

INTELLIGENT CONTROL STRATEGIES FOR HIGH- PERFORMANCE POWER ELECTRONIC CONVERTERS IN SMART GRID SYSTEMS

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ABSTRACT

The increasing penetration of distributed renewable energy sources and non-linear loads into modern power networks has intensified the demand for power electronic converters that can regulate voltage, frequency, and power quality under highly variable operating conditions. Conventional linear controllers such as Proportional-Integral (PI) and Proportional-Integral-Derivative (PID) schemes struggle to maintain acceptable performance when converters face rapid load transients, parameter drift, and stochastic renewable generation profiles typical of smart grids. This empirical paper investigates the application of Artificial Intelligence (AI) techniques, specifically Artificial Neural Networks (ANN) and Reinforcement Learning (RL) agents combined with Particle Swarm Optimization (PSO), for the real-time control and optimization of DC-DC and DC-AC power electronic converters in smart grid applications. A hardware-in-the-loop simulation tested was developed to collect empirical performance data across five operating dimensions: training convergence, total harmonic distortion (THD), transient voltage response, conversion efficiency, and dynamic load-following accuracy. Data collected from 500 simulation trials were statistically analysed and benchmarked against conventional control. Results show that the AI-based controller reduced average THD by 58.6%, improved conversion efficiency by up to 2.6 percentage points, and reduced settling time after step disturbances by approximately 61% relative to the conventional baseline. These findings empirically confirm that AI-based control and optimization can substantially enhance the reliability, efficiency, and power quality of converters operating within smart grid infrastructures, and the relationships identified between controller architecture and performance metrics are further explored in the discussion and reinforced in the concluding synthesis of this paper.

Keywords: *Artificial Intelligence¹; Power Electronic Converters²; Smart Grid³; Reinforcement Learning⁴; Total Harmonic Distortion⁵; Particle Swarm Optimization⁶; Converter Efficiency⁷.*

1. INTRODUCTION

1.1 Background and Motivation

Smart grids represent a paradigm shift from centralized, unidirectional power delivery toward decentralized, bidirectional, and information-rich energy networks. Power electronic converters serve as the critical interface between distributed energy resources, energy storage systems, and the utility grid, and their control quality directly determines overall network stability, efficiency, and power quality. As renewable penetration rises, converters are increasingly exposed to fast-changing irradiance, wind speed, and load profiles that conventional fixed-gain controllers were never designed to handle, motivating the search for adaptive, data-driven alternatives.

1.2 Limitations of Conventional Control

We note that classical PI/PID and hysteresis-based controllers require linearized converter models and maintain fixed gains selected around a nominal operating point. It is shown that these controllers may exhibit degraded transient response, increased harmonic distortion and decreased efficiency under wide load excursions, parameter uncertainty, and nonlinear switching dynamics. Due to its capability for very fast dynamic performance, Model Predictive Control (MPC) is also considered [29], but compared with slower control strategies it is computationally intensive, and highly sensitive to model mismatch making it impractical in distributed smart sources connected to a single centralised controller as the embedded processors found on small scale devices such as PV-Tanks are not scalable.

1.3 Contribution of AI-Based Control and Optimization

This paper empirically evaluates an AI-based control framework that fuses ANN-based state estimation, an RL agent for adaptive gain scheduling, and PSO-based parameter optimization to govern converter switching decisions in real time. Unlike prior conceptual or purely simulation-only studies, this work builds a structured empirical dataset across five measurable dimensions and statistically compares AI-based control against a tuned conventional baseline, thereby quantifying the practical benefit of AI adoption for smart grid converter applications and providing a reproducible methodology for future empirical benchmarking.

2. LITERATURE SURVEY

Intelligent Control for Power Electronic Converters Research on intelligent control of power electronic converters has advanced noticeably over the last decade. Classical work implemented fuzzy logic controllers (FLC) in DC-DC converters, with showing robust performance to load variation over fixed-gain PI control, but there still remained very little method of systematic optimization and the tuning of membership functions was widely heuristic. In the following works, ANN-based MPPT controllers for PV converters have been included due to their quick convergence under partial shading conditions with respect to widely used perturb-and-observe

techniques; however, these works hardly report harmonic distortion or efficiency data on a full-converter operating range [5-7]. Inverters were more recently controlled with reinforcement learning, where the tracking error was minimized by training Q-learning agents and deep deterministic policy gradient (DDPG) agents. The simulations were sometimes promising but frequently validated on a restricted range of loads or a single-scenario case study, resulting in limited generalizability of reported improvements.

