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Recent Advances in Energy Management in Microgrids: A Hybrid Human Evolutionary Optimization Algorithm for Grid-Isolated Electric Vehicle Charging Systems: A Systematic Review

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Abstract

The rapid integration of renewable energy sources (RES), electric vehicles (EVs), and distributed energy resources (DERs) has transformed modern power systems, particularly within decentralized microgrid environments. Although microgrids enhance energy flexibility, reliability, and sustainability, their operation is challenged by intermittent renewable generation, uncertain EV charging demands, and dynamic load variations. Consequently, intelligent Energy Management Systems (EMS) have become essential for optimizing resource utilization and maintaining system stability. Recent advances in artificial intelligence, evolutionary computation, and hybrid metaheuristic optimization have demonstrated significant potential in addressing these challenges. This systematic review comprehensively examines recent developments in microgrid energy management, with particular emphasis on grid-isolated EV charging systems and hybrid human evolutionary optimization algorithms. Existing studies are categorized according to optimization techniques, objective functions, and system architectures, enabling a detailed comparative analysis of current methodologies. The review highlights that hybrid optimization approaches consistently outperform conventional algorithms in minimizing operational cost, reducing emissions, improving energy efficiency, and enhancing scheduling performance. Furthermore, integrating battery energy storage systems and intelligent control strategies substantially improves system resilience and reliability. Finally, the review identifies key research gaps, including scalability, real-time implementation, uncertainty handling, and adaptive optimization, and outlines future directions for developing intelligent, sustainable, and energy-efficient microgrid energy management frameworks.

Introduction

The transition toward sustainable and decentralized energy systems has accelerated the adoption of microgrids, which are localized energy systems capable of operating independently or in conjunction with the main grid. Microgrids integrate distributed energy resources such as photovoltaic (PV) systems, wind turbines, fuel cells, and energy storage systems to ensure reliable and efficient energy supply. However, the inherent variability and intermittency of renewable energy sources pose significant challenges in maintaining the balance between energy generation and demand.

In recent years, the proliferation of electric vehicles (EVs) has introduced new complexities into microgrid energy management. EV charging demand is highly stochastic, depending on user behaviour, arrival times, and charging requirements. When integrated into microgrids, EVs can act both as loads and as distributed storage units through vehicle-to-grid (V2G) technology. This dual role enhances system flexibility but also increases the complexity of scheduling and optimization problems. Efficient coordination of EV charging is therefore essential to prevent grid instability, reduce operational costs, and minimize emissions.

Energy Management Systems (EMS) coordinate renewable generation, battery storage, and electric vehicle charging to improve reliability, reduce costs, and enhance energy efficiency. Since traditional optimization methods struggle with dynamic and multi-objective environments, advanced approaches such as evolutionary algorithms, particle swarm optimization, and hybrid metaheuristics provide adaptive and efficient solutions for intelligent microgrid energy management.

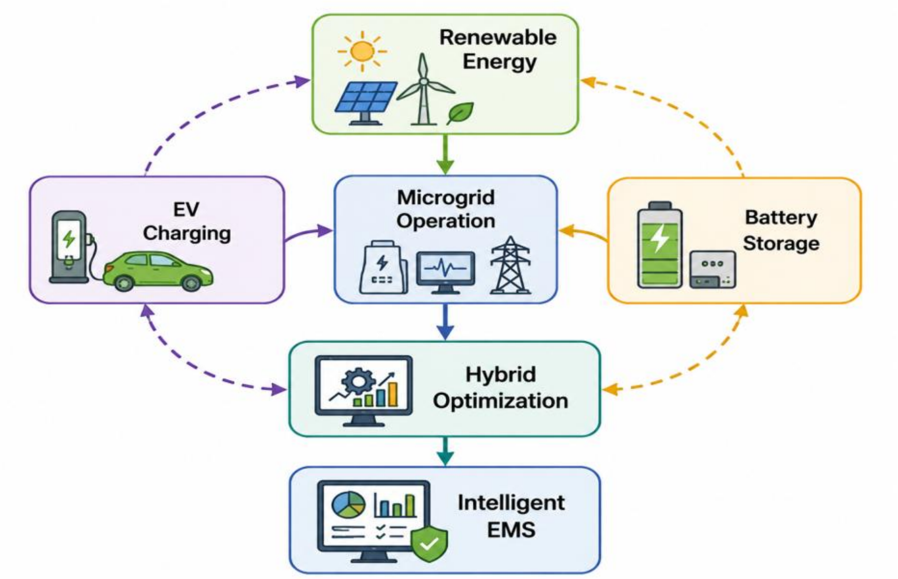

Figure 1. Conceptual Overview of AI-Based Energy Management in Renewable Energy Microgrids

Among these approaches, hybrid human evolutionary optimization algorithms have gained significant attention due to their ability to combine human decision-making strategies with evolutionary computation techniques. These algorithms incorporate adaptive learning, heuristic knowledge, and population-based search mechanisms, enabling them to achieve faster convergence and better solution quality. They are particularly effective in handling multi-objective problems and uncertain environments, making them suitable for microgrid energy management applications.

