Global Research Journal in Engineering, Science, Technology and Management (GRJESTM)
Volume 01, Issue 05 (September-October) 2025, pp. 230-235
GRJESTM :: An odaswa™ Journal
ISSN : 3107-3611 (Online)

RESEARCH ARTICLE

Machine Learning–Based Control and Optimization of Power Electronic Converters

A. K. Sharma[1], R. Patel[1], M. Chen[2], L. García[2], and S. Williams[2]

Abstract. Power electronic converters are core enabling technologies in renewable energy systems, electric transportation, and modern power grids. Their inherent nonlinear dynamics, switching-induced harmonics, and parameter uncertainties pose persistent challenges to conventional control approaches. This paper proposes a machine learning–based control and optimization framework for power electronic converters, aimed at achieving improved dynamic performance, robustness to uncertainties, and higher operational efficiency. A deep reinforcement learning controller is developed to regulate a DC–DC boost converter, replacing conventional proportional–integral control. The proposed controller learns an optimal duty-cycle policy directly from system interaction without relying on an explicit mathematical model. A simulation-based experimental platform is established to train and test the controller under varying load and input voltage conditions. Performance is evaluated in terms of voltage regulation accuracy, transient response, efficiency, and robustness to parameter variation. Results demonstrate that the machine learning controller achieves faster settling time, lower steady-state error, and improved efficiency compared with a benchmark PI controller. Furthermore, the learned policy exhibits strong adaptability to unseen operating conditions. The study confirms the feasibility and advantages of data-driven intelligent control for next-generation power electronic converters and provides a pathway toward real-time embedded implementation.

Keywords: Power electronic converters, machine learning control, reinforcement learning, DC–DC boost converter, intelligent optimization.

*1. Department of Power Electronics, Gujarat Technological University, Ahmedabad, India
2. Department of Industrial Engineering, University of Seville, Seville, Spain

Published By **odaswa**. Published in Chennai, Tamil Nadu, India

1. Introduction

The rapid growth of renewable energy systems, electric vehicles, and smart grids has intensified the demand for efficient and reliable power electronic converters. These converters enable voltage transformation, power conditioning, and bidirectional energy flow between sources, storage systems, and loads. Among various converter topologies, DC–DC converters and voltage-source inverters are widely deployed in photovoltaic systems, battery management units, motor drives, and microgrids [1], [2].

Despite their widespread use, power electronic converters present challenging control problems. Their behavior is inherently nonlinear due to switching actions, saturation effects, and coupling between electrical variables. Moreover, system parameters such as inductance, capacitance, and semiconductor characteristics vary with temperature, aging, and manufacturing tolerances. External disturbances such as load transients and input voltage fluctuations further complicate control design [3]. Ensuring stable operation, fast transient response, minimal overshoot, and high efficiency under all operating conditions remains a critical challenge.

Conventional controllers such as proportional–integral (PI), proportional–integral–derivative (PID), sliding-mode control, and model predictive control have been widely applied to converter regulation [4]–[6]. While these methods can deliver satisfactory performance under nominal conditions, they typically require accurate system models and careful parameter tuning. In practice, modeling uncertainties and changing operating points often degrade controller performance. Advanced control strategies such as model predictive control offer improved performance but at the cost of high computational burden and implementation complexity [7].

In recent years, machine learning (ML) has emerged as a powerful tool for modeling, prediction, and control of complex nonlinear systems. ML algorithms can extract control policies directly from data, learn hidden system dynamics, and adapt to varying environments without explicit mathematical models [8], [9]. These features make ML especially attractive for power electronics, where accurate models are difficult to obtain and real-time adaptation is desirable.

Early applications of ML in power electronics focused on parameter estimation and fault diagnosis [10], [11]. More recently, reinforcement learning (RL) has demonstrated strong potential for real-time control of converters and inverters by learning optimal switching strategies through interaction with the environment [12]–[14]. However, most existing studies remain at proof-of-concept stage, and comprehensive evaluations against conventional controllers under realistic operating conditions are still limited.

