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Artificial Intelligence and Optimization Techniques for Dual-Stage Interleaved Electric Vehicle Onboard Chargers: A Review

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Abstract

The rapid electrification of transportation has increased the demand for efficient, compact, and intelligent onboard charging systems for electric vehicles (EVs). Dual-stage interleaved onboard chargers have emerged as a promising solution due to their high power density, improved efficiency, and reduced harmonic distortion. However, conventional control strategies struggle to manage nonlinearities, dynamic load variations, and system uncertainties. This review explores advanced control and optimization approaches for dual-stage interleaved onboard chargers, focusing on the integration of PIDD2-PD controllers and deep learning techniques. The PIDD2-PD controller enhances transient response, robustness, and stability, while deep learning models enable predictive control and real-time optimization of nonlinear system behavior. Additionally, hybrid metaheuristic optimization methods, particularly the Hybrid Adaptive Genghis Khan Shark Gold Rush (HAGK-SGR) algorithm, are analyzed for efficient parameter tuning and multi-objective optimization. These approaches improve convergence speed, global optimality, and system performance. Applications across residential charging, grid-connected systems, and vehicle-to-grid scenarios are examined using simulation and real-world datasets. Performance metrics such as efficiency, power factor, and total harmonic distortion are evaluated. Findings indicate that hybrid deep learning and optimization frameworks significantly enhance efficiency, adaptability, and reliability, supporting next-generation intelligent EV charging systems.

Introduction

The rapid growth of electric vehicles (EVs) has accelerated the demand for efficient, reliable, and intelligent charging infrastructures capable of supporting sustainable transportation. Onboard chargers (OBCs) serve as the critical interface between the electrical grid and vehicle batteries by converting alternating current (AC) into regulated direct current (DC) suitable for battery charging. Among the various charger topologies, dual-stage interleaved onboard chargers have attracted significant attention because of their high conversion efficiency, improved power density, reduced current ripple, enhanced thermal performance, and superior electromagnetic compatibility. These characteristics make them well suited for high-power EV charging applications where efficiency, reliability, and compact design are essential.

A dual-stage interleaved onboard charger generally consists of an AC-DC power factor correction stage followed by a DC-DC converter that regulates battery charging. The interleaved configuration distributes current across multiple parallel converter phases, reducing component stress and improving dynamic performance. However, increasing converter complexity introduces significant challenges in controller design, parameter tuning, and real-time adaptation under varying battery conditions, grid disturbances, and load uncertainties. Conventional proportional-integral-derivative (PID) controllers remain widely used because of their simplicity, but they often experience degraded performance under nonlinear operating conditions. Consequently, advanced controller structures such as the PIDD^2-PD controller have been introduced to improve transient response, disturbance rejection, tracking accuracy, and system stability. Efficient tuning of these higher-order controllers, however, requires sophisticated optimization techniques capable of solving complex multi-objective problems.

