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From switching to intelligence: emerging ai techniques for power electronic converter design and control

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ABSTRACT

Power electronic converters are fundamental to modern electrical energy systems, enabling efficient conversion and regulation of electrical power in applications such as renewable energy generation, electric vehicles, industrial drives, and smart grids. However, increasing demands for efficiency, power density, reliability, and dynamic performance have made conventional converter design and control increasingly challenging. Artificial intelligence (AI) and computational intelligence offer alternative approaches to address nonlinear system behavior, complex optimization problems, and changing operating conditions. This review examines the application of fuzzy logic, artificial neural networks, evolutionary algorithms, and intelligent predictive control in power electronic converter design and operation. Particular attention is given to switching optimization, maximum power point tracking, converter regulation, and multi-objective design. The review also discusses implementation challenges and identifies research directions for developing more adaptive, efficient, and reliable power electronic systems.

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1. INTRODUCTION

Power electronic converters have become essential components of modern electrical and electronic systems. They regulate voltage, current, frequency, and power flow in applications ranging from renewable energy interfaces and battery systems to electric transportation and industrial automation. Their performance is strongly influenced by semiconductor switching behavior, passive component selection, control strategy, and operating conditions. As power conversion systems become more compact and operate at higher switching frequencies, designers face increasing challenges in balancing efficiency, power quality, thermal performance, and reliability.

Conventional converter design and control generally rely on mathematical modeling, analytical calculations, classical feedback controllers, and experimentally determined switching strategies. These methods remain effective in many applications, but their performance may be restricted when systems exhibit strong nonlinearities, multiple operating modes, parameter variations, or competing design objectives. For example, selecting switching patterns for multilevel converters requires careful consideration of harmonic distortion, switching losses, and output voltage quality. Similarly, controller parameters that provide satisfactory performance under one operating condition may become less effective when the input voltage or load changes.

Artificial intelligence (AI) provides an alternative approach to addressing these challenges by introducing data-driven learning, rule-based reasoning, and computational search techniques into power electronics. Neural networks can approximate complex system behavior, fuzzy logic can represent uncertain or nonlinear relationships, and evolutionary algorithms can explore complicated design and control spaces. These approaches have been investigated in converter applications, including photovoltaic systems, multilevel inverters, and controller parameter optimization [1], [2]. This review examines their contributions, limitations, and potential integration in the development of intelligent power electronic converters.

2. ARTIFICIAL INTELLIGENCE FOR CONVERTER CONTROL

AI-based converter control aims to improve the response of power conversion systems when conventional fixed-parameter strategies become insufficient. Rather than depending exclusively on predefined linear relationships, intelligent controllers can use measured variables, learned patterns, or rule-based decisions to determine appropriate control actions. Their application is particularly relevant to converters with nonlinear characteristics and operating conditions that change over time. However, intelligent control does not automatically guarantee better performance, because its effectiveness depends on controller design, training data, computational capability, and validation.

Fuzzy logic control is one of the established intelligent approaches used in power electronics. It represents control decisions through linguistic rules and membership functions, allowing the controller to respond to system behavior without requiring a highly accurate mathematical model. Cecati, Ciancetta, and Siano demonstrated the application of fuzzy logic in a multilevel inverter for photovoltaic systems, illustrating how intelligent control can be incorporated into renewable energy conversion [2]. Such approaches are attractive when converter dynamics are nonlinear or when expert knowledge can be translated into practical control rules.

Neural networks provide another approach by learning relationships between system inputs and desired outputs from training data. In converter applications, neural networks can approximate nonlinear control functions, estimate operating conditions, and support the development of adaptive control strategies. Subiyanto, Mohamed, and Hannan combined a Hopfield neural network with a fuzzy logic controller to optimize maximum power point tracking (MPPT) in photovoltaic systems [3]. Their approach demonstrates how neural networks can improve the tuning of fuzzy controllers instead of relying entirely on manual adjustment and trial-and-error procedures.

The combination of different intelligent techniques can provide additional flexibility. A neural network may estimate a suitable reference value, while a fuzzy controller determines the converter control action based on the difference between the reference and measured operating conditions. Alternatively, an optimization algorithm can tune the parameters of an existing controller to improve its transient response. Nevertheless, these hybrid architectures require careful design because additional computational stages may increase implementation complexity and make system behavior more difficult to analyze.

