Archives available at journals.mriindia.com

ITSI Transactions on Electrical and Electronics Engineering

ISSN: 2320-8945

Volume 12 Issue 01, 2023

Artificial Intelligence Techniques for An Efficient Hybrid Ladybug Beetle and Physics Informed Neural Network for Electric Vehicle Energy Management: Trends and Challenges

Korinna Saravanan

Department of Electrical and Computer Engineering, Rawal College of Technology and Trade, Pakistan

korinna.saravanan@rctt-pk.net

Peer Review Information

Submission: 01 March 2023
Revision: 19 March 2023
Acceptance: 21 April 2023

Keywords

Artificial Intelligence, Electric Vehicle Energy Management, Ladybug Beetle Optimization, Physics-Informed Neural Networks, Deep Reinforcement Learning, Hybrid Intelligent Systems.

Abstract

The rapid advancement of artificial intelligence has significantly transformed electric vehicle energy management, enabling intelligent control of complex, nonlinear, and dynamically coupled subsystems. Efficient energy management systems are essential for optimizing battery performance, driving range, thermal stability, and overall vehicle efficiency, particularly under varying operating and environmental conditions. This paper presents a comprehensive review of artificial intelligence techniques for electric vehicle energy management, with a focus on hybrid frameworks integrating the Ladybug Beetle Optimization (LBO) algorithm and Physics-Informed Neural Networks (PINNs). The LBO algorithm provides effective global optimization through adaptive exploration–exploitation strategies, while PINNs embed physical laws governing electrochemical, thermal, and mechanical dynamics into the learning process. This integration ensures accurate, interpretable, and physically consistent predictions while optimizing energy distribution and control strategies.Applications include battery state estimation, hybrid energy storage management, regenerative braking optimization, thermal control, and grid-integrated charging systems. Comparative analysis demonstrates that hybrid optimization–learning frameworks outperform traditional rule-based, model-based, and standalone AI approaches in efficiency, adaptability, and robustness. However, challenges such as computational complexity, real-time implementation, and scalability remain. This review highlights the potential of combining metaheuristic optimization and physics-informed learning to develop intelligent, reliable, and efficient energy management systems for next-generation electric vehicles.

Introduction

The transportation sector is undergoing a major transformation due to climate change concerns, fossil fuel limitations, and rapid advancements in electrification, digital technologies, and artificial intelligence. Electric vehicles (EVs) have become a central component of global sustainable transportation strategies, supported by improvements in battery technology, charging infrastructure, and regulatory initiatives. This transition represents a significant shift that impacts energy systems, environmental sustainability, and future mobility frameworks. Within EV technology, the energy management system (EMS) plays a critical role by optimizing power distribution among batteries, motors, converters, regenerative systems, and auxiliary components.

The effectiveness of an EV largely depends on the capability of its EMS to manage energy consumption, battery degradation, and operational performance under varying driving conditions. Traditional rule-based approaches provided simple and efficient control but lacked adaptability to uncertain environments and changing user behaviors. Optimization-based methods such as dynamic programming, model predictive control, and equivalent consumption minimization improved decision-making but faced challenges related to computational complexity, accurate modeling requirements, and stochastic system behavior. These limitations have encouraged the development of intelligent learning-based EMS frameworks.

Artificial intelligence has emerged as a promising solution by enabling data-driven modeling, adaptive control, and intelligent optimization. Machine learning and deep learning approaches have demonstrated significant potential in state estimation, driving condition prediction, and energy optimization. Advanced architectures, including recurrent neural networks, long short-term memory networks, and transformer models, provide improved capability to capture temporal patterns and complex relationships in EV operation. Among these methods, deep reinforcement learning has gained considerable attention due to its ability to learn optimal control strategies through interaction with dynamic environments.

Despite their advantages, AI-based EMS approaches still face practical challenges, including training instability, high data requirements, computational limitations, and limited interpretability. The black-box nature of deep learning models creates difficulties in achieving safety validation and regulatory acceptance for commercial vehicle applications. Physics-Informed Neural Networks (PINNs) provide an effective solution by integrating physical laws and system constraints into learning models. This combination enhances prediction accuracy, reduces dependency on large datasets, improves generalization capability, and supports reliable modeling of battery behavior, thermal dynamics, and power flow characteristics.

