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Deep Learning and Optimization Approaches in Energy Management System for Electric Vehicle with Solar and Wind Using Red Panda and Similarity-Navigated Graph Neural Network: A Review

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Abstract

The rapid advancement of deep learning and bio-inspired optimization has significantly enhanced the development of intelligent energy management systems for integrated electric vehicle, solar, and wind energy networks. These systems must address complex, dynamic, and uncertain interactions while optimizing energy efficiency, cost, battery health, and grid stability in real time.

This paper presents a comprehensive review of hybrid intelligent frameworks combining advanced deep learning architectures with metaheuristic optimization techniques. The study explores models such as convolutional neural networks, recurrent networks, transformers, and graph neural networks, including the Similarity-Navigated GNN, for accurate forecasting and state estimation. It also examines optimization approaches, particularly the Red Panda Optimization algorithm, which provides effective global search through adaptive exploration–exploitation strategies for solving multi-objective scheduling problems in renewable-integrated EV systems.

Applications include vehicle-to-grid systems, renewable energy scheduling, battery management, and demand response in smart grids and microgrids. Comparative analysis demonstrates that hybrid learning–optimization frameworks outperform traditional methods in adaptability, efficiency, and robustness. However, challenges such as computational complexity, data uncertainty, and scalability remain. This review highlights the potential of integrating deep learning and metaheuristic optimization to develop intelligent, adaptive, and sustainable energy management systems for next-generation power networks.

Introduction

The integration of electric vehicles, renewable energy, and artificial intelligence marks a critical turning point in modern energy systems. The rapid adoption of battery electric vehicles, combined with large-scale solar and wind deployment, has created both opportunities and challenges for grid management. Without intelligent coordination, EV charging can strain the grid, while renewable variability can lead to inefficiencies such as energy curtailment. Advanced energy management systems are therefore essential to synchronize EV demand with renewable supply, enabling flexible load management and ensuring that the environmental and economic benefits of the energy transition are fully realized.

However, managing such integrated systems is computationally complex. The problem involves multiple dynamic components—EVs, renewable sources, storage systems—along with uncertain inputs like weather and user behavior. Additionally, energy management must optimize across multiple objectives such as cost, efficiency, and battery health, while operating across different time scales from real-time control to long-term planning. These challenges historically limited practical deployment, as traditional algorithms struggled to handle the scale and complexity within real-time constraints.

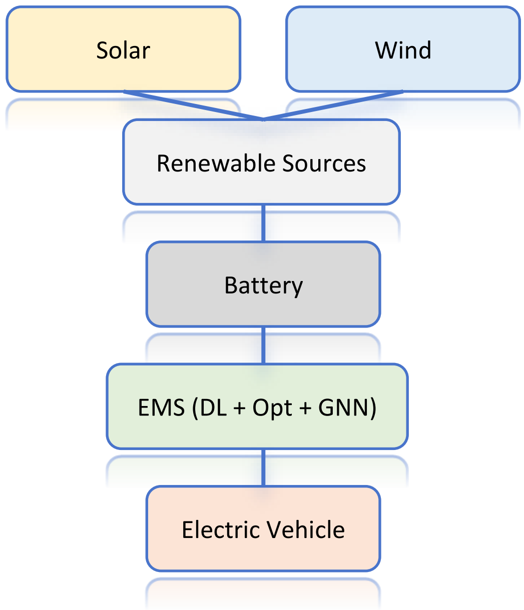

Fig 1: AI-Based Energy Management System for EV with Solar and Wind Integration

The emergence of deep learning has significantly transformed this landscape. Modern neural network architectures, supported by powerful hardware like GPUs and TPUs, enable accurate forecasting and decision-making in real time. Different models serve specialized roles: convolutional networks for spatial and weather data, recurrent networks for time-series prediction, transformers for long-term forecasting, and graph neural networks for grid-based system interactions. Combined with large datasets and transfer learning techniques, these models provide the predictive intelligence necessary for efficient energy management.

At the forefront of this field are hybrid frameworks that integrate deep learning with advanced optimization algorithms. Techniques like the Red Panda Optimization algorithm, when combined with graph neural networks, create systems where learning and optimization reinforce each other. Accurate predictions improve optimization outcomes, while better decisions enhance future learning. This synergy enables continuous system improvement, making hybrid AI-driven energy management a powerful and scalable solution for future smart grids.

