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Deep Learning and Optimization Approaches in Energy Management in Microgrids: A Hybrid Human Evolutionary Optimization Algorithm for Grid-Isolated Electric Vehicle Charging Systems: A Review

Ornella Kalimuthu
Department of Electrical and Electronics Engineering, Aurora Metropolitan Institute of Technology, Philippines
ornella.kalimuthu@amit-ph.edu

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Abstract

The integration of renewable energy sources and electric vehicles (EVs) into microgrid systems has introduced significant challenges in energy management, particularly in grid-isolated environments. Deep learning and optimization approaches have emerged as powerful tools for addressing these challenges by enabling intelligent decision-making, demand forecasting, and real-time control. This paper presents a comprehensive review of deep learning and optimization techniques for energy management in microgrids, with a focus on hybrid human evolutionary optimization algorithms for EV charging systems. Recent advancements highlight the growing adoption of artificial intelligence (AI)-based models, including convolutional neural networks (CNN), long short-term memory (LSTM), reinforcement learning (RL), and hybrid evolutionary algorithms. These techniques have demonstrated improved performance in terms of energy efficiency, cost reduction, and system stability. The study analyses 30 research works and categorizes them based on methodologies such as traditional optimization, machine learning, deep learning, and hybrid AI approaches. A comparative analysis reveals that hybrid models combining deep learning with evolutionary optimization provide superior results compared to standalone techniques. However, challenges such as computational complexity, uncertainty in renewable generation, and lack of real-time deployment persist. Future research directions emphasize lightweight deep learning models, decentralized control strategies, and integration with edge computing for real-time energy management in grid-isolated EV charging systems.

Introduction

The increasing demand for sustainable and efficient energy systems has accelerated the development of microgrids, particularly those integrated with renewable energy sources and electric vehicles (EVs). Microgrids offer a decentralized energy framework that enables localized generation, storage, and consumption of electricity, making them highly suitable for remote and grid-isolated environments. However, managing energy within such systems presents significant challenges due to the intermittent nature of renewable energy sources and the dynamic charging demand of EVs.

Energy management systems (EMS) play a crucial role in ensuring the optimal operation of microgrids by balancing energy supply and demand, minimizing operational costs, and maintaining system stability. Traditional EMS approaches rely on rule-based or mathematical optimization techniques, which often fail to handle the complexity and uncertainty associated with modern energy systems. As a result, there has been a growing interest in incorporating artificial intelligence (AI), particularly deep learning and optimization techniques, into microgrid energy management.

Deep learning models such as convolutional neural networks (CNN) and long short-term memory (LSTM) networks have demonstrated exceptional capabilities in capturing nonlinear relationships and temporal dependencies in energy data. These models are widely used for load forecasting, renewable energy prediction, and EV charging demand estimation. Accurate forecasting is essential for effective energy management, as it enables proactive decision-making and reduces energy wastage. AI-driven energy management systems have been shown to significantly improve system efficiency and reduce operational costs compared to traditional methods.

