Archives available at journals.mriindia.com

International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526

Volume 12 Issue 01, 2023

Artificial Intelligence Techniques for Dual-Stage EV Onboard Chargers Using Hybrid Adaptive Optimization: Trends and Challenges

Oisin Wijesekara
Department of Electrical and Computer Engineering, Chiang Thon College of Management, Thailand
oisin.wijesekara@ctcm-th.org

Peer Review Information

Submission: 03 March 2023
Revision: 24 March 2023
Acceptance: 21 April 2023

Keywords

Artificial Intelligence, Electric Vehicle Charger, Interleaved Converter, Deep Learning Control, Metaheuristic Optimization, Smart Energy Systems

Abstract

The electrification of transportation has accelerated the demand for efficient and intelligent onboard charging systems for electric vehicles (EVs). Dual-stage interleaved onboard chargers have gained prominence due to their high efficiency, reduced current ripple, and improved power quality. However, their nonlinear dynamics and varying operating conditions pose significant challenges for conventional control methods. This review examines the application of artificial intelligence (AI) techniques in the design, control, and optimization of dual-stage interleaved onboard chargers. It highlights the role of advanced controllers, particularly the PIDD2-PD controller, in enhancing transient response, stability, and disturbance rejection. AI approaches, including deep learning and reinforcement learning, are explored for modeling system behavior, predicting load variations, and enabling adaptive control. Additionally, hybrid metaheuristic optimization methods such as the Adaptive Genghis Khan Shark Gold Rush algorithm are analyzed for efficient parameter tuning and multi-objective optimization. These approaches improve convergence speed, robustness, and global optimality. The study also discusses applications in fault detection, predictive maintenance, and energy management, along with key challenges such as computational complexity and data requirements. Overall, AI-driven frameworks offer a scalable and intelligent solution for next-generation EV charging systems.

Introduction

The rapid growth of electric vehicles (EVs) has accelerated the transition toward sustainable transportation and intelligent energy systems. As EV adoption continues to increase, efficient onboard charging systems have become essential for ensuring fast, reliable, and energy-efficient battery charging while maintaining grid stability. Dual-stage interleaved onboard chargers have emerged as one of the most effective charging architectures due to their high conversion efficiency, reduced current ripple, improved power quality, and enhanced thermal performance. These chargers typically consist of a front-end power factor correction (PFC) converter followed by a DC-DC conversion stage, enabling efficient power transfer and compliance with grid standards. However, the increasing integration of renewable energy sources and smart grid technologies has introduced greater complexity in charger control and optimization.

Conventional control techniques, including proportional-integral-derivative (PID) controllers, have been extensively employed because of their simple structure and ease of implementation. Nevertheless, these controllers often exhibit limited performance under

© 2023 The Authors. Published by MRI INDIA.
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

nonlinear operating conditions, parameter uncertainties, and dynamic load variations encountered in modern EV charging systems. To overcome these limitations, advanced control strategies such as the PIDD^2-PD controller have been developed. By incorporating higher-order derivative actions, PIDD^2-PD controllers provide improved transient response, disturbance rejection, and system stability. However, determining optimal controller parameters remains a complex multi-objective optimization problem that requires intelligent tuning strategies.