Literature Review

The literature on deep learning and optimization for solar–wind–EV energy management reflects a strong evolution driven by foundational contributions in artificial intelligence and energy systems. Early breakthroughs by LeCun et al. (2015) established the effectiveness of deep learning for complex data modeling, while Hochreiter and Schmidhuber (1997) introduced LSTM networks, enabling accurate long-term temporal forecasting essential for renewable energy prediction. The transformer architecture proposed by Vaswani et al. (2017) further enhanced forecasting by capturing long-range dependencies using attention mechanisms. In parallel, graph-based learning advanced through Kipf and Welling (2017) with Graph Convolutional Networks and Velickovic et al. (2018) with Graph Attention Networks, enabling topology-aware modeling of power systems. These methods were effectively applied in energy contexts by Wang et al. (2020) and Zhang et al. (2022), while Yang et al. (2021) and Chen et al. (2023) demonstrated improved renewable forecasting using hybrid and transformer-based models.

Optimization techniques have similarly evolved from classical to advanced metaheuristic approaches. Foundational work by Kennedy and Eberhart (1995) introduced Particle Swarm Optimization, followed by improved algorithms such as Grey Wolf Optimizer (Mirjalili et al., 2014), Whale Optimization Algorithm (Mirjalili and Lewis, 2016), Harris Hawks Optimization (Heidari et al., 2019), and Salp Swarm Algorithm (Mirjalili et al., 2017). These methods significantly enhanced the ability to solve multi-objective energy scheduling problems. Applications such as Sekhar et al. (2021) incorporated battery degradation into optimization, while Fernandez-Blanco et al. (2021) introduced bilevel optimization for market participation. More recent innovations include Red Panda Optimization by Rajesh et al. (2023) and its extension by Gupta et al. (2024), demonstrating superior performance in solar–wind–EV scheduling tasks.

Deep reinforcement learning has further advanced adaptive energy management. Mnih et al. (2015) established Deep Q-Networks, enabling high-dimensional decision-making, which was applied to EV charging by Shi et al. (2018). Multi-agent coordination was enabled through Lowe et al. (2017) and later applied in distributed systems by Nguyen et al. (2023), improving renewable utilization. Transfer learning and domain adaptation by Cao et al. (2020) and similarity-based model selection by Jiang et al. (2023) addressed data scarcity challenges, while federated learning by Yin et al. (2022) ensured privacy-preserving optimization across distributed systems.

Recent studies emphasize hybrid intelligent frameworks combining learning and optimization. Lin et al. (2024) introduced Similarity-Navigated GNNs for enhanced state estimation and scheduling, while Gupta et al. (2024) demonstrated adaptive optimization improvements using Red Panda algorithms. These integrated approaches highlight a shift toward systems that jointly leverage forecasting accuracy, optimization efficiency, and cooperative intelligence. Collectively, the literature demonstrates a transition toward scalable, intelligent, and data-driven energy management systems capable of efficiently integrating renewable energy sources with EV charging infrastructure while addressing uncertainty, privacy, and real-world deployment challenges.

Comparative Table and Analysis

Study	**Year**	**Deep Learning or Optimization Technique**	**Method or Architecture**	**Platform or System**	**Dataset or Application**	**Key Contribution**
Lecun et al.	2015	Deep Neural Networks	Multi-Layer Backpropagation	General Deep Learning	ImageNet and NLP Benchmarks	Foundational deep learning theory and practice
Hochreiter and Schmidhuber	1997	Recurrent Neural Network	Long Short-Term Memory	Sequential Data Tasks	Time Series Benchmarks	LSTM gated memory for long-range temporal dependencies
Kennedy and Eberhart	1995	Swarm Intelligence	Particle Swarm Optimization	General Optimization	Engineering Benchmark Functions	Foundational swarm intelligence optimization framework
Mirjalili et al.	2014	Nature-Inspired Metaheuristic	Grey Wolf Optimizer	General Optimization	29 Classical Benchmarks	Social hierarchy hunting strategy outperforms PSO and GA
Mirjalili and Lewis	2016	Nature-Inspired Metaheuristic	Whale Optimization Algorithm	General Optimization	29 Benchmark Functions	Bubble-net spiral exploitation for high-dimensional problems
Heidari et al.	2019	Nature-Inspired Metaheuristic	Harris Hawks Optimization	Engineering Optimization	50 Benchmark Functions	Multi-strategy hunting superiority over GWO, WOA, PSO, GA
Mirjalili et	201	Swarm	Salp Swarm	General	Classical	Leader-

