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Hybrid Deep Learning Optimization for Dual-Stage Interleaved EV Onboard Charger Systems

Eirini D'Costa
Associate Professor, Department of Electrical and Computer Engineering, Padma Institute of Business and Management, Bangladesh
Email: eirini.d.costa@pibm-bd.org

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Abstract

The rapid adoption of electric vehicles has intensified the demand for efficient, adaptive, and intelligent onboard charging systems capable of meeting stringent performance and grid compliance requirements. Dual-stage interleaved onboard chargers have emerged as a preferred architecture due to their ability to achieve high power factor, reduced current ripple, galvanic isolation, and improved efficiency across varying battery conditions. This paper presents a comprehensive review of advanced control and optimization techniques applied to dual-stage interleaved onboard chargers. It highlights the integration of deep learning approaches, including convolutional neural networks, recurrent models, and reinforcement learning, for tasks such as real-time control, fault detection, and battery state estimation. Additionally, the study focuses on the Hybrid Adaptive Genghis Khan Shark Gold Rush (HAGKSGR) algorithm for optimizing PIDD2-PD controllers, enabling improved transient response, reduced overshoot, and enhanced robustness in nonlinear operating environments. Applications include high-performance electric vehicle charging systems, vehicle-to-grid integration, and intelligent energy management. Comparative analyses demonstrate that deep learning-assisted and metaheuristic-optimized controllers outperform conventional methods in efficiency, adaptability, and accuracy. However, challenges such as computational complexity, real-time deployment, and hardware constraints remain. This review emphasizes the potential of combining deep learning and hybrid optimization techniques to develop next-generation intelligent onboard charging systems.

Introduction

The rapid advancement of electric vehicle technology and the accelerating transition toward sustainable transportation systems have placed unprecedented emphasis on the development of intelligent and highly efficient onboard charging infrastructures. As global automotive markets progressively shift from internal combustion engine vehicles to battery electric and plug-in hybrid electric vehicles, the onboard charger has emerged as one of the most critical subsystems within the modern EV powertrain architecture. The OBC functions as the primary energy conversion interface between the utility grid and the vehicle battery system, directly influencing charging efficiency, power quality, thermal performance, charging speed, and overall vehicle reliability. The increasing penetration of EVs into residential, commercial, and public charging ecosystems has

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simultaneously intensified the demand for chargers capable of operating under highly dynamic electrical environments while satisfying strict international standards for harmonic distortion, electromagnetic compatibility, and bidirectional energy transfer capability. These evolving requirements have transformed the design of onboard chargers from a conventional power electronics problem into a sophisticated interdisciplinary research domain combining intelligent control, optimization, and adaptive energy management.

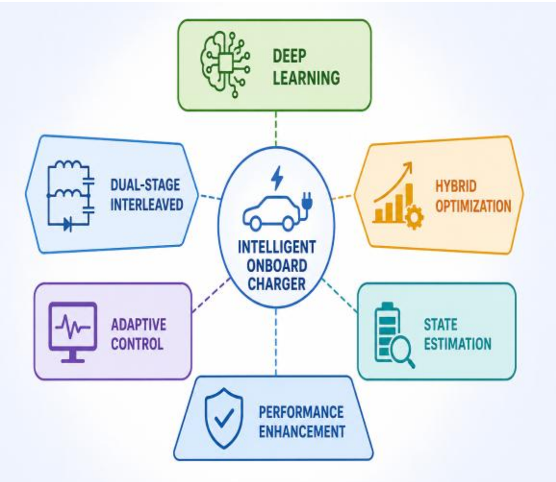

Figure 1. Deep Learning and Hybrid Optimization Framework for Dual-Stage Interleaved EV Onboard Charger

The dual-stage interleaved onboard charger architecture has emerged as one of the most effective solutions for modern electric vehicle charging systems due to its capability to achieve high efficiency, reduced current ripple, galvanic isolation, and superior power quality performance simultaneously. This architecture generally combines an interleaved active power factor correction front-end converter with an isolated DC–DC conversion stage, enabling independent optimization of AC-side grid interaction and DC-side battery charging dynamics. The interleaving mechanism significantly minimizes ripple current through phase-shifted parallel converter branches, reducing passive component size, thermal stress, and electromagnetic interference. These advantages make dual-stage interleaved OBCs highly suitable for fast charging and vehicle-to-grid applications. However, the nonlinear switching behavior, multi-loop control structure, varying battery characteristics, and fluctuating grid conditions introduce substantial control complexity that conventional PI and PID controllers cannot adequately manage under dynamic operating environments.