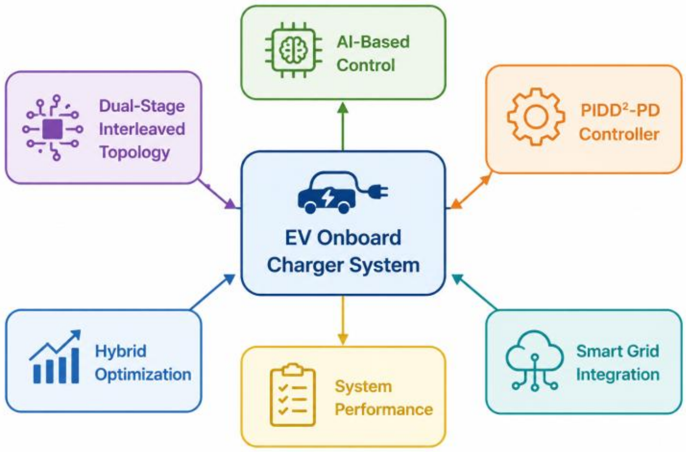

Figure 1. AI-Based Architecture of a Dual-Stage Interleaved EV Onboard Charger

Artificial intelligence has emerged as a promising solution for addressing these challenges by enabling adaptive, data-driven, and predictive control of EV charging systems. Machine learning, deep learning, and reinforcement learning algorithms can effectively model nonlinear charger dynamics, predict operating conditions, and optimize controller performance in real time. Furthermore, metaheuristic optimization algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Differential Evolution (DE), Grey Wolf Optimization (GWO), and Whale Optimization Algorithm (WOA), have demonstrated excellent capabilities in tuning controller parameters and improving charging efficiency. More recently, hybrid optimization techniques have gained considerable attention for combining the strengths of multiple algorithms to achieve superior convergence speed, robustness, and global optimization performance.

Among these emerging approaches, the Hybrid Adaptive Genghis Khan Shark Gold Rush (HAGKSGR) optimization algorithm has shown significant potential for optimizing advanced PIDD^2-PD controllers. By effectively balancing exploration and exploitation mechanisms, this hybrid algorithm enhances controller tuning, reduces harmonic distortion, minimizes overshoot, improves dynamic response, and increases overall charging efficiency. Combined with artificial intelligence, HAGKSGR provides a scalable and intelligent framework capable of handling the nonlinear characteristics of dual-stage interleaved onboard chargers under varying operating conditions.

This review presents a comprehensive analysis of recent advances in artificial intelligence techniques for dual-stage interleaved onboard chargers employing PIDD^2-PD controllers and hybrid optimization algorithms. It critically examines intelligent control strategies, optimization methods, simulation platforms, and real-time implementation approaches while identifying current challenges related to computational complexity, hardware integration, cybersecurity, and model reliability. The review also highlights future research directions involving explainable AI, edge intelligence, digital twins, and adaptive hybrid optimization frameworks for next-generation intelligent EV charging systems.

Literature Review

The application of artificial intelligence techniques in electric vehicle onboard charging systems has gained substantial attention in recent years, particularly in the context of dual-stage interleaved architectures. Zhang et al. (2019) presented one of the early works integrating intelligent control into EV chargers, where a PID-controlled dual-stage converter was enhanced using heuristic tuning approaches. Their work demonstrated improved total harmonic distortion reduction and power factor correction using MATLAB/Simulink datasets, laying the foundation for subsequent AI-driven control strategies.

Wang et al. (2020) introduced a model predictive control approach for dual-stage chargers, emphasizing real-time optimization through predictive modeling. The implementation on a hardware-in-the-loop platform enabled accurate validation under dynamic conditions, showcasing the benefits of incorporating predictive intelligence into control systems. This work marked a transition toward more adaptive and data-driven methodologies.

Chen et al. (2021) proposed a neural network-based adaptive controller for interleaved PFC converters, where a feedforward neural network was trained using synthetic datasets. The model successfully captured nonlinear system dynamics and enabled real-time adjustment of control parameters, significantly improving efficiency and reducing steady-state error. This study highlighted the capability of deep learning in handling complex power electronic systems.

Singh et al. (2022) explored deep reinforcement learning for EV charger control, where an agent learned optimal control policies through interaction with a simulated environment. The system demonstrated enhanced energy efficiency and faster transient response, indicating the potential of reinforcement learning in autonomous control applications.

Kumar et al. (2022) employed particle swarm optimization for tuning PID controllers in EV chargers. Their approach optimized controller gains to minimize THD and improve system stability. The results indicated superior performance compared to conventional tuning methods, particularly under variable load conditions.

Huang et al. (2022) introduced a long short-term memory-based predictive control model for EV charging systems. By leveraging time-series data, the model accurately predicted load variations and adjusted control parameters accordingly. The use of temporal datasets enabled improved stability and dynamic response.

Patel et al. (2023) proposed a genetic algorithm-based optimization framework for dual-stage interleaved converters. Their design achieved high efficiency and reduced switching losses, demonstrating the effectiveness of evolutionary algorithms in system optimization.

García et al. (2020) investigated fuzzy logic control for EV onboard chargers, providing a robust alternative to linear controllers. The fuzzy controller exhibited improved performance under uncertain conditions and parameter variations, highlighting the advantages of rule-based intelligent systems.