3. INTELLIGENT OPTIMIZATION FOR CONVERTER DESIGN

Converter design involves several interacting variables, including switching frequency, inductance, capacitance, semiconductor ratings, thermal characteristics, and modulation strategy. Optimizing these variables simultaneously is difficult because improvements in one performance indicator may negatively affect another. For example, increasing switching frequency can reduce passive component size but may increase switching losses and thermal stress. Intelligent optimization methods are useful because they can search for suitable compromises among multiple design objectives.

Genetic algorithms (GAs) and particle swarm optimization (PSO) are among the metaheuristic techniques investigated in power converter design. GAs use evolutionary operations to explore candidate solutions, while PSO updates candidate solutions according to individual and collective search experience. These techniques have been applied to converter sizing, controller tuning, switching pattern selection, and harmonic reduction. De León Aldaco, Calleja, and Aguayo reviewed metaheuristic optimization methods in power converters and discussed their use in addressing complex design and performance optimization problems [1].

One important application is the optimization of switching patterns in multilevel inverters. The selection of switching angles can influence output voltage harmonics, semiconductor switching activity, and overall conversion quality. Evolutionary algorithms can search for switching configurations that satisfy specified harmonic and operational constraints. This approach is particularly useful when conventional analytical methods become difficult to apply because of multiple switching variables or nontrivial converter configurations.

Intelligent optimization can also improve controller parameter selection. Conventional proportional-integral controllers are often tuned using analytical procedures or empirical adjustment, which may require repeated testing when system parameters change. PSO and GAs can search for controller parameters that minimize selected performance criteria, such as transient error, overshoot, or settling time. However, optimization results depend on the chosen objective function, search boundaries, and algorithm settings, so an optimized controller must still be evaluated for stability and robustness.

4. INTELLIGENT TECHNIQUES IN RENEWABLE ENERGY CONVERTERS

Renewable energy applications provide an important environment for intelligent converter control because their operating conditions are often variable and uncertain. Photovoltaic systems, for example, experience changes in output power due to irradiance, temperature, and partial shading. Their power electronic interfaces must therefore maintain efficient energy extraction while regulating voltage and current according to system requirements. Intelligent control can support this task by adapting converter operation to changing photovoltaic characteristics.

MPPT is a well-established application of intelligent control in photovoltaic converters. Conventional perturb-and-observe methods are relatively simple, but they may oscillate around the maximum power point or respond slowly to rapidly changing irradiance. Subiyanto et al. proposed a Hopfield neural network-optimized fuzzy controller to improve the tuning of fuzzy membership functions for photovoltaic MPPT [3]. This example illustrates how neural networks and fuzzy logic can be combined to improve converter-level energy extraction.

Fuzzy logic has also been applied to photovoltaic inverter control beyond MPPT. Hannan et al. investigated the real-time performance of a fuzzy-logic-controller-based grid-connected photovoltaic inverter system, demonstrating the relevance of experimental implementation rather than relying exclusively on simulation results [4]. This distinction is important because an intelligent controller must operate within the sampling, processing, and protection constraints of actual converter hardware. Real-time validation is therefore a necessary step in assessing the practical value of AI-based control.

Predictive control offers another computationally intensive approach to converter operation. Model predictive control evaluates possible future system behavior and selects a control action according to a defined performance objective. Vázquez et al. reviewed developments in model predictive control for power converters and drives, highlighting the importance of prediction models, cost functions, and optimization algorithms [5]. Although conventional model predictive control is not inherently a machine-learning technique, it represents an important form of optimization-based intelligent control that can be combined with learning methods in more advanced architectures.

5. COMPARATIVE ANALYSIS OF INTELLIGENT METHODS

Different AI and computational intelligence techniques address different converter design and control requirements. Fuzzy logic is particularly useful when expert knowledge and nonlinear control rules are available, while neural networks are suited to learning relationships from measured or simulated data. Evolutionary algorithms are more directly associated with searching for optimized design parameters and switching configurations. Model predictive control provides a structured way to select control actions through online optimization, although its implementation depends on model quality and computational resources.

Table 1 summarizes the main methods discussed in this review and compares their typical applications, advantages, and limitations. The comparison indicates that the selection of an intelligent technique should be based on the converter topology, control objective, available hardware, and required response time. No single method is suitable for all power electronic applications, and hybrid approaches may be appropriate when their additional complexity is justified.