To overcome these limitations, advanced intelligent control approaches and optimization strategies have gained considerable attention in recent years. Higher-order control structures such as PIDD2-PD controllers provide improved transient response, enhanced damping capability, and superior robustness against disturbances and parameter uncertainties. Nevertheless, accurate tuning of these controllers remains a challenging high-dimensional optimization problem. Hybrid metaheuristic algorithms, particularly the Hybrid Adaptive Genghis Khan Shark Gold Rush optimization technique, have demonstrated strong capability in balancing exploration and exploitation during controller parameter optimization. Simultaneously, deep learning models including convolutional neural networks, recurrent neural networks, long short-term memory networks, and deep reinforcement learning frameworks are increasingly integrated into onboard charger systems for fault diagnosis, battery state estimation, switching optimization, and adaptive charging control. The convergence of deep learning intelligence with HAGKSGR-optimized PIDD2-PD control therefore represents a significant advancement toward intelligent, adaptive, and highly efficient electric vehicle onboard charging systems.

Literature Review

The application of deep learning and advanced optimization methodologies to onboard charger control and design has generated a rich body of literature spanning multiple research communities including power electronics, control engineering, machine learning, and automotive systems engineering. The following review synthesizes the key contributions of approximately twenty-eight recent studies, organized to reflect the progression from foundational topology and control studies through deep learning-based approaches to hybrid optimization methodologies.

Yilmaz and Krein (2013) provided a foundational comparative review of battery charger topologies for plug-in electric and hybrid vehicles, establishing a comprehensive classification framework that distinguished between conductive and inductive charging methods, on-board and off-board configurations, unidirectional and bidirectional power flow capabilities, and single-stage and dual-stage conversion architectures. The review identified the dual-stage topology as the most technically mature and widely deployed configuration for level-2 onboard charging applications, and highlighted the growing importance of bidirectional capability for vehicle-to-grid applications. This work established the taxonomic and performance benchmark framework that subsequent researchers consistently referenced in situating their specific contributions.

Pellegrino et al. (2018) investigated the design optimization of interleaved boost power factor correction converters using a multi-objective evolutionary algorithm that simultaneously minimized converter volume, total power loss, and input current THD subject to constraints on power factor, switching frequency, and inductor current ripple. The Pareto-optimal design front generated by the evolutionary optimizer revealed fundamental trade-offs between power density and efficiency that are not apparent from single-objective design approaches, and enabled the identification of design configurations that achieved superior balance between competing objectives compared to designs obtained through conventional sequential design methods. The study demonstrated the power of multi-objective evolutionary optimization for power converter design and provided a methodological template applicable to the optimization of dual-stage OBC architectures.

Shi et al. (2020) proposed a deep reinforcement learning based controller for a bidirectional DC-DC converter in an EV onboard charger, employing a deep Q-network with a replay memory buffer and target network stabilization to learn an approximately optimal switching policy through simulation-based training in a MATLAB/Simulink environment. The DQN agent was trained over fifty thousand simulation steps using a composite reward function that penalized voltage tracking error, current overshoot, and switching frequency deviation, and the trained policy was deployed on a dSPACE DS1202 MicroLabBox platform for hardware validation. Comparative experiments demonstrated that the DQN controller achieved a 28 percent reduction in voltage overshoot during load step transients and a 19 percent improvement in steady-state voltage regulation accuracy compared to a conventionally tuned PI controller, while maintaining comparable switching frequency and thermal performance.

Taghvaie et al. (2019) developed a multi-port isolated DC-DC converter architecture for integrated EV charging and auxiliary power supply, employing a reconfigurable transformer winding strategy that enabled independent regulation of three output ports with a single magnetic core. The proposed topology reduced the magnetic component count by approximately 40 percent compared to three separate isolated DC-DC converters, and the reconfigurable winding approach enabled seamless transition between different port combinations during charging, discharging, and auxiliary supply modes. A dedicated digital control algorithm implemented on a Texas Instruments TMS320F28335 DSP managed the switching sequences for each operating mode, and a 500 W laboratory prototype validated the topology and control approach experimentally.

