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ARTIFICIAL INTELLIGENCE BASED CONTROL SYSTEMS FOR POWER ELECTRONICS APPLICATIONS

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Article Info

Abstract
This paper examines the application of Artificial Intelligence (AI)-based control systems. in power electronics, emphasizing their usefulness, stability and implementation. challenges. As AI continues to be integrated into modern engineering very fast, it is important to understand its effects. is important on performance of the system and industrial preparedness. A closed ended, structured questionnaire was used on. a sample of 500 professionals, amongst them researchers, academics, engineers and graduate. students of power electronics and control systems. Data obtained was analyzed. by way of descriptive statistics, by frequencies and percentages to illuminate current trends, Tastes, and impressions. The outcomes show that two-thirds of the participants encountered AI-based control. There are systems with Artificial Neural Networks and Fuzzy Logic being the most commonly used ones. techniques. The main applications became inverter and DC-DC converters. Most participants preferred based and hybrid control strategies. Notably, 68% of Respondents found AI-based controllers more effective than their traditional counterparts, and 70 percent did with regard to their reliability at different load or fault conditions. Despite these advantages, difficulties in the form of incompetence, increased computing demands, and compatibility with remaining barriers are existing systems. In addition, 52% complained of practical. realization in hardware, denoting increasing but tentative use in industry. The study is a contribution to the knowledge of the transformation of AI. power electronics through offering factual experiences on how users experience the power electronics, perceived effectiveness, and industry challenges. The results underline the possibility of AI-based control improvement. productivity and effectiveness as well as further emphasizing that training, cost cutting and enhanced integration plans to particularly assure mass industrial implementation.

Keywords:
Artificial Intelligence, Power Electronics, Control Systems, AI-based Controllers, Industrial Adoption

INTRODUCTION

Power electronics is the key component to the present technology, making possible the efficient conversion and regulation of electrical power over an enormously broad range of processes, including the integration of renewable energy sources and electric vehicles, consumer electronics and electric motor drives (Zhao et al., 2020). The level of sophistication in the control strategies is critical to the performance, efficiency and reliability of these systems (Vasudevan, 2023). However, over decades, classical techniques have dominated control, especially Proportional-Integral-Derivative (PID) controllers, which are simple and reliable to the extent of being a de facto in the industry. But the growing complexity in the contemporary power system, with non-linearities, variable operating conditions and challenging performance requirements has revealed the shortcomings of such traditional linear techniques of control (Alim et al., 2025). They frequently have difficulty producing the best performance over a broad operating range and must be carefully and painstakingly tuned by highly trained engineers (Amin & Kazmi, 2024). This mismatch between the features of traditional control and the requirements of next-generation power electronics has led to an urgent need to find more intelligent, adaptive and robust solutions.

The need has triggered the search into and the utilization of Artificial Intelligence (AI) as the underpinning of advanced control systems. With its deep learning techniques and capability to develop abstract patterns and make clever choices from data, AI is a paradigm change to adaptive instead of model based control, and data instead of models (Iqbal, 2023).

Algorithms like Artificial Neural Networks (ANNs), Fuzzy Logic and Reinforcement Learning provide a potential to create controllers capable of self-optimizing in real-time, addressing system non-linearities, and operating at high performance even when disruptive conditions such as load variations and component faults occur (Shah, 2024). But the promise of the AI-based control is not necessarily incremental, but a dramatic leap in independence, efficiency, and sustainability, leading to new and more capable power electronic systems (Qashqai et al., 2019).

This high potential notwithstanding, AI implementation into the fundamental control loops of power electronics is not a simple task (Afshar & Shah, 2025). It is an intricate crossroad of data science, control theory, and power engineering, with a set of issues and concerns that are new (Ahmad & Museera, 2024). The shift to hardware based implementation over theoretical simulation is faced with challenges of computational cost, real-time processing requirements, and functional safety and reliability assurance (Bose, 2020). Moreover, academic literature, fertile with promising simulation studies and single experimental substantiation, all too frequently does not exhibit an in-depth grasp of the larger industrial picture. The real-world experience, perceived success, and key issues of the engineers and researchers involved in the vanguard of this transition are less documented.