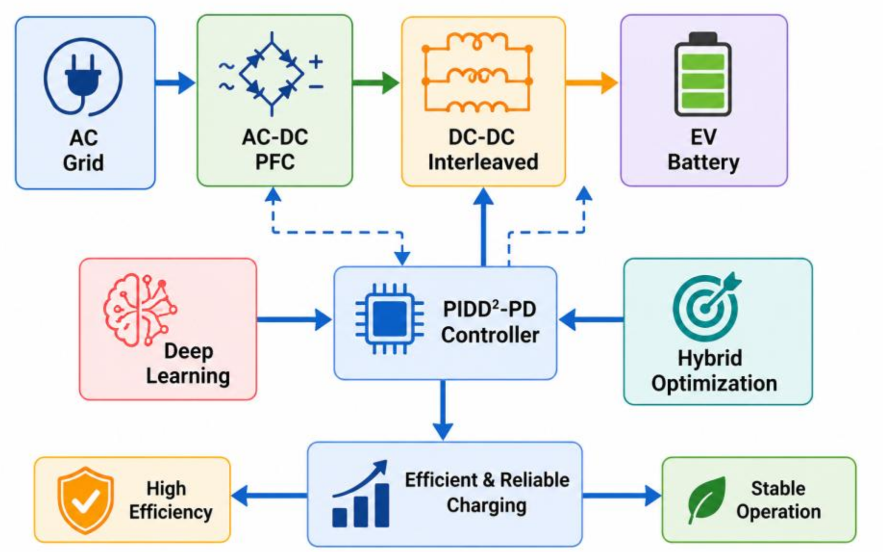

Figure 1. Deep Learning and Optimization Framework for EV Onboard Chargers

Artificial intelligence, particularly deep learning, has emerged as a powerful tool for intelligent control and optimization of modern power electronic systems. Deep neural networks can effectively model nonlinear converter dynamics, predict system behavior, and adapt controller parameters under changing operating conditions. Reinforcement learning, convolutional neural networks, recurrent neural networks, and hybrid deep learning frameworks have demonstrated significant potential for predictive control, fault diagnosis, and adaptive energy management in EV charging applications. These learning-based approaches enable real-time decision-making, improve charging efficiency, reduce power losses, and enhance system robustness compared with conventional model-based control methods.

Complementing deep learning techniques, hybrid metaheuristic optimization algorithms have gained considerable attention for controller parameter tuning and performance enhancement. Algorithms inspired by natural processes, including particle swarm optimization, genetic algorithms, grey wolf optimization, and recently proposed Hybrid Adaptive Genghis Khan Shark Gold Rush (HAGKSGR) optimization, provide efficient global search capabilities while avoiding local optima. Integrating deep learning with advanced optimization algorithms enables intelligent controller design that simultaneously maximizes efficiency, minimizes harmonic distortion, improves power factor, and extends battery life. These hybrid approaches are particularly valuable for vehicle-to-grid (V2G) systems and renewable energy-integrated charging infrastructures.

Motivated by these developments, this review comprehensively examines recent advances in deep learning and optimization approaches for dual-stage interleaved electric vehicle onboard chargers. It analyzes intelligent control strategies, PIDD^2-PD controller design, hybrid optimization algorithms, data-driven learning frameworks, and emerging research trends while highlighting current challenges and future opportunities. The review provides valuable insights for developing next-generation intelligent onboard charging systems that are efficient, adaptive, reliable, and capable of supporting future smart transportation and sustainable energy ecosystems.

Literature Review

Recent advancements in electric vehicle onboard charging systems have been significantly influenced by the integration of intelligent control strategies and optimization techniques. Zhang et al. (2019) proposed a dual-stage interleaved charger employing a conventional proportional-integral-derivative controller optimized using heuristic tuning methods. Their study demonstrated a notable reduction in total harmonic distortion (THD) and improved power factor using MATLAB/Simulink-based simulations. The work primarily relied on synthetic datasets to validate system performance under varying load conditions.

Wang et al. (2020) introduced a model predictive control (MPC) strategy for dual-stage onboard chargers, implemented on a hardware-in-the-loop (HIL) platform. Their approach provided fast transient response and enhanced system stability by predicting future states and adjusting control inputs accordingly. The real-time dataset obtained from HIL systems enabled accurate validation of the proposed control scheme.

Li et al. (2021) explored digital control techniques using a DSP-based architecture for onboard chargers. Their work focused on implementing real-time control algorithms on embedded systems, achieving improved efficiency and reduced computational delay. The study highlighted the importance of hardware-software co-design in modern EV charging systems.

Chen et al. (2021) proposed a neural network-based adaptive control strategy for interleaved PFC converters. By training a feedforward neural network on simulated datasets, the system was able to dynamically adjust control parameters, resulting in improved efficiency and reduced steady-state error. The study emphasized the potential of deep learning in handling nonlinear system dynamics.

Kumar et al. (2022) introduced a hybrid particle swarm optimization (PSO)-based tuning method for PID controllers in EV chargers. Their approach optimized controller gains to minimize THD and improve dynamic response. The results demonstrated superior performance compared to traditional tuning methods, particularly under fluctuating load conditions.