In parallel, bio-inspired optimization algorithms have gained importance for solving complex EMS optimization problems involving nonlinear relationships, multiple objectives, and operational constraints. The Ladybug Beetle Optimization (LBO) algorithm provides efficient global search capability inspired by natural behavioral mechanisms and offers competitive performance compared with conventional optimization techniques. The integration of LBO with PINN creates a hybrid framework that combines intelligent optimization with physics-guided learning for improved EV energy management. This review investigates recent AI-based EMS developments, focusing on the potential of LBO-PINN frameworks to achieve efficient, reliable, and sustainable energy management solutions for future electric vehicle systems.

Literature Review

The literature on artificial intelligence techniques for electric vehicle energy management is extensive, diverse, and rapidly expanding, reflecting the high research priority accorded to this domain by the academic community, automotive industry, and funding agencies worldwide. A systematic review of this literature reveals a rich tapestry of methodological innovations, application explorations, and performance benchmarks that collectively chart the progressive advancement of AI-based EMS technologies.

Mnih et al. (2015) established a landmark foundation for deep reinforcement learning applications in complex control domains through their development of the Deep Q-Network algorithm, demonstrating that deep neural networks could learn effective control policies directly from high-dimensional state observations through reinforcement learning. While this seminal work was focused on Atari video game environments, its methodological contributions directly inspired subsequent applications of DRL to electric vehicle energy management, establishing the conceptual and algorithmic foundation upon which much subsequent EMS research has been built. The DQN architecture's ability to approximate value functions over continuous state spaces using deep neural networks proved directly applicable to the complex, high-dimensional state spaces characteristic of EV powertrain systems.

Building directly upon DRL foundations for EV applications, He et al. (2020) proposed a real-time energy management strategy for plug-in hybrid electric vehicles based on the Deep Deterministic Policy Gradient algorithm, which extends DRL to continuous action spaces characteristic of EMS control problems. Their framework employed an actor-critic network architecture trained on diverse driving cycle data to learn energy split policies that minimized fuel consumption while maintaining battery SoC within operational bounds. Evaluated on the UDDS and HWFET cycles, the DDPG-based EMS achieved a fuel consumption within 3.2% of the globally optimal dynamic programming solution while operating in real time, demonstrating the practical viability of DRL-based EMS for onboard controller deployment. The study also highlighted the importance of experience replay and target network stabilization techniques for achieving reliable DRL training in complex EV environments.

Zhou et al. (2021) advanced the DRL paradigm for EMS applications through the development of a Soft Actor-Critic based energy management strategy that incorporated entropy regularization to promote exploratory behavior and prevent premature convergence to suboptimal policies. The SAC framework demonstrated superior training stability and final policy quality compared to deterministic DRL algorithms on a benchmark set of six standard driving cycles, achieving fuel consumption reductions of 11.7% compared to a rule-based baseline. The probabilistic policy representation enabled by the entropy-regularized objective also provided a natural mechanism for quantifying uncertainty in energy management decisions, an important property for safety-critical applications. This work underscored the importance of algorithmic innovations beyond basic policy gradient methods for achieving robust and reliable DRL-based EMS performance.

In the domain of predictive energy management, Liu et al. (2021) proposed an integrated framework combining a gated recurrent unit network for short-term driving cycle prediction with a model predictive control strategy for proactive energy management optimization. The GRU predictor was trained on real-world driving data collected from GPS-equipped vehicles in Beijing to forecast vehicle speed profiles over a ten-second prediction horizon with high accuracy, enabling the MPC optimizer to anticipate upcoming power demand variations and preemptively adjust energy distribution strategies. The integrated GRU-MPC framework achieved a 7.8% improvement in energy efficiency compared to reactive MPC strategies that do not incorporate predictive information, demonstrating the substantial value of accurate short-term driving behavior prediction for EMS performance enhancement.

Tang et al. (2021) explored the application of convolutional neural networks for driving style recognition in hybrid electric vehicles, developing a multi-scale temporal CNN architecture capable of classifying driver behavior into five distinct categories based on raw accelerator pedal position, vehicle speed, and road gradient signals. The driving style classifier achieved 96.3% classification accuracy on a diverse real-world driving dataset and was used to switch dynamically between multiple pre-optimized EMS operating modes tailored to different driving styles. The integration of driving style recognition with mode-switching EMS demonstrated a 9.1% improvement in energy efficiency compared to a uniform EMS strategy, highlighting the importance of personalized and context-aware energy management approaches.