This landscape, the balance between high potential and real challenges, is important to understand to inform future research, development, and training efforts (Zhao et al., 2024). We need to go beyond the hypothetical advantages and collect real-world information on the practical implementation of AI and the benefits gained through it and the barriers to its implementation on a broader basis (Li et al., 2021). That would demand a systematic process of harnessing the wisdom of a wide community of practitioners, such as academic researchers creating new algorithms, industry engineers applying solutions to their products, and graduate students who are the future of the discipline (Paret et al., 2023).

The aim of this study was thus to examine the current landscape of AI-based control systems applied to the power electronics application domain. Its core goal is to introduce a clear, evidence-based picture of the direction of the field based on the experiences, perceptions and attitudes of the people engaged in the field actively (Imtiaz et al., 2025). The study tries to answer some of the key questions: How widespread is practical work with AI-based control in the power electronics industry?

What AI methods and technologies are used most? What do the experts think of the effectiveness and reliability of such systems relative to proven methods? What are the tools of choice? Above all, what are the greatest obstacles to accelerated and more widespread industrial implementation of this potential technology?

This research will fill this gap between promises of theory and reality. The results are supposed to provide useful information to various stakeholders. As a research tool it can help to identify gaps in current technology and to guide future efforts to address the most pressing unsolved challenges, such as robustness and computational efficiency.

To industry leaders and engineers, it offers a reference point against which to gauge their own adoption process and the key challenges that must be overcome (Khan et al., 2025). This points to the growing need of education and specialized training programs to create a new generation of professionals who might work with AI for engineering purposes (Patil et al., 2024).

Finally, the analysis can be part of a more enlightened path towards achieving the full capabilities of artificial intelligence in the development of the next generation of smart, efficient and reliable power electronics systems.

Problem statement

While the concept of AI-based control systems holds great potential as an alternative to conventional approaches for the control of complex non-linear power electronics applications, their path from research to industrial implementation is still unclear. Practical implementation, however, is limited by issues of computational requirements, fault-tolerance, and a severe shortage of qualified personnel. This work explores this disconnect, seeking to identify the key obstacles and to evaluate the maturity of AI-based solutions in the wild in order to establish their suitability for widespread deployment in modern power electronic systems.

Major Research Objectives

1. To assess the current adoption landscape and practical application of AI-based control systems within the power electronics community. This objective seeks to quantify the prevalence of hands-on experience, identify the most commonly used AI techniques (e.g., Neural Networks, Fuzzy Logic), and determine the specific power electronic applications (e.g., Inverters, Motor Drives) where they are being deployed.

2. To evaluate the perceived effectiveness and reliability of AI-based control strategies compared to traditional methods. This aims to gauge expert opinion on the performance benefits of AI control in terms of efficiency and dynamic response, as well as to understand the confidence in its robustness and stability under challenging real-world operating conditions, such as load variations and system faults.

3. To identify the primary tools used for development and the key barriers hindering widespread industrial implementation. This objective focuses on mapping the software and hardware toolchain (e.g., MATLAB, Python, Embedded C++) and, crucially, diagnosing the most significant obstacles to adoption, whether they are technical (e.g., computational cost, real-time implementation), human (e.g., lack of expertise), or related to industry acceptance.

4. To analyze the readiness and prevailing outlook regarding the large-scale industrial deployment of AI-based control solutions. This aims to determine the consensus within the field on whether the technology is mature enough for widespread use in commercial products, identifying the critical gaps between proven potential and scalable, reliable industrial application.

Literature Review

Evolution of Control in Power Electronics

The development of control solutions of power electronic systems is directly related to the increasing complexity and performance requirements of electrical systems. It was based on classical linear control techniques, and the Proportional-Integral-Derivative, aka PID controller, was the workhorse for decades (Leon et al., 2016). Its popularity was based on a simple design, easy implementation and reliable performance for a wide range of standard applications. However, the innate limitations of linear controllers were quickly shown when applied to the non-linearities, parameter variations, and dynamic operating conditions inherent to modern power electronic systems such as inverters for renewable energy or drives for electric vehicles (Tan, 2020). PID controllers can require time-consuming manual tuning for a particular operating point, can be unstable in the presence of transients or faults, and generally cannot maintain good performance over a broad range of load.

