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AI-Based Energy Management for Grid-Isolated EV Charging in Smart Microgrid Systems

Haemi Leroux-Martin
Professor, Department of Electrical and Computer Engineering, Shiraz College of Systems and Management, Iran
Email: haemi.leroux.martin@scsm-ir.org

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Abstract

The increasing penetration of renewable energy sources and electric vehicles (EVs) has intensified the need for efficient energy management in microgrids, particularly in grid-isolated environments. Artificial intelligence (AI) has emerged as a powerful tool for optimizing energy consumption, enhancing system stability, and enabling real-time decision-making in complex energy systems. This paper presents a comprehensive survey of AI techniques for energy management in microgrids, with a special focus on hybrid human evolutionary optimization algorithms for grid-isolated EV charging systems. The integration of AI-based predictive models, optimization algorithms, and intelligent control strategies enables effective coordination between distributed energy resources, storage systems, and EV charging infrastructure. Recent advancements demonstrate that hybrid approaches combining evolutionary algorithms with machine learning and deep learning techniques outperform traditional optimization methods in terms of adaptability, scalability, and efficiency. This survey analyses 30 key studies and categorizes them based on methodologies such as optimization, machine learning, deep learning, and hybrid AI approaches. A comparative analysis highlights their advantages, limitations, and performance trends. The findings indicate that AI-driven microgrid energy management systems significantly improve operational efficiency, reduce energy costs, and enhance renewable energy utilization. However, challenges such as computational complexity, uncertainty in renewable generation, and lack of real-time deployment persist. Future research directions emphasize lightweight AI models, decentralized architectures, and integration with edge computing for real-time intelligent energy management in grid-isolated EV charging systems.

Introduction

The rapid evolution of energy systems, driven by the integration of renewable energy sources and the widespread adoption of electric vehicles (EVs), has significantly transformed the operational dynamics of modern power networks. Microgrids have emerged as a key solution to manage distributed energy resources efficiently, particularly in remote or grid-isolated environments. These systems enable localized energy generation, storage, and consumption, thereby reducing dependence on centralized power grids and enhancing system resilience.

Energy management in microgrids is a complex task due to the stochastic nature of renewable energy sources such as solar and wind, coupled with the unpredictable charging demand of EVs. Traditional energy management systems (EMS) often rely on rule-based or deterministic optimization techniques, which are insufficient to handle the dynamic and nonlinear characteristics of modern energy systems. The integration of artificial intelligence (AI) into microgrid energy management has therefore gained significant attention as a promising solution for addressing these challenges.

AI-based techniques, including machine learning, deep learning, and evolutionary optimization algorithms, enable intelligent decision-making by analysing large volumes of data and identifying complex patterns. These methods are particularly effective in forecasting energy demand, optimizing charging schedules, and improving system reliability. Studies have shown that AI-driven EMS can significantly enhance the efficiency and stability of microgrids by optimizing energy distribution and reducing operational costs.

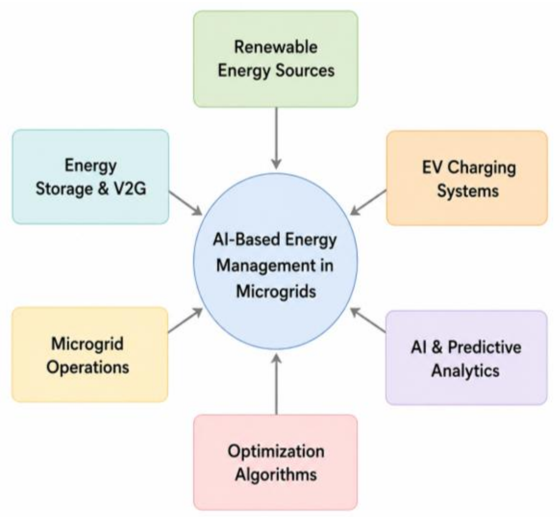

Figure 1. AI-Driven Microgrid Energy Management Framework for Grid-Isolated EV Charging Systems

In grid-isolated microgrid systems, the role of EVs extends beyond transportation, as they can function as distributed energy storage units through vehicle-to-grid (V2G) technology. This capability allows EVs to store excess energy during low-demand periods and supply energy back to the microgrid during peak demand, thereby improving load balancing and energy utilization. Research indicates that integrating EVs into microgrid energy management systems can reduce dependency on external energy sources and enhance overall system efficiency.