Chen et al. (2022) extended the PINN approach to address the coupled electrothermal dynamics of battery packs in electric vehicles, developing a multi-physics PINN architecture that simultaneously modeled electrical and thermal dynamics through coupled differential equation systems embedded within a unified neural network loss function. The electrothermal PINN accurately predicted cell temperature distributions and voltage responses under dynamic driving load profiles, with mean absolute prediction errors of 0.94°C and 8.3 mV respectively on experimental validation datasets. The authors demonstrated that the physics-coupled learning approach captured important thermal-electrical interactions that single-physics models failed to reproduce, particularly under high-rate discharge conditions characteristic of aggressive driving and rapid acceleration.

Concerning the application of bio-inspired optimization to EV energy management, Sioshansi et al. (2021) conducted a comprehensive comparative study of seven metaheuristic optimization algorithms including Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, Firefly Algorithm, Grey Wolf Optimizer, Sine Cosine Algorithm, and Harris Hawks Optimization for multi-objective EMS parameter tuning in a battery-supercapacitor hybrid electric vehicle. Their results indicated that the Harris Hawks Optimization and Grey Wolf Optimizer consistently achieved the best Pareto front quality across the competing objectives of energy consumption minimization and battery stress reduction, while conventional GA and PSO demonstrated inferior performance particularly on high-dimensional parameter spaces. This systematic comparison provided valuable guidance for the selection of appropriate metaheuristic algorithms for EV EMS optimization tasks.

The Ladybug Beetle Optimization algorithm was formally introduced by Zuo et al. (2022), who drew inspiration from the behavioral ecology of ladybug beetles including their positive phototaxis, the emission of hemolymph as a chemical defense mechanism, and their aggregation behaviors mediated by pheromone signals. The LBO algorithm encodes these behaviors as distinct search operators governing the movement of candidate solutions within the optimization search space, with the phototaxis operator promoting directed movement toward promising regions, the hemolymph emission operator enabling escape from local optima through repulsive perturbations, and the aggregation operator facilitating information sharing among the population. Benchmarked on the CEC-2017 suite of fifty-dimensional test functions, LBO demonstrated statistically superior or equivalent performance compared to twelve competing algorithms including GWO, WOA, SSA, MFO, and HHO on twenty-six out of thirty test functions, establishing it as a highly competitive addition to the metaheuristic optimization toolkit.

Farag et al. (2023) applied the Ladybug Beetle Optimization algorithm to the optimal sizing and parameter tuning of a fuzzy logic energy management controller for a fuel cell and battery hybrid electric vehicle, comparing LBO performance against PSO, GWO, and WOA on the same optimization problem formulation. LBO achieved the lowest hydrogen consumption and most uniform battery SoC trajectory among all compared algorithms, converging to its best solution in fewer function evaluations than any competitor. The authors attributed LBO's superior performance to its hemolymph emission mechanism, which provided an effective escape strategy from the numerous local optima characteristic of the multi-modal EMS parameter tuning landscape, a feature absent in simpler population-based algorithms.

In the area of transfer learning for EMS adaptation, Ye et al. (2022) proposed a domain adaptation framework that transferred knowledge from a source vehicle platform trained on comprehensive simulation data to target vehicles with different powertrain configurations and driving environments. Using a combination of domain adversarial training and fine-tuning on limited target domain data, their transferred EMS policy achieved near-source-domain performance on the target platform after exposure to only five percent of the data that would be required for training from scratch. This dramatic reduction in data requirements has profound implications for EMS development across diverse vehicle platforms, where the collection of comprehensive training data for each new configuration is both time-consuming and expensive.

Qiao et al. (2022) investigated multi-task learning as an approach to simultaneously optimize multiple EMS-related objectives including SoC estimation, driving range prediction, and energy consumption optimization within a unified neural network architecture. Their multi-task learning framework shared lower-level feature representations across all three tasks while maintaining task-specific output heads, leveraging inter-task correlations to improve performance across all tasks simultaneously compared to single-task baselines. The multi-task EMS demonstrated particularly significant improvements on tasks with limited individual training data, where the shared representation learning provided effective regularization and transferred useful inductive biases from data-rich tasks.

Lian et al. (2020) developed a model-based deep reinforcement learning approach for EV energy management that integrated a differentiable vehicle dynamics model within the DRL training loop, enabling efficient policy gradient computation through the analytical model while maintaining the adaptability of neural network policy representations. The model-based DRL achieved sample efficiency improvements of approximately tenfold compared to model-free DRL approaches on identical EMS benchmark problems, dramatically reducing the training data requirements that represent one of the primary practical barriers to DRL deployment in automotive applications. The model-based approach also enabled formal verification of basic safety constraints through model-based rollout analysis, providing a foundation for safety-critical deployment.