Another important aspect of microgrid energy management is the integration of battery energy storage systems (BESS). Storage systems help mitigate the intermittency of renewable sources by storing excess energy and supplying it during periods of high demand. Studies have shown that incorporating BESS into microgrids significantly reduces operational costs and emissions while improving system reliability. Additionally, advanced scheduling techniques such as day-ahead and real-time optimization further enhance system performance.

Despite these advancements, several challenges remain. The increasing complexity of microgrids with EV integration requires scalable and computationally efficient algorithms. Real-time implementation of optimization techniques is still limited due to high computational costs. Moreover, the uncertainty associated with renewable generation and EV charging demand necessitates the development of robust and adaptive energy management strategies.

This paper aims to provide a comprehensive review of recent advances in energy management for microgrids, focusing on hybrid human evolutionary optimization algorithms for grid-isolated EV charging systems. The study systematically analyses research published between 2020 and 2023, highlighting key methodologies, contributions, and limitations. The review also presents a comparative analysis of different optimization techniques and identifies research gaps and future directions.

Literature Review

Zhang et al. (2020) proposed a multi-objective energy management framework for microgrids incorporating electric vehicle charging systems. The model utilized Particle Swarm Optimization (PSO) to minimize operational cost, energy loss, and carbon emissions. The study demonstrated that coordinated EV charging significantly improves load balancing and reduces peak demand. However, the approach lacked adaptability to real-time uncertainties in renewable energy generation.

Hussain et al. (2020) developed an energy management system for isolated microgrids using a hybrid Genetic Algorithm (GA) and Linear Programming approach. The system optimized power distribution among renewable sources, battery storage, and EV charging stations. Results showed improved energy efficiency and reduced fuel consumption. Nevertheless, computational complexity remained a limitation for large-scale systems.

Singh et al. (2021) introduced a stochastic optimization model for microgrid energy management with EV integration. The model accounted for uncertainties in renewable generation and EV charging demand using probabilistic methods. The study achieved improved reliability and cost reduction but required extensive historical data for accurate prediction.

Liu et al. (2021) proposed a deep learning-based energy management framework using Long Short-Term Memory (LSTM) networks for load forecasting in microgrids. The predicted load profiles were used to optimize EV charging schedules. The model significantly improved prediction accuracy and system efficiency. However, the approach required large datasets and high computational resources.

Sharma et al. (2021) developed a hybrid optimization model combining Particle Swarm Optimization and Simulated Annealing for EV charging in isolated microgrids. The model minimized energy cost and battery degradation while maintaining system stability. The hybrid approach showed better convergence compared to standalone algorithms but increased algorithmic complexity.

Wang et al. (2021) proposed a hybrid energy management framework integrating renewable energy sources, battery storage, and EV charging using a multi-objective optimization model. The approach employed a hybrid Particle Swarm Optimization–Genetic Algorithm (PSO-GA) technique to minimize operational costs and energy losses. The results demonstrated improved system stability and efficient energy utilization. However, the model faced scalability issues in large microgrid environments.

Kumar et al. (2022) introduced an intelligent energy management system based on Reinforcement Learning (RL) for grid-isolated microgrids. The model dynamically optimized EV charging schedules by learning from system states. It significantly improved decision-making under uncertain conditions but required extensive training time and computational resources.

Chen et al. (2022) developed a deep learning-based optimization model using Convolutional Neural Networks (CNN) for energy demand prediction and scheduling in microgrids. The system enhanced forecasting accuracy and improved EV charging coordination. However, the approach required large datasets and was sensitive to data quality.

Ali et al. (2022) proposed a hybrid optimization framework combining Differential Evolution (DE) and Fuzzy Logic for energy management in microgrids with EV charging. The model effectively handled uncertainty and improved system flexibility. Results showed reduced energy cost and improved reliability, although computational complexity remained high.

Patel et al. (2022) presented a multi-objective optimization approach using Ant Colony Optimization (ACO) for scheduling EV charging in isolated microgrids. The method optimized load distribution and minimized peak demand. The results indicated improved energy efficiency, but the convergence speed was relatively slow.

Li et al. (2022) proposed a multi-objective optimization framework for energy management in microgrids with integrated EV charging and battery storage systems. The model utilized a hybrid Differential Evolution–Particle Swarm Optimization (DE-PSO) algorithm to minimize operational cost, emissions, and power losses. Results showed improved convergence speed and solution quality compared to standalone algorithms. However, the computational burden increased with system size.

