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A Review of Artificial Intelligence Based Control Techniques for Power Electronics

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Abstract

The integration of Artificial Intelligence (AI) into power electronics marks a major advancement in control techniques, providing increased efficiency, adaptability, and reliability across various industrial and commercial applications. This research paper aims to present and review the fields of AI in control systems, focusing on key AI-based techniques such as neural networks, fuzzy logic, genetic algorithms, and reinforcement learning, and their use in power converters, renewable energy systems, electric drives, and smart grids. Through case studies, it demonstrates the practical benefits of these techniques in optimizing performance. While the advantages are significant, the paper also examines the technical challenges, ethical concerns, and societal implications related to AI adoption in power electronics. Future trends, including the development of hybrid AI techniques and the need for explainable AI models, are discussed to ensure transparency and accountability. Although AI is set to revolutionize power electronics, overcoming existing challenges is crucial for its full potential to be realized.

Keywords: Artificial intelligence, control techniques, power electronics, renewable energy systems, smart grids.
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1. Introduction

Since it has a direct impact on how an organization conducts business, information security ought to be its top priority. There are both technical and non-technical aspects to information security. Technical security issues can be resolved by installing a firewall, antivirus software, backing up data, implementing access control measures, encrypting the system, and continuously monitoring it for threats. Measures of employee behavior are considered non-technical measures. Information security-related sociological, psychological, and organizational behavioral theories are included in these procedures to guarantee that employees follow information security policies [1].

Power electronics is a critical field in electrical engineering that handles the conversion of electrical power using electronic devices. These systems are essential in a wide range of applications, including household electronics, industrial automation, renewable energy systems, and electric vehicles. Power electronics enables efficient power conversion processes, which include rectification, inversion, and voltage regulation, to meet the specific requirements of different electrical systems [6, 13, 17, 22].

The primary components of power electronics systems include DC-DC power converters, inverters, and rectifiers. DC-DC converters are widely used to step up (boost) or step down (buck) the voltage level in systems where the input and output are both Direct Current (DC), making them essential in battery-powered devices, electric vehicle powertrains, and renewable energy systems like solar photovoltaic arrays. Alternating Current (AC) systems, on the other hand, require power electronics interfaces such as rectifiers (AC-to-DC), inverters (DC-to-AC), and AC-AC converters to control frequency, phase, or amplitude. These converters enable grid integration of renewable sources, motor drives, uninterruptible power supplies, and voltage regulation in modern power grids [6, 13, 17, 22].

Recently, there has been an interest in the use of AI techniques in power electronics systems. The design, control, and preventative maintenance are three key areas where AI is currently being used in power electronics systems as illustrated in Figure 1. This figure illustrates how AI integrates control, maintenance, and design in power electronics, enabling proper sizing, adaptive control, fault diagnosis, and parameter optimization across the system lifecycle [11].

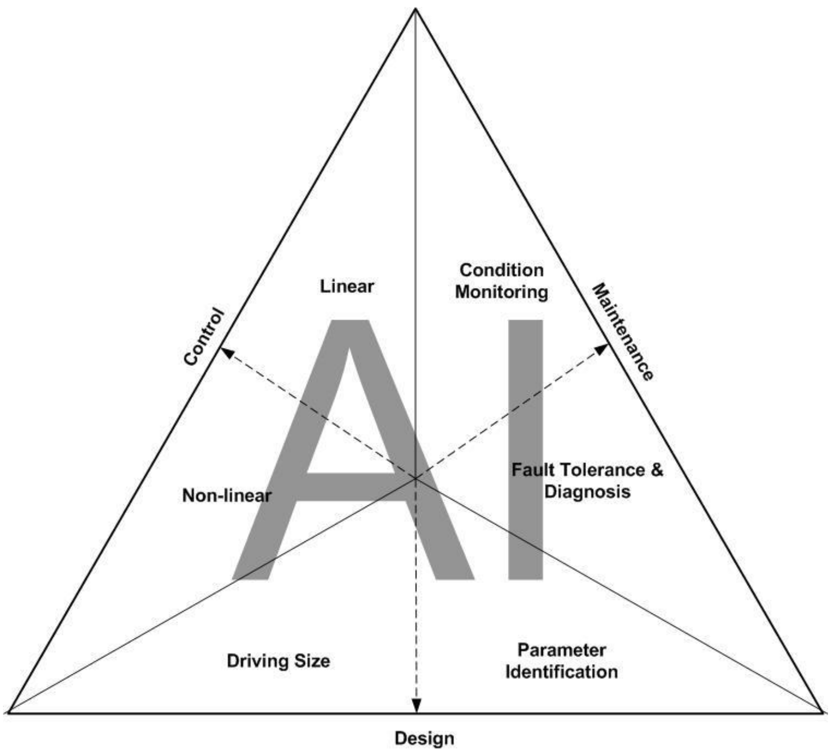

Figure 1: *Artificial Intelligence Applications in Power Electronics [11]*

Control techniques in power electronics have evolved significantly over the past few decades. Initially, simple analog control methods, such as Proportional-Integral-Derivative (PID) controllers, were used to manage power converters. These traditional methods, while effective in certain scenarios, often struggled with nonlinearities, variations in load conditions, and the demand for higher efficiency and faster response times. As the complexity and performance requirements of power electronics systems grew, more advanced control strategies were developed, including digital control methods that allowed for greater precision and adaptability. However, the limitations of conventional control methods became apparent, especially in applications requiring real-time decision-making and adaptability to dynamic condition [5, 11].