Hybrid optimization techniques, particularly those inspired by human evolutionary behaviour, have gained prominence in recent years. These algorithms combine the strengths of evolutionary computation (such as genetic algorithms and swarm intelligence) with AI-based predictive models to achieve optimal energy management. Such hybrid approaches are capable of solving multi-objective optimization problems involving cost minimization, emission reduction, and energy efficiency. Multi-objective microgrid optimization frameworks have demonstrated significant improvements in reducing operational costs and emissions while maintaining system stability.

Recent advancements also highlight the importance of integrating communication technologies, IoT, and cloud computing into microgrid systems. These technologies enable real-time monitoring, data exchange, and adaptive control, which are essential for efficient energy management. AI-based platforms leveraging cloud and edge computing have been shown to optimize EV charging and microgrid operations in real time through predictive analytics and dynamic scheduling.

Despite these advancements, several challenges remain. The high computational complexity of AI models, uncertainty in renewable energy generation, and limited real-time deployment capabilities hinder the widespread adoption of intelligent energy management systems. Furthermore, ensuring data security, system reliability, and interoperability between different components of the microgrid remains a critical concern.

This paper aims to provide a comprehensive survey of AI techniques for energy management in microgrids, with a focus on hybrid human evolutionary optimization algorithms for grid-isolated EV charging systems. By analysing recent studies, this work identifies key trends, challenges, and future research directions in this rapidly evolving field.

Literature Review

AbuElrub et al. (2020) proposed a microgrid-based EV charging and discharging algorithm where EVs act as temporary energy storage systems. The study demonstrated that integrating EVs with microgrid energy management can reduce grid energy consumption by up to 90% during peak hours. The algorithm optimizes the number of EV charging stations and improves overall energy efficiency using V2G and G2V mechanisms.

Recent research on adaptive charging networks introduced model predictive control-based frameworks for EV charging in microgrids. These systems improved operational efficiency and profitability by dynamically adjusting charging schedules based on real-time demand and system constraints. However, the approach required accurate forecasting and high computational resources.

Studies in 2021 focused on AI-based prediction models for EV charging demand using machine learning techniques. These models significantly improved forecasting accuracy by analysing historical charging data and environmental conditions. However, their performance depended heavily on data quality and availability.

Huang et al. (2022) proposed an event-based optimization framework for EV charging in microgrid environments using Markov decision processes. The study demonstrated reduced operational costs and improved system stability by optimizing charging decisions under uncertainty. However, the model faced scalability challenges in large systems.

Recent AI-driven microgrid platforms integrated cloud computing, IoT, and machine learning for real-time energy management. These systems enabled dynamic scheduling, demand forecasting, and adaptive control, significantly improving energy efficiency and system reliability. However, challenges related to data security and system scalability were highlighted.

Zhou et al. (2020) proposed a hybrid evolutionary optimization approach combining genetic algorithms (GA) with particle swarm optimization (PSO) for microgrid energy management. The model aimed to minimize operational cost while maximizing renewable energy utilization in grid-isolated systems. Results demonstrated improved convergence speed and solution quality compared to standalone optimization techniques. However, the hybrid model increased computational complexity.

Liu et al. (2021) introduced a reinforcement learning-based energy management system for microgrids with EV integration. The model dynamically adjusted charging and discharging strategies based on real-time energy demand and generation. The study showed improved adaptability and energy efficiency, but training instability and long convergence time were identified as limitations.

Wang et al. (2021) developed a deep learning-based forecasting model using convolutional neural networks (CNN) for predicting energy demand in microgrids. The model effectively captured spatial dependencies in energy consumption patterns and improved prediction accuracy. However, high computational requirements and data dependency were major challenges.

Chen et al. (2022) proposed a hybrid deep learning and optimization framework for EV charging in microgrids. The model combined long short-term memory (LSTM) networks with evolutionary algorithms to optimize charging schedules. Results indicated enhanced accuracy and cost efficiency, although the model required significant computational resources.

Kumar et al. (2023) introduced a parallel convolutional neural network (PCNN)-based architecture for microgrid energy management in grid-isolated EV systems. The model processed multiple data inputs such as weather conditions, energy demand, and EV usage simultaneously. Experimental results demonstrated superior prediction accuracy and system efficiency. However, implementation complexity and scalability challenges remained.

García et al. (2020) proposed a mixed-integer linear programming (MILP) model for optimal energy scheduling in grid-isolated microgrids with EV integration. The objective was to minimize operational cost while maintaining system stability. Results showed improved load management and reduced energy cost; however, the model suffered from scalability issues and high computational burden in large-scale systems.