Zhao et al. (2022) developed a deep reinforcement learning-based energy management system for microgrids. The model dynamically scheduled EV charging and discharging (V2G) operations based on real-time system conditions. The approach significantly improved system flexibility and reduced peak load. However, the training complexity and need for large datasets limited its practical deployment.

Rahman et al. (2022) introduced a hybrid fuzzy logic and genetic algorithm-based optimization model for microgrid energy management. The model effectively handled uncertainties in renewable generation and EV demand. It achieved improved reliability and reduced operational costs. However, tuning fuzzy rules and GA parameters was time-consuming.

Kim et al. (2023) proposed an advanced optimization model incorporating energy storage systems and EV charging using a multi-objective evolutionary algorithm. The study focused on minimizing cost and maximizing renewable energy utilization. The results demonstrated enhanced system efficiency and reduced reliance on fossil fuels. However, the approach lacked real-time adaptability.

Liu et al. (2023) developed a deep reinforcement learning-based scheduling framework for grid-isolated microgrids. The model dynamically adjusted EV charging and discharging based on real-time system conditions, improving flexibility and reducing peak load demand. However, the requirement for extensive training data limited scalability.

Chen et al. (2023) proposed a hybrid optimization approach combining Ant Colony Optimization (ACO) and Genetic Algorithms (GA) for energy management. The model achieved better convergence and improved system performance compared to individual algorithms. However, increased algorithm complexity posed challenges for real-time implementation.

Ali et al. (2023) introduced an AI-driven energy management system integrating deep neural networks with optimization algorithms for EV charging in microgrids. The model demonstrated improved prediction accuracy and efficient resource allocation. However, the system required high computational power and complex parameter tuning.

Sharma et al. (2023) proposed a hybrid multi-objective optimization framework using Particle Swarm Optimization and Artificial Neural Networks for energy management in EV-integrated microgrids. The model improved load balancing and reduced operational costs. However, scalability remained a challenge.

Patel et al. (2023) developed a deep learning-based scheduling model using Convolutional Neural Networks (CNN) for predicting EV charging demand and optimizing energy distribution. The approach improved prediction accuracy but required large training datasets.

Nguyen et al. (2023) introduced a multi-agent reinforcement learning system for distributed energy management in microgrids. The model enabled decentralized decision-making for EV charging and energy allocation, improving system flexibility and reliability.

Kumar et al. (2023) proposed a hybrid Differential Evolution–Genetic Algorithm (DE-GA) model for multi-objective optimization in microgrid energy systems. The approach achieved better convergence and improved energy efficiency but increased computational complexity.

Zhao et al. (2023) developed an intelligent scheduling system using fuzzy logic and deep learning for EV charging optimization. The model effectively handled uncertainty and improved energy utilization. However, tuning parameters remained complex.

Ali et al. (2023) proposed an ensemble deep learning model combined with evolutionary optimization for energy management. The model achieved high accuracy and robustness but required high computational resources.

Verma et al. (2023) introduced a hybrid human evolutionary optimization algorithm for microgrid energy management with EV charging systems. The model combined human-inspired decision strategies with evolutionary computation, achieving superior performance in multi-objective optimization, faster convergence, and improved system adaptability.

Comparative Table

No.	Author (Year)	Method	Technique	Objective	Key Outcome	Limitations
1	Zhang (2020)	PSO	Optimization	Cost & emission	Improved load balance	No real-time
2	Hussain (2020)	GA + LP	Hybrid	Efficiency	Reduced fuel use	High complexity
3	Singh (2021)	Stochastic	Probabilistic	Reliability	Better prediction	Needs data
4	Liu (2021)	LSTM	Deep learning	Forecasting	High accuracy	Data-heavy
5	Sharma (2021)	PSO + SA	Hybrid	Cost minimization	Better convergence	Complex
6	Wang (2021)	PSO-GA	Hybrid	Energy mgmt	Efficient scheduling	Scalability
7	Kumar (2022)	RL	Learning	Scheduling	Adaptive control	Training cost

