World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

AI-driven control systems for embedded devices: Evolution and impact

Pratikkumar Dilipkumar Patel *

Arizona State University, USA.

World Journal of Advanced Research and Reviews, 2025, 26(02), 3450–3455

Publication history: Received on 16 April 2025; revised on 24 May 2025; accepted on 26 May 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.26.2.2037

Abstract

Artificial intelligence is fundamentally transforming power and performance control mechanisms in embedded systems across numerous industries. Traditional control methodologies like PID controllers and model-based approaches have long dominated embedded applications but face inherent limitations when managing complex, nonlinear system dynamics. The integration of neural networks and machine learning techniques represents a significant advancement that addresses these challenges. These AI-enhanced control systems demonstrate superior adaptation speed, accuracy, and disturbance rejection while capturing intricate relationships between system variables without explicit modeling requirements. Despite higher initial development investments, these intelligent controllers offer substantial long-term benefits through reduced maintenance needs and enhanced performance. Hybrid architectures combining conventional control theory with machine learning show particular promise by leveraging the predictability of traditional approaches alongside the adaptability of neural networks. As embedded processors continue advancing, on-device learning capabilities will enable unprecedented personalization and efficiency, with systems adapting to usage patterns, component aging, and environmental factors in real-time. The standardization of interfaces, pre-trained models, and optimization tools for resource-constrained environments will accelerate industry adoption, ultimately revolutionizing how embedded devices balance performance requirements with power constraints.

Keywords: Embedded Systems; Neural Networks; Control Optimization; Power Management; Artificial Intelligence

1. Introduction

Embedded systems form the computational backbone of modern electronics, from consumer devices to industrial machinery. These specialized computing units must carefully balance performance requirements with power constraints, a challenge that grows increasingly complex as devices become more sophisticated [1]. The control systems responsible for managing this equilibrium have traditionally relied on algorithmic approaches requiring substantial engineering expertise to implement and optimize.

Recent industry data reveals that embedded systems now power billions of devices worldwide, with applications spanning from simple microcontrollers to complex SoCs in smartphones and automotive systems [1]. These purpose-built combinations of hardware and software perform dedicated functions within larger mechanical or electrical systems, with power management remaining a critical challenge. Studies show that embedded systems typically operate with severely constrained resources, making efficient control algorithms essential for maintaining performance while extending battery life in portable devices.

This research examines the historical progression of control methodologies in embedded systems, from conventional feedback-based approaches to the current integration of artificial intelligence. We explore how these developments are reshaping not only the technical implementation of control systems but also their effectiveness in meeting the demands of contemporary embedded applications. Quantitative assessments demonstrate that AI-enhanced controllers can

* Corresponding author: Pratikkumar Dilipkumar Patel

achieve significant improvements in both performance and power efficiency metrics across multiple application domains [2].

The integration of machine learning techniques, particularly neural networks, represents a significant departure from traditional control engineering paradigms and merits detailed analysis. Neural network approaches to power management have shown particular promise in handling the complex, nonlinear relationships between system variables that traditional controllers struggle to model efficiently [2]. Recent implementations using reinforcement learning techniques have demonstrated the ability to reduce energy consumption while maintaining performance requirements across varying workload conditions.

The sections that follow will examine traditional control approaches and their limitations, explore the mechanics of AI-enhanced control systems, evaluate performance metrics across different methodologies, and consider the broader implications for embedded systems engineering. Through this investigation, we aim to provide a comprehensive understanding of how AI is fundamentally changing power and performance management in embedded computing.

Table 1 Global Embedded Systems Distribution by Application [1]

Application Domain	Market Share (%)	Annual Growth Rate (%)	Performance Requirements (Relative Units)	Power Constraints (mW)
Consumer Electronics	38.5	8.7	6.8	425
Automotive Systems	24.7	12.3	8.4	720
Industrial Control	18.2	6.5	7.2	1250
Medical Devices	12.5	9.8	9.1	380
Smart Infrastructure	6.1	15.4	5.3	840

2. Traditional Control Methodologies and Their Limitations PID Controllers

Proportional-Integral-Derivative (PID) controllers have historically dominated embedded control systems due to their relative simplicity and robustness. According to industry analyses, PID controllers remain the cornerstone of industrial automation, with widespread applications across process industries and embedded systems [3]. These controllers operate by calculating error values between measured process variables and desired setpoints, then applying corrections based on proportional, integral, and derivative calculations of this error.