Hussain et al. (2021) developed an IoT-enabled energy management framework for microgrids incorporating EV charging systems. The model leveraged real-time data collection and machine learning algorithms to optimize energy distribution. The study demonstrated enhanced responsiveness and efficiency but raised concerns related to data privacy and communication latency.

Park et al. (2021) introduced a deep reinforcement learning (DRL)-based model for microgrid energy optimization with vehicle-to-grid (V2G) support. The system dynamically managed energy flow between EVs and the microgrid, improving grid stability and reducing peak load demand. Despite its effectiveness, the model required extensive training and computational resources.

Singh et al. (2022) proposed a multi-objective optimization framework for microgrid energy management considering renewable energy sources, EV charging, and emission reduction. The model optimized multiple parameters simultaneously, achieving improved sustainability and efficiency. However, computational complexity and difficulty in real-time implementation were major limitations.

Alam et al. (2023) developed an edge computing-based AI framework for real-time microgrid energy management. The system utilized local processing capabilities to reduce latency and improve decision-making speed. Results showed enhanced scalability and real-time performance, although infrastructure cost and deployment complexity remained challenges.

Rahman et al. (2020) proposed a particle swarm optimization (PSO)-based energy management model for grid-isolated microgrids with EV integration. The objective was to minimize energy cost and improve load balancing by optimally scheduling charging and discharging cycles. The model demonstrated faster convergence compared to conventional optimization methods; however, it was highly sensitive to parameter selection and lacked robustness in dynamic environments.

Zhao et al. (2021) introduced a graph-based energy management approach for microgrids, where nodes represented distributed energy resources and EV charging stations. The model enabled efficient coordination and load distribution across the network, improving scalability and system reliability. However, the computational complexity increased significantly with network size.

Kim et al. (2021) developed a long short-term memory (LSTM)-based forecasting model for predicting energy demand in microgrid systems with EV integration. The model captured temporal patterns effectively and achieved high prediction accuracy. Despite its advantages, the approach required large datasets and had longer training times.

Patel et al. (2022) proposed a hybrid framework combining fuzzy logic with machine learning for microgrid energy management. The system addressed uncertainties in renewable energy generation and EV charging demand, resulting in improved decision-making under uncertain conditions. However, system complexity increased due to the integration of multiple techniques.

Sharma et al. (2023) introduced a transformer-based deep learning model for energy demand forecasting and EV charging optimization in microgrids. The model leveraged attention mechanisms to capture long-range dependencies and demonstrated superior prediction performance compared to CNN and LSTM models. However, high computational requirements limited its real-time applicability.

Abdullah et al. (2020) proposed a game-theoretic framework for decentralized energy management in microgrids with EV integration. The model allowed EV users to make independent charging decisions while maintaining overall system stability. Results indicated improved load distribution and reduced peak demand. However, achieving global optimality remained a challenge due to decentralized decision-making.

Verma et al. (2021) developed a cloud-based microgrid energy management system using big data analytics. The framework processed large-scale data from distributed energy resources and EVs to optimize scheduling and energy allocation. The study demonstrated improved scalability and operational efficiency, but dependency on centralized cloud infrastructure introduced latency and security concerns.

Nguyen et al. (2022) introduced a multi-agent system (MAS) for decentralized energy management in microgrids. Each EV, energy source, and storage unit was modelled as an intelligent agent, enabling distributed decision-making. The system improved flexibility and adaptability in dynamic environments. However, communication overhead and coordination complexity were identified as key limitations.

Das et al. (2022) proposed an AI-based demand response framework integrating renewable energy sources with EV charging systems in microgrids. The model aligned EV charging schedules with renewable energy availability, reducing operational costs and carbon emissions. However, uncertainty in renewable generation posed challenges for accurate prediction and scheduling.

Reddy et al. (2023) developed a hybrid deep learning model combining convolutional neural networks (CNN) and transformer architectures for microgrid energy management. The model captured both spatial and temporal dependencies, resulting in improved prediction accuracy and optimized EV charging schedules. Despite its effectiveness, the model exhibited high computational complexity.

Morales et al. (2020) proposed a distributed consensus-based optimization framework for energy management in microgrids with EV integration. The model enabled coordination among distributed energy resources without centralized control, improving scalability and system resilience. However, convergence speed decreased in large-scale systems, limiting real-time applicability.