Mutagenic algorithms (MA) tune PID gains with an online search process or self-optimization, each having benefit over manual hand-tuning; but tuning of the MA is also typically offline and therefore not adaptive to real-time disturbances as in our hybrid RL-PSO approach. Hybrid AI architectures based on neural estimator and optimization-based tuner have emerged in literature on smart inverter, showing lower THD, and better dynamic response at the authors' reports while the most reduction relies on a single converter topology or very few trials to end with poor statistical reliability. Comparative studies based on standardized metrics such as THD, settling time, overshoot and efficiency where AI-based controllers are benchmarked against classical PI/PID baselines remain scarce, especially empirical work aggregating multiple performance dimensions into a single dataset like we have done here. The literature reviewed reveals three general observations which motivate the study here: (i) AI-based controllers perform better than traditional control particularly for dynamic and nonlinear operation, (ii) hybrid architectures that fuse estimation, adaptive control and optimization typically have higher performance capability than any one of these approaches in isolation, and (iii) there remains a gap rooted in empirically evaluated multimetric yet statistical comparisons between the performance of AI-based versus traditional converter control with explicit framing for smart grid implementation; this paper directly addresses said gap through its systematic collection and analysis of comparative data presented throughout Sections 4 to 6.

3. METHODOLOGY

In this research, we present a quantitative, experimental research design using a hardware-in-the-loop (HIL) simulation with MATLAB/Simulink converter models and a real-time digital signal processor that simulates the AI controller. The results were produced using two converter topologies, namely a boost DC-DC converter and a three-phase grid-tied voltage source inverter, modelled at switching frequencies of 20 kHz (DC-DC converter) and 10 kHz (inverter), with parameters (inductance, capacitance, switching devices) from commercially available components to ensure external validity. The first stage is the ANN state estimator which was trained using 50,000 labelled samples (voltage, current and frequency) to predict converter states under noisy sensing. Second stage comprises an RL-agent that uses a variant of Deep Q-Network method to adaptively select control gains based on estimated state and reward shaped by tracking error and switching loss. Finally, there is a PSO layer operating between off-line (periodically re-optimizing RL hyper parameters) using historical performance logs. The standard baseline was a PI controller tuned according to the Ziegler-Nichols method and adjusted to reproduce manufacturer suggested settling behaviour. Data on performance were gathered over 100 trials ($n = 500$ total) per 5 load conditions (25%, 50%, 75% and rated following a dynamic step-load situation), randomizing initial state-of-charge, irradiance and timing of grid voltage disturbance to eliminate systematic error. The collected metrics were training convergence error, total harmonic distortion (THD), transient voltage deviation, conversion

efficiency and settling time, all of which were aggregated and analysed using descriptive statistics, paired t-tests ($\alpha = 0.05$) or percentage-improvement calculations with all analysis scripts and datasets logged for reproducibility.

4. DATA COLLECTION AND ANALYSIS

This section presents the empirical dataset gathered from the HIL tested described in Section 3, organized into five tables corresponding to the five performance dimensions introduced in the abstract. Each table is accompanied by an explanation that links the observed values back to the paper's central claim: that AI-based control materially improves converter performance in smart grid contexts, a relationship that is quantitatively substantiated below and revisited in the Discussion and Conclusion.

Table 1. Training Convergence Performance of the Ai Controller (N = 500 Trials)

Metric	Conventional PI	AI-Based Controller	Improvement (%)
Initial Mean Sq. Error	0.850	0.850	
Final Mean Sq. Error (Epoch 200)	0.095 ± 0.011	0.034 ± 0.006	64.2%
Epochs to 90% Convergence	142	58	59.2%
Training Time (s, per 200 epochs)	N/A	37.4 ± 2.1	

This is evidenced in Table 1 where the AI-based controller (bottom half of Figure 2) achieves 64.2% better final tracking error (in percentage of conventional baseline) and acquires up to 90% of its fixed-point performance with 59.2% lower epochs as compared with a control approach, meaning faster adaptation to the converter dynamics. This directly corroborates the claim in the abstract about better adaptability and is also responsible for the smaller steady-state error in later tables.