In embedded systems contexts, PID controllers offer quantifiable advantages, with implementation requiring minimal computational resources and providing predictable behavior under normal operating conditions. The standardized PID algorithm's ubiquity has made it accessible to engineers across industries, with proven implementations available for virtually all embedded platforms [3]. This accessibility has contributed to PID controllers' persistent market dominance despite newer technologies.

However, significant limitations persist, with empirical studies revealing concerning efficiency gaps. The manual tuning process represents a considerable engineering investment, with each new application context requiring iterative adjustment of gain parameters. Performance optimization through loop tuning remains challenging, with studies indicating that poorly tuned controllers are common in industrial environments [3]. Additionally, PID controllers struggle with nonlinear dynamics and multi-variable systems commonly found in modern embedded applications.

2.1. Model-Based Control Approaches

Model-based control strategies attempt to address PID limitations through mathematical system representations. Model Predictive Control (MPC) implementations have demonstrated particular effectiveness in complex control scenarios by leveraging system models to predict future states and optimize control actions accordingly [4]. Recent research has shown MPC adoption increasing in embedded applications, particularly where system dynamics can be accurately modeled.

While offering improved performance, quantitative assessment reveals significant implementation barriers. MPC requires substantially more computational resources than PID control, with matrix operations and optimization algorithms necessitating more powerful processors [4]. The development of accurate system models represents a substantial front-loaded engineering investment, often requiring specialized domain knowledge and extensive system characterization. Research indicates that model uncertainty remains a critical challenge, with performance degradation occurring when operating beyond modeled conditions [4]. These resource requirements for development and maintenance remain prohibitive for many resource-constrained embedded applications.

Table 2 Model-Based Control Performance Metrics [4]

Approach Type	Performance Improvement vs PID (%)	Development Time (Hours)	Computational Requirements (MIPS)	Model Accuracy (%)
Linear State Space	18.5	45.3	3.2	87.4
Model Predictive Control	32.7	76.8	8.7	92.5
Nonlinear Model Control	41.2	124.5	12.4	78.3

3. AI-Enhanced Control Systems: Principles and Implementation

3.1. Neural Network Fundamentals in Control Applications

The application of neural networks to control systems represents a paradigm shift in approach. Comprehensive reviews of artificial neural network applications show that control systems represent one of the fastest-growing implementation areas, with pattern recognition capabilities enabling sophisticated response to complex system states [5]. Unlike traditional controllers, neural networks can capture nonlinear relationships without explicit modeling, allowing them to adapt to the multidimensional parameter spaces common in modern embedded systems.

Neural network architectures in embedded control typically follow multi-layer perceptron designs, with research indicating that even relatively simple networks can outperform conventional controllers for certain tasks. The structural modularity of these networks allows for significant customization based on application requirements, with input layers processing system state variables (e.g., current load, temperature), hidden layers capturing complex relationships, and output layers determining control actions [5]. This adaptive architecture has proven particularly valuable for embedded applications where system dynamics may change during operation.

3.2. Learning Methodologies

Several learning approaches have demonstrated measurable benefits in embedded applications. Recent research in expert systems emphasizes the effectiveness of supervised learning when high-quality training data is available, particularly for well-defined control problems with clear optimization targets [6]. This approach requires datasets of optimal control actions for given system states, often generated through expert systems or simulation.

Reinforcement learning has emerged as a particularly promising approach for embedded control, allowing systems to learn optimal policies through environmental interaction rather than pre-labeled examples. Analysis of reinforcement learning applications shows significant advantages in dynamic environments where control objectives may involve multiple competing factors (e.g., maintaining performance while minimizing power consumption) [6]. Transfer learning techniques have further enhanced implementation efficiency by allowing pre-trained networks to be adapted to new but similar control tasks, reducing training requirements for new applications. Research demonstrates this approach is particularly valuable in resource-constrained embedded environments where training data or computational capacity may be limited.

Table 3 Neural Network Architectures in Control Applications [5]

Network Architecture	Memory Requirements (KB)	Processing Requirements (MIPS)	Control Accuracy (%)	Adaptation Speed (ms)
Single Hidden Layer	45.2	3.8	88.7	175
Deep Feedforward	78.6	8.2	94.5	125
Recurrent Networks	124.3	12.7	96.8	85
Convolutional Networks	156.7	18.5	97.2	76

4. Comparative Analysis: Traditional vs. AI-Enhanced Control

4.1. Performance Metrics

Empirical evaluations of AI-enhanced control systems demonstrate several key performance advantages when compared to traditional approaches. Studies examining artificial neural networks in automatic control applications have documented significant improvements in adaptation speed across various implementation scenarios [7]. In dynamic workload conditions, neural controllers consistently achieve desired setpoints with fewer oscillations and faster settling times compared to conventional PID implementations.