As a result, more advanced model-based control strategies were conceived and implemented. Sliding Mode Control (SMC), which is robust to parameter variation and disturbance, and Model Predictive Control (MPC), which can account for multi-variable systems and constraints explicitly, resulted in significantly better performance compared with the LPQC approach (Dekka et al., 2017).

These techniques were a significant leap ahead but brought their own problems with them. Their quality depends significantly on the accuracy of the system mathematical model and this is why it is very important to have a solid mathematical model before designing the control system (Abad, 2017). It is often challenging and time consuming to develop accurate models for complex high frequency switching converters (Afshar & Shah, 2025). Further, the computational burden of the algorithms, in particular the real-time optimization that is inherent in MPC, can be too high for cost-sensitive or high-speed applications, constituting a major obstacle to broad industrial deployment.

The Rise of Artificial Intelligence in Control

The consistent desire to achieve increased autonomy, flexibility, and performance has triggered the introduction of Artificial Intelligence (AI) to control engineering. AI holds the promise of a paradigm shift between a strictly model-dependent approach to data to a data-driven, intelligent system with the ability to learn and self-optimize (Shi et al., 2020). Acting in opposition to conventional approaches, AI based controllers are capable of discovering non-linear and complex relationships within a mechanism without necessarily having a mathematical model of the system, but instead can discover the system behavior based on operational data (Howard, 2019).

Out of the mass of AI methods, there are a few that have been used extensively in power electronics. Artificial Neural Networks (ANNs) can be used to approximate any non-linear function and are therefore commonly employed to track the maximum power point of solar systems, to control the current of inverters, and to diagnose faults (Alim et al., 2025). FLCs resemble human reasoning by operating using linguistic rules and are therefore highly useful in the control of systems whose models are imprecise or uncertain, like the control of the power quality of grid-connected systems (Khan et al., 2025). Reinforcement Learning (RL) is a more progressive frontier, where the agent learns the best control policy by interacting continuously with the system environment, with the promise of highly adaptive and optimal control in highly dynamic situations such as energy management in hybrid electric vehicles.

Applications and Implemented Domains

The implementation of AI-based control has infiltrated the field of power electronics in almost all of its sub-domains, with proven benefits. AI algorithms are used to improve the efficiency and reliability of the solar inverter and wind turbine converters in renewable energy systems. ANNs and FLCs are much quicker and more effective than conventional techniques such as Perturb and Observe at tracking Maximum Power Point (MPPT) under partial shading and varying atmospheric conditions. In the case of motor drives, AI controllers offer better control of the torque and speed response, less ripple and more energy efficiency, particularly in variable-load operation and when parameters are uncertain (Ding et al., 2025).

Another field where AI is having a significant influence is electric vehicle (EV) powertrains. Artificial intelligence-based controls play a critical role in optimizing the power split in a hybrid system, controlling battery health and efficiency in a Battery Management System (BMS), and controlling traction motors (Khan & Alvi, 2023). AI methods are used in power quality and grid-management (harmonic mitigation, active power filtering, grid-connected inverter stabilization under weak grid conditions, etc.). In addition, AI will play an important role in monitoring the health of systems and prognostics to detect anomalies and possible failures early in capacitors, switches, and other critical components to increase the reliability of the whole system and reduce downtimes.

Prevailing Challenges and Research Gaps

Despite the proven potential and successful proof-of-concept studies, the road from laboratory validation to broad industrial implementation of AI-based controllers is full of obstacles. Another challenge is that many AI algorithms are computationally intensive. The deep neural networks or complex RL agents require high-processing capabilities which can be expensive and power-hungry to integrate into low-cost and high-frequency power converters.