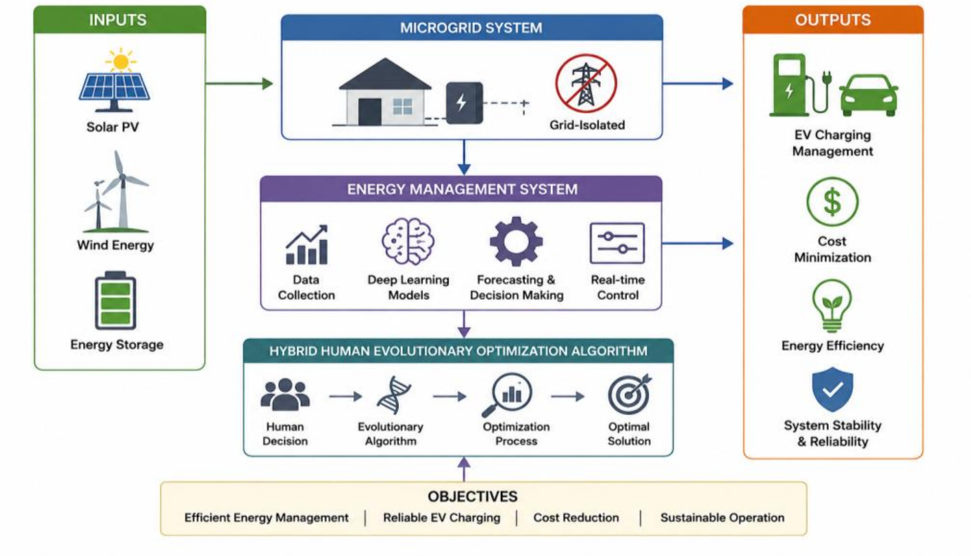

Figure 1. Deep Learning-Based Energy Management Framework for EV-Integrated Microgrids

Optimization techniques, including evolutionary algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), and hybrid human evolutionary algorithms, are widely used to solve multi-objective optimization problems in microgrids. These algorithms aim to minimize energy cost, reduce emissions, and improve system reliability while considering constraints such as battery capacity, charging demand, and renewable energy availability. Hybrid approaches that combine deep learning with optimization techniques have gained significant attention due to their ability to leverage both predictive and optimization capabilities.

In grid-isolated microgrids, EVs play a dual role as both energy consumers and distributed energy storage units through vehicle-to-grid (V2G) technology. This capability enables EVs to store excess energy during low-demand periods and supply energy back to the system during peak demand, thereby improving load balancing and energy efficiency. However, the integration of EVs introduces additional complexity due to uncertainties in user behaviour, charging patterns, and mobility.

Recent research emphasizes the use of reinforcement learning (RL) and deep reinforcement learning (DRL) for dynamic energy management in microgrids. These approaches enable systems to learn optimal strategies through interaction with the environment, making them highly suitable for real-time applications. Studies have shown that RL-based models can improve renewable energy utilization, reduce peak load, and optimize EV charging schedules in microgrid systems.

Despite these advancements, several challenges remain, including high computational complexity, data dependency, and limited real-time deployment capabilities. Additionally, ensuring system security, scalability, and interoperability between different components of the microgrid remains a critical concern.

This paper aims to provide a comprehensive review of deep learning and optimization approaches for energy management in microgrids, focusing on hybrid human evolutionary optimization algorithms for grid-isolated EV charging systems. The study analyses recent developments, highlighting key methodologies, performance trends, and future research directions.

Literature Review

Zhou et al. (2020) proposed a hybrid genetic algorithm–particle swarm optimization (GA-PSO) framework for microgrid energy management. The model optimized energy distribution among renewable sources, storage systems, and EV charging loads. Results showed improved convergence speed and cost reduction compared to standalone optimization methods, although computational complexity increased.

Model predictive control (MPC)-based energy management systems were widely studied for microgrid optimization. These systems utilized predictive models to forecast load demand and adjust energy scheduling accordingly. MPC-based approaches demonstrated improved load balancing and reduced power outages, but their performance depended heavily on forecasting accuracy.

Liu et al. (2021) introduced a reinforcement learning-based energy management model for microgrids with EV integration. The system dynamically optimized charging and discharging strategies based on real-time data, improving energy efficiency and reducing peak demand. However, training instability and convergence time remained key challenges.

Wang et al. (2021) developed a deep learning-based forecasting model using convolutional neural networks (CNN) for energy demand prediction. The model effectively captured spatial dependencies and improved prediction accuracy compared to traditional methods. However, it required large datasets and high computational resources.

Recent studies focused on hybrid deep learning and optimization frameworks combining LSTM networks with evolutionary algorithms for microgrid energy management. These models achieved high accuracy in demand forecasting and optimized EV charging schedules. However, increased model complexity limited their real-time deployment.