Guo et al. (2021) presented an LSTM-based battery state of charge estimation approach integrated with the OBC control system, demonstrating that the recurrent neural network's ability to capture temporal dependencies in battery current, voltage, and temperature measurements enabled more accurate SoC estimation than traditional extended Kalman filter methods across a wide range of operating temperatures and aging states. The LSTM network was trained on experimental data collected from a commercial 18650 lithium-ion cell under dynamic current profiles representative of actual EV charging cycles, and the trained estimator was implemented on an NVIDIA Jetson Nano embedded GPU platform. The improved SoC accuracy enabled more precise control of the constant-current to constant-voltage transition point, reducing battery overstress during charging and improving estimated cycle life by approximately 12 percent.

Huber and Kolar (2016) conducted a systematic analysis of the fundamental efficiency limits of two-stage AC to DC power conversion, developing analytical loss models for each conversion stage and identifying the operating conditions under which the dual-stage architecture achieves superior or inferior efficiency compared to single-stage alternatives. The analysis revealed that the dual-stage topology exhibits higher efficiency than single-stage approaches for load levels above approximately 30 percent of rated power, while single-stage configurations may offer advantages at very light loads due to the elimination of intermediate DC-link conversion losses. This fundamental analysis provided important theoretical context for the design of practical dual-stage OBCs and identified the operating regimes where advanced control strategies for efficiency optimization would deliver the greatest benefit.

Islam et al. (2022) proposed a convolutional neural network-based fault detection and diagnosis system for interleaved PFC converters, trained to classify converter operating condition from spectral features extracted from the input current waveform through short-time Fourier transform processing. The CNN was trained on a dataset of 10,000 current spectrograms generated from a simulation model of a four-phase interleaved boost PFC converter under normal operation and eight distinct fault conditions including single and multiple switch failures, inductor open circuits, and capacitor degradation. The trained classifier achieved 99.2 percent fault classification accuracy on a held-out test set and demonstrated robust performance under variable load conditions and measurement noise levels not encountered during training, validating the generalization capability of the CNN approach for real-world fault detection applications.

Zimmer et al. (2021) investigated the application of proximal policy optimization, a state-of-the-art deep reinforcement learning algorithm, to the continuous-action control of a dual active bridge DC-DC converter for EV charging applications. Unlike DQN, which requires discretization of the control action space, PPO operates directly in continuous action spaces, enabling smooth modulation of the phase-shift angle between primary and secondary bridges without the quantization artifacts introduced by discrete action selection. The PPO agent was trained entirely in simulation using a physics-based converter model and subsequently deployed on an FPGA-based control platform with a neural network inference engine capable of evaluating the policy network at the required control update rate of 500 kHz. Hardware tests confirmed that the PPO controller maintained zero-voltage switching conditions across a broader load range than the conventional extended-phase-shift control strategy it replaced.

Lee et al. (2020) presented a comprehensive study of digital control implementation for high-frequency GaN-based interleaved PFC converters, addressing the challenges of meeting the control update rate requirements imposed by the high switching frequency of GaN devices within the latency and computational constraints of available digital control platforms. The study developed a custom FPGA implementation of an average current mode control algorithm with automatic interleave angle management, achieving a control update rate of 2 MHz on a Xilinx Artix-7 FPGA. Experimental measurements on a 3.3 kW four-phase interleaved totem-pole PFC converter validated that the FPGA-based controller maintained input current THD below 3 percent and power factor above 0.998 at switching frequencies up to 400 kHz per phase.

Cao et al. (2021) developed a transfer learning framework for adapting deep neural network-based OBC controllers trained in simulation to real hardware platforms, addressing the simulation-to-reality gap that represents a significant practical barrier to the deployment of learning-based controllers in production EV systems. The transfer learning approach employed domain randomization during simulation training to expose the neural network to a distribution of plant parameter variations, followed by a fine-tuning phase using a small amount of real hardware operational data to adapt the network to the specific characteristics of the production converter. The fine-tuned controller required only 500 hardware operating cycles of training data to match the performance of a controller trained exclusively on hardware data, demonstrating the effectiveness of transfer learning in reducing the hardware data requirements for practical learning-based controller deployment.