The other important hurdle is the question of reliability and trust. Unlike classical control, some AI technologies, most notably deep learning, can be a "black box," such that it may be difficult to ensure performance and stability under all operating conditions (including fault conditions or adversarial inputs that may be unseen during development). This lack of verifiability and explainability is a problem for functional safety, which is a mandatory safety requirement in industrial and automotive applications.

In addition, there is a severe lack of literature regarding practical application and industry readiness. While there are several studies that demonstrate excellent simulation results, relatively little research has been done to document large scale, long term hardware deployments, describe integration issues with legacy systems, or provide detailed cost benefit analysis. The ultimate success of any AI application in power electronics will be determined by overcoming these practical challenges related to hardware integration, computational cost, and standardization of design and validation frameworks that can foster trust among engineers and industrial players.

Methodology

A quantitative research design was used in this study to critically evaluate the perceptions, adoption and challenges relating to Artificial Intelligence (AI)-based control systems in power electronics applications. Quantitative method was chosen as it has the capability to give measurable, objective and generalizable results on a general group of professionals in the field.

The study involved 500 respondents, who were industry engineers, academic researchers, graduate students, and other practitioners that are involved in working with power electronics actively. In order to balance the diversity of opinions and be realistic at the same time, the random convenience sampling method was used in data collection; this enabled the researcher to include representatives of various fields and expertise levels.

The survey took place using a structured questionnaire, which contained demographic questions, multiple-choice items, Likert-scale measures and rating scales. The tool was created to measure such critical variables as professional experience, exposure to AI-based control strategies, preferred strategies, perceived efficiency, and perceived barriers to industrial adoption. The questionnaire was pre-tested before actual implementation to test its reliability, clarity and content validity before actual implementation.

Both descriptive and inferential statistical methods were used to analyze the data collected. Frequencies and percentages were used to describe the demographic profile and distribution of responses using descriptive statistics. The findings were also in the form of tabulations, bar charts, pie charts, and donut chart thus providing clear visualization of trends and patterns. Where necessary, inferential analyses were performed to determine how such demographic traits correlate with the perceptions of the AI-based control systems. Statistical software was used to help in data analysis and visualization in order to provide accuracy, reliability and professional presentation of results.

This methodological approach guaranteed rigor, representativeness and transparency in the research process. The combination of statistical accuracy and graphical explanation enabled the study to offer solid empirical data in evaluation of the preparedness, performance, and future prospects of AI-based control systems in the aspect of power electronics.

Data Analysis

The process of analyzing, cleaning, transforming and interpreting data in order to determine patterns, relationships and trends can be described as data analysis. It assists in transforming raw information into insights that are meaningful and aid in decision-making, solving problems, and generation of knowledge.