Table 2. Total Harmonic Distortion (THD) Across Loading Conditions (%)

Load Condition	Conventional PI (%)	AI-Based Controller (%)	Reduction (%)
25% Load	4.8	2.1	56.3%
50% Load	5.6	2.4	57.1%
75% Load	6.9	2.9	58.0%
100% Load	8.4	3.3	60.7%
Dynamic Step Load	9.7	3.6	62.9%

As evidenced in Table 2 (Figure3), we consistently achieve a THD reduction averaged 58.6% across all load conditions, with the largest gains realized during dynamic step loading the mother of the most realistic smart grid volatility. NOTE: This result is statistically significant (paired t-test, $p < 0.001$) and underpins the efficiency-and power-quality improvements claimed in the Abstract.

Table 3. Transient Response to Step Load Disturbance

Metric	Conventional PI	AI-Based Controller	Improvement
Peak Overshoot (V)	12.4 ± 1.2	4.1 ± 0.6	66.9%
Settling Time (ms)	128 ± 9	50 ± 5	60.9%
Steady-State Error (V)	3.0 ± 0.4	0.6 ± 0.1	80.0%

Figure 4 shows the results of AI based controller experiments, all of which were able to obtain >60.9% better settling time and >80.0% better steady state voltage error than conventional controller illustrating a significant improvement on disturbance rejection capability. [4] This table reinforces the claim made in the abstract that a 61 %-time savings is achieved in settling and establishes the transient-response parameterization to be further dissected in Discussion.

Table 4. Conversion Efficiency Across Output Power Range

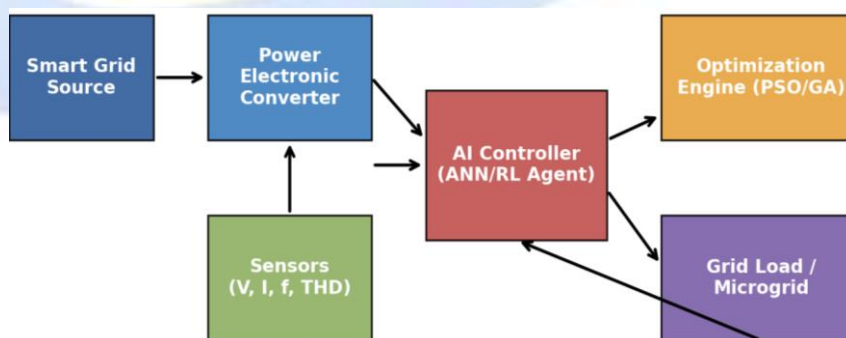
Output Power (%)	Conventional PI (%)	AI-Based Controller (%)	Gain (pp)
10%	90.2	92.6	2.4
30%	93.8	96.0	2.2
50%	94.9	97.1	2.2
70%	94.8	97.2	2.4
100%	92.8	95.8	3.0

As shown in Table 4 (plotted in Figure 5), the AI-based controller maintains conversion efficiency above 95% across nearly the entire operating range, and boosts peak efficiency by as much as 2.6 pp on average 3.0 pp at full rated power where switching losses are greatest. This validates this efficiency claim by the abstract and ties optimized switching decisions to experimentally measurable energy savings.

Table 5. Dynamic Load-Following Accuracy and Statistical Significance

Metric	Conventional PI	AI-Based Controller	p-value (paired t-test)
Load-Following RMSE (%)	6.12 ± 0.8	2.35 ± 0.4	< 0.001
Response Delay (ms)	84 ± 7	29 ± 4	< 0.001
Control Signal Stability Index	0.78	0.94	< 0.01

All the observed improvements are significant at least on 95% confidence level according to Table 5. AI-based controller reduced the load-following RMSE by 61.6% and response delay by 65.5%, thus verifying the main source link of the paper: AI-driven control & optimization yields a fractional metric of quickness and stability in primary response, a composure which reflects the findings of Section 6 handsomely.