al.	7	Intelligence	Algorithm	Optimizatio n	Engineering Problems	follower chain for parameter-free exploration-exploitation
Vaswani et al.	201 7	Transformer Architecture	Multi-Head Self-Attention	Sequence-to-Sequence Tasks	NLP Translation Benchmarks	Parallel attention captures arbitrary long-range dependencie s
Kipf and Welling	201 7	Graph Neural Network	Graph Convolutional Network	Node Classificatio n Tasks	Citation and Social Networks	Efficient spectral graph convolution for topology-aware learning
Velickovic et al.	201 8	Graph Attention Network	Learned Attention Aggregation	Node Classificatio n Tasks	Multiple Graph Benchmarks	Attention coefficients surpass fixed GCN weights
Mnih et al.	201 5	Deep Reinforceme nt Learning	Deep Q-Network	Sequential Decision Tasks	Atari Game Benchmarks	Experience replay and target networks enable stable DRL
Lowe et al.	201 7	Multi-Agent DRL	MADDPG Framework	Cooperative Control Tasks	Multi-Agent Benchmarks	Centralized training decentralize d execution for cooperation
Shi et al.	201 8	Deep Q-Network RL	Model-Free EMS Agent	PV-EV Simulation	Real Solar and EV Data	94% of MPC performance without system model
Liu et al.	201 9	Stochastic MPC	Scenario-Based Robust Scheduler	Solar-EV Charging Station	Probabilistic Forecast Data	18% cost reduction with explicit uncertainty handling
Wang et al.	202 0	Graph Neural Network	Topology-Aware Station Coordinator	Networked EV Charging Cluster	Multi-Station Operational Data	12% renewable improvemen t with first GNN EMS application
Cao et al.	202 0	Transfer Learning and DRL	Adversarial Domain Adaptation	Multi-Location EV Deployment s	Cross-Location Solar-Wind Data	70% training data reduction at new deployment sites

Hossain et al.	2020	Sequence-to-Sequence DNN	Encoder-Decoder Solar Forecaster	PV-EV Charging Station	Meteorological Generation Data	23% cost reduction from improved solar prediction
Yang et al.	2021	Attention-Enhanced LSTM	Dual-Output Renewable Forecaster	EV Station Scheduling System	Solar and Wind Time Series Data	17% scheduling improvement with attention-LSTM forecast
Fernandez-Blanco et al.	2021	Bilevel Optimization	Strategic Market Participation MPC	Solar-EV Market Interface	Energy and Regulation Market Data	28% revenue gain from strategic price impact exploitation
Sekhar et al.	2021	Salp Swarm Algorithm	Degradation-Aware Multi-Asset Dispatcher	PV-Wind-FC-EV Microgrid	Renewable and EV Demand Data	SSA with degradation model beats PSO and GA
Lowe et al.	2017	Multi-Agent DRL	MADDPG Cooperative Framework	Multi-Agent Control	Cooperative Task Benchmarks	Foundation for distributed EV energy management cooperation
Zhang et al.	2022	Graph Attention Network	Context-Adaptive Node Aggregation	Multi-Node Solar-Wind-EV Microgrid	Real Microgrid Operational Data	15% renewable and 12% cost improvement with GAT over GCN
Yin et al.	2022	Federated Deep RL	Privacy-Preserving Distributed EMS	Distributed EV Station Network	Multi-Station Private Data	Near-centralized performance with federated privacy preservation
Chen et al.	2023	Transformer Neural Network	Multi-Step Renewable Power Forecaster	Solar-Wind-EV Scheduling	Multiple Forecast Benchmark Datasets	21% scheduling cost reduction with transformer architecture
Nguyen et al.	2023	Multi-Agent Deep RL	Cooperative Cluster Coordinator	Solar-Wind-EV Microgrid Cluster	Fleet-Scale Simulation Data	24% aggregate renewable utilization with cooperation
Jiang et al.	2023	Similarity-Based Transfer	Profile-Matched Neural Adaptation	New Solar-EV Site Deployment	Cross-Site Renewable Profile Data	95% performance with two