Accuracy metrics show similarly promising results, with neural network controllers demonstrating superior ability to maintain target performance levels under varying conditions. Research published in the International Journal of Simulation has highlighted the enhanced precision of AI-controlled systems, particularly in complex embedded applications with nonlinear dynamics [7]. These controllers can capture and adapt to subtle system variations that traditional controllers typically struggle to address.

Disturbance rejection capabilities represent another significant advantage, with AI controllers exhibiting enhanced resilience to external disturbances and unexpected system changes. Experimental results demonstrate that neural networks can maintain stability under conditions that would typically require manual retuning of traditional controllers, providing more robust operation in variable environments [7].

4.2. Resource Requirements

The resource implications of AI-enhanced control systems present a more nuanced picture with clear tradeoffs. Systematic reviews of AI implementations across various domains highlight that while traditional controllers require substantial manual tuning efforts, AI controllers necessitate significant initial investment in training infrastructure and data collection [8]. However, this investment is increasingly amortized through reusable components and transfer learning techniques.

Runtime resource considerations reveal an evolving landscape, with neural network inference historically requiring more computational resources than simpler control calculations. However, recent research documented in systematic reviews suggests that advances in network optimization techniques have dramatically reduced this overhead [8]. These improvements make neural network controllers increasingly viable even for constrained embedded platforms.

Maintenance resource requirements demonstrate potential long-term advantages, with research indicating that traditional controllers often require returning when system parameters change or new use cases emerge. In contrast, AI controllers can adapt to these changes through continued learning, potentially reducing maintenance overhead [8]. This shift in engineering effort profile from continuous manual optimization to front-loaded system design and training may offer substantial resource efficiencies over system lifecycles despite higher initial complexity.

Table 4 Control Quality Metrics Across Methodologies [7]

Control Type	Settling Time (ms)	Steady-State Error (%)	Disturbance Recovery (ms)	Overshoot (%)
PID Controllers	245	8.7	375	18.5
Model-Based Control	185	6.2	298	12.3
Neural Network Control	153	2.3	134	5.8
Hybrid Control	162	3.4	165	7.2

5. Future Directions and Implications

5.1. Hybrid Approaches

Emerging research indicates that hybrid systems combining traditional control theory with AI techniques may offer the best performance across a wide range of embedded applications. Studies examining hybrid learning systems have demonstrated that integrating traditional methodologies with deep learning techniques can provide complementary strengths that address the limitations of either approach used in isolation [9]. These hybrid architectures leverage the predictability and theoretical guarantees of conventional controllers while enhancing them with the adaptability and learning capabilities of neural networks.

Recent research has highlighted several promising hybrid architectures, including neural networks for adaptive parameter tuning of conventional controllers, which maintain the familiar structure of traditional control systems while adding intelligence to the parameter selection process [9]. Similarly, model-based controllers with neural network components for system identification have shown potential for improving model accuracy without sacrificing the theoretical foundations of conventional approaches. The research also identifies hierarchical systems where AI provides high-level optimization while traditional controllers handle low-level control loops as particularly effective for complex embedded applications.

5.2. On-Device Learning

As embedded processors become more powerful, the potential for on-device learning represents a significant frontier. Current research in edge computing and resource-efficient machine learning has demonstrated the viability of adapting control strategies based on actual usage patterns [10]. This capability offers unprecedented personalization and efficiency potential for embedded systems.

Research in on-device learning has explored several promising directions, including devices that learn user behavior patterns to optimize power management, potentially reducing energy consumption while maintaining performance. Studies have also examined systems that adapt to component aging and environmental factors, extending operational lifetimes and maintaining consistent performance despite changing conditions [10]. Additionally, controllers that continuously refine their strategies based on performance feedback show potential for ongoing improvement throughout system lifecycles, rather than remaining static after deployment.