AI has emerged as a transformative force in modern power electronics, offering innovative solutions to many of the challenges faced by traditional control techniques. AI, particularly machine learning and deep learning, enables systems to learn from data, adapt to changing conditions, and make decisions that optimize performance in real-time. AI-based control techniques are particularly valuable in applications where the system dynamics are complex and nonlinear, such as in renewable energy systems, electric vehicles, and smart grids. By leveraging AI, these systems can achieve higher efficiency, better stability, and improved fault tolerance. The integration of AI into power electronics is not only enhancing performance but also paving the way for the development of more intelligent, autonomous energy systems [5, 11, 28].

In addition to improved performance, the adoption of AI in power electronics supports predictive and condition-based maintenance strategies, minimizing downtime and extending equipment lifetime. For instance, data-driven models can forecast converter faults, predict capacitor aging, and detect anomalies before they cause catastrophic failure [14, 28]. Such predictive capabilities are crucial in high-stakes environments like microgrids and utility-scale renewable power plants, where system reliability is paramount [2, 18, 24].

Another key driver for the application of AI is the increasing penetration of renewable energy sources and electric mobility, both of which introduce high variability and uncertainty into the grid. AI algorithms such as reinforcement learning, fuzzy inference systems, and neural networks are well-suited for handling stochastic behavior, adapting to disturbances, and providing optimal control actions in real-time [7, 11, 26]. This is particularly important in grid-forming converter control, power-sharing optimization, and active power quality management—areas where conventional linear controllers may be insufficient [5, 12, 27].

Moreover, the evolution of high-speed processors, embedded systems, and communication platforms has made it feasible to implement computationally intensive AI models directly on hardware in real-time applications. Edge AI deployment in power converters is an emerging trend, allowing intelligent decision-making at the converter level without relying on cloud computation [14, 23]. This decentralization enhances system robustness and cybersecurity, two pressing concerns in modern power grids [2, 16].

The primary contribution of this paper is to provide a detailed and structured review of AI-based control techniques for power electronics, emphasizing both theoretical foundations and real-world applications. Specifically, the paper:

- Classifies AI control methods as applied to power converters.
- Analyzes their suitability for different power electronics applications, including DC-DC converters, grid-connected inverters, and electric vehicle chargers.
- Discusses implementation challenges, such as computational burden, training data availability, and real-time deployment issues.
- Highlights research gaps and suggests future research directions toward scalable, reliable, and interpretable AI-based control solutions.

By synthesizing existing literature and presenting a critical evaluation, this paper serves as a reference point to understand the current state of AI-driven control in power electronics and its potential to shape future intelligent energy systems.

This paper is organized as follows: Section I provides the introduction and outlines the motivation for integrating AI into power electronics control systems. Section II reviews related work, while Section III introduces the fundamentals of AI in control systems. Section IV presents AI-based

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control techniques in power electronics, and Section V highlights their key applications. Section VI discusses challenges and future directions, and Section VII concludes the paper.

2. Related Work on AI-Based Control in Power Electronics

Several studies have explored the integration of Artificial Intelligence (AI) into power electronics for improved control, optimization, and reliability. [11] provided a recent overview of AI techniques applied to power converter-based systems, classifying them into machine learning, deep learning, fuzzy logic, and reinforcement learning, while highlighting benefits such as improved stability, robustness, and adaptability. [5] presented a foundational reference on modeling and control of power electronics converters, establishing a baseline for comparing AI-based controllers with conventional strategies.

[8] discussed AI applications in smart grids and renewable energy, demonstrating that fuzzy logic and neural networks can mitigate renewable intermittency and enhance grid stability. [14] extended this by presenting AI for power electronics and renewable systems, including case studies on adaptive control and AI-driven grid synchronization. Similarly, [25] and [15] reviewed AI-based control for power electronics and drives, concluding that hybrid AI methods offer improved dynamic response and robustness but face challenges related to computational complexity and real-time implementation.

Several works investigated fuzzy logic and neural network control schemes in detail. [12] designed a fuzzy logic-based PWM charge controller for photovoltaic systems, achieving higher charging efficiency and reduced switching stress. [27] implemented an Artificial Neural Network (ANN) based direct power control scheme for Photovoltaic (PV) grid connected systems, demonstrating superior harmonic performance and faster dynamic response. [23] emphasized the effectiveness of neuro-fuzzy approaches, reporting smoother control action and enhanced disturbance rejection compared to single-method controllers.