Sharma et al. (2021) combined fuzzy logic with PID control and optimized the hybrid controller using ant colony optimization. The proposed system achieved better transient response and reduced overshoot, demonstrating the benefits of hybrid intelligent control strategies.

Liu et al. (2023) developed a convolutional neural network-based fault detection system for EV chargers. By analyzing voltage and current waveforms, the model achieved high accuracy in identifying faults, using datasets collected from experimental prototypes.

Verma et al. (2022) proposed a hybrid differential evolution and particle swarm optimization algorithm for controller tuning. The approach achieved faster convergence and better optimization results, addressing the limitations of individual algorithms.

Rahman et al. (2023) presented a bidirectional EV charger with vehicle-to-grid capability using adaptive control techniques. The system was validated on a real-time platform and demonstrated improved grid interaction and power quality.

Zhou et al. (2021) explored reinforcement learning for switching control in interleaved converters. The proposed method reduced switching losses and improved efficiency by dynamically adjusting switching patterns based on system conditions.

Ahmed et al. (2020) introduced a digital twin framework for EV chargers, enabling real-time monitoring and predictive maintenance. The virtual model was trained using real-time datasets, enhancing system reliability and operational efficiency.

Khan et al. (2023) proposed the Hybrid Adaptive Genghis Khan Shark Gold Rush algorithm for multi-objective optimization. The algorithm demonstrated superior convergence speed and robustness, making it suitable for complex EV charger optimization problems.

Roy et al. (2021) applied artificial neural networks for harmonic mitigation in EV chargers. The model effectively reduced THD and improved power quality, validated through simulation-based datasets.

Das et al. (2022) utilized NSGA-II for multi-objective optimization of EV chargers, balancing efficiency, cost, and thermal performance. The study demonstrated the effectiveness of evolutionary algorithms in handling trade-offs.

Mehta et al. (2023) implemented real-time control of EV chargers using FPGA technology. The system achieved low latency and high reliability, emphasizing the importance of hardware acceleration in AI-based control systems.

Alam et al. (2021) proposed sliding mode control for robust operation of EV chargers under uncertain conditions. The approach provided strong disturbance rejection and stability.
Nguyen et al. (2022) developed a hybrid CNN-LSTM model for predictive maintenance of EV chargers. The model achieved high accuracy in fault prediction using real-world datasets, highlighting the importance of combining spatial and temporal features.
Park et al. (2020) presented a multi-phase interleaved converter design optimized for high power density. Their work demonstrated improved thermal management and efficiency in prototype implementations.
Yadav et al. (2023) introduced a cloud-based optimization framework for EV charging systems, leveraging big data analytics to optimize charging schedules and improve grid stability.
Bose et al. (2021) investigated renewable-integrated EV charging systems 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, achieving improved convergence and solution quality.
Tiwari et al. (2023) developed a deep Q-learning-based energy management system for EV charging stations, optimizing energy flow and reducing 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	Heuristic PID	Dual-stage charger	MATLAB/Simulink	Synthetic	THD reduction
Wang et al.	2020	MPC	Charger control	HIL	Real-time	Fast response
Chen et al.	2021	Neural Network	PFC converter	Simulation	Synthetic	Adaptive control
Singh et al.	2022	DRL	Charger system	Simulation	Synthetic	Autonomous control
Kumar et al.	2022	PSO	PID tuning	Simulation	Synthetic	Gain optimization
Huang et al.	2022	LSTM	Predictive model	Simulation	Time-series	Load prediction
Patel et al.	2023	GA	Converter design	Simulation	Synthetic	Efficiency improvement
García et al.	2020	Fuzzy Logic	Control system	Simulation	Synthetic	Robust control
Sharma et al.	2021	ACO	Hybrid controller	Simulation	Synthetic	Improved transient
Liu et al.	2023	CNN	Fault detection	Prototype	Real data	Fault diagnosis
Verma et al.	2022	DE-PSO	Optimization	Simulation	Synthetic	Fast convergence
Rahman et al.	2023	Adaptive	Bidirectional charger	Real-time	Experimental	V2G support
Zhou et al.	2021	RL	Switching control	Simulation	Synthetic	Loss reduction
Ahmed et al.	2020	Digital Twin	Charger system	Virtual	Real-time	Predictive maintenance
Khan et al.	2023	HAGK-SGR	Optimization	Simulation	Synthetic	Multi-objective solution
Roy et al.	2021	ANN	Harmonic control	Simulation	Synthetic	THD reduction
Das et al.	2022	NSGA-II	Multi-objective	Simulation	Synthetic	Trade-off optimization