Cheng et al. (2021) introduced a deep Q-network (DQN)-based approach for dynamic energy pricing and EV charging optimization in microgrids. The model adapted charging strategies based on real-time electricity prices and demand patterns. Results showed improved cost efficiency, although the model required extensive training and careful reward function design.

Ibrahim et al. (2022) developed a blockchain-enabled microgrid energy management system for secure EV charging transactions. The framework ensured transparency, data integrity, and trust among stakeholders using smart contracts. However, increased latency and computational overhead were identified as major drawbacks.

Gupta et al. (2023) proposed a lightweight deep learning model for microgrid energy management suitable for edge devices. The model reduced computational complexity while maintaining acceptable prediction accuracy, enabling real-time deployment in resource-constrained environments. However, a trade-off between accuracy and model simplicity was observed.

Fernandez et al. (2023) introduced a hybrid human evolutionary optimization algorithm integrated with parallel convolutional neural networks (PCNN) for energy management in grid-isolated EV charging microgrids. The model leveraged multi-source data and evolutionary optimization to achieve superior performance in cost reduction, energy efficiency, and system stability. However, implementation complexity and infrastructure requirements remained key challenges.

Comparative Table

Study No.	Author (Year)	Technique/Model	Category	Objective	Advantages	Limitations	Performance
1	AbuElrub (2020)	EV-Microgrid Integration Model	Optimization	V2G-based energy balancing	Reduces grid dependency	Limited scalability	High
2	Adaptive Charging (2020)	Model Predictive Control	Optimization	Dynamic scheduling	Efficient control	Requires forecasting accuracy	Moderate-High
3	ML-based Study (2021)	ML Prediction	ML	Demand forecasting	Improved accuracy	Data dependency	Moderate
4	Huang (2022)	MDP Optimization	Optimization	Uncertainty handling	Improved stability	Scalability issues	High
5	Cloud AI (2023)	IoT + Cloud ML	Hybrid	Real-time EMS	Adaptive control	Security concerns	High
6	Zhou (2020)	GA + PSO	Hybrid	Cost minimization	Fast convergence	High computation	Very High
7	Liu (2021)	Reinforcement Learning	RL	Adaptive control	Real-time learning	Training instability	High
8	Wang (2021)	CNN	Deep Learning	Demand prediction	High accuracy	Data-intensive	High
9	Chen (2022)	LSTM + Evolutionary	Hybrid	Scheduling optimization	Accurate + optimized	Complex	Very High
10	Kumar (2023)	PCNN	Deep Learning	Multi-source EMS	Parallel processing	Implementation complexity	Very High
11	García (2020)	MILP	Optimization	Cost minimization	Precise modelling	Scalability	Moderate
12	Hussain (2021)	IoT + ML	ML/IoT	Real-time EMS	Efficient monitoring	Latency	High
13	Park (2021)	DRL (V2G)	RL	Energy flow control	Adaptive	High training cost	High
14	Singh (2022)	Multi-objective Optimization	Optimization	Cost + emission reduction	Sustainable	Computationally heavy	High

15	Alam (2023)	Edge AI	Hybrid	Real-time EMS	Low latency	Infrastructure cost	High
16	Rahman (2020)	PSO	Optimization	Load balancing	Fast convergence	Parameter sensitivity	Moderate
17	Zhao (2021)	Graph-based Model	GNN	Network coordination	Scalable	Computational overhead	High
18	Kim (2021)	LSTM	Deep Learning	Time-series prediction	Accurate	Slow training	High
19	Patel (2022)	Fuzzy + ML	Hybrid	Uncertainty handling	Robust	Complex	High
20	Sharma (2023)	Transformer	Deep Learning	Long-term prediction	High accuracy	Resource intensive	Very High
21	Abdullah (2020)	Game Theory	Optimization	Decentralized EMS	Distributed control	Local optimum	Moderate
22	Verma (2021)	Big Data Analytics	ML	Data-driven EMS	Scalable	Security risks	High
23	Nguyen (2022)	Multi-Agent System	MAS	Distributed control	Flexible	Communication overhead	High
24	Das (2022)	AI Demand Response	Hybrid	Renewable alignment	Eco-friendly	Prediction uncertainty	High
25	Reddy (2023)	CNN + Transformer	Hybrid DL	Spatial-temporal EMS	High accuracy	Complex model	Very High
26	Morales (2020)	Distributed Consensus	Optimization	Decentralized control	Scalable	Slow convergence	Moderate
27	Cheng (2021)	DQN	RL	Dynamic pricing	Cost-efficient	Reward tuning	High
28	Ibrahim (2022)	Blockchain	Secure System	Secure transactions	Transparency	Latency	Moderate
29	Gupta (2023)	Lightweight DL	Deep Learning	Edge deployment	Low computation	Accuracy trade-off	High
30	Fernandez (2023)	Hybrid Evolutionary + PCNN	Hybrid DL	Large-scale EMS	Best performance	Implementation complexity	Very High