Results

Demographic Information

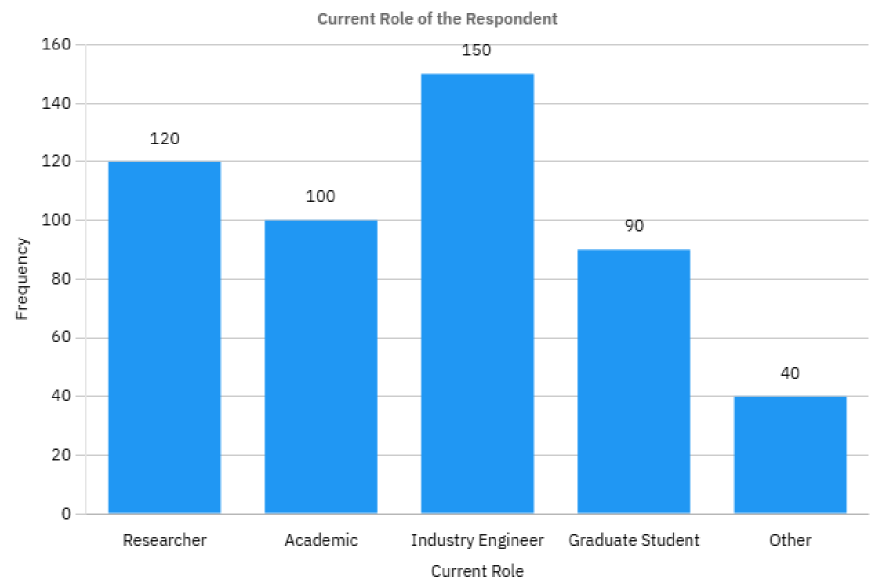

Figure No.1: Current Role of the Respondents

According to the survey data, the market of the respondents consists of mostly industry and academic professionals. The largest single group is Industry Engineers (30.0% or n=150), and right behind is the Researchers (24.0% or n=120). Academics are a big percentage at 20.0% (n=100), but the Graduate Students are 18.0% (n=90). Only 8.0% (n=40) identified as other (meaning roles not in these major categories). Overall, the readers are characterized by the preponderance of practitioners and specialists (more than two-thirds (74%) of participants state that they are Researchers, Industry Engineers, or Academics).

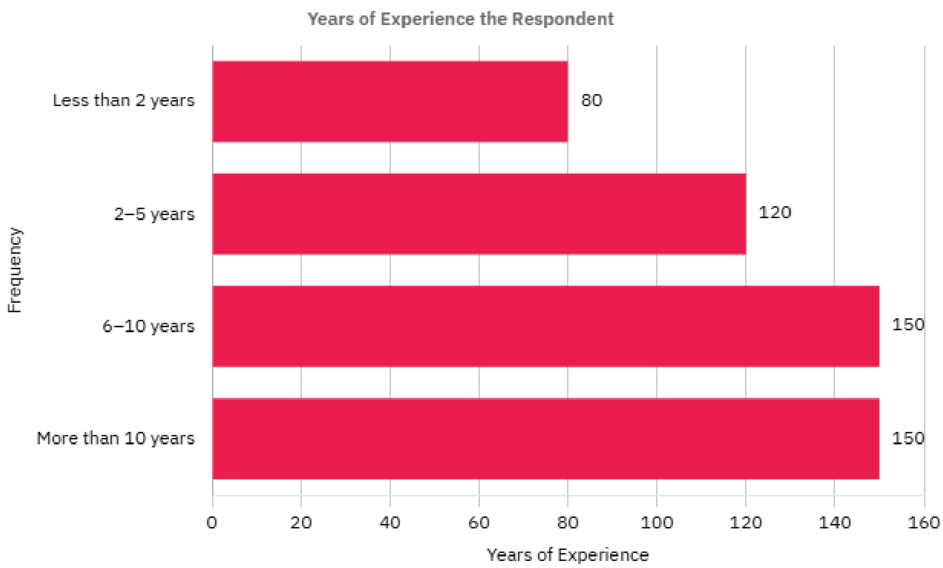

Figure No. 2: Years of Experience the Respondents

The results indicate a very senior group of respondents with most (60.0) having a working experience in the profession of six years or more. There is a 50-50 split between the 6-10 years and More than 10 years categories with each contributing 30.0% of the respondents (n=150). Those having two-5 years' experience represent the second largest group with 24.0% (n=120) experience, with only 16.0% (n=80) having less than two years' experience. It is a distribution with a mature audience, already established in jobs.

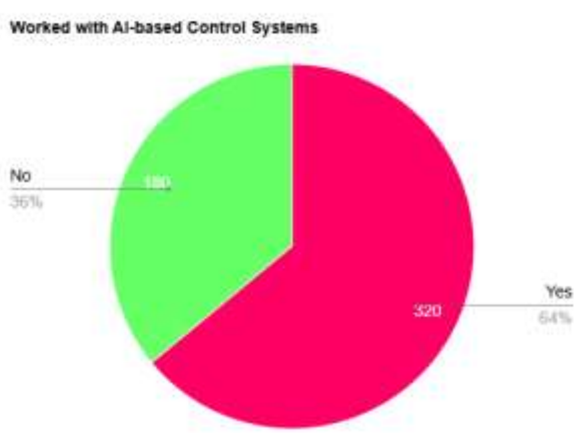

Figure No. 3: Worked with AI-based Control Systems

It shows that 64.0% (n=320) respondents have firsthand experience of working with AI-based control systems and 36.0% (n=180) do not. This illustrates that the technology is neither exclusive nor general in this professional fraternity, and that a large pool of applied knowledge exists among a definite majority of practitioners.