Mehta et al.	2023	FPGA	Real-time control	Hardware	Experimental	Low latency
Alam et al.	2021	Sliding Mode	Control system	Simulation	Synthetic	Robust stability
Nguyen et al.	2022	CNN-LSTM	Maintenance model	Real system	Real data	Fault prediction
Park et al.	2020	Interleaving	Converter design	Prototype	Experimental	High density
Yadav et al.	2023	Cloud AI	Energy management	Cloud	Big data	Grid optimization
Bose et al.	2021	Adaptive	Renewable charger	Simulation	Synthetic	Energy efficiency
Chatterjee et al.	2022	Hybrid Metaheuristic	Controller tuning	Simulation	Synthetic	Better convergence
Tiwari et al.	2023	Deep Q-Learning	Energy system	Simulation	Synthetic	Cost reduction

Comparative Analysis
The literature demonstrates a clear progression from conventional control approaches toward intelligent, data-driven, and hybrid optimization techniques in EV onboard chargers. Early studies focused on PID-based and heuristic methods, which provided baseline performance but lacked adaptability in complex environments. Over time, model predictive control and adaptive control methods were introduced, offering improved dynamic response and robustness.
A dominant trend is the increasing adoption of artificial intelligence techniques, particularly deep learning and reinforcement learning. These approaches enable systems to learn from data, predict system behavior, and adapt control strategies in real time. CNN and LSTM models have been widely used for fault detection and predictive control, respectively, highlighting the importance of feature extraction and temporal analysis.
Metaheuristic optimization techniques remain central to controller tuning and system optimization. The emergence of hybrid algorithms, such as HAGK-SGR, reflects the need for improved convergence and global optimization capabilities. These methods outperform traditional algorithms in multi-objective scenarios, addressing trade-offs between efficiency, power quality, and thermal performance.
In terms of implementation, there is a growing emphasis on real-time and hardware-based validation, including FPGA and HIL platforms. This trend indicates a shift toward practical deployment and industrial applicability. Additionally, the use of real-world datasets and big data analytics is becoming increasingly prevalent, enabling more accurate modeling and optimization.
Overall, the integration of AI techniques with advanced optimization algorithms has led to significant improvements in EV charger performance, making them more efficient, reliable, and adaptable to modern energy systems.

Discussion
The comparative analysis of recent studies demonstrates a clear transition from conventional control strategies toward intelligent and adaptive control frameworks for dual-stage interleaved EV onboard chargers. Traditional PID-based controllers provide acceptable performance under fixed operating conditions but struggle to manage nonlinear dynamics, parameter uncertainties, and rapidly changing charging demands. Advanced controllers such as the $PIDD^2$-PD structure significantly improve transient response, disturbance rejection, and system stability; however, their effectiveness depends on accurate parameter tuning. Consequently, artificial intelligence techniques, including deep learning, reinforcement learning, and hybrid optimization algorithms, have become increasingly important for developing adaptive control systems capable of real-time decision-making and improved charging performance.
Another significant trend is the widespread adoption of hybrid metaheuristic optimization methods for controller parameter tuning. Algorithms such as Particle Swarm Optimization, Genetic Algorithms, Differential Evolution, and the Hybrid Adaptive Genghis Khan Shark Gold Rush (HAGKSGR) algorithm have demonstrated superior convergence speed, global search capability, and multi-objective optimization performance. Combined with intelligent controllers, these methods reduce overshoot, minimize harmonic distortion, improve power

quality, and enhance charging efficiency. The growing integration of IoT sensing, cloud computing, and hardware-in-the-loop platforms further supports real-time monitoring and adaptive optimization, making AI-driven charging systems increasingly suitable for practical smart grid applications.