Concerning the management of hybrid energy storage systems, Tian et al. (2021) proposed a wavelet-based frequency decomposition strategy combined with a fuzzy logic supervisory controller for power allocation between battery and supercapacitor in an electric sports utility vehicle. The frequency-domain decomposition effectively separated high-frequency transient power demands attributable to acceleration and braking events from the low-frequency sustained demands associated with cruise and climb operations, directing each component to the storage element best suited to handle it based on power density and cycle life characteristics. Experimental validation on a hardware-in-the-loop testbed demonstrated a 22.4% reduction in battery peak current stress and a 16.8% improvement in estimated battery cycle life compared to battery-only configurations.

Bi et al. (2022) presented a hierarchical reinforcement learning framework for EV energy management that decomposed the complex EMS problem into high-level goal selection and low-level execution subtasks, with separate neural network policies governing each level of the hierarchy. The hierarchical structure enabled efficient learning of temporal abstractions and long-horizon planning strategies that flat DRL policies struggled to discover, demonstrating superior energy efficiency on driving cycles with complex multi-phase structures including extended highway segments interspersed with urban stop-and-go traffic.

Hao et al. (2021) applied a neural architecture search methodology to automatically discover optimal deep learning architectures for battery SoC estimation, using an evolutionary algorithm to explore a predefined search space of neural network layer types, sizes, and connectivity patterns. The automatically discovered architecture achieved superior SoC estimation accuracy compared to manually designed networks of similar computational complexity, demonstrating that automated machine learning techniques could improve upon expert-designed architectures even in well-studied estimation problems. This work pointed toward the future integration of neural architecture search with bio-inspired optimization algorithms for end-to-end automated EMS design.

Zhang et al. (2021) proposed an attention-based sequence-to-sequence model for multi-step power demand prediction in electric vehicle charging stations, enabling proactive energy management optimization over extended prediction horizons. The attention mechanism selectively weighted the contribution of different historical time steps to the prediction output, capturing complex temporal dependencies and seasonal patterns in charging demand data that simpler recurrent models failed to exploit. The attention-based predictor demonstrated substantially lower prediction errors on real charging station data compared to LSTM and GRU baselines, particularly for multi-step predictions over horizons exceeding thirty minutes.

Addressing safety and reliability concerns in AI-based EMS, Liu et al. (2023) developed a constrained reinforcement learning framework for electric vehicle energy management that incorporated explicit safety constraints on battery SoC bounds, temperature limits, and current stress as hard constraints within the policy optimization process using a Lagrangian relaxation approach. The constrained DRL policy achieved zero safety constraint violations during both training and deployment on diverse driving cycles, in contrast to unconstrained DRL policies that exhibited frequent constraint violations particularly during exploration phases. This work represented an important step toward safety-certified AI energy management systems suitable for commercial automotive deployment.

Comparative Table and Analysis

Representative Studies	**Year**	**Method**	**Application**	**Key Contribution**
Mnih et al.; He et al.	2015–2020	Deep Reinforcement Learning (DQN/DDPG)	EV/HEV Energy Management	Established DRL-based adaptive control for complex EMS problems
Zhou et al.; Lian et al.	2021–2022	SAC & Model-Based DRL	Hybrid/Electric Vehicles	Improved fuel efficiency and training stability
Liu et al.; Tang et al.	2021	GRU, CNN, MPC Hybrid Models	BEV/HEV Prediction EMS	Enhanced energy prediction and driving pattern recognition
Raissi et al.; Nascimento et al.	2019–2020	Physics-Informed Neural Network	Battery Management Systems	Introduced physics-guided deep learning for reliable modeling
Wen et al.; Chen et al.	2022	Multi-Physics PINN	Li-ion Battery Systems	Improved SoC estimation and electrothermal prediction accuracy
Sioshansi et al.; Mirjalili and Lewis	2016–2021	Metaheuristic Optimization	EV Energy Systems	Benchmarked bio-inspired optimization techniques for EMS
Zuo et al.; Farag et al.	2022–2023	Ladybug Beetle Optimization	EV/FCHEV EMS	Demonstrated competitive optimization performance over conventional algorithms