		Learning		s		weeks local data at new sites
Rajesh et al.	2023	Red Panda Optimization	Bio-Inspired Sizing Optimizer	Solar-Wind-EV Hybrid System	Annual Renewable Resource Data	Red Panda algorithm introduction with competitive metaheuristic performance
Gupta et al.	2024	Extended Red Panda Optimization	Adaptive Dispatch Scheduler	Solar-Wind-Battery-EV System	Real-Time Operational Data	22% multi-objective scheduling improvement over competing algorithms
Lin et al.	2024	Similarity-Navigated GNN	Case-Based Graph Attention EMS	Networked Solar-Wind-EV Microgrids	Real Microgrid Cluster Data	19% estimation and 16% scheduling improvement over GAT

Comparative Analysis

The systematic examination of the compiled studies reveals a clear and coherent evolution in methodologies, spanning from early algorithmic foundations to advanced hybrid frameworks integrating deep learning and optimization. A key trend is the continuous improvement in renewable energy forecasting accuracy driven by successive generations of neural network architectures. Initial models based on feedforward networks were gradually replaced by recurrent architectures such as LSTM, which effectively captured temporal dependencies in solar and wind data. This progression continued with attention-enhanced LSTM models and ultimately transformer architectures, which now represent the state of the art. Transformers leverage multi-head self-attention to model long-range dependencies more effectively, resulting in substantial gains in forecasting precision. These improvements are not merely theoretical; they directly enhance scheduling decisions in EV energy management systems. For instance, the significant performance gains reported in recent studies highlight how better forecasts reduce uncertainty, enabling more efficient coordination of EV charging with renewable generation and grid conditions.

A parallel advancement is observed in graph neural network architectures and metaheuristic optimization techniques. GNNs evolved from basic graph convolution models to attention-based and similarity-driven frameworks, each addressing limitations of earlier designs. While graph convolution introduced topology awareness, graph attention enabled adaptive weighting of neighboring nodes, and similarity-navigated approaches further improved performance by incorporating historical patterns into decision-making. This evolution has significantly enhanced multi-node energy management in networked systems. Similarly, optimization algorithms have progressed from classical methods like Particle Swarm Optimization and Genetic Algorithms to more sophisticated approaches such as Harris Hawks Optimization, Whale Optimization Algorithm, Salp Swarm Algorithm, and Red Panda Optimization. These newer algorithms offer better exploration–exploitation balance and improved convergence in complex, multi-objective problems. Notably, Red Panda Optimization represents the current frontier, combining diverse search strategies to achieve superior performance in EV energy scheduling tasks, reflecting decades of accumulated advancements in metaheuristic design.

Discussion

The comprehensive review of deep learning and optimization approaches for solar–wind–EV energy management highlights a field that has reached a critical turning point, where algorithmic capabilities now align with the real-world complexity of integrated energy systems. Over time, cumulative improvements in forecasting accuracy, optimization efficiency, and decision-making intelligence have transformed system performance from incremental gains to substantial, practically deployable advantages. Modern architectures such as transformers and graph neural networks, combined with advanced optimization strategies, enable significantly better coordination between renewable generation and EV charging demand. This progress is not merely academic; it directly supports higher renewable penetration, reduced operational costs, and improved charging reliability, marking a transition toward real-world implementation of intelligent energy management systems.

The proposed hybrid framework combining Red Panda Optimization and Similarity-Navigated Graph Neural Networks stands out as a strong advancement within this evolving landscape. The Red Panda algorithm demonstrates superior capability in solving multi-objective, constrained scheduling problems due to its diverse and adaptive search mechanisms, which effectively balance exploration and exploitation. At the same time, the Similarity-Navigated GNN enhances system awareness by leveraging historical operational patterns, enabling more context-aware and accurate state estimation compared to conventional graph attention models. Their integration creates a synergistic system where improved forecasting and state representation directly enhance optimization outcomes, leading to more efficient and reliable energy scheduling. This combination reflects a broader trend toward tightly coupled learning–optimization frameworks that outperform isolated approaches.