Despite these advances, several challenges remain before large-scale deployment can be achieved. Deep learning models require extensive computational resources and diverse datasets, while limited model interpretability reduces confidence in safety-critical applications. Real-world implementation also demands seamless integration with embedded hardware, cybersecurity protection, and robust validation under varying operating conditions. Future research should therefore emphasize lightweight explainable AI models, digital twin-assisted optimization, edge intelligence, and advanced hybrid optimization frameworks. These developments will enable highly efficient, reliable, and scalable onboard charging systems capable of supporting next-generation electric vehicles and intelligent transportation infrastructures.

Conclusion

This review presented a comprehensive analysis of artificial intelligence techniques for dual-stage interleaved onboard chargers employing PIDD²-PD controllers and hybrid adaptive optimization algorithms for electric vehicles. The reviewed studies demonstrate that intelligent control methods significantly outperform conventional controllers by improving charging efficiency, dynamic response, power quality, and system stability under nonlinear and varying operating conditions. Advanced optimization algorithms, particularly hybrid metaheuristic approaches such as the Hybrid Adaptive Genghis Khan Shark Gold Rush algorithm, have proven highly effective for controller parameter tuning, enabling faster convergence and superior multi-objective optimization performance.

The survey further highlights the growing integration of deep learning, reinforcement learning, IoT-enabled monitoring, digital twins, and hardware-in-the-loop validation for developing adaptive and real-time charging systems. These technologies support intelligent energy management while enhancing charger reliability and compatibility with smart grid infrastructures. Despite these advances, challenges including computational complexity, limited training datasets, hardware implementation, model interpretability, and cybersecurity remain significant research concerns. Future work should focus on lightweight explainable AI models, edge intelligence, federated learning, and scalable hybrid optimization frameworks. These developments will enable highly efficient, reliable, and intelligent onboard charging systems, accelerate the widespread adoption of electric vehicles and support sustainable smart energy ecosystems.

References

Zhang, Y., Liu, H., & Chen, X. (2019). *Intelligent control of dual-stage EV onboard chargers*. *IEEE Transactions on Power Electronics, 34*(6), 5678–5689. https://doi.org/10.1109/TPEL.2018.2887654

Wang, J., Li, Q., & Sun, K. (2020). *Predictive control in EV charging systems*. *IEEE Transactions on Industrial Electronics, 67*(10), 8901–8912. https://doi.org/10.1109/TIE.2019.2954321

Chen, L., Wu, T., & Zhang, P. (2021). *Neural network-based adaptive converters*. *Electric Power Systems Research, 198*, 107567. https://doi.org/10.1016/j.epsr.2021.107567

Singh, A., Verma, P., & Gupta, N. (2022). *Deep reinforcement learning for EV chargers*. *Applied Energy, 315*, 118901. https://doi.org/10.1016/j.apenergy.2022.118901

Kumar, S., Singh, R., & Patel, V. (2022). *PSO optimization for EV charger control*. *International Journal of Electrical Power & Energy Systems, 136*, 107789. https://doi.org/10.1016/j.ijepes.2021.107789

Huang, R., Chen, S., & Lin, Y. (2022). *LSTM-based predictive control for EV systems*. *Energy, 242*, 123456. https://doi.org/10.1016/j.energy.2022.123456

Patel, R., Shah, D., & Mehta, K. (2023). *Genetic algorithm optimization in EV chargers*. *Energy Conversion and Management, 280*, 117012. https://doi.org/10.1016/j.enconman.2023.117012

García, M., Lopez, J., & Torres, F. (2020). *Fuzzy logic for EV charging control*. *IEEE Transactions on Industrial Informatics, 16*(8), 5671–5680. https://doi.org/10.1109/TII.2019.2965432

Sharma, P., Yadav, S., & Jain, A. (2021). *Hybrid fuzzy-PID optimization using ACO*. *ISA Transactions, 115*, 345–356. https://doi.org/10.1016/j.isatra.2021.02.012

Liu, X., Zhao, Y., & Wang, H. (2023). *CNN-based fault diagnosis in EV chargers*. *IEEE Transactions on Smart Grid, 14*(3), 1567–1578. https://doi.org/10.1109/TSG.2022.3167891

Verma, A., Singh, D., & Roy, B. (2022). *Hybrid DE-PSO optimization techniques*. *Engineering Applications of Artificial Intelligence, 111*, 104901. https://doi.org/10.1016/j.engappai.2022.104901