Evolutionary algorithms and hybrid AI methods have also been applied for converter optimization. [19] optimized switching angles of multilevel converters using genetic algorithms (GAs), significantly reducing total harmonic distortion (THD) compared to analytical approaches.

Physics-informed and reinforcement learning techniques have recently emerged for advanced control of power electronics. [29] proposed physics-informed neural networks for parameter estimation in converters, reducing data requirements and enhancing estimation accuracy. [26] employed reinforcement learning to tune virtual synchronous generator parameters dynamically, improving frequency stability and power sharing under grid disturbances.

In the context of energy management and smart grids, [24] applied AI techniques for microgrid control, using ANN-based strategies to improve voltage stability and minimize power loss. [2] and [18] reviewed distributed AI techniques for smart grids, highlighting the potential of multi-agent systems and reinforcement learning for real-time demand response and decentralized voltage control. [1] further summarized AI-driven energy management strategies for hybrid renewable and storage systems, reporting improved efficiency and reliability.

Finally, several studies applied AI to specific converter control problems. [10] developed a backstepping-fuzzy neural network controller for uninterruptible power supplies, yielding improved voltage regulation and lower THD under nonlinear load conditions. [3] used machine learning for closed-loop battery fast-charging optimization, reducing charging time while preserving battery health — an approach with strong implications for power electronics in electric vehicles.

Overall, these studies, summarized in Table 1, confirm that AI-based controllers significantly improve dynamic performance, fault tolerance, and adaptability of power electronics systems. However, existing research is often application-specific and lacks a unified comparative analysis across converter types and AI methodologies. The present paper addresses this gap by classifying

AI-based control strategies, benchmarking their performance, and identifying open challenges for future research in intelligent power electronics control systems.

Table 1: Summary of Related Work on AI-Based Control in Power Electronics

Ref.	Technique	Application	Key Results / Contributions
[11]	Review of AI	Power electronics converters	Categorized AI techniques; highlighted improvements in control performance and identified real-time implementation challenges.
[5]	Conventional and digital control	Power electronics converters	Provided fundamental modeling, modulation, and control theory for converters, serving as a baseline for AI comparisons.
[8]	Fuzzy logic and ANN	Smart grid and renewable systems	Demonstrated intelligent controllers mitigate renewable intermittency and enhance grid stability.
[14]	AI for modeling, control and optimization	Renewable energy systems	Bridged theory and practice through case studies on AI-driven grid synchronization and adaptive control.
[25]	Comprehensive review	Power electronics and drives	Identified performance gains of AI controllers; discussed challenges in computational burden and industrial deployment.
[15]	Review of AI control methods	Power electronics and drives	Highlighted hybrid AI approaches as most promising for industrial adoption.
[12]	Fuzzy logic controller	PV charge control	Increased charging efficiency and minimized switching stress on converters.
[27]	ANN-based direct power control	PV-grid connected converters	Achieved lower harmonic distortion and faster transient response compared with conventional direct power control.
[23]	Neuro-fuzzy control	Power electronics and motor drives	Demonstrated smoother control action and better disturbance rejection than single-method controllers.
[19]	Genetic algorithm	Multilevel converter optimization	Minimized harmonic distortion by optimally selecting switching angles, outperforming Fourier-based methods.
[29]	Physics-informed neural network	Parameter estimation of converters	Improved accuracy with less training data by incorporating physical constraints into machine learning model.
[26]	Reinforcement learning	Virtual synchronous generator control	Enhanced frequency stability and power sharing by adaptive parameter tuning under grid disturbances.
[24]	ANN-based controllers	Microgrid integration	Improved voltage stability and reduced energy loss under variable generation scenarios.
[2]	Multi-agent systems	Distributed smart grid management	Reduced communication overhead and improved scalability of distributed controllers.
[18]	Supervised and unsupervised learning	Smart grid applications	Emphasized reinforcement learning for real-time demand response and decentralized voltage regulation.
[1]	ANN, fuzzy logic and optimization	Hybrid renewable and storage systems	Improved energy management efficiency and system reliability.
[10]	Backstepping and fuzzy neural networks	Uninterruptible power supply voltage control	Improved voltage regulation and reduced harmonic distortion under nonlinear load conditions.
[3]	Machine learning optimization	Battery fast charging	Reduced charging time while preserving battery health.

3. Fundamentals of AI in Control Systems

3.1 AI **Basics**

Artificial Intelligence (AI) refers to the development of computational systems capable of simulating human-like reasoning, learning, and decision-making. It encompasses several subfields, including machine learning, natural language processing, computer vision, and robotics. In the context of

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control systems, AI is utilized to design algorithms that can autonomously make decisions, predict system behavior, and optimize performance without requiring direct human intervention [5, 8, 11, 14].