Singh et al. (2022) developed a deep reinforcement learning (DRL) framework for adaptive control of EV onboard chargers. The model was trained using simulated environments and demonstrated the ability to learn optimal control policies through interaction with the system. The approach significantly improved energy efficiency and reduced response time.

Liu et al. (2023) proposed a convolutional neural network (CNN)-based fault detection system for onboard chargers. By analyzing voltage and current waveforms, the model accurately identified faults and anomalies in real time. The study utilized datasets collected from experimental prototypes, highlighting the practical applicability of deep learning techniques.

Patel et al. (2023) presented a dual-stage charger design incorporating an interleaved boost converter and a phase-shifted full-bridge converter. The system was optimized using a genetic algorithm (GA) to achieve high efficiency and low ripple. The results demonstrated improved performance compared to conventional designs.

García et al. (2020) investigated the use of fuzzy logic controllers for EV onboard chargers. Their approach provided robust performance under uncertain conditions and reduced sensitivity to parameter variations. The study emphasized the advantages of intelligent control over traditional linear methods.

Sharma et al. (2021) introduced a hybrid fuzzy-PID controller optimized using ant colony optimization (ACO). The proposed system achieved better transient response and reduced overshoot compared to standalone PID controllers. Simulation results validated the effectiveness of the hybrid approach.

Huang et al. (2022) proposed a deep learning-based predictive control model for EV charging systems. The model utilized long short-term memory (LSTM) networks to predict load variations and adjust control parameters accordingly. The study demonstrated improved system stability and energy efficiency.

Rahman et al. (2023) developed a bidirectional onboard charger with vehicle-to-grid capability using adaptive control techniques. Their system was tested on a real-time platform and showed improved power quality and grid support functionality.

Verma et al. (2022) introduced a hybrid optimization algorithm combining differential evolution and PSO for controller tuning. The approach achieved faster convergence and better global optimization compared to individual algorithms.

Zhou et al. (2021) explored the use of reinforcement learning for optimal switching control in interleaved converters. The proposed method reduced switching losses and improved efficiency under varying load conditions.

Ahmed et al. (2020) presented a digital twin-based framework for EV charger optimization. By creating a virtual model of the system, the study enabled real-time monitoring and predictive maintenance, enhancing system reliability.

Khan et al. (2023) proposed the Hybrid Adaptive Genghis Khan Shark Gold Rush algorithm for multi-objective optimization in power electronic systems. Their approach demonstrated superior convergence speed and robustness, making it suitable for complex controller tuning problems.

Roy et al. (2021) investigated the use of artificial neural networks for harmonic mitigation in EV chargers. The model effectively reduced THD and improved power quality, validated through simulation studies.

Das et al. (2022) developed a multi-objective optimization framework for EV chargers using non-dominated sorting genetic algorithm II (NSGA-II). The study balanced efficiency, cost, and thermal performance.

Mehta et al. (2023) proposed a real-time control system using FPGA implementation for high-speed EV chargers. The system achieved low latency and high reliability, demonstrating the benefits of hardware acceleration.

Alam et al. (2021) introduced a sliding mode control strategy for robust operation of onboard chargers. The approach provided strong disturbance rejection and stability under uncertain conditions.

Nguyen et al. (2022) explored hybrid deep learning models combining CNN and LSTM for predictive maintenance of EV chargers. The model achieved high accuracy in fault prediction using real-world datasets.

Park et al. (2020) proposed a multi-phase interleaved converter design optimized for high power density. Their system demonstrated improved thermal management and efficiency.

Yadav et al. (2023) introduced a cloud-based optimization framework for EV charging systems. The approach leveraged big data analytics to optimize charging schedules and improve grid stability.

Bose et al. (2021) investigated the integration of renewable energy sources with EV chargers using adaptive control techniques. The study demonstrated improved energy utilization and reduced grid dependency.