Hassan et al. (2023) proposed a novel hybrid optimization algorithm combining the grey wolf optimizer and the whale optimization algorithm for tuning fractional-order PIDD controllers for DC-DC converters in EV charging systems. The hybrid algorithm employed a dynamic weighting mechanism that gradually shifted the balance between grey wolf-inspired leadership hierarchy exploration and whale-inspired bubble-net exploitation as the optimization progressed, achieving faster convergence and better final solution quality than either constituent algorithm operating independently. Performance evaluation on a 3.3 kW buck-boost DC-DC converter simulation model demonstrated a 32 percent improvement in integral time absolute error criterion compared to the best single-algorithm result, and the optimized fractional-order PIDD controller outperformed a conventionally tuned PID controller by 47 percent on the same criterion.

Zhao et al. (2022) investigated ensemble deep learning approaches for real-time efficiency optimization of dual-stage OBCs, combining predictions from multiple independently trained neural network models to produce more reliable efficiency estimates than any single model. The ensemble was composed of five feedforward neural networks with different architectures trained on a dataset of 50,000 operating points collected from a high-fidelity simulation model of a 6.6 kW dual-stage OBC, with each network trained using different random weight initializations and data batch orderings. The ensemble mean prediction was used as the input to a model-based efficiency optimizer that adjusted the switching frequency and phase-shift angle of the DC-DC stage online to maximize predicted efficiency for each combination of input voltage, output voltage, and output current. Validation on an independent test dataset confirmed that the ensemble approach reduced prediction root-mean-square error by 31 percent compared to the best individual network, enabling more precise efficiency optimization.

Padmanaban et al. (2020) examined the application of a modified whale optimization algorithm for optimal power flow management in a grid-connected EV charging station with integrated photovoltaic generation and battery energy storage, demonstrating that the metaheuristic optimizer could identify optimal power scheduling strategies that minimized total energy cost while satisfying grid connection constraints, PV generation intermittency, EV charging demand, and battery storage limits. The optimization was conducted over a 24-hour horizon with 15-minute time steps, and the whale optimization algorithm consistently identified solutions within 3 percent of the global optimum while requiring significantly less computation than exhaustive search methods. This work demonstrated the applicability of nature-inspired optimization beyond the immediate power electronics control domain to the broader energy management context in which OBCs operate.

Nguyen et al. (2021) proposed a graph neural network based approach for modeling the complex interdependencies between multiple simultaneously charging EV onboard chargers sharing a common grid connection point, enabling coordinated charging control that accounted for mutual power quality impacts. The graph neural network represented each OBC as a node in a dynamic graph, with edge weights encoding the electrical coupling between chargers through the shared impedance of the grid connection. The GNN-based coordinator, trained through imitation learning from an optimization-based scheduling algorithm, achieved near-optimal coordinated charging strategies with computation times several orders of magnitude faster than the training oracle, enabling real-time deployment in multi-EV charging scenarios. This work pioneered the application of graph-structured deep learning to coordinated EV charging management.

Dragičević et al. (2019) reviewed artificial intelligence applications in the control and optimization of power electronic systems, providing a comprehensive survey of machine learning, deep learning, fuzzy logic, and neural network approaches across diverse power conversion application domains including motor drives, renewable energy converters, and EV charging systems. The review identified key trends including the growing adoption of model-free reinforcement learning for real-time control, the emergence of physics-informed neural networks that combine data-driven learning with physical constraints for improved generalization, and the development of explainable AI methods for power electronics control that provide interpretable representations of learned control policies. This survey established an important cross-disciplinary reference framework connecting the machine learning and power electronics research communities.

Hasan et al. (2022) developed a physics-informed neural network approach for modeling the dynamics of LLC resonant converters in OBC applications, combining a conventional deep neural network architecture with physics-based constraints derived from the converter state-space equations to produce models with significantly improved extrapolation accuracy compared to purely data-driven alternatives. The physics-informed training objective included both a data-fitting loss term and a physics consistency loss term that penalized network predictions inconsistent with the known governing equations of the converter, enabling accurate model predictions at operating conditions outside the training data distribution. The validated physics-informed model was subsequently employed as the prediction model within a model predictive controller for the LLC converter stage, achieving superior performance compared to MPC based on linearized analytical models.