3.2 Machine Learning and Deep Learning

Machine Learning (ML), a subset of Artificial Intelligence, focuses on developing algorithms that can be learned from data and make data-driven predictions or decisions. In power electronics, ML algorithms are widely used to model complex converter dynamics, identify patterns in operational data, and optimize control strategies for improved performance. ML techniques can generally be categorized into three major types: supervised learning, where the system is trained on labeled datasets to learn the relationship between inputs and outputs; unsupervised learning, where the system discovers hidden patterns and correlations in unlabeled data; and reinforcement learning, where the system learns optimal actions by interacting with its environment and receiving rewards or penalties as feedback. These approaches are particularly relevant for power electronics control systems, as they enable the development of predictive models and adaptive controllers capable of handling nonlinearities, parameter variations, and changing operating conditions [5, 11, 14, 25].

3.3 AI Algorithms in Control Systems

AI algorithms in control systems can be categorized into several types based on their functionality and power electronics application, such as:

Expert Systems: These systems are built to emulate the specialized knowledge of human experts in a particular field, enabling them to solve problems typically managed by professionals in that area [8, 25].

Neural Networks: These algorithms imitate the structure and processes of the human brain to model intricate relationships between inputs and outputs. In control systems, neural networks can approximate nonlinear functions and enhance control strategies for optimized performance [8, 14, 24].

Fuzzy Logic: This approach deals with reasoning that is approximate rather than fixed and exact. Fuzzy logic controllers are particularly effective in systems with a high degree of uncertainty or where precise mathematical models are unavailable [21, 27].

Genetic Algorithms: These optimization methods are inspired by natural selection and genetic principles. In control systems, genetic algorithms help identify optimal solutions for complex issues, such as fine-tuning control parameters [20, 23].

Reinforcement Learning: This is a machine learning approach where an agent learns to make decisions by interacting with an environment, aiming to maximize cumulative rewards. In power electronics, reinforcement learning can be used to create adaptive control strategies that enhance system performance progressively [8, 14, 24, 25].

4. AI-Based Control Techniques in Power Electronics

4.1 Expert Systems

Figure 2 shows the main components of an Expert System (ES), with the knowledge base as its core. The knowledge base includes both expert knowledge and a database containing data, facts, and statements that support this expertise. The database serves a similar role to cataloged information in human knowledge systems. Additionally, data-related computational functions may be connected to the expert knowledge for further support [8, 14, 24, 28].

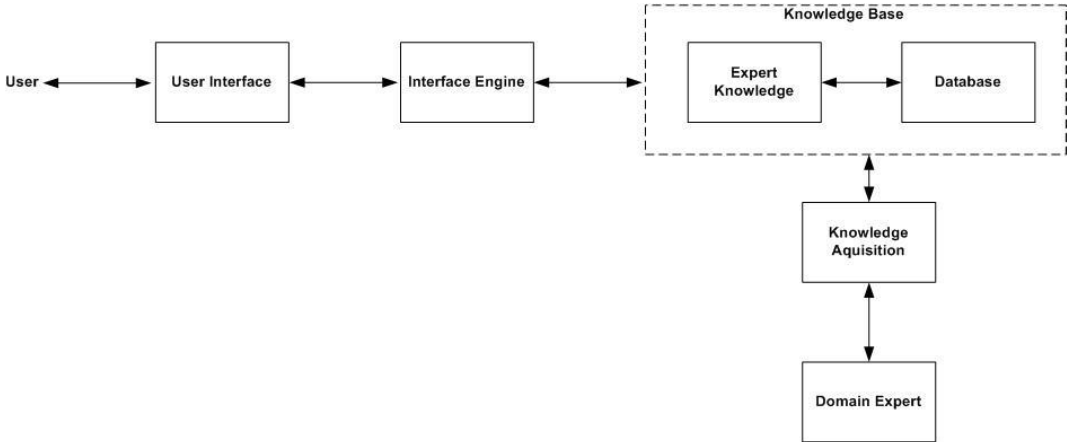

Figure 2: Components of Expert Systems [8]

It's worth noting that expert systems have a low usage rate of just 0.9% [28]. This is largely because they rely on specific system principles and rules that apply only to well-defined domains with strong expert guidance, limiting their universality. Additionally, with the rapid advancement in computational technologies, the functions of expert systems are often outperformed by advanced AI techniques, such as fuzzy logic and machine learning, which provide more superior inference and approximation capabilities [8, 24, 28].

4.2 Neural Network Control

Neural Networks (NNs) have gained significant attention in power electronics for their ability to model nonlinear systems and provide adaptive control strategies. A neural network consists of layers of interconnected neurons that process data input to produce an output. These networks are particularly effective in scenarios where the system dynamics are too complex for traditional control methods to handle [8, 14, 25, 28].

In the control of inverters, neural networks can be used to regulate the output voltage and frequency in real-time, ensuring that the inverter operates efficiently under varying load conditions. For instance, in renewable energy systems, where the power generated by sources like solar panels or wind turbines can fluctuate, a neural network controller can adapt to these changes and maintain a stable output [14, 27, 28].