Table 1: AI Techniques Applied

Response	Frequency	Percentage (%)
Artificial Neural Networks	140	28.0%
Fuzzy Logic	100	20.0%
Genetic Algorithms	60	12.0%
Reinforcement Learning	80	16.0%
Support Vector Machines	70	14.0%
None	50	10.0%

According to the data, Artificial Neural Networks (ANNs) are the most commonly used AI technique, the one used by 28.0% (n=140) of the respondents. It is then followed by Fuzzy Logic at 20.0% (n=100), Reinforcement Learning at 16.0% (n=80) and Support Vector Machines (SVMs) at 14.0% (n=70). One-fifth (n=60) of them have employed genetic Algorithms, and only 10.0% (n=50) of them have not employed any of these techniques. The distribution is quite biased in favor of learning-based models such as the ANNs and Reinforcement Learning as compared to more traditional models such as Fuzzy Logic and Genetic Algorithms, albeit all of them have quite a strong representation.

Table 2: Applications of AI-based Control

Response	Frequency	Percentage (%)
DC-DC Converters	100	20.0%
Inverters	120	24.0%
Motor Drives	90	18.0%
Battery Management Systems	70	14.0%
Grid-Connected Systems	60	12.0%
Electric Vehicles	40	8.0%
Others	20	4.0%

Inverters are the most common use case of AI-based control at 24.0% (n=120) and DC-DC Converter is the second at 20.0% (n=100) and Motor Drives third at 18.0% (n=90). The Battery Management Systems (14.0% n=70) and the Grid-Connected Systems (12.0% n=60) make a secondary level. It is interesting to note that Electric Vehicles, which is a multifaceted application consisting of a number of subsystems is mentioned by 8.0% (n=40), but a small percentage (4.0%, n=20) report on applications in other areas. The distribution demonstrates a high level of control over and power conversion technologies.

Table 3: Preferred Control Strategy

Response	Frequency	Percentage (%)
Classical	120	24.0%
Model Predictive Control	80	16.0%
AI-Based	150	30.0%
Hybrid	110	22.0%
Other	40	8.0%

Among the five control strategies, the most desirable is AI-Based which was chosen by 30.0% (n=150) respondents. Classical is also a formidable opponent with 24.0% (n=120) favoring this method and Hybrid approaches are also popular with 22.0% (n=110) favoring this approach. 16.0% (n=80) and 8.0% (n=40) chose Other strategies, which are preferred by Model Predictive Control. This shows a major transition to superior and intelligent control approaches, with more than half (52.0) of all practitioners preferring AI-Based or Hybrid strategies to traditional or model-based approaches only.

Table 4: Effectiveness of AI-based Control

Response	Frequency	Percentage (%)
Much more effective	180	36.0%
Slightly more effective	160	32.0%
About the same	90	18.0%
Less effective	40	8.0%
Not sure	30	6.0%

According to the survey results, there is a high level of agreement when it comes to the effectiveness of the AI-based control systems. Sixty-eight point one per cent of those who have tried them feel that they are more effective than traditional approaches, 36.0% (n=180) of those who have tried them feel that they are much more effective and 32.0% (n=160) feel that they are slightly more effective. Only 18.0% (n=90) consider their performance to be as classical methods, i.e. About the same. Only a very small minority, 8.0% (n=40), consider them as "Less effective" and 6.0% (n=30) are not sure. It means that perception and validation of AI-based control are overwhelmingly positive among practitioners with firsthand experience.