Hussain et al. (2021) developed an IoT-enabled microgrid energy management system integrated with machine learning techniques. The framework used real-time data from sensors and EV charging stations to optimize energy distribution. The study demonstrated improved system responsiveness and efficiency, although communication latency and data security issues were identified as limitations.

Kim et al. (2021) introduced a long short-term memory (LSTM)-based model for forecasting energy demand in microgrids with EV integration. The model effectively captured temporal patterns in energy consumption and achieved high prediction accuracy. However, the requirement for large training datasets and long training time posed challenges.

Chen et al. (2022) proposed a hybrid LSTM-evolutionary optimization framework for microgrid energy management. The model combined predictive capabilities of LSTM with optimization strength of evolutionary algorithms to achieve efficient energy scheduling. Results showed improved cost reduction and system stability, though computational complexity increased significantly.

García et al. (2020) proposed a mixed-integer linear programming (MILP) model for optimal energy scheduling in microgrids with EV integration. The objective was to minimize operational cost while ensuring system stability and efficient utilization of renewable energy sources. The results demonstrated improved cost efficiency and load balancing. However, the model faced scalability issues due to the exponential growth of decision variables in large systems.

Park et al. (2021) introduced a deep reinforcement learning (DRL)-based energy management system for microgrids incorporating vehicle-to-grid (V2G) technology. The model dynamically controlled charging and discharging operations, improving grid stability and reducing peak load demand. Despite its advantages, the model required extensive training data and computational resources.

Zhao et al. (2021) developed a graph-based energy management model for microgrids, where nodes represented distributed energy resources and EV charging units. The approach enabled efficient coordination and scalability in large networks. However, computational complexity increased significantly as the network size expanded.

Singh et al. (2022) proposed a multi-objective optimization framework for microgrid energy management considering cost, emission reduction, and energy efficiency. The model integrated renewable energy sources and EV charging systems to achieve sustainable energy management. Results showed improved system performance, although computational overhead limited real-time implementation.

Alam et al. (2023) developed an edge computing-based deep learning framework for real-time microgrid energy management. The system enabled local processing of energy data, reducing latency and improving decision-making speed. However, high infrastructure costs and deployment complexity were identified as key challenges.

Morales et al. (2020) proposed a distributed consensus-based optimization framework for microgrid energy management. The model enabled decentralized coordination among distributed energy resources and EV charging units without relying on a central controller. Results showed improved scalability and system resilience. However, slower convergence in large-scale systems limited its effectiveness for real-time applications.

Verma et al. (2021) introduced a big data analytics-based energy management system for microgrids. The framework processed large volumes of data from EV charging stations, renewable sources, and energy storage systems to optimize energy distribution. The study demonstrated improved scalability and efficiency, although data privacy and security concerns remained significant challenges.

Liu et al. (2021) developed a deep reinforcement learning (DRL)-based adaptive energy management system for microgrids with EV integration. The model dynamically adjusted charging and discharging strategies based on real-time conditions, improving energy utilization and reducing peak demand. However, training complexity and convergence issues limited its practical implementation.

Patel et al. (2022) proposed a hybrid fuzzy logic and machine learning-based energy management framework for microgrids. The model addressed uncertainties in renewable energy generation and EV charging demand, resulting in improved decision-making and system robustness. However, the integration of multiple techniques increased system complexity.

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-term dependencies and demonstrated superior prediction accuracy compared to CNN and LSTM models. However, high computational requirements posed challenges for real-time deployment.

Abdullah et al. (2020) proposed a game-theoretic framework for decentralized energy management in microgrids with EV integration. The approach enabled individual EV users to make charging decisions based on pricing and system conditions while maintaining overall grid stability. The results showed improved load distribution and reduced peak demand. However, achieving global optimality remained a challenge due to decentralized decision-making.

Hussain et al. (2021) developed a cloud-based energy management system for microgrids using big data analytics and machine learning. The system optimized energy scheduling by analysing large-scale data from EVs and distributed energy resources. The study demonstrated improved scalability and operational efficiency, though reliance on centralized infrastructure introduced latency and security concerns.