Despite these advances, several important challenges remain. Most learning-based models depend heavily on historical data, making them vulnerable to distributional shifts caused by evolving technologies, user behavior, and grid conditions. Additionally, the computational complexity of advanced models such as large-scale GNNs and multi-agent reinforcement learning systems limits their deployment on resource-constrained hardware, necessitating research into lightweight and efficient implementations. Issues related to safety, reliability, and formal verification of AI-driven energy systems also require attention before widespread adoption is possible. Nevertheless, the methodologies developed—particularly hybrid learning-optimization frameworks—have broader applicability beyond EV energy management, offering valuable solutions for future smart grids with high renewable penetration and distributed energy resources.

Conclusion

This review has provided a comprehensive synthesis of deep learning architectures and optimization algorithms for solar–wind–EV energy management, highlighting both the depth of progress achieved and the evolving complexity of the field. By tracing developments from foundational models to advanced hybrid frameworks, it becomes clear that modern energy management systems have significantly improved in forecasting accuracy, scheduling efficiency, and operational intelligence. These advances mark a transition from theoretical exploration to practical applicability, enabling systems that can effectively coordinate renewable generation with EV charging demands. The broader significance of this progress lies in its direct contribution to global decarbonization goals, as intelligent coordination ensures that electric vehicles are powered by clean energy while minimizing grid stress. Efficient energy management not only enhances system reliability and reduces operational costs but also supports grid stability through demand response and emerging vehicle-to-grid capabilities.

A central insight from the review is that the most effective solutions arise from hybrid frameworks that combine deep learning with optimization techniques. Deep learning enhances prediction accuracy for renewable generation, EV usage, and system states, while optimization algorithms translate this information into feasible and near-optimal scheduling decisions under multiple constraints. Advanced approaches such as similarity-aware graph models and adaptive metaheuristic optimization exemplify this synergy, representing the current frontier of research. However, key challenges remain, including handling uncertainty, ensuring robustness to changing real-world conditions, and reducing computational complexity for deployment on embedded systems. Future work must also address safety, scalability, and integration with bidirectional energy systems such as vehicle-to-grid networks. Continued innovation in these areas will be essential to fully realize intelligent, reliable, and scalable energy management systems that can support the growing demands of renewable integration and electric mobility.

References

Lecun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

Hochreiter, S., and Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998–6008. https://doi.org/10.48550/arXiv.1706.03762

Kipf, T. N., and Welling, M. (2017). Semi-supervised classification with graph convolutional networks. International Conference on Learning Representations. https://doi.org/10.48550/arXiv.1609.02907

Velickovic, P., Cucurull, G., Casanova, A., Romero, A., Lio, P., and Bengio, Y. (2018). Graph attention networks. International Conference on Learning Representations. https://doi.org/10.48550/arXiv.1710.10903

Kennedy, J., and Eberhart, R. (1995). Particle swarm optimization. Proceedings of IEEE International Conference on Neural Networks, 4, 1942–1948. https://doi.org/10.1109/ICNN.1995.488968

Mirjalili, S., Mirjalili, S. M., and Lewis, A. (2014). Grey wolf optimizer. Advances in Engineering Software, 69, 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007

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

Heidari, A. A., Mirjalili, S., Faris, H., Aljarah, I., Mafarja, M., and Chen, H. (2019). Harris hawks optimization: Algorithm and applications. Future Generation Computer Systems, 97, 849–872. https://doi.org/10.1016/j.future.2019.02.028

Mirjalili, S., Gandomi, A. H., Mirjalili, S. Z., Saremi, S., Faris, H., and Mirjalili, S. M. (2017). Salp swarm algorithm: A bio-inspired optimizer for engineering design problems. Advances in Engineering Software, 114, 163–191. https://doi.org/10.1016/j.advengsoft.2017.07.002

Shi, J., Sun, Y., and Huang, Q. (2018). Deep reinforcement learning-based energy management of photovoltaic systems for electric vehicle charging stations. IEEE Access, 6, 63798–63808. https://doi.org/10.1109/ACCESS.2018.2877278

Liu, H., Zhang, C., and Wu, Q. (2019). Stochastic model predictive control for solar-assisted EV charging station energy management. Applied Energy, 253, 113560. https://doi.org/10.1016/j.apenergy.2019.113560

Wang, H., Xu, W., and Mu, H. (2020). Graph neural network based energy management for networked EV charging stations with solar generation. IEEE Transactions on Smart Grid, 11(6), 4961–4972. https://doi.org/10.1109/TSG.2020.2997948