2. System Description and Problem Formulation

2.1. DC–DC Boost Converter Model

A DC–DC boost converter is selected as the study platform due to its wide application in renewable energy and battery-powered systems. The converter steps up a lower input voltage $V_{in}$to a higher output voltage $V_o$using an inductor, switch, diode, and output capacitor.

The averaged state-space model of the boost converter in continuous conduction mode is given by [15]:

$$\frac{di_L}{dt} = \frac{1}{L}(V_{in} - (1 - D)V_o)$$

$$\frac{dV_o}{dt} = \frac{1}{C}((1 - D)i_L - \frac{V_o}{R})$$

where $i_L$is inductor current, $L$and $C$are inductance and capacitance, $R$is load resistance, and $D$is the duty ratio of the switching signal.

The control objective is to regulate $V_o$to a reference voltage V_{ref}despite variations in V_{in}, load R, and component parameters.

2.2. Control Objective

The controller must:

- Maintain output voltage at V_{ref}
- Minimize overshoot and settling time
- Reduce steady-state error
- Maintain high conversion efficiency
- Remain robust under disturbances and uncertainties

This represents a nonlinear, multivariable, and time-varying control problem, motivating the adoption of data-driven learning-based control.

3. Machine Learning–Based Controller Design

3.1. Reinforcement Learning Framework

Reinforcement learning is adopted to learn an optimal control policy through trial-and-error interaction with the converter environment. The control problem is modeled as a Markov Decision Process defined by:

- **State** s_t: $[V_o, i_L, V_{in}, e]$, where $e = V_{ref} - V_o$
- **Action** a_t: Duty-cycle command $D \in [0,1]$
- **Reward** r_t: Penalizes voltage error and control effort

The reward function is defined as:

$$r_t = -(\alpha e^2 + \beta \Delta D^2)$$

where α and β are weighting coefficients.

The objective is to learn a policy $\pi(a_t \mid s_t)$ maximizing cumulative reward.

3.2. Deep Neural Network Policy

A deep neural network approximates the policy function. The network consists of:

- Input layer: 4 state variables
- Two hidden layers: 64 neurons each, ReLU activation
- Output layer: Duty-cycle action

The Deep Deterministic Policy Gradient (DDPG) algorithm is used due to the continuous nature of the duty-cycle control [16].

3.3. Training Procedure

The RL agent interacts with a simulated converter environment. Training episodes involve random variations in:

- Input voltage: 18–30 V
- Load resistance: 10–40 Ω
- Inductance and capacitance ±20% variation

The agent explores control actions using Gaussian noise and updates network weights using experience replay and target networks.

4. Baseline Conventional Controller

To provide a fair benchmark for evaluating the proposed machine learning–based control strategy, a conventional proportional–integral (PI) controller is implemented as the baseline control scheme for the DC–DC boost converter. PI controllers are widely adopted in industrial power electronic applications due to their simple structure, ease of implementation, and satisfactory performance under nominal operating conditions [4]. Despite their popularity, PI controllers exhibit limitations when dealing with nonlinear dynamics, parameter uncertainties, and rapidly varying disturbances, which motivates their use as a reference for comparison with intelligent controllers.

4.1. Controller Structure

The PI control law determines the duty-cycle command $D(t)$ based on the voltage error between the reference output voltage V_{ref} and the measured output voltage $V_o(t)$. The control equation is expressed as:

$$D(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau$$

where $e(t) = V_{ref} - V_o(t)$, K_p is the proportional gain, and K_i is the integral gain. The proportional term provides an immediate corrective response to voltage deviations, while the integral term eliminates steady-state error by accumulating past error values.

4.2. Gain Tuning Methodology

The PI gains are tuned using a frequency-domain small-signal model of the boost converter under nominal operating conditions. A standard pole-zero cancellation approach is applied to place the closed-loop poles in desired locations for stable and fast response. The crossover frequency is selected to be approximately one-tenth of the switching frequency to ensure adequate separation between control and switching dynamics. The final tuned values are:

$$K_p = 0.18, K_i = 85$$

These gains provide a compromise between transient response speed and closed-loop stability. The tuning process ensures minimal overshoot and acceptable settling time under nominal load and input voltage.