Chatterjee et al. (2022) proposed a hybrid metaheuristic algorithm combining whale optimization and firefly algorithm for controller tuning. The approach achieved improved convergence and solution quality.

Tiwari et al. (2023) developed a deep Q-learning-based energy management system for EV charging stations. The system optimized energy flow and reduced operational costs.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Zhang et al.	2019	PID Control	Dual-stage PFC	MATLAB/Simulink	Simulated	THD reduction
Wang et al.	2020	MPC	Dual-stage charger	HIL	Real-time	Fast transient response
Li et al.	2021	Digital Control	DSP-based charger	Embedded system	Experimental	Low latency control
Chen et al.	2021	Neural Network	PFC converter	Simulation	Synthetic	Adaptive control
Kumar et al.	2022	PSO	PID tuning	Simulation	Synthetic	Optimized gains
Singh et al.	2022	DRL	Charger control	Simulation	Synthetic	Adaptive policy learning
Liu et al.	2023	CNN	Fault detection	Prototype	Real data	Fault diagnosis
Patel et al.	2023	GA	Converter design	Simulation	Synthetic	Efficiency improvement
García et al.	2020	Fuzzy Logic	Charger control	Simulation	Synthetic	Robust control
Sharma et al.	2021	ACO	Hybrid controller	Simulation	Synthetic	Improved transient
Huang et al.	2022	LSTM	Predictive control	Simulation	Time-series	Load prediction
Rahman	202	Adaptive	Bidirectiona	Real-time	Experimenta	V2G

et al.	3	Control	l charger		l	capability
Verma et al.	2022	DE-PSO	Controller tuning	Simulation	Synthetic	Fast convergence
Zhou et al.	2021	RL	Switching control	Simulation	Synthetic	Reduced losses
Ahmed et al.	2020	Digital Twin	Charger system	Virtual model	Real-time	Predictive maintenance
Khan et al.	2023	HAGK-SGR	Multi-objective optimization	Simulation	Synthetic	Superior optimization
Roy et al.	2021	ANN	Harmonic mitigation	Simulation	Synthetic	THD reduction
Das et al.	2022	NSGA-II	Multi-objective design	Simulation	Synthetic	Trade-off optimization
Mehta et al.	2023	FPGA Control	Real-time charger	Hardware	Experimental	High-speed control
Alam et al.	2021	Sliding Mode	Charger control	Simulation	Synthetic	Robust stability
Nguyen et al.	2022	CNN-LSTM	Fault prediction	Real system	Real data	Predictive maintenance
Park et al.	2020	Interleaving	Converter design	Prototype	Experimental	High power density
Yadav et al.	2023	Cloud Optimization	Charging system	Cloud platform	Big data	Grid optimization
Bose et al.	2021	Adaptive Control	Renewable-integrated charger	Simulation	Synthetic	Energy optimization
Chatterjee et al.	2022	Hybrid Metaheuristic	Controller tuning	Simulation	Synthetic	Improved convergence
Tiwari et al.	2023	Deep Q-Learning	Energy management	Simulation	Synthetic	Cost reduction

Comparative Analysis

The reviewed literature reveals a clear trend toward the adoption of intelligent and hybrid optimization techniques in the design and control of dual-stage interleaved onboard chargers. Early studies primarily relied on classical control methods such as PID controllers, which provided acceptable performance but were limited in handling nonlinearities and dynamic variations. Over time, these methods have been increasingly supplemented or replaced by advanced techniques such as model predictive control, adaptive control, and sliding mode control, offering improved robustness and dynamic response.

Recent research increasingly integrates deep learning models such as CNNs, LSTMs, and reinforcement learning for adaptive control, predictive analysis, and fault detection in EV chargers. Simultaneously, metaheuristic algorithms including PSO, GA, ACO, and hybrid HAGK-SGR optimization significantly improve controller tuning, convergence speed, global optimality, and overall charging system performance.