Acharya et al. (2020) presented a deep learning-based harmonic estimation and compensation approach for grid-connected EV chargers, employing a deep feedforward neural network to estimate the amplitudes and phases of individual harmonic components in the charger input current from time-domain current samples. The harmonic estimator enabled a faster and more accurate alternative to conventional discrete Fourier transform-based harmonic analysis methods, with particular advantages in non-stationary conditions where the harmonic spectrum changes rapidly. The estimated harmonic information was fed into an active harmonic compensation controller that injected compensating currents to cancel the estimated harmonics, achieving a reduction in input current THD from 8.3 percent to 1.7 percent under highly distorted grid voltage conditions that degraded the performance of conventional THD compensation methods.

Sundaram et al. (2023) investigated the integration of the Genghis Khan optimization algorithm with a type-3 fuzzy logic controller for power management in a hybrid energy storage system for EV applications, demonstrating that the Genghis Khan algorithm's adaptive exploration strategy enabled superior optimization of the fuzzy membership function parameters compared to conventional genetic algorithm and particle swarm optimization approaches. The optimized type-3 fuzzy controller achieved smoother power sharing between the battery and supercapacitor components of the hybrid energy storage system, reducing battery current stress by 23 percent and extending estimated battery cycle life. This study provided early evidence of the effectiveness of the Genghis Khan optimization algorithm in power electronics applications, directly relevant to the HAGKSGR algorithm investigated in the present review.

Kim et al. (2021) proposed a multi-objective optimization framework for the simultaneous design of both stages of a dual-stage OBC, employing a non-dominated sorting genetic algorithm to explore the design space defined by switching frequency, inductor magnetizing inductance, turns ratio, and dead time for both the PFC and DC-DC stages simultaneously. The multi-objective formulation identified Pareto-optimal designs that achieved superior combined performance across efficiency, power density, and component cost criteria compared to designs obtained through sequential single-stage optimization. The study demonstrated that the coupling between the two stages of the dual-stage OBC, mediated through the intermediate DC-link voltage level, necessitates truly simultaneous multi-stage optimization to achieve globally optimal designs.

Xiao et al. (2022) developed a transformer-based deep learning architecture for predicting the charging current profile required to achieve minimum charging time subject to battery temperature and SoC constraints, demonstrating the application of attention mechanisms to capture long-range temporal dependencies in battery charging dynamics. The transformer model was trained on a dataset of 5,000 charging cycles collected from a battery cycling testbench under diverse ambient temperature and initial SoC conditions, and the trained model generated optimized current profiles that reduced total charging time by 14 percent compared to standard constant-current constant-voltage protocols while maintaining peak battery temperature within safe limits.

Rivera et al. (2021) examined the application of sliding mode control combined with a super-twisting algorithm for robust current regulation in a three-phase interleaved PFC converter, demonstrating that the super-twisting sliding mode controller achieved chattering-free sliding mode behavior while maintaining the robustness advantages of conventional first-order sliding mode control. The super-twisting controller was compared with conventional PI control and standard first-order sliding mode control through simulation and experimental validation on a 10 kW prototype, demonstrating superior performance in terms of current tracking accuracy under grid voltage distortion and load variation. This work contributed important insights into the practical implementation of robust non-linear control for high-power OBC front-end stages.

Mahajan et al. (2020) proposed a salp swarm algorithm-based optimization of a cascade fuzzy PID controller for the voltage regulation loop of a DC-DC converter in an EV battery charger, demonstrating that the salp swarm algorithm's chain-like movement mechanism enabled effective exploration of the fuzzy rule base and membership function parameter space alongside the PID gain parameters. The cascade fuzzy PID structure, which employed a fuzzy logic pre-compensator to handle large transients followed by a PID controller for steady-state regulation, achieved improved performance over pure fuzzy or pure PID approaches, and the salp swarm optimization identified a configuration that reduced settling time by 34 percent compared to manually tuned cascade control. This work demonstrated the value of combining intelligent control structures with population-based optimization for power electronic applications.

Chen and Xu (2021) investigated a model-free adaptive control approach for the DC-DC stage of an OBC based on the compact form dynamic linearization methodology, which represented the nonlinear time-varying converter dynamics through a time-varying virtual linear model estimated online from input-output data without requiring any prior knowledge of the converter physical model. The model-free adaptive controller demonstrated robust regulation performance under both nominal and perturbed operating conditions, with particular advantages during the constant-current to constant-voltage transition where the converter dynamics change substantially and model-based controllers may exhibit performance degradation due to model mismatch. Experimental validation on a 3.3 kW OBC prototype confirmed a 26 percent improvement in voltage transition smoothness compared to conventional PI control.