Table 1. Comparison of intelligent techniques in power electronic converters

Technique	Main application	Key advantage	Main limitation
Fuzzy logic control	Converter regulation and inverter control	Handles nonlinear behavior using rule-based reasoning	Membership functions and rules require careful design
Artificial neural networks	Nonlinear modeling, prediction, and MPPT	Learns complex input-output relationships	Requires representative training data
Genetic algorithms	Converter design and switching optimization	Explores complex multi-variable search spaces	Can require substantial computation
Particle swarm optimization	Controller tuning and parameter optimization	Relatively simple search mechanism	Sensitive to parameter settings and convergence behavior
Model predictive control	Switching-state selection and converter regulation	Handles multiple objectives and operating constraints	Requires an adequate prediction model and sufficient processing capability
Hybrid intelligent methods	Adaptive control and combined optimization	Combines complementary capabilities	Increases architecture and validation complexity

As shown in Table 1, intelligent methods differ in their computational requirements and suitability for specific engineering tasks. Fuzzy logic and neural networks are mainly useful for control and system approximation, whereas GAs and PSO are often employed during design or parameter optimization. Model predictive control is particularly relevant when switching decisions must account for multiple system

variables and constraints. Hybrid methods may combine these strengths, but their practical value must be demonstrated through comparative testing rather than assumed from algorithmic complexity.

6. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite promising developments, several challenges limit the widespread adoption of AI in power electronic converters. One major concern is the computational burden associated with training, optimization, and real-time decision-making. Converter controllers operate within strict sampling intervals, meaning that an algorithm must produce reliable control actions before the next switching decision is required. Complex neural networks or optimization procedures may therefore need simplification or dedicated hardware implementation.

Another challenge is the reliability and generalization of intelligent controllers. Neural networks trained using a limited range of operating conditions may not respond correctly when input voltage, load, temperature, or component characteristics change significantly. Similarly, an evolutionary algorithm may produce a solution that performs well for a particular objective function but does not satisfy all practical requirements. These issues emphasize the need for systematic testing under different operating conditions and the inclusion of physical constraints in intelligent algorithm development.

Future research should focus on integrating data-driven learning with established converter models and control principles. Such hybrid architectures could retain the stability and interpretability of conventional control while using intelligent methods to estimate parameters, tune controllers, or improve switching decisions. Further work is also needed on real-time implementation, fault tolerance, cybersecurity, and standardized performance evaluation. These developments would help bridge the gap between promising simulation results and dependable industrial applications.

7. CONCLUSION

AI and intelligent optimization have expanded the available approaches to power electronic converter design and control. Fuzzy logic, neural networks, GAs, and PSO can support nonlinear control, parameter tuning, switching optimization, and renewable energy conversion. Model predictive control further demonstrates how online optimization can improve converter operation when multiple constraints and performance objectives must be considered. Together, these methods provide opportunities to move beyond conventional fixed-parameter control strategies.

However, successful implementation requires more than selecting an advanced algorithm. Training data, model accuracy, computational requirements, stability, and real-time validation remain essential considerations. The most promising direction is likely to involve hybrid architectures that combine physical knowledge, conventional control, and intelligent computation. Through careful design and experimental validation, these approaches can contribute to power electronic converters with improved efficiency, adaptability, and operational reliability.

REFERENCES

[1] S. E. De Leon-Aldaco, H. Calleja, and J. Aguayo Alquicira, "Metaheuristic optimization methods applied to power converters: a review," *IEEE Transactions on Power Electronics*, vol. 30, no. 12, pp. 6791–6803, 2015, doi: 10.1109/TPEL.2015.2397311.

[2] C. Cecati, F. Ciancetta, and P. Siano, "A multilevel inverter for photovoltaic systems with fuzzy logic control," *IEEE Transactions on Industrial Electronics*, vol. 57, no. 12, pp. 4115–4125, 2010, doi: 10.1109/TIE.2010.2044119.

[3] S. Subiyanto, A. Mohamed, and M. A. Hannan, "Intelligent maximum power point tracking for PV system using Hopfield neural network optimized fuzzy logic controller," *Energy and Buildings*, vol. 51, pp. 29–38, 2012, doi: 10.1016/j.enbuild.2012.04.012.

[4] M. A. Hannan, Z. A. Ghani, A. Mohamed, and M. N. Uddin, "Real-time testing of a fuzzy-logic-controller-based grid-connected photovoltaic inverter system," *IEEE Transactions on Industry Applications*, vol. 51, no. 6, pp. 4775–4784, 2015, doi: 10.1109/TIA.2015.2455025.

[5] S. Vazquez, J. Rodriguez, M. Rivera, L. G. Franquelo, and M. Norambuena, "Model predictive control for power converters and drives: advances and trends," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 2, pp. 935–947, 2017, doi: 10.1109/TIE.2016.2625238.