4.3. Implementation Details

The PI controller operates in a discrete-time framework with a sampling frequency equal to the switching frequency (50 kHz). The computed duty-cycle command is constrained within the allowable range $0 \leq D \leq 0.9$to prevent overmodulation and ensure safe converter operation. Anti-windup protection is implemented to avoid integrator saturation during large transients or startup conditions.

4.4. Expected Performance Characteristics

Under nominal conditions, the PI controller is expected to achieve reliable voltage regulation with limited steady-state error. However, because the controller gains are fixed, performance degrades when system parameters deviate from their nominal values. Variations in inductance, capacitance, or load resistance alter the converter dynamics and may lead to increased overshoot, slower settling, or even oscillatory behavior. Similarly, sudden changes in input voltage introduce disturbances that the PI controller can only compensate after an error develops, resulting in temporary voltage sag or overshoot.

These inherent limitations of fixed-parameter PI control provide a meaningful baseline for assessing the adaptive and data-driven capabilities of the proposed machine learning–based controller.

5. Simulation Setup

The proposed machine learning–based controller and the baseline PI controller are evaluated using a detailed MATLAB/Simulink simulation model of the DC–DC boost converter. The converter parameters are presented in Table 1. The model incorporates realistic switching behavior, parasitic resistances, and sampling delays to reflect practical operating conditions. The switching frequency is set to 50 kHz, and the control algorithms operate at the same sampling rate. Training and testing scenarios include step changes in load resistance, input voltage disturbances, and parameter variations in inductance and capacitance to assess robustness. All simulations are executed with a fixed-step solver to ensure consistent control timing and accurate comparison of dynamic responses.

Table 1: Converter Parameters

Parameter	Symbol	Value
Input voltage	Vin	24 V
Reference voltage	Vref	48 V
Inductance	L	1 mH
Capacitance	C	470 μF
Switching frequency	fs	50 kHz
Nominal load	R	20 Ω

Training is performed over 3000 episodes, each lasting 0.5 s simulation time. After training, the learned controller is tested under unseen operating conditions and compared with the PI controller.

6. Results

6.1. Training Convergence

The reinforcement learning agent demonstrates stable convergence during the training process. The cumulative reward increases steadily over episodes, indicating progressive improvement in voltage regulation and smoother duty-cycle actions. After approximately 2500 episodes, reward oscillations diminish, confirming that the policy network has learned a near-optimal control strategy. No divergence or unstable learning behavior is observed, validating the suitability of the selected network architecture and reward design.

6.2. Voltage Regulation Performance

The output voltage response under a sudden 50% load change is used to evaluate transient performance. The ML-based controller achieves a faster rise time and significantly lower overshoot compared to the PI controller. Steady-state error is reduced to less than 0.5%, whereas the PI controller exhibits nearly 2% error under identical conditions. These results confirm that the learned policy effectively compensates for nonlinear converter dynamics.

6.3. Robustness to Input Voltage Variation

To assess disturbance rejection capability, the input voltage is reduced from 24 V to 20 V during steady operation. The PI controller experiences a noticeable voltage sag before restoring regulation, reflecting delayed corrective action. In contrast, the ML-based controller maintains output voltage within ±1% of the reference with minimal transient deviation. This demonstrates superior adaptability of the learned control policy to external disturbances.

6.4. Parameter Uncertainty Test

Converter parameters are varied by ±20% to emulate component tolerances and aging effects. Under these uncertainties, the PI controller exhibits oscillatory behavior and prolonged settling time. The ML controller maintains stable operation with only minor degradation in transient response. This confirms that the data-driven controller generalizes well to unseen system parameter variations.

6.5. Efficiency Improvement

Converter efficiency is computed by averaging input–output power ratios under dynamic load conditions. The ML-based controller achieves an efficiency improvement of approximately 2–3% over the PI controller. This gain is attributed to smoother duty-cycle modulation and reduced switching stress. Higher efficiency highlights the optimization capability inherently learned by the reinforcement learning framework.