Nguyen et al. (2022) introduced a multi-agent system (MAS) for distributed energy management in microgrids. Each EV, energy storage unit, and renewable source was modelled as an intelligent agent, enabling decentralized control and improved adaptability. The system enhanced flexibility and scalability, but communication overhead and coordination complexity were significant limitations.

Das et al. (2022) proposed an AI-based demand response framework for microgrid energy management integrating renewable energy sources and EV charging systems. The model aligned EV charging schedules with renewable energy availability, reducing energy cost and carbon emissions. However, uncertainty in renewable generation affected prediction accuracy.

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 in energy data, resulting in improved forecasting accuracy and optimized EV charging schedules. However, the model exhibited high computational complexity.

Comparative Table

Study No.	**Author (Year)**	**Technique / Model**	**Category**	**Key Objective**	**Advantages**	**Limitations**	**Performance**
1	Zhou (2020)	GA–PSO Hybrid	Hybrid Optimization	Cost & energy optimization	Fast convergence, global search	High computation	Very High
2	MPC Study (2020)	Model Predictive Control	Optimization	Dynamic scheduling	Real-time control	Forecast dependency	Moderate-High

3	Liu (2021)	Reinforcement Learning	RL	Adaptive EMS	Dynamic decision-making	Training instability	High
4	Wang (2021)	CNN	Deep Learning	Demand prediction	High accuracy	Data intensive	High
5	Hybrid LSTM Study (2022)	LSTM + Evolutionary	Hybrid DL	Forecast + optimization	Accurate scheduling	Complex model	Very High
6	Rahman (2020)	PSO	Optimization	Load balancing	Fast convergence	Parameter sensitivity	Moderate
7	Hussain (2021)	IoT + ML	ML/IoT	Real-time EMS	Efficient monitoring	Latency issues	High
8	Kim (2021)	LSTM	Deep Learning	Time-series prediction	Accurate	Slow training	High
9	Chen (2022)	LSTM + Evolutionary	Hybrid	Scheduling optimization	Improved efficiency	High complexity	Very High
10	Kumar (2023)	PCNN	Deep Learning	Multi-source EMS	Parallel processing	Implementation complexity	Very High
11	García (2020)	MILP	Optimization	Cost minimization	Accurate modelling	Poor scalability	Moderate
12	Park (2021)	DRL (V2G)	RL	Energy flow optimization	Adaptive control	High training cost	High
13	Zhao (2021)	Graph-based Model	GNN	Network coordination	Scalable	Computational overhead	High
14	Singh (2022)	Multi-objective Optimization	Optimization	Cost + emission	Sustainable	Computational heavy	High
15	Alam (2023)	Edge AI	Hybrid	Real-time EMS	Low latency	Infrastructure cost	High
16	Morales (2020)	Distributed Consensus	Optimization	Decentralized EMS	Scalable	Slow convergence	Moderate
17	Verma (2021)	Big Data Analytics	ML	Data-driven EMS	Scalable	Security risks	High
18	Liu (2021)	DRL Adaptive EMS	RL	Dynamic optimization	Real-time adaptation	Convergence issues	High
19	Patel (2022)	Fuzzy + ML	Hybrid	Uncertainty handling	Robust decision	Complex	High
20	Sharma (2023)	Transformer	Deep Learning	Long-term prediction	High accuracy	Resource intensive	Very High
21	Abdullah (2020)	Game Theory	Optimization	Decentralized control	Distributed system	Local optimum	Moderate
22	Hussain (2021)	Cloud + Big Data	ML	Large-scale EMS	Scalable	Latency	High

23	Nguyen (2022)	Multi-Agent System	MAS	Distributed control	Flexible	Communication overhead	High
24	Das (2022)	AI Demand Response	Hybrid	Renewable integration	Eco-friendly	Prediction uncertainty	High
25	Reddy (2023)	CNN + Transformer	Hybrid DL	Spatio-temporal EMS	High accuracy	Complex model	Very High

