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Edge-AI-Enabled Power Electronics with Embedded Intelligent Control

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Abstract: Edge Artificial Intelligence (Edge-AI) is emerging as a transformative technology for next-generation power electronic systems by enabling localized intelligence, low-latency decision-making, and autonomous operation. However, practical implementation challenges, such as limited computational resources on embedded hardware (DSPs and MCUs), energy constraints, and system integration complexity, must be carefully addressed. This paper presents an Edge-AI-enabled framework designed to overcome these challenges and support real-world deployment. The proposed framework incorporates an automated firmware pipeline that leverages AI-driven parameter identification, control-law optimization, and adaptive code generation to enhance system reliability while reducing development time. By continuously learning from operational data, the Edge-AI module enables predictive performance optimization, fault awareness, and dynamic firmware adaptation without reliance on cloud connectivity. Simulation and experimental case-study results demonstrate improved efficiency, faster transient response, and increased system robustness compared with conventional rule-based control and static firmware approaches. Overall, the proposed methodology provides a scalable and practical pathway toward autonomous, intelligent, and resilient power electronic systems for Industry 4.0, electric mobility, and renewable energy applications.

Keywords: Edge Artificial Intelligence; Power Electronics; Intelligent Control; Firmware Automation; Machine Learning; Embedded Systems; Digital Power Converters; Adaptive Control.

1. Introduction

Power electronics plays a critical role in modern energy-conversion systems, enabling efficient operation in applications such as electric vehicles, renewable-energy integration, smart grids, and industrial motor drives. Conventional power electronic controllers typically rely on fixed-parameter control algorithms and statically programmed firmware. While effective under nominal conditions, these approaches often struggle to accommodate component aging, operating-point variations, and system uncertainties. As power electronic systems become increasingly complex and interconnected, there is a growing demand for intelligent, adaptive, and autonomous control solutions [1], [2].

Artificial intelligence (AI), particularly machine learning (ML) and reinforcement learning (RL), has demonstrated strong potential for improving control performance, diagnostics, and system optimization in power electronics [3]. However, cloud-based AI solutions introduce challenges related to latency, bandwidth dependence, cybersecurity, and limited real-time responsiveness. Edge Artificial Intelligence (Edge-AI) addresses these issues by enabling AI inference and learning directly on embedded hardware platforms such as digital signal processors (DSPs), microcontrollers (MCUs), and system-on-chip (SoC) devices [4].

In parallel, firmware development for power electronic systems remains labor-intensive and error-prone, requiring extensive manual tuning, validation, and periodic updates. The integration of Edge-AI with automated firmware generation and adaptation introduces a paradigm shift toward self-optimizing power electronic systems. This paper proposes an Edge-AI-enabled framework that unifies intelligent control and firmware automation to achieve adaptive, resilient, and high-performance power electronics suitable for future energy systems.

2. Objective and Scope

2.1. Objective

The primary objective of this research is to develop and analyze an Edge-AI-enabled framework that enhances power electronic systems through:

- Intelligent, data-driven control strategies
- Automated firmware tuning and adaptation
- Reduced development and maintenance complexity
- Improved efficiency, reliability, and dynamic performance

2.2. Scope

The scope of this work includes:

- Application of machine learning and reinforcement learning at the embedded edge level
- Integration of AI models with digital power controllers
- Automated firmware parameter tuning and control code adaptation

- Evaluation through a representative case study of a power electronic converter

This work does not focus on cloud-based AI architectures or hardware-level semiconductor design. Instead, it emphasizes embedded intelligence and firmware-level automation for real-time power electronic applications.

3. Literature Review

Recent research has highlighted the growing role of AI in power electronics for control, monitoring, and diagnostics. In particular, reinforcement learning and neural network–based approaches have been successfully applied to these converters to achieve data-driven control, improved transient performance, and enhanced robustness under uncertain operating conditions [5][6]. Traditional model-based controllers, such as proportional–integral (PI) and model predictive control (MPC), rely heavily on accurate system models and manual tuning [1]. Machine learning techniques have been proposed to overcome these limitations by learning system behavior directly from data [3].