4.3 Fuzzy Logic Control

Fuzzy Logic Control (FLC) is a technique that mimics human reasoning by handling imprecision and uncertainty in control systems. Unlike traditional binary logic, which requires precise inputs, fuzzy logic works with degrees of truth rather than the usual "true" or "false" binary values. This allows FLC to deal with vague or ambiguous information, making it particularly useful in complex and nonlinear systems where exact mathematical modeling is difficult or impossible. FLC systems use "fuzzy sets" to categorize input data and apply a set of rules, often derived from expert knowledge, to make decisions. Typically, these rules are written as "if-then" statements, defining the relationship between input variables and the corresponding control actions [14, 20, 21, 25].

The Fuzzy logic controller is widely used in power converters, such as DC-DC converters and AC-DC rectifiers. It manages the variations in input voltage and load conditions to maintain a stable output. For example, in a DC-DC converter, fuzzy logic can adjust the duty cycle of the switching elements to regulate the output voltage, even in the presence of input voltage fluctuations or load changes [8, 14, 21, 24]. Figure 3 illustrates the basic structure of a fuzzy logic controller, where the

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error and derivative error are fuzzified, processed through fuzzy rules and an inference mechanism, and then defuzzified to generate a duty cycle for controlling a power converter.

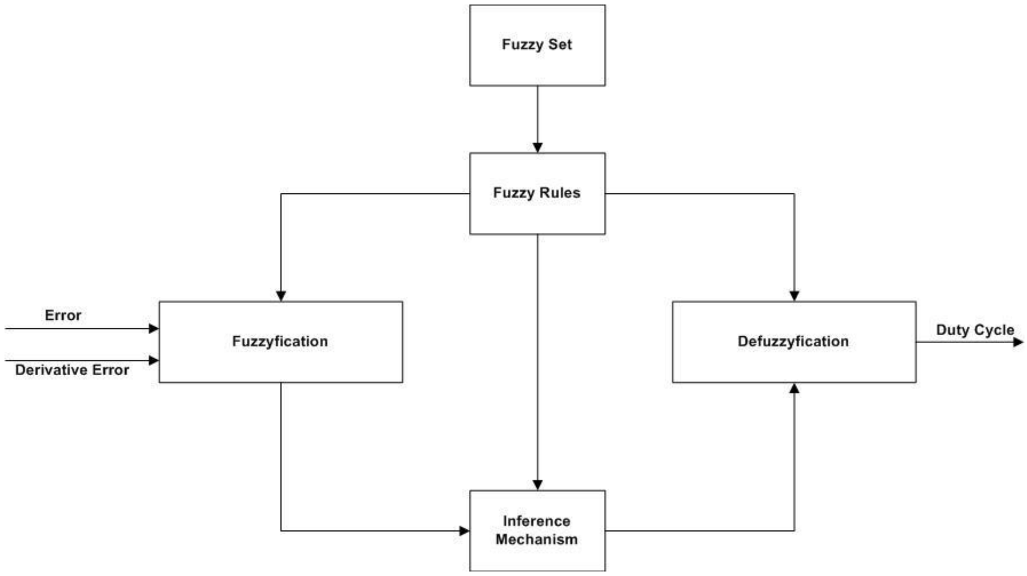

Figure3: *Fuzzy Logic Controller [20]*

4.4 Genetic Algorithms

Genetic Algorithms are optimization methods inspired by genetics and natural selection. They work by iteratively refining a population of candidate solutions across several generations to find an optimal or near-optimal solution. This evolution process includes selection, crossover, and mutation operations, simulating biological evolution [21, 23-25].

In power electronics, GAs are used to optimize control parameters, such as the gain values in PID controller — a widely used control strategy where the proportional term reduces the present error, the integral term eliminates steady-state error by considering past values, and the derivative term predicts future error to improve system stability. GAs can also optimize switching angles in Pulse-Width Modulation (PWM) schemes in power converters. They are particularly useful in scenarios where the search space is large and complex, and traditional optimization methods may fail to find a global optimum [21, 23-25].

One of the key applications of genetic algorithms in power electronics is in the optimization of control strategies for power converters. For instance, GAs can be used to determine the optimal switching sequence in a multilevel inverter, minimizing harmonic distortion while maximizing efficiency [19].

GAs have also been applied in the design of filters, where they can optimize the component values to achieve the desired frequency response while minimizing cost and size. The ability of GAs to handle multi-objective optimization makes them ideal for such complex design problems [9].

4.5 Reinforcement Learning

Reinforcement Learning (RL) is a machine learning approach where an agent learns to make decisions through interaction with its environment, receiving feedback in the form of rewards or penalties. The objective of the RL agent is to maximize cumulative rewards over time by choosing actions that lead to favorable results.

In power electronics, RL can be used to develop adaptive control strategies that improve system performance over time. Unlike traditional control methods, which require a pre-defined model of the system, RL allows the controller to learn directly from the interaction with the system, making it well-suited for applications with dynamic and uncertain environments [11, 25, 28].