5.3. Standardization and Tooling

For AI-enhanced control to achieve widespread adoption in embedded systems, standardization of methodologies and development of accessible tooling will be crucial. Research examining the implementation challenges for machine learning in resource-constrained environments emphasizes the need for standardized frameworks that reduce development complexity [10]. Current research efforts are focusing on creating standardized interfaces between control systems and AI components to simplify integration.

Research also highlights the importance of pre-trained models for common embedded control scenarios, which can reduce implementation barriers for teams without extensive AI expertise [9]. Additionally, automated tools for neural network design and optimization in resource-constrained environments are being developed to address the specific challenges of embedded deployment. These developments will be essential for transitioning AI control techniques from research environments to practical industry applications across diverse embedded domains.

6. Conclusion

The evolution from traditional control methodologies to AI-enhanced systems represents a transformative shift in embedded computing that extends beyond incremental improvements. Neural networks fundamentally alter how embedded systems manage the critical balance between performance requirements and power constraints, offering substantive advantages in adaptation speed, accuracy, and disturbance rejection capabilities. While conventional PID controllers and model-based approaches continue to serve important roles, their limitations become increasingly apparent in complex, nonlinear applications characteristic of modern embedded environments. The emergence of hybrid architectures that integrate traditional control theory with machine learning techniques provides an optimal middle ground, combining theoretical guarantees with adaptive capabilities. On-device learning capabilities stand as particularly promising developments, enabling embedded systems to continuously refine control strategies based on actual usage patterns rather than predetermined models. These advances allow for unprecedented personalization, with devices adapting to specific usage contexts, environmental conditions, and component aging characteristics. As standardization efforts and development tools mature, implementation barriers will continue to decrease, accelerating adoption across diverse application domains. This progression toward intelligent, adaptive control systems signifies a fundamental reconceptualization of embedded system design philosophy shifting from static, manually tuned implementations toward dynamic, self-optimizing architectures that continuously evolve throughout their operational lifecycle.

References

[1] Alexander S. Gillis, "Embedded System," IoT Agenda, TechTarget. 2024. Available: https://www.techtarget.com/iotagenda/definition/embedded-system

[2] Takuma Yabe, and Takuya Azumi, "Exploring the Performance of Deep Neural Networks on Embedded Many-Core Processors," 2022 ACM/IEEE 13th International Conference on Cyber-Physical Systems (ICCPS) 2022. Available: https://ieeexplore.ieee.org/document/9797582

[3] Karl J. Åström, and Tore Hägglund, "Advanced PID Control," International Society of Automation, 2006. Available: https://www.isa.org/products/advanced-pid-control

[4] Pablo Krupa, "Implementation of model predictive control for tracking in embedded systems using a sparse extended ADMM algorithm," 2021. Available: https://arxiv.org/pdf/2008.09071

[5] Oludare Isaac Abiodun, et al., "Comprehensive Review of Artificial Neural Network Applications to Pattern Recognition," ResearchGate, 2019. Available: https://www.researchgate.net/publication/336267803_Comprehensive_Review_of_Artificial_Neural_Network_Applications_to_Pattern_Recognition

[6] Jun Zheng, et al., "Sample-efficient reinforcement learning with knowledge-embedded hybrid model for optimal control of mining industry," Expert Systems with Applications, 2024. Available: https://dl.acm.org/doi/10.1016/j.eswa.2024.124402

[7] Gao Shuangxi, Li Xi, "Study on Neural Network Controller Based on Embedded System," International Journal of Simulation: Systems, Science & Technology, vol. 17, no. 3, 2016. Available: https://ijssst.info/Vol-17/No-3/paper9.pdf

[8] Poornachandar Pokala, "Artificial Intelligence in Enterprise Resource Planning: A Systematic Review of Innovations, Applications, and Future Directions," ResearchGate, 2024. Available: https://www.researchgate.net/publication/388156032_Artificial_Intelligence_in_Enterprise_Resource_Planning_A_Systematic_Review_of_Innovations_Applications_and_Future_Directions

[9] Vedika Bengani, "Hybrid Learning Systems: Integrating Traditional Machine Learning with Deep Learning Techniques," ResearchGate, 2024. Available: https://www.researchgate.net/publication/380366289_Hybrid_Learning_Systems_Integrating_Traditional_Machine_Learning_with_Deep_learning_Techniques

[10] Enzo Scaffi, et al., "Usability and Performance Analysis of Embedded Development Environment for On-device Learning" arXiv, 2024. Available: https://arxiv.org/abs/2404.07948