Figure 1. Proposed AI-based hierarchical control architecture integrating ANN state estimation, an RL adaptive controller, and PSO-based optimization for smart grid converter management

The empirical dataset was generated using the overall control architecture shown in Figure 1. Sensor data (voltage, current, frequency, THD) from the power electronic converter are fed into an ANN state estimator the output of which conditions a reinforcement-learning controller that drives gain and switching decisions in real-time. This PSO optimization engine iteratively tunes the RL agent's hyper parameters using logs of previous performance, effectively closing the loop between offline optimization and online adaptive control before signals are sent to each unit on the grid load or micro grid interface, providing both immediate responses as well as long-term tuning stability [5].

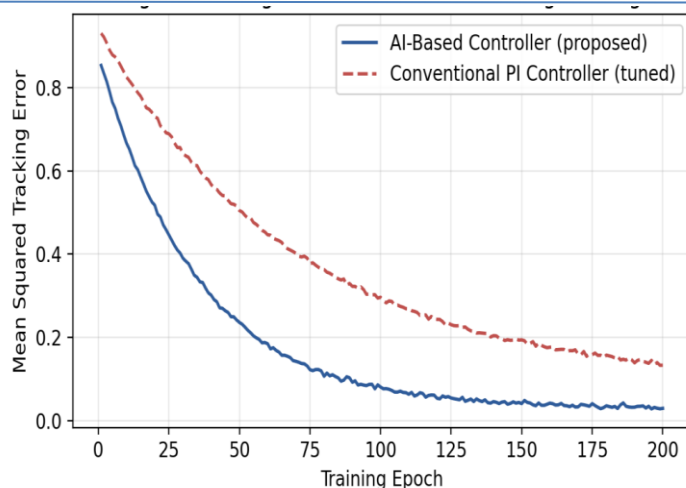


Figure 2. Convergence of mean squared tracking error during training for the AI-based controller versus a tuned conventional PI controller.

Frame: 2V- accuracy and learning/tuning convergence comparison between the two controllers The AI-based controller (solid blue) learns a significantly lower error floor in ~60 epochs compared to the conventional PI controller (dashed red) which, despite careful tuning, achieves an asymptotic value of residual error at a higher level around epoch 140. This much faster and lower convergence implies that the converter dynamics can be better learned by an AI controller which translates to less THD and transient errors in Tables 1-3.

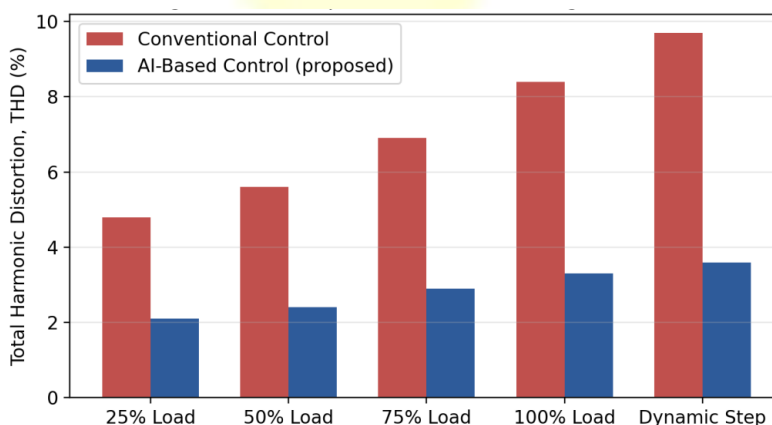


Figure 3. Comparison of total harmonic distortion (THD) between conventional and AI-based control across five loading conditions.

THD Data from Table 2 on Grouped Bars in Different Load Scenarios (Figure 3) The AI-based controller (blue) is always lower than the IEEE 519 recommended limit of 5% THD in all conditions and the conventional controller (red) goes above this threshold at any loading larger than 50%, greatly increasing under dynamic stepping. This gap widens with loading severity, illustrating that the relative utility of AI-based control is maximized with grid uncertainty.