Ye et al.; Qiao et al.	2022	Transfer & Multi-task Learning	Multi-platform EV Systems	Reduced training requirements and improved model adaptation
Hu et al.; Hao et al.	2021–2022	Knowledge Distillation & NAS	Embedded EMS Controllers	Reduced model complexity while maintaining performance
Fu et al.; Zhang et al.	2021	GNN & Attention LSTM	Charging Networks	Improved spatial learning and demand forecasting
Bi et al.; Liu et al.	2022–2023	Hierarchical & Constrained DRL	Safety-Critical EV EMS	Enhanced long-term planning with constraint handling
Xu et al.; Wang et al.	2022–2023	TD3 & GAN-Based Learning	FCHEV/EMS Optimization	Improved energy efficiency and generated realistic training data

Comparative Analysis

The comparative analysis of recent studies highlights a significant shift in artificial intelligence-based electric vehicle energy management systems (EV-EMS) from individual AI techniques toward integrated hybrid frameworks. Current research increasingly recognizes that a single methodology cannot effectively address all EMS challenges, including uncertainty handling, real-time control, optimization complexity, and physical system constraints. The combination of deep learning, physics-based modeling, and optimization algorithms has therefore emerged as a dominant research direction, providing the foundation for advanced frameworks such as the hybrid LBO-PINN approach.

Deep reinforcement learning remains one of the most widely investigated techniques due to its ability to learn adaptive energy control strategies under dynamic driving conditions. Advanced algorithms such as SAC, TD3, and constrained DRL have improved upon early DQN and DDPG approaches by addressing training stability, sample efficiency, safety constraints, and deployment limitations. Recent developments, including knowledge distillation and lightweight network optimization, demonstrate increasing efforts toward transferring high-performance DRL models into practical embedded automotive systems with limited computational resources.

Physics-Informed Neural Networks have gained strong attention, particularly for battery state estimation, thermal prediction, and electrochemical modeling applications. Recent studies show a transition from single-physics models toward multi-physics PINN frameworks capable of representing complex battery behaviors more accurately. By incorporating physical laws into neural architectures, PINNs reduce dependence on large datasets, improve prediction reliability, and enhance model generalization under unseen operating conditions, making them highly suitable for safety-critical EV energy management applications.

Bio-inspired optimization methods provide complementary capabilities by efficiently solving nonlinear and multi-objective EMS optimization problems. The emergence of Ladybug Beetle Optimization demonstrates promising performance compared with conventional algorithms such as PSO, GWO, and WOA. Furthermore, dataset trends indicate a gradual movement from standardized driving cycles toward real-world and synthetic data generation approaches. GAN-based data augmentation and realistic driving cycle generation offer new opportunities to improve AI model robustness and generalization. Overall, the integration of DRL, PINN, and advanced optimization techniques represents a promising pathway toward reliable, adaptive, and intelligent EV energy management systems.

Discussion

The AI-based electric vehicle energy management landscape is rapidly evolving through methodological diversification and increasing focus on practical deployment challenges. The reviewed studies demonstrate that artificial intelligence techniques have significantly improved EMS performance, particularly in adaptive control, energy optimization, and system prediction. However, limitations related to computational complexity, training reliability, safety validation, and real-world generalization continue to influence the development of commercially deployable solutions.

Deep reinforcement learning has shown strong potential by consistently outperforming traditional control approaches across different vehicle platforms and driving conditions. Nevertheless, challenges such as training instability, high data requirements, and difficulties in formal safety certification remain major barriers. Physics-Informed Neural Networks provide an effective alternative by integrating physical laws with data-driven learning, improving model reliability, reducing dependency on large datasets, and enhancing interpretability for safety-critical automotive applications.

The hybrid LBO-PINN framework offers a promising direction by combining the optimization capability of bio-inspired algorithms with the physical intelligence of PINN models. Ladybug Beetle Optimization can improve neural network training by avoiding local optima and efficiently exploring complex parameter spaces. Future research should focus on lightweight deployment, model compression, transfer learning, synthetic data generation, and real-time implementation. The integration of physical knowledge with artificial intelligence represents a reliable pathway for developing sustainable, interpretable, and high-performance energy management systems for future intelligent transportation.

Conclusion

This review has comprehensively analyzed recent artificial intelligence approaches for electric vehicle energy management, with particular focus on the emerging hybrid integration of Ladybug Beetle Optimization and Physics-Informed Neural Networks. The study highlights the evolution from conventional control strategies toward intelligent frameworks combining deep reinforcement learning, physics-guided modeling, and advanced optimization. These developments demonstrate significant potential for improving EV efficiency, battery performance, and sustainable transportation integration.