A notable application of reinforcement learning in power electronics is in the control of smart grids, where the goal is to balance supply and demand while minimizing costs and maintaining system stability. An RL-based controller can learn to adjust the output of distributed energy resources, such as solar panels and wind turbines, in response to changes in demand and weather conditions [14, 23].

4.6 Hybrid AI Control Techniques

Hybrid AI control methods integrate multiple AI approaches, combining their strengths while reducing the limitations of each individual technique. For example, a hybrid control system might use a neural network for modeling the system dynamics, fuzzy logic for decision-making, and a genetic algorithm for optimization. This combination allows for more robust and adaptable control strategies. Hybrid AI techniques are particularly effective in complex power electronics systems where multiple objectives must be balanced, such as efficiency, stability, and response time. By integrating different AI methods, hybrid controllers can achieve superior performance compared to single-method approaches [21, 23-25].

A common hybrid AI approach in power electronics is the combination of fuzzy logic and neural networks, known as a neuro-fuzzy system. In this system, the neural network is used to tune the membership functions and rules of the fuzzy logic controller, allowing for real-time adaptation to changing conditions [21].

Another example is the use of genetic algorithms to optimize the architecture and parameters of a neural network, resulting in a more efficient and effective control strategy. This approach has been successfully applied in the control of grid-connected inverters, where the hybrid system can adapt to varying grid conditions while maintaining high power quality [21, 23-25].

5. Applications of AI-Based Control Techniques

5.1 AI in Power Converters

Power converters are critical components in modern electrical systems, responsible for converting electrical power from one form to another, such as AC to DC or DC to AC. AI-based control techniques have been increasingly applied in power converters to enhance their efficiency, performance, and adaptability [5, 8, 11, 25].

In DC-DC converters, AI techniques such as neural networks and fuzzy logic are used to regulate the output voltage under varying load conditions. A neural network controller can learn the nonlinear characteristics of the converter and adjust the duty cycle of the switching elements in real-time, ensuring stable output even in the presence of input voltage fluctuations. Similarly, fuzzy logic controllers can handle uncertainties and variations in load conditions by applying heuristic rules that adjust the control parameters dynamically [23, 29].

5.2 AI in Renewable Energy Systems

Renewable energy sources, like solar and wind power, are highly variable and often unpredictable. AI-based control methods are used to manage these fluctuations and optimize the incorporation of renewable energy into the power grid [8, 20, 26, 29].

Maximum Power Point Tracking (MPPT) is a critical function in photovoltaic systems, enabling solar panels to achieve maximum power output under varying sunlight conditions. AI techniques,

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including neural networks, genetic algorithms, and fuzzy logic, improve MPPT efficiency. For instance, a genetic algorithm can enhance the search for the maximum power point by evolving potential solutions over time, leading to faster convergence and higher energy yield. Similarly, a neural network-based MPPT can learn the relationship between environmental conditions (such as irradiance and temperature) and the optimal operating point, allowing for more precise and adaptive control [8, 11, 15, 28].

5.3 AI in Electric Drives

Electric drives, which control the speed and torque of electric motors, are another area where AI-based control techniques have made significant contributions. Traditional control methods often struggle with the nonlinear dynamics of electric motors, especially under variable load conditions [15, 20, 23, 28].

Induction motors are widely used in industrial applications due to their robustness and simplicity. However, controlling their speed and torque with high precision can be challenging, especially when the motor operates under varying load conditions. AI techniques, such as Model Predictive Control (MPC) combined with neural networks, have been employed to address these challenges. In an AI-controlled induction motor, a neural network can be trained to predict the motor's behavior in response to different control inputs, allowing the MPC algorithm to optimize the control actions in real-time. This approach has been shown to improve the efficiency and dynamic performance of induction motors, particularly in applications where precise speed control is required [23, 28].

5.4 AI in Smart Grids

Smart grids represent the future of electrical power distribution, integrating advanced communication and control technologies to optimize the generation, distribution, and consumption of electricity. AI plays a critical role in the management of smart grids, enabling many applications such as Distributed Energy Resources (DER) integration, Renewable Energy Resources (RES) integration, real-time monitoring, demand-response strategies, coordination for Regional Transmission Organization (RTO) and Independent System Operator (ISO) as shown in Figure 4 [2, 8, 16, 20].