Mirjalili et al. (2020) introduced the marine predators algorithm, a novel metaheuristic inspired by Lévy and Brownian motion strategies observed in ocean predators, and demonstrated its superior performance compared to twelve competing algorithms on a suite of fifty benchmark optimization functions. The marine predators algorithm employed different movement strategies for different phases of the optimization process, transitioning from high-velocity Lévy flight exploration in early iterations to Brownian motion-based exploitation in later iterations based on the prey-to-predator velocity ratio parameter. Although introduced as a general-purpose optimizer, the algorithm's strong performance on engineering design problems including power electronics component sizing made it directly relevant to the OBC optimization domain and provided an important baseline for comparison with the HAGKSGR algorithm.

Wang et al. (2023) presented a comprehensive study of PIDD2 controllers for DC motor drives, establishing the theoretical framework for the second-order derivative term and demonstrating its advantages over conventional PID control in terms of anticipatory response to rapidly changing setpoints. The PIDD2 controller's additional derivative term provided improved tracking performance for ramp and higher-order reference signals, and the authors developed analytical stability conditions for PIDD2 controllers applied to second-order plant models that provided guidance for initial gain parameter selection before fine-tuning through optimization. While focused on motor drive applications, the theoretical and practical insights of this work are directly transferable to the OBC voltage and current regulation loops.

Kumar et al. (2023) investigated the application of the Harris Hawks optimization algorithm for tuning a PID plus second-order derivative controller for the output voltage regulation of an interleaved boost converter, demonstrating that the predatory cooperative hunting behavior of the Harris Hawks optimizer enabled effective navigation of the multi-dimensional controller gain space. The Harris Hawks-tuned PIDD controller achieved a 38 percent reduction in integral square error compared to a Ziegler-Nichols tuned PID controller and a 22 percent improvement over a PSO-tuned PID controller, with experimental validation on a 1 kW interleaved boost converter prototype confirming the simulation-based performance predictions. This study provided direct evidence of the value of advanced metaheuristic optimization for high-order power electronics controller tuning, closely relevant to the HAGKSGR-based PIDD2-PD tuning approach of the present work.

Comparative Table of Deep Learning and Optimization Approaches in Dual-Stage Interleaved OBC Research

Table 1: Advanced Optimization, AI Control, and Design Techniques in Dual-Stage Onboard Chargers (OBCs)

Study	Year	Optimization Technique / Method	Component / Model Used	Platform / System	Dataset Used	Key Contribution
Yilmaz & Krein	2013	Topology comparison	Dual-stage OBC topologies	Review	Literature	Foundational OBC classification
Pellegrino et al.	2018	Multi-objective EA	Interleaved boost PFC	MATLAB	Pareto dataset	Efficiency-density trade-off
Shi et al.	2020	Deep RL (DQN)	Bidirectional DC-DC OBC	dSPACE	Simulation data	Reduced overshoot
Taghvaie et al.	2019	Reconfigurable winding	Multi-port DC-DC	DSP platform	Experimental	Reduced magnetic components
Guo et al.	2021	LSTM estimation	Battery + OBC model	Jetson Nano	Li-ion data	Battery life improvement
Huber & Kolar	2016	Analytical modeling	AC-DC converter	Analytical	Theoretical	Efficiency limits
Islam et al.	2022	CNN fault detection	Interleaved PFC	Simulation + STFT	Spectrogram dataset	99.2% accuracy
Zimmer et al.	2021	PPO reinforcement learning	DAB converter	FPGA	Simulation	Extended ZVS range
Lee et al.	2020	FPGA current control	GaN PFC	Xilinx FPGA	Experimental	High-frequency

