications, such as power systems and robotic platforms. The comparative analysis indicates that hybrid control architectures, involving the combination of AI principles with the principles of classical control theory, are a feasible and efficient way into the future. These methods provide a moderate solution to most of the available limitations by integrating learning capabilities with analytical stability and interpretability. The future research directions should thus focus on large scale experimental validation, creation of standard evaluation benchmarks, better model transparency and integration of domain specific knowledge in learning-based controllers. Advancements in these fields will be necessary so that it is possible to safely, reliably, and widely apply AI-enabled control systems to the next generation of robots and renewable energy use.

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