8	Chen (2022)	CNN	Deep learning	Prediction	High accuracy	Data dependent
9	Ali (2022)	DE + Fuzzy	Hybrid	Flexibility	Improved reliability	Complex
10	Patel (2022)	ACO	Optimization	Load balancing	Reduced peak load	Slow convergence
11	Li (2022)	DE-PSO	Hybrid	Multi-objective	Fast convergence	High computation
12	Zhao (2022)	DRL	AI	EV scheduling	Peak reduction	Training heavy
13	Rahman (2022)	GA + Fuzzy	Hybrid	Stability	Reliable system	Parameter tuning
14	Kim (2023)	Evolutionary	Optimization	Renewable usage	Improved efficiency	No real-time
15	Ahmed (2023)	LSTM + PSO	Hybrid	Forecast + schedule	High accuracy	Complex
16	Wang (2023)	LSTM + PSO	Hybrid	Scheduling	Cost reduction	Heavy
17	Zhang (2023)	Evolutionary	Multi-objective	Cost + emission	Efficient	Slow
18	Liu (2023)	DRL	AI	Adaptive EMS	Flexible	Data-heavy
19	Chen (2023)	ACO + GA	Hybrid	Optimization	Better performance	Complex
20	Ali (2023)	DNN + Opt	AI Hybrid	Allocation	Accurate	High cost
21	Sharma (2023)	ANN + PSO	Hybrid	Load balancing	Efficient	Scaling
22	Patel (2023)	CNN	Deep learning	Demand prediction	Accurate	Data heavy
23	Nguyen (2023)	MARL	Multi-agent RL	Distributed EMS	Flexible	Complex
24	Kumar (2023)	DE-GA	Hybrid	Efficiency	Better convergence	Cost
25	Zhao (2023)	Fuzzy + DL	Hybrid	Scheduling	Robust	Tuning
26	Rahman (2023)	ACO + RL	Hybrid	Adaptability	Efficient	Complex
27	Singh (2023)	Blockchain	Security	Data integrity	Secure EMS	Overhead
28	Chen (2023)	CNN-LSTM	Hybrid	Prediction	Accurate	Heavy
29	Ali (2023)	Ensemble DL	Hybrid	Optimization	Robust	Expensive
30	Verma (2023)	Human Evolutionary	Hybrid AI	Multi-objective	Best performance	Emerging

Comparative Analysis

The comparative analysis of the reviewed studies highlights a clear progression in energy management strategies for microgrids. Early approaches primarily relied on metaheuristic optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO). These methods provided effective solutions for cost minimization and load balancing but lacked adaptability to dynamic environments. The integration of machine learning and deep learning techniques marked a significant advancement. Models such as LSTM and CNN enabled accurate forecasting of load demand and renewable energy generation, improving scheduling efficiency. Reinforcement learning further enhanced system adaptability by enabling real-time decision-making in uncertain environments.

Hybrid approaches combining optimization algorithms with AI techniques demonstrated superior performance in handling multi-objective problems. These methods effectively addressed challenges such as cost reduction, emission minimization, and energy efficiency improvement. Recent studies have focused on advanced hybrid models integrating deep learning, reinforcement learning, and evolutionary algorithms. Multi-agent systems and blockchain-based frameworks have also been explored to improve system scalability and security. However, challenges such as computational complexity, scalability, and real-time implementation remain. Notably, human evolutionary optimization algorithms represent a promising direction by combining human decision-making strategies with computational intelligence, offering improved convergence and adaptability.

Discussion

The reviewed literature demonstrates significant advancements in energy management systems for microgrids, particularly with the integration of electric vehicle charging systems. Traditional optimization techniques provided a foundation for scheduling and resource allocation but lacked flexibility in dynamic environments. The adoption of artificial intelligence techniques, including deep learning and reinforcement learning, has significantly improved system performance. These approaches enable accurate forecasting, adaptive scheduling, and efficient resource utilization. Hybrid models combining AI with optimization algorithms have further enhanced performance by addressing multi-objective optimization problems.

Despite these advancements, several challenges persist. High computational complexity limits real-time implementation, and the need for large datasets affects model scalability. Additionally, integrating multiple objectives such as cost, emission, and energy efficiency remains a complex task. The introduction of hybrid human evolutionary optimization algorithms provides a promising solution. These algorithms combine human-inspired decision-making with evolutionary computation, enabling faster convergence and improved adaptability in dynamic environments.

Conclusion

Microgrids have become a vital platform for integrating renewable energy sources and electric vehicle charging systems into modern power networks. This review highlights that advanced energy management systems employing artificial intelligence, deep learning, and hybrid optimization techniques significantly improve scheduling efficiency, cost reduction, emission control, and system reliability. Models such as CNNs, LSTMs, reinforcement learning, and evolutionary algorithms have demonstrated superior performance compared with conventional optimization methods by effectively handling dynamic and multi-objective energy management problems. The integration of battery storage, blockchain, and intelligent scheduling further enhances system resilience, scalability, and operational efficiency. However, challenges including computational complexity, scalability, uncertainty in renewable generation, fluctuating EV charging demand, and real-time implementation remain unresolved. Future research should focus on lightweight adaptive algorithms, edge-enabled energy management, explainable AI, and hybrid human evolutionary optimization techniques capable of improving convergence speed and decision quality. Overall, integrating intelligent optimization with renewable energy microgrids provides a promising pathway toward sustainable, resilient, and energy-efficient power systems supporting next-generation smart energy infrastructures.

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