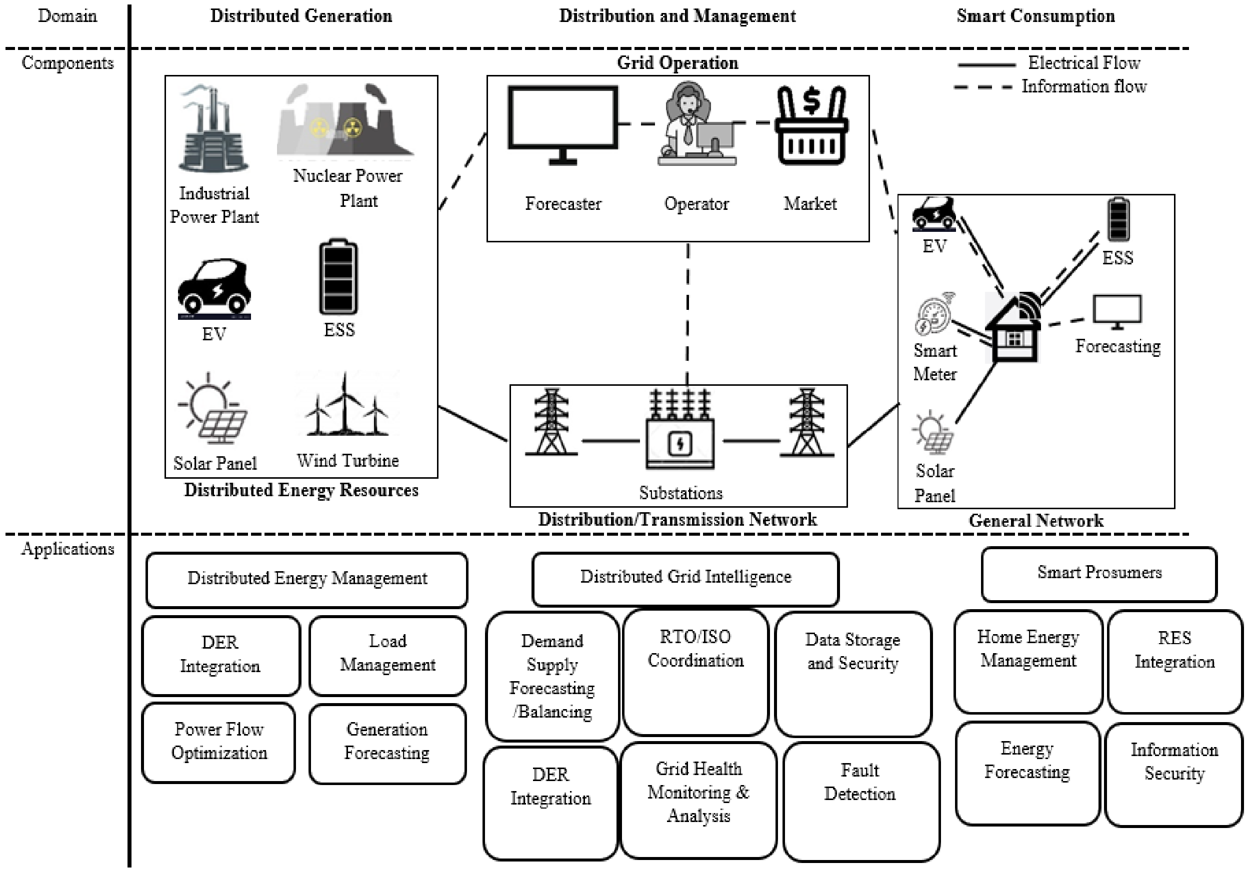

Figure 4: AI Applications in Smart Grids [2]

A major application of AI in smart grids is predictive maintenance, where AI algorithms analyze sensor data to identify early signs of potential failures. Machine learning and deep learning techniques are used to detect patterns that suggest wear, overheating, or other issues that may lead to equipment malfunctions. By anticipating faults, AI-driven systems can better schedule maintenance, minimizing downtime and boosting grid reliability. This proactive approach is especially valuable in critical infrastructure, where unexpected outages can have substantial economic and social consequences [4, 18].

5.5 AI in Industry

Uninterruptible Power Supply (UPS) systems are crucial in industries where power reliability is essential, such as data centers, hospitals, and manufacturing plants. Figure 5 illustrates the basic power flow within a UPS. Normally, AC input power is converted to DC to charge the battery, and then the inverter converts it back to clean AC for the output. The bypass mode shown is a secondary path that directly routes AC input to the output, bypassing the battery and inverter for efficiency [10].

A UPS system provides backup power when the main power source fails, ensuring continuous operation of critical equipment. Inverters in UPS systems are responsible for converting batteries' DC power to AC power for the loads. In industrial UPS systems, the inverter's performance directly impacts the reliability and efficiency of the power supply during outages. AI algorithms are used to enhance the performance of these inverters [10, 21].

Fuzzy neural network algorithms can optimize the inverter's control strategy by learning from the system's operational data. For example, RL can adjust the inverter's switching patterns in real-time to improve power quality and reduce the transition time between grid power and battery power. This

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ensures a smoother and more efficient power transfer, minimizing downtime and protecting sensitive equipment [10].