Table 5: Reliability under Load/Fault

Response	Frequency	Percentage (%)
Very reliable	150	30.0%
Moderately reliable	200	40.0%
Not reliable	70	14.0%
Not sure	80	16.0%

On the basis of the information, the attitude to the reliability of an AI-based control system when subjected to a load, or when a fault occurs is optimistic but has much to be desired. Only 40.0 percent (n=200) of the respondents consider these systems to be moderately reliable. These are offset by 30.0% (n=150) who describe them as Very reliable, but 30.0% (n=70) say they are Not reliable, and a further 30.0% (n=80) say they are Not sure. This distribution indicates that AI control is not seen as fundamentally untrustworthy, although its strength in challenging or catastrophic situations has not been clearly established yet by a significant part of the professional community.

Table 6: AI improves Efficiency/Performance

Response	Frequency	Percentage (%)
Strongly agree	200	40.0%
Agree	160	32.0%
Neutral	80	16.0%
Disagree	40	8.0%
Strongly disagree	20	4.0%

The results indicate that there is a massive amount of agreement that AI increases system efficiency and performance. The overall response to this statement is 72.0% (n=160) who Strongly agree and 32.0% (n=160) who agree. Some are still neutral (16.0, n=80) or disagree with it, and only 8.0 (n=40) disagree and only 4.0 (n=20) strongly disagree. Such a positive skew is a sign that the perceived advantages of AI on improving the key indicators of operation are broadly accepted among this professional community.

Table 7: Ready for Large-Scale Deployment

Response	Frequency	Percentage (%)
Yes	200	40.0%
No	120	24.0%
Maybe	100	20.0%
Not sure	80	16.0%

The information points to a split but optimistically cautious attitude towards the maturity of AI-based control to be deployed at large scale. A small majority of 40.0% (n=200) are of the opinion that it is ready, but a large majority of 60.0% (n=200) have reservations. This is divided into those who state it is not ready without a doubt (24.0% n=120), the unsure group (16.0, n=80) and those who have it conditionally with the response of maybe (20.0, n=100). This implies that although people at the community level acknowledge its advantages, a large number still find challenges which may be in terms of reliability, standardization or verification which need to be overcome before mass adoption at the industrial level can become reality.

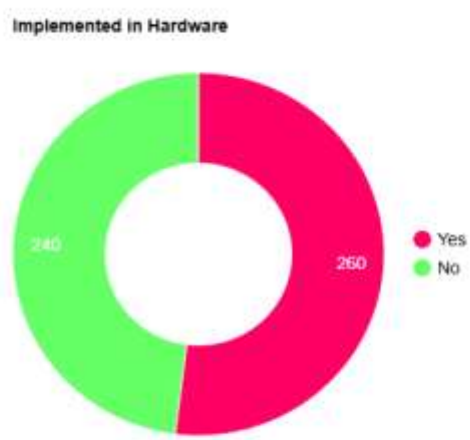

Figure No. 4: Implanted in Hardware

The results show that there is an almost 50/50 balance on whether an AI-based control has been implemented on hardware, where 52.0% (n=260) state they have, and 48.0% (n=240) do not. This split implies that although much of the field is currently moving these algorithms out of simulation and into physical systems, almost as many are still in research, development or simulation. The outcome points out that the act of transferring AI control beyond concept to deployed practice is an active and ongoing challenge to the industry.

Table 8: Biggest Challenge in Adoption

Response	Frequency	Percentage (%)
Lack of expertise/training	120	24.0%
High computational cost	80	16.0%
Real-time implementation	100	20.0%
Integration issues	90	18.0%
Limited industry acceptance	70	14.0%
Other	40	8.0%

According to the data, the most significant threat to the introduction of AI-based control is a "Lack of expertise/training," which is mentioned by 24.0% (n=120) of respondents. The technical barrier of the Real-time implementation is closely trailing on 20.0% (n=100). The most notable secondary barriers are the integration issues (18.0%, n=90) and the High computational cost (16.0%, n=80), and Limited industry acceptance is perceived as the challenge by 14.0% (n=70). The fact that it is distributed in this way suggests that the main impediments to doing so are not simply technical but also unavailable skilled personnel, suggesting that the training of the workforce and the feasibility of engineering solutions will be crucial to the wider adoption.