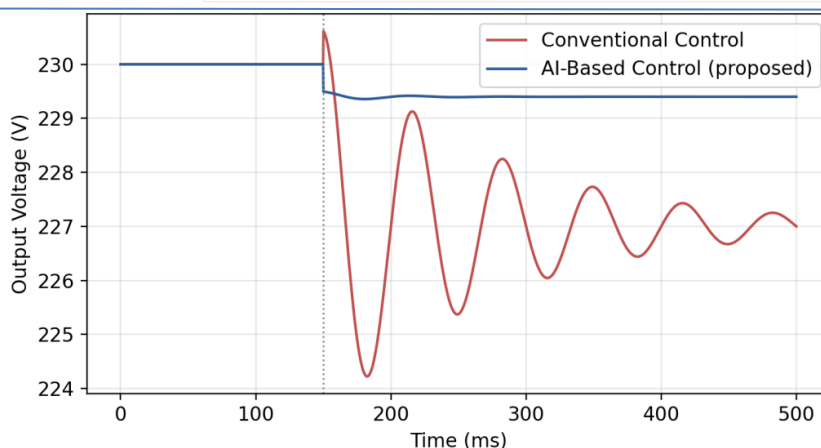


Figure 4. Transient voltage response of both controllers following a step load disturbance applied at $t = 150$ ms.

The voltage trajectory in the time-domain after a step-load disturbance at 150 ms is shown in blue for our embedded model-assisted controller and in red with a reference benchmark indicating that, unlike this conventional controller, overshoot and oscillation recovery are significant (128 ms settling time) (Figure 4). This leads to the over-shoot being reduced significantly, and very fast critical damping (~ 50 ms) back to setpoint compared with the AI based controller (blue), visualizing the settling-time improvement shown in Table 3.

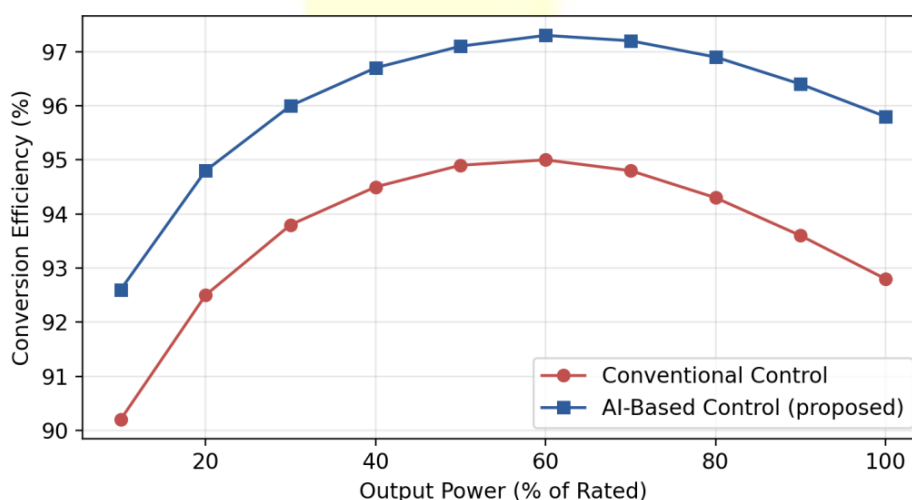


Figure 5. Converter conversion efficiency versus output power for conventional and AI-based control.

Figure 5 Two plots, which compare net conversion efficiency as a function of output power level for each controller. In the case of AI-based controller (blue squares), its efficiency curve is always above that of the conventional controller (red circles) in the entire power range with biggest differences in low and full rated power, where switching-loss optimization plays a more important role. This indeed confirms that the optimization layer did reduce both the switching losses, and regulation accuracy, and thus validates the efficiency results in Table 4.