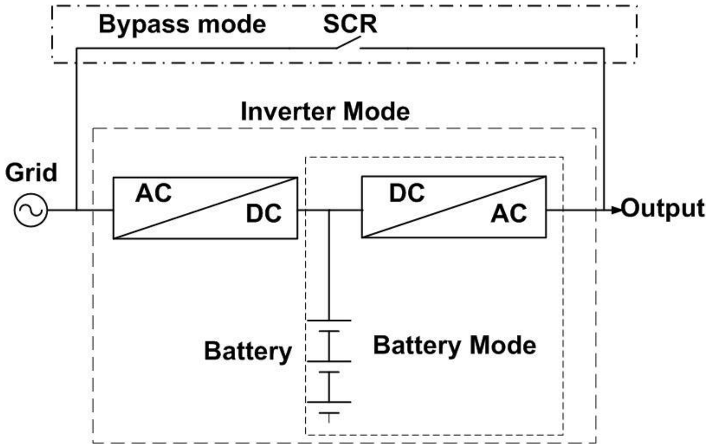

Figure 5: *Online UPS Working Modes [10]*

5.6 AI in Energy Storage Systems

Energy Storage Systems (ESS) are essential for balancing supply and demand in modern power grids, particularly when integrating renewable energy sources. AI techniques are used to optimize the operation of ESS, enhancing their performance and extending their lifespan [3, 15].

Battery Management Systems (BMS) are critical for monitoring and controlling the operation of batteries in energy storage systems. AI algorithms, such as neural networks and reinforcement learning, are used to predict the State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL) of batteries. In a case study involving a large-scale lithium-ion battery storage system, a neural network-based BMS was implemented to optimize the charging and discharging cycles, taking into account factors such as temperature, load demand, and battery aging. The AI-based BMS demonstrated improved accuracy in SOC estimation and better management of battery degradation, leading to a longer lifespan and higher reliability of the ESS [1, 15].

5.7 AI in Autonomous Power Systems

Autonomous power systems, such as microgrids and isolated power systems, require advanced control strategies to operate independently and efficiently. AI-based control techniques are increasingly being used to manage these systems, enabling them to adapt to changing conditions and maintain stable operation without human intervention [4, 11, 18].

Electric vehicles (EVs) represent a significant application of autonomous power systems, where AI-based control techniques are used to manage the vehicle's power electronics, battery systems, and overall energy management. A case study on autonomous electric vehicles applied reinforcement learning to optimize charging schedules and route planning, considering factors like traffic, battery levels, and energy availability. The AI-controlled system demonstrated improved energy efficiency and reduced charging times, contributing to the overall sustainability and practicality of autonomous EVs [4, 11, 18].

6. Challenges and Future Directions

6.1 Technical Challenges

While AI-based control techniques offer significant advantages in power electronics, several technical challenges remain. One of the primary challenges is the integration of AI algorithms into existing control systems, which often requires significant computational resources and specialized hardware. Additionally, the training of AI models requires large datasets, which may not always be available, particularly for novel or emerging applications [4, 18, 25, 28].

Another challenge is the robustness of AI-based controllers in the face of unexpected conditions or disturbances. Unlike traditional control methods, which are often designed with specific failure modes in mind, AI-based controllers may behave unpredictably if they encounter scenarios that were not covered during training [2, 4, 18, 25].

6.2 Ethical and Societal Implications

The adoption of AI in power electronics raises ethical concerns, especially around privacy, as smart grids and energy management systems often rely on detailed user data. Additionally, the automation brought by AI may impact jobs in areas traditionally reliant on manual control and maintenance [2, 4, 23, 25].

Moreover, the reliance on AI for critical infrastructure raises concerns about accountability and transparency. In the event of a malfunction or accident involving an AI-based control system, assigning responsibility can become complex—particularly when the underlying decision-making process is opaque or not fully interpretable by human operators [2, 4, 18, 28].

6.3 Future Trends in AI-Based Control

Despite these challenges, the future of AI-based control in power electronics remains promising. Advances in computational power, data availability, and AI algorithms are expected to drive further innovations in this field. One of the key trends is the development of more interpretable and explainable AI models, which will help address concerns about transparency and accountability [2, 4, 18, 25].

A growing trend is the use of hybrid AI approaches that combine different AI techniques for more robust, adaptable and resilient control systems. Integrating AI with technologies like IoT and blockchain is expected to create new applications and business models in power electronics, contributing to more efficient, reliable, and intelligent systems that support renewable energy, electric vehicles, and smart grids [2, 4, 18, 25].

7. Conclusion

The integration of AI-based control techniques into power electronics represents a significant advancement in the field, offering new opportunities to enhance the efficiency, reliability, and adaptability of these systems. From improving the performance of power converters and electric drives to optimizing the operation of renewable energy systems and smart grids, AI has the potential to transform the way electrical power is managed and controlled. However, the adoption of AI in power electronics introduces technical, ethical, and implementation challenges that must be carefully addressed.

This review has consolidated and critically analyzed recent advances in AI-based control for power electronics, highlighting the comparative strengths and limitations of different approaches. Future research should focus on scalable real-time AI controllers, hybrid physics-informed models, and standardized benchmarks to ensure robust, interpretable, and industry-ready solutions.

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