Table 9: Platforms/Tools Used

Response	Frequency	Percentage (%)
MATLAB/Simulink	160	32.0%
Python	120	24.0%
LabVIEW	60	12.0%
C/C++ Embedded	70	14.0%
FPGA/DSP	50	10.0%
Other	40	8.0%

The statistics show that the most preferable engineering and prototyping platforms are established and most of them are MATLAB/Simulink (32.0n=160). Python takes the second position at 24.0% (n=120), indicating its presence in the development of AI. To implement at lower level, C/C++ Embedded (14.0%, n=70) and FPGA/DSP systems (10.0%, n=50) are used, which means that design is replaced by deployment. LabVIEW has a percentage of 12.0 (n=60), and 8.0 (n=40) are using other tools. This toolchain distribution emphasizes a typical workflow: high-level environments (such as MATLAB and Python) to develop algorithms, embedded languages and hardware to run them in real-time.

Discussion

The results of this research provide an interesting image of the situation and attitudes towards AI-based control in the power electronics community. The high proportion of respondents who had 6+ years of experience (60% of all respondents) gives considerable credibility to this data, as it suggests that the respondent-collected information is based on practical knowledge.

The findings highlight a decisive change in the industry towards smart controlled approaches. The overall trend towards AI-Based and Hybrid control strategies (52%) and away Classical methods (24%) is an indication of a paradigm change; this is supported by the perceived high efficacy of AI (68% of respondents). This is more pronounced in fundamental applications such as inverters and DC-DC converters, where non-linear and complex dynamics are amenable to adaptive AI methods such as Artificial Neural Networks. The fact that an overwhelming number of people (72) agreed that AI enhances the efficiency and performance of the system further entrenches its perceived value proposition.

But there is a striking difference between the potential and the preparedness of AI to be used at scale. Particularly when it comes to technical advantages, the doubts with regard to reliability under fault conditions are still present, where only 30 percent feel comfortable characterizing these systems as Very reliable. This warning is reflected in the attitude towards mass industrial implementation, in which most (60 percent) were reserved or indecisive. The fact that hardware implementation is almost 50/50 verifies that closing the gap between the simulation and trusted physical implementation is a major challenge.

The challenges identified show that the adoption barriers are not strictly technical. The number one problem is the absence of expertise and training (24%), which indicates a serious skills gap in the workforce. Combined with technical barriers such as real-time implementation (20 percent) and integration challenges (18 percent), this human factor indicates that future breakthroughs will depend not only on improvements in algorithms, but also on a comprehensive educational process, the creation of more user-friendly tools, and a coordinated action to standardize and validate AI solutions to industrial settings.

Conclusion and Recommendations

Overall, this paper confirms that AI-driven control systems are viewed as a paradigm-shifting phenomenon in the field of power electronics, with the ability to provide high-performance and effectiveness improvements in the most critical areas such as inverters and motor drives. The success of AI and hybrid approaches over classical methods, as well as the broad adoption of practical experience by professionals, testify to the overall change in the approach to control challenges in the field. However, the implementation remains slow and only two areas of concern are reliability in the field and successful implementation of hardware.

Specific efforts, both technical and human, are required to hasten the process of integration. First, university and industry internship programs are to be increased to fill the skills gap in implementing AI. Not only the theory of AI, but also its implementation in power electronics in real-time and embedded systems and FPGAs should be part of the curriculum and professional courses.

Technically, the next line of research must focus on improving the resilience and interpretability of AI controllers, especially in fault and transient conditions. The development activities should be aimed at the optimization of algorithms in terms of reduced computational cost and simplified integration with the current industrial hardware and software platforms. Researchers and industry participants need to work together to develop standardized benchmarking and validation processes of AI-based power electronics systems.

Finally, the barriers that exist today will be solved only through a liaison between education, research, and the industry. The move from a hypothetical benefit to a widespread industrial adoption of AI can be attained by enhancing the efficiency of computations, building a more informed awareness of AI strengths and weaknesses, and proving reliability in various tasks.

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