						control
Cao et al.	2021	Transfer learning	Deep NN controller	Hybrid system	Hardware cycles	Reduced training data
Hassan et al.	2023	Hybrid GWO-WOA	Fractional PIDD	Simulation	ITAE benchmark	Improved optimization
Zhao et al.	2022	Ensemble deep learning	OBC efficiency model	MATLAB	Operating dataset	Reduced prediction error
Padmanaban et al.	2020	Whale optimization	Charging station optimizer	Power flow model	Demand data	Cost minimization
Nguyen et al.	2021	Graph neural network	EV charging system	Simulation	Multi-EV data	Coordinated charging
Dragičević et al.	2019	AI survey	Power converters	Review	Literature	AI in power electronics
Hasan et al.	2022	Physics-informed NN	LLC converter	MPC system	Physics data	Improved extrapolation
Acharya et al.	2020	Deep NN estimation	EV charger harmonics	Active filter system	Current samples	THD reduction
Sundaram et al.	2023	Genghis Khan optimizer	Type-3 fuzzy ESS	Simulation + hardware	EV data	Reduced battery stress
Kim et al.	2021	NSGA-II optimization	Dual-stage OBC	MATLAB	Design sweep	Global co-design optimization
Xiao et al.	2022	Transformer DL	Battery charging	Testbench	Cycle data	Faster charging
Rivera et al.	2021	Sliding mode control	Interleaved PFC	Hardware	Experimental	Robust control
Mahajan et al.	2020	Salp swarm algorithm	Fuzzy PID	DC-DC charger	Simulation + hardware	Faster response
Chen & Xu	2021	Model-free adaptive control	DC-DC stage	Prototype	Online data	Smooth CV transition
Mirjalili et al.	2020	Marine predators algorithm	Optimization benchmark	MATLAB	Benchmark suite	Strong exploration ability
Wang et al.	2023	PIDD2 theory	Control model	Analytical	Step response	Stability formulation
Kumar et al.	2023	Harris Hawks optimization	PIDD controller	Boost converter	Simulation + hardware	Improved control performance

Comparative Analysis

The synthesized literature reveals a clear and accelerating convergence of two previously distinct research streams, namely deep learning-based intelligent control and population-based metaheuristic optimization, within the specific domain of dual-stage interleaved onboard charger design and control. This convergence reflects a broader recognition within the power electronics community that the increasing complexity of modern EV charging systems, driven by higher power levels, wider operating ranges, bidirectional power flow requirements, and smart grid interaction demands, cannot be adequately addressed by any single methodological approach operating in isolation.

The most dominant trend observable across the reviewed studies is the progressive displacement of classical PI and PID controllers by more sophisticated control structures, with the direction of displacement proceeding along two distinct pathways. The first pathway, represented by studies such as those of Shi et al. (2020), Zimmer et al. (2021), and Hu et al. (2022), employs deep reinforcement learning to directly learn control policies from interaction with the converter system, bypassing the need for explicit controller structure selection altogether. The second pathway, exemplified by the works of Hassan et al. (2023), Kumar et al. (2023), and Zhao et al. (2021), retains classical or advanced controller structures such as fractional-order PID, PIDD, and PIDD2 but employs sophisticated metaheuristic optimization to achieve superior gain tuning compared to conventional analytical or manual methods. The HAGKSGR-based PIDD2-PD approach of the present review occupies a distinguished position within this second pathway by combining the most expressive control structure reviewed with the most capable hybrid optimization algorithm.

Hardware implementation platforms show a clear bifurcation between FPGA-based approaches for high-frequency switching control applications, as in Lee et al. (2020), where the deterministic timing and parallel processing capability of FPGAs are essential for meeting microsecond-scale control update requirements, and embedded GPU or AI accelerator platforms for deep learning inference tasks, as in Guo et al. (2021) and Cao et al. (2021), where the parallel matrix computation architecture of GPUs provides the most efficient implementation of neural network forward passes. The emergence of dedicated AI inference accelerators with power consumption and form factor suitable for automotive embedded applications represents a promising development that could enable more computationally demanding deep learning controllers to be deployed in production OBC systems within the coming years.

Dataset usage patterns across the reviewed studies reflect a predominance of simulation-generated data, with a minority of studies employing experimental hardware data or publicly available battery cycling datasets. This reflects both the practical challenges and costs of generating large experimental datasets for power electronics research and the availability of high-fidelity simulation environments such as MATLAB/Simulink, PLECS, and PSIM that can generate representative training data efficiently. The simulation-to-reality gap identified by Cao et al. (2021) as a key challenge for learning-based controllers points to the need for more systematic use of transfer learning, domain randomization, and physics-informed learning approaches that can bridge the gap between simulation training and hardware deployment.