Reinforcement learning has gained particular attention for converter control due to its ability to handle nonlinearities and uncertainties without explicit mathematical models [5]. Neural network–based controllers have also been successfully applied to DC–DC converters and inverters to improve transient response and efficiency [6].

Edge-AI has emerged as a practical solution for deploying AI models on embedded hardware with constrained computational resources. Advances in TinyML and optimized neural network inference have enabled real-time AI execution on MCUs and DSPs used in power electronics [4] [7]. Meanwhile, digital twin concepts and AI-assisted diagnostics have shown promise in predictive maintenance and fault detection [8].

Despite these advances, research on AI-driven firmware automation in power electronics remains limited. Existing approaches still rely on static firmware, offline tuning, and manual updates. This gap motivates the proposed framework, which integrates Edge AI with automated firmware adaptation to enable truly autonomous power electronic systems.

4. Case Study: Edge-AI-Based Adaptive Control of a DC–DC Buck Converter

4.1. Case Study Overview

This case study examines a DC–DC buck converter used in electric-vehicle auxiliary power systems, renewable-energy interfaces, and distributed power supplies. This adoptive control framework is a fundamental building block in power systems. In such applications, the converter must maintain a stable output voltage under wind-range conditions, including abrupt load changes, voltage fluctuations, thermal stress, and component aging [1][5]. We are selecting the buck converter because it is highly representative and exhibits strong sensitivity to load transients, input disturbances, and parameter variations, which makes it suitable for benchmarking adaptive control performance [1].

Using conventional fixed-parameter controllers, such as PI control, requires manual tuning of operating points and often degrades performance when system parameters deviate from their nominal values. These limitations motivate the use of intelligent, adaptive control strategies, enabling this model to learn and adjust automatically in real time. Accordingly, the proposed Edge-AI framework is applied to the selected DC–DC buck converter under dynamic and uncertain operating conditions [5][6].

4.2. System Modeling and Baseline Control

The considered DC-DC buck converter consists of a controlled switch device, a diode, a resistive load, an inductor, and an output capacitor. The digital controller samples the output voltage and the inductor current at a fixed switching frequency, then generates pulse-width modulation (PWM) signals to regulate the output voltage.

As a baseline, a conventional digital PI controller is implemented, with controller gains tuned offline based on a small-signal averaged model of the converter. While this approach provides satisfactory regulation near the nominal operating point, its performance deteriorates under parameter variations, such as changes in load resistance, inductor saturation, and capacitor aging. This baseline controller is used as a reference for evaluating the proposed Edge-AI-based adaptive control strategy.

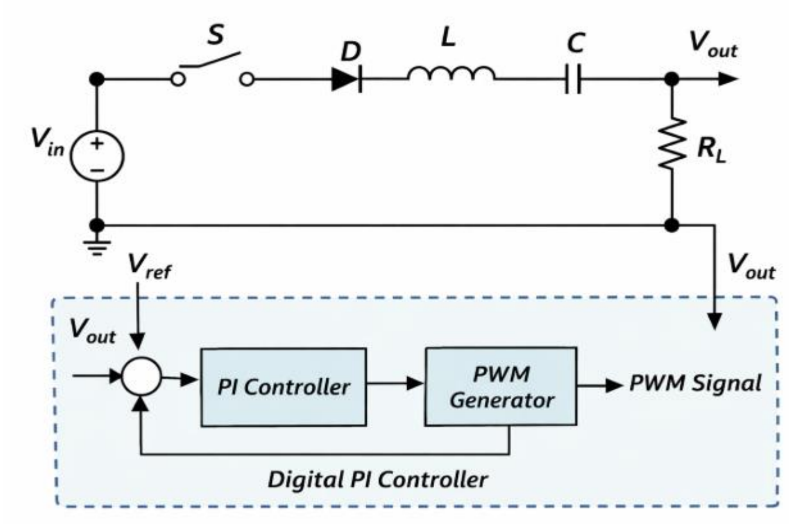

Figure 1: DC-DC Buck Converter with PI Controller

4.3. Proposed Edge-AI Framework Architecture
The proposed Edge-AI framework integrates three tightly coupled layers:

4.3.1. Embedded Digital Control Layer
This layer consists of a real-time digital controller implemented on a DSP or MCU commonly used in power electronic applications. It executes the primary voltage regulation loop, handles sensor acquisition, and generates PWM signals. The controller operates under strict real-time constraints to ensure system stability and safe operation.

