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Physics-Informed Deep Learning for Adaptive Power Converter Control in IoT-Integrated Smart Grid Systems

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Abstract

The increasing integration of renewable energy sources and the growing complexity of modern power grids necessitate the development of intelligent and adaptive control strategies for power electronic converters. Traditional control techniques often fail to provide the required flexibility and real-time adaptability to dynamic grid conditions. Physics-Informed Deep Learning (PIDL) has emerged as a transformative approach that combines deep learning with fundamental physical principles to enhance the efficiency, stability, and reliability of power converter control in IoT-integrated smart grids. By embedding domain knowledge into data-driven models, PIDL ensures physically consistent and generalizable solutions while optimizing real-time decision-making processes.

This chapter explores the role of PIDL in adaptive power converter control, highlighting its advantages over conventional control methods. The integration of IoT and edge computing technologies enables real-time monitoring, decentralized decision-making, and predictive analytics, enhancing the resilience and efficiency of smart grids. The computational challenges associated with real-time implementation, including data scarcity, model complexity, and processing latency, are addressed through optimization techniques such as federated learning, hardware acceleration, and lightweight neural network architectures. Case studies on renewable energy grids demonstrate the effectiveness of PIDL-driven adaptive control strategies in managing fluctuations in generation and demand while improving grid reliability.

The chapter further discusses future research directions in PIDL for smart grids, emphasizing the potential of quantum computing, neuromorphic processors, and hybrid AI models for enhancing computational efficiency and scalability. The convergence of physics-informed AI, IoT-driven adaptive control, and decentralized intelligence was expected to play a pivotal role in the evolution of next-generation power systems. This research contributes to the advancement of sustainable energy management by providing a framework for the deployment of intelligent, self-optimizing power converter control mechanisms in modern smart grids.

Keywords: Physics-Informed Deep Learning, Adaptive Power Converter Control, Smart Grid Optimization, IoT-Enabled Energy Management, Real-Time Adaptive Control, Renewable Energy Integration.

Introduction

The increasing complexity of modern power grids, driven by the integration of renewable energy sources and DERs, necessitates advanced control strategies that can dynamically adapt to fluctuating grid conditions [1]. Traditional control mechanisms, such as PID controllers and MPC, often rely on predefined mathematical models that not fully capture the nonlinear, time-varying characteristics of power electronics in smart grids [2]. As a result, these conventional approaches struggle to maintain stability and efficiency, particularly under high penetration of variable renewable energy sources [3,4]. The emergence of AI and deep learning has introduced data-driven control strategies capable of learning complex system dynamics [5]. Purely data-driven models often function as black-box systems, lacking physical interpretability and requiring extensive training data. To bridge this gap, PIDL has gained attention as a powerful approach that integrates fundamental physical laws with deep learning models, enabling adaptive and intelligent control of power electronic converters in smart grids [6-8].

The core principle of PIDL was the incorporation of physical constraints and governing equations, such as Kirchhoff's laws, power flow equations, and thermal dynamics, into deep learning architectures [9]. Unlike conventional AI models that rely solely on historical and real-time data, PIDL ensures that learned representations adhere to well-established physical principles [10]. This hybrid approach enhances the generalization capability of neural networks, reduces dependency on large labeled datasets, and improves the robustness of control decisions under varying grid conditions. Power converters play a critical role in modern energy systems, facilitating voltage regulation, frequency stabilization, and power quality management [11]. The integration of PIDL into power converter control enables real-time optimization, adaptive parameter tuning, and predictive maintenance, addressing key challenges associated with renewable energy intermittency and grid disturbances. By leveraging IoT-enabled sensing and edge computing technologies, PIDL-based control systems can process real-time data efficiently and execute dynamic control actions with minimal latency [12].

The application of PIDL in adaptive power converter control has significant implications for grid resilience and operational efficiency [13]. Traditional power electronic controllers are often designed based on worst-case scenarios, leading to conservative control settings that not be optimal under real-time grid conditions [14]. PIDL-driven controllers, on the other hand, can dynamically adjust to changes in energy generation, demand fluctuations, and system disturbances, ensuring optimal performance under diverse operating conditions [15]. The fusion of deep learning with physics-based models mitigates common issues associated with data-driven approaches, such as overfitting, lack of explainability, and computational inefficiency [16]. Recent advancements in hardware acceleration, including graphics processing units (GPUs) and tensor processing units (TPUs), have facilitated the deployment of complex PIDL models in real-time grid environments. Additionally, federated learning frameworks and decentralized AI architectures offer new possibilities for scaling PIDL-based control across large-scale power systems without compromising security or computational efficiency [17-20].

Promising potential, the implementation of PIDL for real-time power converter control poses several challenges that must be addressed [21]. One of the primary concerns was the computational complexity associated with solving physics-informed neural networks (PINNs) in real time. While traditional deep learning models rely on optimization techniques such as backpropagation, PIDL models require additional constraints that increase computational overhead. Efficient training algorithms, adaptive learning rate mechanisms, and lightweight neural network architectures are necessary to ensure real-time inference capabilities [22]. Additionally, data availability remains a critical issue, as labeled datasets for power converter control are often scarce and domain-specific. Hybrid modeling approaches that combine synthetic data generation, transfer learning, and reinforcement learning-based adaptation strategies can help mitigate these limitations. Another challenge was ensuring the interpretability and trustworthiness of PIDL-based control decisions, particularly in safety-critical applications such as power grid management [23].

Future research in PIDL for adaptive power converter control should focus on improving scalability, robustness, and computational efficiency. The integration of emerging technologies such as quantum computing, neuromorphic processors, and edge AI can further enhance the capabilities of PIDL-driven control frameworks [24]. Quantum-enhanced deep learning algorithms have the potential to accelerate physics-informed training processes, enabling real-time adaptation to grid dynamics with minimal computational overhead. Explainable AI (XAI) techniques can be leveraged to enhance the transparency and interpretability of PIDL-based decision-making, facilitating regulatory compliance and industry adoption [25]. As the global energy landscape continues to evolve, the convergence of PIDL, IoT-driven adaptive control, and decentralized intelligence was expected to play a pivotal role in shaping the next generation of smart grids. By addressing existing challenges and refining current methodologies, PIDL has the potential to revolutionize power converter control, ensuring sustainable, resilient, and efficient energy management for future power systems.