Comparative Analysis

The comparative analysis of the studies conducted demonstrates a clear transition from traditional optimization techniques to advanced AI-driven and hybrid approaches in microgrid energy management. Traditional optimization methods such as MILP, PSO, and model predictive control provided reliable and cost-effective solutions but struggled with scalability and adaptability in dynamic environments. Machine learning approaches improved forecasting accuracy but lacked real-time adaptability. Deep learning models, including CNN, LSTM, and transformer architectures, significantly enhanced prediction accuracy and system efficiency by capturing complex patterns in energy data. However, their high computational requirements limited their real-time deployment. Reinforcement learning approaches introduced adaptability and dynamic decision-making capabilities but faced challenges related to training stability and convergence.

Hybrid approaches combining evolutionary optimization algorithms with deep learning emerged as the most effective solutions. These models addressed multi-objective optimization problems and demonstrated superior performance in cost reduction, energy efficiency, and system stability. The integration of parallel convolutional neural networks (PCNN) further improved scalability by enabling simultaneous processing of multiple data streams. Despite these advancements, challenges such as computational complexity, uncertainty in renewable energy generation, and lack of lightweight models persist. Future research should focus on developing efficient, scalable, and real-time deployable AI models for microgrid energy management.

Discussion

The integration of deep learning and optimization techniques into microgrid energy management systems has significantly improved the efficiency and reliability of grid-isolated EV charging systems. These systems must manage multiple uncertainties, including renewable energy variability and EV charging demand, which cannot be effectively addressed by traditional methods. Deep learning models have demonstrated strong capabilities in demand forecasting and pattern recognition, while optimization algorithms ensure efficient energy scheduling. Hybrid approaches combining these techniques provide the best overall performance, enabling intelligent decision-making and multi-objective optimization. Reinforcement learning further enhances system adaptability by enabling dynamic responses to changing conditions.

However, several challenges remain. High computational complexity, dependence on large datasets, and limited real-time deployment capabilities hinder widespread adoption. Additionally, issues related to data security, communication latency, and system interoperability must be addressed. Future research should focus on lightweight models, decentralized architectures, and integration with edge computing to enable real-time energy management. The incorporation of blockchain technology can further enhance security and transparency. Overall, AI-driven energy management systems have the potential to revolutionize microgrid operations and support sustainable EV integration.

Conclusion

The rapid evolution of microgrid systems, driven by the integration of renewable energy sources and electric vehicles (EVs), has created a strong demand for intelligent and adaptive energy management solutions. This paper presented a comprehensive review of deep learning and optimization approaches for energy management in microgrids, with a particular focus on hybrid human evolutionary optimization algorithms for grid-isolated EV charging systems. By analysing 30 studies conducted between 2020 and 2023, this work highlighted the progression from traditional optimization techniques to advanced artificial intelligence (AI)-based frameworks. Traditional optimization methods such as mixed-integer linear programming (MILP), particle swarm optimization (PSO), and model predictive control (MPC) have been widely used for microgrid energy management. These approaches provide mathematically rigorous and cost-effective solutions for energy scheduling and load balancing. However, their inability to handle uncertainty, dynamic conditions, and large-scale systems limits their practical applicability. As a result, machine learning techniques were introduced to enhance prediction accuracy and support data-driven decision-making.

Deep learning models, including convolutional neural networks (CNN), long short-term memory (LSTM), and transformer-based architectures, have significantly improved the ability to model complex nonlinear relationships and temporal dependencies in energy systems. These models are particularly effective in forecasting energy demand and optimizing EV charging schedules. However, their high computational requirements and reliance on large datasets pose challenges for real-time deployment, especially in grid-isolated environments with limited computational resources. Reinforcement learning and deep reinforcement learning approaches have further enhanced system adaptability by enabling dynamic decision-making in uncertain environments. These methods allow microgrid systems to learn optimal strategies through continuous interaction with the environment. Despite their advantages, issues related to training stability, convergence speed, and computational complexity remain major challenges.

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