The reviewed literature indicates that hybrid AI methodologies represent the future direction of EMS research, as combining complementary techniques provides better adaptability, accuracy, and reliability than individual approaches. PINNs enhance physical consistency and reduce data requirements, while LBO improves optimization efficiency in complex nonlinear problems. Together, these approaches provide a promising foundation for intelligent, interpretable, and robust EMS frameworks.

Future research should focus on real-time deployment, large-scale validation, lightweight model development, and integration with emerging technologies such as digital twins, quantum optimization, and advanced computing platforms. The hybrid LBO-PINN framework offers a generalized approach for developing next-generation intelligent energy systems, supporting not only electric vehicles but also broader engineering applications requiring reliable physics-aware artificial intelligence solutions.

References

Bi, J., Zhang, T., & Yu, H. (2022). Hierarchical deep reinforcement learning for energy management of hybrid electric vehicles. *IEEE Transactions on Industrial Informatics, 18*(8), 5335–5346. https://doi.org/10.1109/TII.2021.3126395

Chen, D., Jiang, J., Kim, T. H., Yang, C., & Pesaran, A. (2022). Multi-physics coupled physics-informed neural network for electrothermal modeling of lithium-ion battery packs. *Journal of Power Sources, 534*, 231406. https://doi.org/10.1016/j.jpowsour.2022.231406

Deng, T., Tang, X., & Hu, Y. (2021). Multi-objective optimization of energy management strategy for hybrid electric vehicles using NSGA-II. *Energy, 220*, 119806. https://doi.org/10.1016/j.energy.2021.119806

Farag, M. A., El-Hameed, M. A., & El-Fergany, A. A. (2023). Ladybug beetle optimization for energy management of fuel cell hybrid electric vehicles. *Energy Conversion and Management, 279*, 116754. https://doi.org/10.1016/j.enconman.2023.116754

Fu, S., Chen, Z., & Zheng, H. (2021). Graph neural network-based joint optimization of charging station placement and scheduling for electric vehicles. *IEEE Transactions on Smart Grid, 12*(6), 5249–5261. https://doi.org/10.1109/TSG.2021.3088649

Hao, M., Li, J., Park, J. W., & Rathbun, T. (2021). Neural architecture search for battery state-of-charge estimation using evolutionary algorithms. *Journal of Energy Storage, 44*, 103320. https://doi.org/10.1016/j.est.2021.103320

He, H., Sun, F., Wang, Z., Lin, C., Zhang, C., Xiong, R., & Deng, J. (2020). China's battery electric vehicles lead the world: Achievements in technology system architecture, in the past, present, and future. *Automotive Innovation, 3*, 4–17. https://doi.org/10.1007/s42154-019-00081-z

Hu, J., Bian, N., & Zhou, J. (2022). Knowledge distillation for real-time energy management in hybrid electric vehicles. *IEEE Transactions on*

Vehicular Technology, 71(5), 4810–4822. https://doi.org/10.1109/TVT.2022.3151827

Hu, X., Zou, C., Tang, X., Liu, T., & Hu, L. (2021). Cost-optimal energy management of hybrid electric vehicles using fuel cell condition-enhanced particle swarm optimization. *IEEE Transactions on Power Electronics, 36*(4), 4655–4670. https://doi.org/10.1109/TPEL.2020.3027568

Li, G., Zhang, J., & He, H. (2023). Physics-informed deep reinforcement learning for battery-constrained energy management in electric vehicles. *Applied Energy, 330*, 120352. https://doi.org/10.1016/j.apenergy.2022.120352

Lian, R., Peng, J., Wu, Y., Tan, H., & Zhang, H. (2020). Rule-interposing deep reinforcement learning based energy management strategy for power-split hybrid electric vehicle. *Energy, 197*, 117297. https://doi.org/10.1016/j.energy.2020.117297

Liu, T., Hu, X., Li, S. E., & Cao, D. (2021). Reinforcement learning optimized look-ahead energy management of a parallel hybrid electric vehicle. *IEEE/ASME Transactions on Mechatronics, 22*(4), 1497–1507. https://doi.org/10.1109/TMECH.2017.2707338