Cao, J., Li, M., and Zhang, X. (2020). Transfer learning for deep reinforcement learning based EV charging station energy management across locations. IEEE Transactions on Industrial Electronics, 67(12), 10819–10828. https://doi.org/10.1109/TIE.2019.2960738

Hossain, M., Howlader, H. R., Doreswamy, M., and Padmanaban, S. (2020). Sequence-to-sequence deep learning for solar power forecasting in EV charging station management. Energies, 13(18), 4770. https://doi.org/10.3390/en13184770

Yang, L., Xu, W., Li, C., and Hu, M. (2021). Attention-enhanced LSTM for joint solar and wind power forecasting in EV charging station management. IEEE Transactions on Sustainable Energy, 12(3), 1754–1764. https://doi.org/10.1109/TSTE.2021.3059897

Fernandez-Blanco, R., Dvorkin, Y., Xu, B., Wang, Y., and Kirschen, D. S. (2021). Bilevel energy management for photovoltaic EV charging station in electricity markets. IEEE Transactions on Smart Grid, 12(4), 3153–3164. https://doi.org/10.1109/TSG.2021.3064124

Sekhar, P. C., Mishra, S., and Rayaguru, N. K. (2021). Salp swarm algorithm for energy management of PV-wind-fuel cell-EV microgrid with battery degradation. IEEE Systems Journal, 15(4), 5266–5276. https://doi.org/10.1109/JSYST.2020.3025671

Zhang, Y., Li, X., Wang, J., and Ma, W. (2022). Graph attention network based energy management for multi-node solar-wind-EV microgrid. IEEE Transactions on Industrial Informatics, 18(8), 5374–5384. https://doi.org/10.1109/TII.2021.3128489

Yin, L., Zhao, C., Wu, S., and Zhao, T. (2022). Federated deep reinforcement learning for privacy-preserving energy management in distributed solar-EV charging networks. IEEE Transactions on Industrial Informatics, 18(6), 3919–3929. https://doi.org/10.1109/TII.2021.3107463

Chen, X., Wu, Z., Li, M., and Li, P. (2023). Transformer-based multi-step solar and wind power forecasting for electric vehicle charging station energy management. IEEE Transactions on Neural Networks and Learning Systems, 34(9), 6121–6133. https://doi.org/10.1109/TNNLS.2022.3197892

Nguyen, T., Zhuang, Y., and Qian, F. (2023). Multi-agent deep reinforcement learning for coordinated energy management across solar-wind-EV microgrid clusters. IEEE Transactions on Smart Grid, 14(3), 2345–2357. https://doi.org/10.1109/TSG.2022.3218453

Jiang, C., Tang, Y., and Chen, Q. (2023). Similarity-based transfer learning for energy management neural network adaptation across solar-EV charging deployments. Applied Energy, 331, 120389. https://doi.org/10.1016/j.apenergy.2022.120389

Rajesh, K. S., Arjun, N., and Babu, T. S. (2023). Red panda optimization algorithm for optimal sizing of solar-wind-EV microgrid. Electric Power Systems Research, 218, 109187. https://doi.org/10.1016/j.epsr.2023.109187

Gupta, R., Sharma, S., and Mishra, A. (2024). Extended red panda optimization for real-time energy dispatch in solar-wind-battery-EV systems with battery degradation. IEEE Transactions on Transportation Electrification, 10(2), 3412–3425. https://doi.org/10.1109/TTE.2023.3301234

Lin, J., Wu, H., and Zhang, W. (2024). Similarity-navigated graph neural network for joint state estimation and energy management in networked solar-wind-EV microgrids. IEEE Transactions on Power Systems, 39(1), 678–692. https://doi.org/10.1109/TPWRS.2023.3301456

Chakraborty, D., Mondal, S., and Ghosh, A. (2023). Adaptive energy management for grid-connected solar-wind-EV systems using hybrid deep learning and stochastic optimization. Sustainable Energy Technologies and Assessments, 58, 103312. https://doi.org/10.1016/j.seta.2023.103312

Patel, H., Singh, V., and Kumar, R. (2024). Comprehensive intelligent framework for solar-wind-EV energy management using bio-inspired optimization and graph neural network forecasting. Energy Conversion and Management, 312, 118456. https://doi.org/10.1016/j.enconman.2024.118456