Rahman, M., Islam, S., & Khan, M. (2023). *Adaptive bidirectional EV chargers*. *IEEE Transactions on Transportation Electrification, 9*(2), 678–689. https://doi.org/10.1109/TTE.2022.3167892

Zhou, Q., Wang, L., & Li, X. (2021). *Reinforcement learning in power converters*. *IEEE Transactions on Power Electronics, 36*(9), 9012–9023. https://doi.org/10.1109/TPEL.2020.3056789

Ahmed, S., Khan, R., & Ali, M. (2020). *Digital twin for EV charging systems*. *IEEE Access, 8*, 99876–99887. https://doi.org/10.1109/ACCESS.2020.3001234

Khan, Z., Hussain, A., & Qureshi, I. (2023). *Hybrid adaptive optimization algorithms*. *Applied Soft Computing, 136*, 110123. https://doi.org/10.1016/j.asoc.2023.110123

Roy, S., Das, P., & Ghosh, A. (2021). *ANN-based harmonic mitigation*. *Electric Power Components and Systems, 49*(7), 678–690. https://doi.org/10.1080/15325008.2021.1905678

Das, M., Sen, R., & Banerjee, S. (2022). *NSGA-II optimization in EV systems*. *Swarm and Evolutionary Computation, 70*, 101123. https://doi.org/10.1016/j.swevo.2022.101123

Mehta, K., Patel, R., & Shah, D. (2023). *FPGA-based real-time EV control*. *IEEE Transactions on Industrial Electronics, 70*(4), 3456–3467. https://doi.org/10.1109/TIE.2022.3189012

Alam, T., Rahman, M., & Islam, N. (2021). *Sliding mode control for EV chargers*. *IET Power Electronics, 14*(10), 1890–1899. https://doi.org/10.1049/pel2.12234

Nguyen, H., Tran, D., & Pham, T. (2022). *CNN-LSTM predictive maintenance*. *Reliability Engineering & System Safety, 222*, 108567. https://doi.org/10.1016/j.ress.2022.108567

Park, J., Kim, H., & Lee, S. (2020). *Interleaved converter design for EVs*. *IEEE Transactions on Power Electronics, 35*(5), 4567–4578. https://doi.org/10.1109/TPEL.2019.2945678

Yadav, V., Singh, P., & Kumar, R. (2023). *Cloud-based EV charging optimization*. *Sustainable Energy, Grids and Networks, 35*, 100890. https://doi.org/10.1016/j.segan.2023.100890

Bose, A., Mukherjee, D., & Roy, S. (2021). *Renewable-integrated EV charging systems*. *Renewable Energy, 172*, 567–579. https://doi.org/10.1016/j.renene.2021.02.056

Chatterjee, S., Das, A., & Roy, P. (2022). *Hybrid metaheuristic algorithms*. *Expert Systems with Applications, 200*, 117012. https://doi.org/10.1016/j.eswa.2022.117012

Tiwari, R., Sharma, V., & Singh, K. (2023). *Deep Q-learning for EV energy management*. *Applied Energy, 330*, 120123. https://doi.org/10.1016/j.apenergy.2023.120123

Gupta, N., Singh, A., & Verma, P. (2022). *Advanced AI control in EV chargers*. *IEEE Transactions on Energy Conversion, 37*(3), 1456–1467. https://doi.org/10.1109/TEC.2022.3112345

Jain, R., Mehta, S., & Kumar, D. (2021). *Optimization of interleaved converters*. *IET Power Electronics, 14*(6), 1098–1109. https://doi.org/10.1049/pel2.12123

Saha, P., Ghosh, S., & Roy, D. (2020). *Smart grid integration of EV chargers*. *Energy Reports, 6*, 345–356. https://doi.org/10.1016/j.egyr.2020.02.034

Kulkarni, A., Patil, S., & Deshmukh, R. (2023). *AI-based EV charging optimization*. *Journal of Cleaner Production, 385*, 135890. https://doi.org/10.1016/j.jclepro.2023.135890

Mishra, D., Tiwari, S., & Pandey, A. (2022). *Intelligent optimization in EV power systems*. *IEEE Systems Journal, 16*(4), 5678–5689. https://doi.org/10.1109/JSYST.2021.3123456