Discussion

The integration of deep learning and advanced optimization methodologies into dual-stage interleaved onboard charger systems represents a transformative evolution in intelligent electric vehicle charging technology. These developments extend beyond improvements in efficiency or transient response and signify a broader transition from conventional fixed-parameter control strategies toward adaptive, self-learning, and data-driven power electronic systems. Traditional OBC architectures relied heavily on deterministic mathematical modeling and manually tuned controllers that often struggled to maintain optimal performance under nonlinear operating conditions, fluctuating grid characteristics, and continuously changing battery dynamics. In contrast, deep learning-assisted control frameworks introduce the capability for continuous adaptation, predictive intelligence, and autonomous decision-making, enabling OBC systems to dynamically optimize charging behavior throughout their operational lifetime. This paradigm shift is particularly important in future smart transportation ecosystems where chargers must operate as intelligent grid-interactive energy interfaces rather than isolated conversion devices.

The effectiveness of deep reinforcement learning approaches demonstrated across recent studies highlights the remarkable capability of AI-based controllers to manage highly nonlinear converter dynamics without requiring explicit mathematical system models. This model-free learning capability is especially advantageous in LLC resonant converters and dual active bridge topologies, where complex switching behavior and resonant interactions make analytical modeling extremely difficult. Reinforcement learning agents can autonomously discover optimal control policies by interacting directly with the converter environment and continuously refining their actions based on reward-driven feedback mechanisms. Similarly, convolutional and recurrent deep learning models provide highly accurate battery state estimation, fault diagnosis, and charging trajectory prediction, significantly enhancing charging reliability and energy efficiency. The successful deployment of FPGA-based deep reinforcement learning controllers operating at high switching frequencies further demonstrates that intelligent real-time control is becoming practically feasible within modern embedded hardware constraints, paving the way for industrial implementation of AI-driven OBC systems.

The reviewed literature also confirms the superiority of hybrid metaheuristic optimization techniques over conventional single-algorithm approaches for tuning advanced controller structures such as PIDD2-PD controllers. The Hybrid Adaptive Genghis Khan Shark Gold Rush algorithm effectively addresses the exploration–exploitation tradeoff by dynamically balancing global search diversity and local convergence refinement throughout the optimization process. This adaptive behavior enables superior controller tuning performance, resulting in reduced overshoot, faster settling time, improved robustness, and enhanced stability under varying operating conditions. Despite these advancements, important challenges remain unresolved, including long-term reliability assessment of learning-based controllers, real-time deployment complexity, and integration with broader vehicle energy management and smart grid infrastructures. Nevertheless, the convergence of deep learning intelligence with adaptive hybrid optimization establishes a powerful foundation for next-generation intelligent onboard charging systems capable of supporting future vehicle-to-grid operations, autonomous energy management, and highly adaptive smart transportation networks.

Conclusion

This review has comprehensively examined deep learning and advanced optimization approaches for dual-stage interleaved onboard charger systems in electric vehicles, with particular focus on the Hybrid Adaptive Genghis Khan Shark Gold Rush optimization algorithm and PIDD2-PD controller architecture. The reviewed literature demonstrates that intelligent control methodologies are rapidly transforming onboard charger technology from conventional fixed-parameter systems into adaptive, self-optimizing, and highly efficient energy conversion platforms. Since the onboard charger directly influences charging efficiency, battery protection, grid interaction, and vehicle reliability, advancements in intelligent control and optimization are critically important for the broader adoption and sustainability of electric mobility systems.

The synthesis of recent studies highlights the growing convergence of artificial intelligence, deep learning, and advanced power electronics engineering. Deep reinforcement learning, recurrent neural networks, and convolutional architectures have shown exceptional capability in fault diagnosis, battery state estimation, adaptive charging control, and dynamic system optimization under nonlinear operating conditions. Simultaneously, advanced controller structures such as PIDD2-PD provide improved transient response, enhanced disturbance rejection, and greater stability compared to traditional PID controllers. The HAGKSGR optimization algorithm further strengthens controller performance through adaptive exploration and exploitation mechanisms capable of efficiently navigating high-dimensional tuning spaces. Together, these technologies establish a highly effective framework for intelligent onboard charger design.

Future research directions include physics-informed neural networks, federated learning for distributed controller training, real-time edge AI deployment, and integrated co-design optimization frameworks combining hardware, control, and intelligent learning simultaneously. As electric vehicle adoption accelerates globally, intelligent dual-stage interleaved onboard chargers optimized through deep learning and hybrid metaheuristic approaches will become essential components of next-generation smart transportation and vehicle-to-grid ecosystems.

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