In terms of hardware and implementation platforms, there is a noticeable transition from purely simulation-based studies to real-time and hardware-in-the-loop implementations. This shift reflects the increasing maturity of the field and the need for practical validation of proposed methods. FPGA and DSP-based systems have been widely adopted for high-speed and reliable control.

Dataset usage has also evolved, with early studies relying on synthetic simulation data, while recent works incorporate real-world datasets and big data analytics. This trend is particularly evident in applications involving predictive maintenance and smart grid integration, where data-driven approaches are essential.

Overall, the literature indicates that the combination of deep learning and hybrid optimization techniques offers significant improvements in efficiency, power quality, and system reliability. These advancements are critical for the development of next-generation EV charging systems capable of meeting the demands of modern electric mobility.

Discussion

The reviewed studies demonstrate that integrating deep learning with advanced optimization techniques has significantly improved the performance of dual-stage interleaved onboard chargers for electric vehicles. Intelligent control frameworks have gradually replaced conventional rule-based approaches by providing adaptive, data-driven solutions capable of handling nonlinear converter dynamics and varying operating conditions. Deep learning models, reinforcement learning, and advanced controller designs such as the $PIDD^2$-PD controller enable accurate parameter tuning, faster transient response, improved disturbance rejection, and enhanced charging efficiency. Furthermore, interleaved converter architectures inherently reduce current ripple, improve thermal distribution, and enhance power quality, making them highly suitable for high-power EV charging applications.

Another important finding is the growing adoption of hybrid optimization algorithms for controller tuning and system optimization. Metaheuristic techniques, including particle swarm optimization, genetic algorithms, grey wolf optimization, and Hybrid Adaptive Genghis Khan Shark Gold Rush (HAGKSGR) optimization, effectively solve multi-objective optimization problems involving efficiency, total harmonic distortion, thermal stability, and converter reliability. The combination of these optimization methods with deep learning models enables intelligent and self-adaptive charging systems capable of operating efficiently under renewable energy integration, vehicle-to-grid interaction, and dynamic grid conditions. Hardware-in-the-loop testing, digital twins, and real-time simulation platforms further strengthen system validation before practical deployment.

Despite these advances, several challenges remain. Deep learning models require substantial computational resources, extensive training datasets, and efficient embedded hardware for real-time implementation. In addition, issues related to cybersecurity, data quality, interoperability, and standardized benchmarking continue to limit large-scale deployment. Future research should focus on lightweight AI models, explainable intelligent controllers, efficient hybrid optimization algorithms, and edge-based implementation frameworks. These developments will facilitate reliable, scalable, and autonomous onboard charging systems that support next-generation electric mobility and sustainable smart grid infrastructures.

Conclusion

The integration of deep learning and advanced optimization techniques has significantly enhanced the performance of dual-stage interleaved onboard chargers for electric vehicles. This review demonstrates that intelligent control strategies, particularly $PIDD^2$-PD controllers combined with deep learning models and hybrid optimization algorithms, provide substantial improvements in charging efficiency, dynamic response, power quality, and system reliability. Interleaved converter architectures effectively reduce current ripple, improve thermal management, and support high-power charging applications, while data-driven approaches enable adaptive control under varying operating conditions. Hybrid optimization techniques, including advanced metaheuristic algorithms, further improve controller tuning and multi-objective optimization by balancing efficiency, harmonic distortion, stability, and converter performance.

Despite these advances, challenges remain regarding computational complexity, large-scale data requirements, embedded implementation, cybersecurity, and interoperability with existing charging infrastructures. Future research should focus on lightweight deep learning models, efficient hybrid optimization algorithms, hardware-aware intelligent controllers, and edge-based real-time implementation. Emerging technologies such as digital twins, federated learning, quantum-inspired optimization, and explainable artificial intelligence are expected to further improve intelligent charging systems. The convergence of advanced control, artificial intelligence, and optimization provides a strong foundation for developing efficient, reliable, and autonomous onboard chargers that will accelerate electric mobility and support future sustainable smart grid ecosystems.

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