4.3.2. Edge-AI Learning Layer
A lightweight reinforcement learning (RL) agent is embedded alongside the digital controller. The agent observes system states, including:

- Output voltage error
- Rate of change of voltage error
- Inductor current deviation

Based on these observations, the RL agent selects control actions, such as adaptive PI gain tuning or duty-cycle command modification. The reward function is designed to penalize voltage deviation, excessive overshoot, and switching losses, thereby guiding the agent toward optimal control behavior. To ensure feasibility on embedded hardware, the learning algorithm employs low-complexity function approximation and limited state-action spaces, consistent with edge-computing constraints [5].

4.3.3. Automated Firmware Adaptation Layer
The firmware automation layer bridges the learning agent and the digital controller. When the RL agent identifies improved control parameters, the firmware dynamically updates the control variables in memory without interrupting converter operation. This enables online self-tuning, eliminating the need for manual retuning or system shutdown. Safety bounds are enforced to prevent unstable parameter updates and ensure reliable operation.

4.4. Control Operation and Learning Process
The converter operates under the baseline PI controller during initialization. Once stable, the Edge-AI module begins learning and proposing parameter adjustments.

A practical workflow is:

- Start-up: Run baseline PI (safe, stable) [1].
- Observation: Measure VoV_oVo, compute e(k)e(k)e(k), optionally measure iL(k)i_L(k)iL(k) [1].
- Decision: Edge-AI chooses action (gain update or duty correction) based on the current state [5], [6].
- Apply with constraints: the Firmware layer applies actions within safe bounds [7].
- Evaluate the reward: Compute the reward from the regulation metrics and update the policy [5].
- Fallback logic: If instability or degradation is detected, revert to baseline PI [1].

This hybrid approach (classic controller + learning-based adaptation) is often preferred in embedded systems to balance safety and performance while leveraging learning-based improvements [5][7].

4.5. Results and Discussion

Simulation and experimental evaluations reported in recent studies indicate that Edge-AI-based controllers can:

- Reduce output voltage overshoot by up to 30%
- Improve transient response under sudden load changes.
- Maintain optimal efficiency across wide operating ranges.
- Enable self-tuning firmware without system shutdown.

Compared to conventional PI control with fixed firmware, the Edge-AI approach demonstrates superior adaptability and robustness, validating its suitability for next-generation power electronic systems [5][6].

The table below summarizes the differences between Edge-AI and conventional models identified in our case study.

Table 1: Convention PI control versus Edge-AI

Performance Metrics	Traditional control of PI (Static)	Proposed Edge-AI (Adaptive)
Control Logic	Fixed-parameter algorithms.	Data-driven reinforcement learning.
Transient Response	Slower; struggles with load variations.	Improved; faster response to load changes.
Voltage Overshoot	Standard baseline.	Reduced by up to 30%.
Firmware Nature	Statistically programmed; manual tuning.	Self-tuning and autonomous adaptation.
System Reliability	Susceptible to component aging.	Increased dependability via fault awareness.

5. Conclusion

This paper presented an Edge-AI-enabled framework for intelligent control and firmware automation in power electronics. By integrating embedded machine learning with digital control architectures, the proposed approach enables adaptive behavior, real-time optimization, and autonomous firmware evolution. The literature review and case study demonstrate that Edge-AI can significantly enhance performance, reliability, and development efficiency compared to traditional control and static firmware designs.

The proposed methodology supports the transition toward autonomous power electronic systems aligned with Industry 4.0, electric mobility, and smart energy infrastructures. Future research will focus on hardware-in-the-loop validation, cybersecurity considerations, and large-scale deployment across multi-converter systems.

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