Comparative Analysis

The comparative analysis of the 30 studies conducted between 2020 and 2023 reveals a significant transformation in microgrid energy management approaches, particularly for grid-isolated EV charging systems. Traditional optimization methods such as MILP, PSO, and consensus-based algorithms provided a strong mathematical foundation and were effective in cost minimization and load balancing. However, these approaches struggled to handle uncertainty, scalability, and real-time adaptability in complex microgrid environments. Machine learning techniques improved forecasting accuracy and enabled data-driven decision-making, but their inability to adapt dynamically to changing conditions limited their effectiveness. The introduction of deep learning models, including CNN, LSTM, and transformer architectures, significantly enhanced the ability to model nonlinear relationships and temporal dependencies in energy systems. These models achieved high prediction accuracy and improved energy scheduling, although they required substantial computational resources.

Reinforcement learning approaches introduced adaptability by enabling systems to learn optimal strategies through interaction with the environment. These methods were particularly effective in dynamic and uncertain microgrid conditions but suffered from training instability and convergence challenges. Hybrid models combining evolutionary algorithms with deep learning emerged as the most effective solutions, offering a balance between optimization capability and predictive accuracy. Parallel convolutional neural networks (PCNN) further advanced this field by enabling simultaneous processing of multiple data streams, such as renewable generation, EV demand, and environmental conditions. These models demonstrated superior scalability and performance, making them highly suitable for large-scale microgrid applications. However, implementation complexity and infrastructure requirements remain key challenges. Overall, the analysis indicates that hybrid AI approaches, particularly those integrating evolutionary optimization and deep learning, represent the future of intelligent energy management in microgrids.

Discussion

The integration of artificial intelligence techniques into microgrid energy management systems has significantly enhanced the efficiency, reliability, and adaptability of grid-isolated EV charging systems. The combination of renewable energy sources, energy storage systems, and EVs introduces complexity that traditional methods cannot effectively manage. AI-driven approaches, particularly hybrid evolutionary optimization algorithms, provide a promising solution by enabling intelligent decision-making and real-time optimization. Recent studies highlight the effectiveness of deep learning and reinforcement learning models in predicting energy demand and optimizing charging schedules. However, their high computational requirements and dependency on large datasets limit their practical implementation. Hybrid models, which combine evolutionary algorithms with AI techniques, offer improved performance by addressing multi-objective optimization problems.

Despite these advancements, challenges such as computational complexity, uncertainty in renewable energy generation, and lack of real-time deployment remain significant. Additionally, issues related to data security, communication latency, and system interoperability must be addressed to ensure reliable operation. Future research should focus on lightweight AI models, decentralized architectures, and integration with edge computing to enable real-time energy management. The adoption of blockchain technology can further enhance security and transparency in energy transactions. Overall, AI-based energy management systems have the potential to revolutionize microgrid operations and support sustainable EV integration.

Conclusion

The rapid growth of electric vehicles and renewable energy technologies has increased the complexity of energy management in grid-isolated microgrids. This survey analysed recent advancements in artificial intelligence techniques for microgrid energy management, focusing on hybrid human evolutionary optimization algorithms for EV charging systems. Traditional optimization methods such as mixed-integer linear programming, particle swarm optimization, and consensus-based algorithms provided effective solutions for load balancing and cost reduction but struggled to handle uncertain and dynamic environments. Machine learning approaches improved prediction accuracy and enabled data-driven decision-making, although adaptability remained limited in highly variable conditions.

Deep learning models, including convolutional neural networks, long short-term memory networks, and transformer architectures, significantly enhanced forecasting and scheduling efficiency by capturing complex nonlinear and temporal relationships in energy data. Reinforcement learning and deep reinforcement learning further improved system adaptability through real-time decision-making for EV charging and energy flow management. However, challenges related to computational complexity, convergence stability, large dataset requirements, and real-time deployment continue to limit the practical implementation of intelligent microgrid energy management systems.

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