7. Discussion

The results confirm that ML-based control can outperform conventional PI control in regulation accuracy, transient response, and robustness. Unlike fixed-parameter controllers, the RL agent learns a nonlinear control policy that adapts to varying operating conditions without explicit system modeling. However, several challenges remain. Training requires a simulated environment and extensive interaction data. Stability guarantees are not analytically derived, although empirical tests indicate stable behavior. Computational requirements for embedded implementation must be carefully addressed, potentially through network pruning or lightweight architectures.

Despite these challenges, the study demonstrates that data-driven intelligent controllers are viable candidates for next-generation converter control. For real-time deployment, the trained neural network can be implemented on digital signal processor (DSP) or field-programmable gate array (FPGA) platforms commonly used in power electronic controllers. The inference time per control step is below 10 μs for the developed network architecture, ensuring compatibility with the selected switching frequency and real-time control requirements. The memory footprint remains under 200 kB, allowing efficient storage and execution on embedded hardware with limited resources. These computational characteristics confirm that the proposed ML-based controller is practically feasible for integration into modern power electronic control systems.

8. Conclusion

This research presented a machine learning–based control framework for power electronic converters using deep reinforcement learning. A DC–DC boost converter case study demonstrated that the proposed controller achieves superior voltage regulation, faster transient response, higher efficiency, and stronger robustness compared with a conventional PI controller. The results validate the potential of ML-based controllers for intelligent power conversion systems. Future work will focus on hardware implementation and formal stability assurance.

Acknowledgement

The authors thank their institutions for providing the necessary facilities to conduct this research. They are grateful to colleagues and lab members for their technical support and helpful discussions. The authors also acknowledge the computational resources used for simulations. Finally, they appreciate the reviewers for their valuable suggestions to improve the manuscript.

References

[1] R. Erickson and D. Maksimović, Fundamentals of Power Electronics, Springer, 2001.

[2] M. H. Rashid, Power Electronics: Circuits, Devices and Applications, Pearson, 2014.

[3] J. Sun, "Small-signal methods for AC distributed power systems," IEEE Transactions on Power Electronics, Volume 24, Issue 11, pp. 2545–2554, 2009.

[4] S. Bacha, I. Munteanu, and A. Bratcu, Power Electronic Converters Modeling and Control, Springer, 2014.

[5] V. Utkin, "Sliding mode control in power electronics," IEEE Transactions on Industrial Electronics, Volume 40, Issue 1, pp. 23–36, 1993.

[6] P. Cortés et al., "Model predictive control of power converters," IEEE Transactions on Industrial Electronics, Volume 56, Issue 6, pp. 1817–1825, 2009.

[7] J. Rodriguez et al., "Model predictive control of multilevel converters," IEEE Transactions on Industrial Electronics, Volume 57, Issue 8, pp. 2694–2705, 2010.

[8] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, Volume 521, Issue 7553, pp. 436–444, 2015.

[9] R. Sutton and A. Barto, Reinforcement Learning: An Introduction, MIT Press, 2018.

[10] S. Yin et al., "Data-driven fault diagnosis for power converters," IEEE Transactions on Industrial Electronics, Volume 62, Issue 12, pp. 7721–7731, 2015.

[11] J. Wang et al., "Neural-network-based parameter estimation of DC–DC converters," IEEE Transactions on Power Electronics, Volume 33, Issue 1, pp. 875–885, 2018.

[12] L. Zhang et al., "Reinforcement learning-based switching control of power converters," IEEE Journal of Emerging and Selected Topics in Power Electronics, Volume 9, Issue 3, pp. 2875–2886, 2021.

[13] M. G. Simões and F. Farret, Renewable Energy Systems: Design and Analysis with Induction Generators, CRC Press, 2014.

[14] A. Ghosh et al., "Deep reinforcement learning for real-time control of DC–DC converters," IEEE Transactions on Industrial Electronics, Volume 69, Issue 6, pp. 6023–6033, 2022.

[15] D. Maksimović, "Averaged switch modeling of converters," Proceedings of the IEEE, Volume 90, Issue 6, pp. 986–1003, 2002.

[16] T. Lillicrap et al., "Continuous control with deep reinforcement learning," Proceedings of the International Conference on Learning Representations (ICLR), 2016.