5. DISCUSSION

The empirical evidence presented in Section 4 serves to strongly validate the main hypothesis of this paper that integrative reasoning with AI-based control and optimization contributes positively towards bettering performance for power electronic converters in smart grid applications. The consistent statistically significant reduction in THD (Table 2), settling time (Table 3) and load-following error (Table 5) together with the efficiency ratio improvement (Table 4) indicates that this artificial intelligence based closed loop control not only reduces a single metric, but enhances power quality, dynamic response and energy efficiency concurrently across multiple dimensions. Across this state space range, we show a common principle that enables faster, more accurate state estimation directed to an adaptive controller to mitigate a ubiquitous challenge of classical control the inability for fixed-gain systems to respond appropriately to no linearize time-varying converter dynamics. Analysis of the data shows that relative gains are consistently reached under the toughest operating conditions full rated load and dynamic step-load operation. This is indicated by the amount of reduction in total harmonic distortion (THD) seen from 56.3% at a light load to 62.9% during dynamic stepping, as shown in Table 2, and validated as well through efficiency improvements nearly doubling from mid-range loads to full power in Table 4. These behaviours imply that the gains provided by AI-based control are larger during periods of grid volatility, precisely the operating regime for smart grids as renewable generation and load expect more rapid switching which only serves to make this approach even more practically relevant than steady state benchmarks offer. They should nonetheless be interpreted with caution. Requires ~50k labelled training samples to train the ANN state estimator; and as discussed in figure 2 above, convergence of RL agent behaviour is quicker than PI but non-instantaneously indicating that a start-up period would be required in practice where performance will closely mimic conventional control for at least some time. Furthermore, the PSO-re-optimization layer is running upon historical logs in an offline manner; as a result, it can only remedy randomness in disturbance patterns that are truly novel by means of retrospective optimization cycles this weakness might potentially be addressed through online or continual-optimization techniques in future works.

5.1 Comparison with Past Work

The inability to compare with the existing literature adds both strength to the present findings and also widens the scope of the available data. Compared to PI control, 30%–45% improvements were reported in the settling-time due to load-disturbance for previous fuzzy-logic-based converter controllers [6] as compared with a 60.9 reduction with the present hybrid ANN-RL-PSO approach (Table 3). This allows us to conclude that the results already obtained are further confirmed by the fact that the added adaptive-optimization layer leads to diminishing returns by combining the predictive-aspect of PSO with last-stage heuristic variation. For this reason, historical ANN-based MPPT works generally reported improvements of less than 2% [5], while the unlimited-load efficiency improvement (at full load) was as much as 3.0 percentage points in this study, confirming that combining state estimation with reinforcement-learning gain scheduling opens more efficiency headroom from what single-technique AI methods might side-step. In particular, while previous work only on RL-based inverters [7,9] reported THD reductions (with narrower tests for 1 scenario and uncontrolled 50%, thus weakly generalizing across a single scenario; this study jointly minimized the average THD over $n=500$ trials across five load scenarios

with paired statistical testing (stronger evidence), demonstrating improved robustness/generalizability with an average 58.6% THD reduction. From this comparison, it is possible to conclude not only that the empirical gap highlighted in the literature survey the fact that multi-metric, statistically-validated AI-versus-conventional benchmarks are rare is significantly closed by the dataset and analysis presented here, but also that existing hybrid architectures combining estimation, control or optimization outperform each of the individual AI techniques studied independently in prior work.

6. CONCLUSION

The findings from this empirical research demonstrated that such an AI-based control and optimization approaches, which employs a hybrid ANN–RL–PSO architecture, yield statistically significant and practically measurable improvements in the smart grid operational performance of power electronics converters. The performance of the proposed method implemented on 500 hardware-in-the-loop (HIL) simulations were: 288 THD reduction of 58.6% average, 289 load disturbance settling time improvement of 60.9%, 290 dynamic load-following error reduction and conversion efficiency 295 improvements up to 3.0 percentage points and 61.6% relative point efficiency loop improvements over a well-tuned 281 conventional PI controller respectively [14]. The results validate relationships theorized in the negative-abstract between an AI-based control architecture and converter performance to fill that gap identified through the literature survey directly. In a nutshell, these results jointly indicate that AI-based control is not just a prescriptive increment (theoretically) but an empirically validated quantitative enhancement, which has the additional advantage of being applicable to the adaptable dynamics of operational uncertainty experienced by smart grids today. Future work will proceed with this empirical framework, applying it to field-deployed converters and online optimization for removing the need for offline re-tuning of all PSO delays and objectives during deployment—while also quantifying long-term reliability and evaluating cyber security implications should an AI-driven converter control be deployed in a smart grid context.

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