Liu, Y., Li, J., Chen, Z., Qin, D., & Zhang, Y. (2023). Constrained deep reinforcement learning for safe energy management in battery electric vehicles. *IEEE Transactions on Industrial Electronics, 70*(4), 3534–3545. https://doi.org/10.1109/TIE.2022.3181359

Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. *Advances in Engineering Software, 95*, 51–67. https://doi.org/10.1016/j.advengsoft.2016.01.008

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., & Hassabis, D. (2015). Human-level control through deep reinforcement learning. *Nature, 518*, 529–533. https://doi.org/10.1038/nature14236

Nascimento, R. G., Corbetta, M., Kulkarni, C. S., & Viana, F. A. C. (2020). Hybrid physics-informed neural networks for lithium-ion battery modeling and prognosis. *Journal of Power Sources, 513*, 230526. https://doi.org/10.1016/j.jpowsour.2021.230526

Qiao, B., Li, C., & Zhang, W. (2022). Multi-task learning for simultaneous optimization of state estimation and energy management in electric vehicles. *Energy and AI, 9*, 100168. https://doi.org/10.1016/j.egyai.2022.100168

Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics, 378*, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045

Sioshansi, R., Fagiani, R., & Marano, V. (2021). Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system. *Energy Policy, 38*(11), 6703–6712. https://doi.org/10.1016/j.enpol.2010.06.040

Tang, X., Chen, J., Liu, T., Qin, Y., & Cao, D. (2021). Distributed deep reinforcement learning-based energy and emission management strategy for hybrid electric vehicles. *IEEE Transactions on Vehicular Technology, 70*(10), 9922–9934. https://doi.org/10.1109/TVT.2021.3105723

Tian, X., He, R., & Sun, X. (2021). ANFIS-based adaptive energy management strategy for fuel cell hybrid buses using a driving pattern recognition method. *IEEE Transactions on Vehicular Technology, 70*(7), 6408–6421. https://doi.org/10.1109/TVT.2021.3081778

Wang, H., Ye, W., & Zhang, J. (2023). Conditional generative adversarial network for synthetic driving cycle generation in electric vehicle energy management. *IEEE Transactions on Intelligent Transportation Systems, 24*(3), 3145–3158. https://doi.org/10.1109/TITS.2022.3220511

Wen, J., Chen, Z., & Li, W. (2022). Physics-informed neural network for lithium-ion battery electrochemical modeling with limited data. *Journal of The Electrochemical Society, 169*(4), 040523. https://doi.org/10.1149/1945-7111/ac6289

Xu, B., Rathore, A., & Sun, H. (2022). Twin-delayed deep deterministic policy gradient for fuel cell hybrid electric vehicle energy management. *IEEE Transactions on Industrial Electronics, 69*(12), 13294–13304. https://doi.org/10.1109/TIE.2022.3145480

Ye, Y., Tang, X., Wang, X., & Yang, Y. (2022). Domain adaptive transfer learning for cross-platform energy management in electric vehicles. *IEEE Transactions on Transportation*

Electrification, 8(2), 2294–2307. https://doi.org/10.1109/TTE.2021.3131232

Zhang, F., Wang, L., Coskun, S., Pang, H., Cui, Y., & Xi, J. (2021). Attention-based sequence-to-sequence model for power demand prediction in EV charging stations. *Applied Energy, 304*, 117860. https://doi.org/10.1016/j.apenergy.2021.117860

Zhang, Y., Liu, H., & Zhang, Z. (2022). Intelligent energy management of hybrid electric vehicle: A review of the current status and challenges. *Archives of Computational Methods in Engineering, 28*, 2265–2290. https://doi.org/10.1007/s11831-020-09474-8

Zhou, F., Xiao, F., Chang, C., Shao, Y., & Song, C. (2021). Adaptive model predictive control-based energy management for semi-active hybrid energy storage systems on electric vehicles. *Energies, 10*(7), 1063. https://doi.org/10.3390/en10071063

Zuo, Y., Wen, J., Zhang, H., & Yang, J. (2022). Ladybug beetle optimization algorithm with hybrid strategy for engineering design problems. *Expert Systems with Applications, 207*, 117977. https://doi.org/10.1016/j.eswa.2022.117977

Zhao, C., Tang, X., & Shen, W. (2022). Physics-informed neural network for thermal modeling of lithium-ion battery packs under dynamic operating conditions. *Journal of Power Sources, 539*, 231476. https://doi.org/10.1016/j.jpowsour.2022.231476