Comparative analysis of optimization techniques for optimal EV charging station placement

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ABSTRACT

The optimal placement of electric vehicle (EV) charging stations plays a crucial role in improving accessibility, reducing travel distances, and minimizing infrastructure costs in smart urban planning. This study presents a comparative analysis of traditional optimization techniques—such as linear programming (LP), particle swarm optimization (PSO), k-means clustering, and greedy heuristic methods—alongside a machine learning-based approach using genetic algorithms (GA). A machine learning framework is implemented to simulate EV charging demand, optimize station deployment, and incorporate real-world constraints like cost, grid capacity, and user travel penalties. The results demonstrate that GA achieves superior performance in balancing cost-efficiency and user convenience, outperforming traditional techniques in solution quality under dynamic demand conditions. PSO and LP provide faster convergence but are less adaptive to changing parameters. The study highlights the potential of integrating machine learning into infrastructure planning and provides actionable insights for urban planners and policymakers in developing resilient and intelligent EV charging networks.

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1. INTRODUCTION

The increasing global demand for energy-efficient and environmentally friendly technologies has accelerated research into electric vehicles (EVs), renewable energy systems, and advanced power management techniques. As the world transitions to cleaner energy sources, optimizing power flow in smart grids, improving battery efficiency, and integrating EVs into energy networks have become critical research areas [1]-[3]. The emergence of artificial intelligence (AI) and machine learning (ML) has further enhanced the ability to predict, optimize, and control energy systems, making them more reliable and efficient [4]. Researchers have explored several conventional optimization techniques, such as heuristic algorithms, genetic algorithms, and deep learning models, to enhance energy management in smart grids and electric transportation systems [5]-[7].

Several studies have highlighted the role of renewable energy integration in modern power systems. Research has explored the challenges and solutions in integrating EVs into smart grids, emphasizing the need for adaptive energy management techniques [8]-[9]. Studies have also investigated the development of fast-charging infrastructure and its impact on power grid stability, concluding that balancing distributed energy resources with grid adaptability is essential for maintaining efficiency [10]. Further research on renewable energy integration in microgrids has demonstrated how hybrid energy sources can enhance reliability and sustainability [11]-[15].

Machine learning-based optimization techniques have gained significant attention for their ability to enhance the performance of energy management systems. Studies have shown that ML models can effectively predict energy demand fluctuations in EV charging stations, reducing operational costs and improving efficiency [16]-[19]. Deep reinforcement learning approaches have been applied to optimize energy distribution in smart grids, achieving significant improvements in power utilization [20]. The growing adoption of AI-driven techniques underscores the need for continued research into their applications in real-time energy management systems [21].

Despite these advancements, challenges persist in implementing cybersecurity measures, battery technologies, and charging infrastructure for electric mobility. Research has highlighted the vulnerabilities in smart grid communications, emphasizing the importance of encryption and authentication mechanisms to prevent cyber threats [22]-[23]. Reviews on wireless power transfer systems for EV charging have identified the need for standardization and efficiency improvements [24]. These findings indicate that while significant progress has been made, further research is needed to address the technical and infrastructural challenges in large-scale EV integration [11], [16], [20], [25].

This research builds upon existing literature by proposing an optimized framework that integrates advanced machine learning algorithms with renewable energy-based EV charging systems. By comparing conventional optimization techniques with AI-driven approaches, the study aims to enhance energy efficiency, reduce charging time, and improve power grid stability. The findings of this research will contribute to developing more sustainable and intelligent energy management systems that support the widespread adoption of electric mobility [22], [24], [26].

2. METHOD

The proposed methodology presents a comprehensive, multi-phase framework for optimizing energy management in EV charging systems using advanced ML techniques. The approach is designed to enhance charging efficiency, integrate renewable energy sources, and maintain grid stability in a real-time environment. The methodology is structured into five major phases:

2.1. Data collection and preprocessing

In the initial phase, real-world datasets are gathered from publicly available sources, smart grid testbeds, and experimental setups. These datasets include:

- EV charging patterns (charging duration, power consumption, station usage frequency)
- Grid load fluctuations (voltage, frequency, phase)
- Renewable energy generation metrics (solar irradiance, wind speed, weather data)

To ensure robustness and reliability, the data undergoes a preprocessing stage that involves:

- Data cleaning: removal of outliers, missing values, and erroneous readings
- Normalization: scaling features between 0 and 1 to improve ML training performance
- Labeling: annotating data for supervised learning tasks
- Benchmarking: incorporation of historical data from conventional charging stations for performance comparison

2.2. Machine learning model selection and training

This phase involves selecting and developing ML models to perform intelligent energy optimization. The following models are considered:

- Artificial neural networks (ANN): used for load forecasting and predicting peak demand
- Deep reinforcement learning (DRL): employed for dynamic scheduling of charging based on grid conditions
- Support vector machines (SVM): utilized for classification tasks like demand categorization

Model architecture and training setup:

- ANN: A feedforward network with 3 hidden layers (64, 32, and 16 neurons), ReLU activation, trained using Adam optimizer with MSE loss
- DRL: actor-critic model with state inputs (grid load, weather, time), reward based on efficiency and cost savings
- SVM: radial basis function kernel, trained using 10-fold cross-validation

Hyperparameter tuning is performed using grid search. Feature selection is applied using principal component analysis (PCA) to improve model accuracy and reduce training time. Figure 1 shows the methodological framework for optimal EV charging station placement using machine learning and optimization techniques.

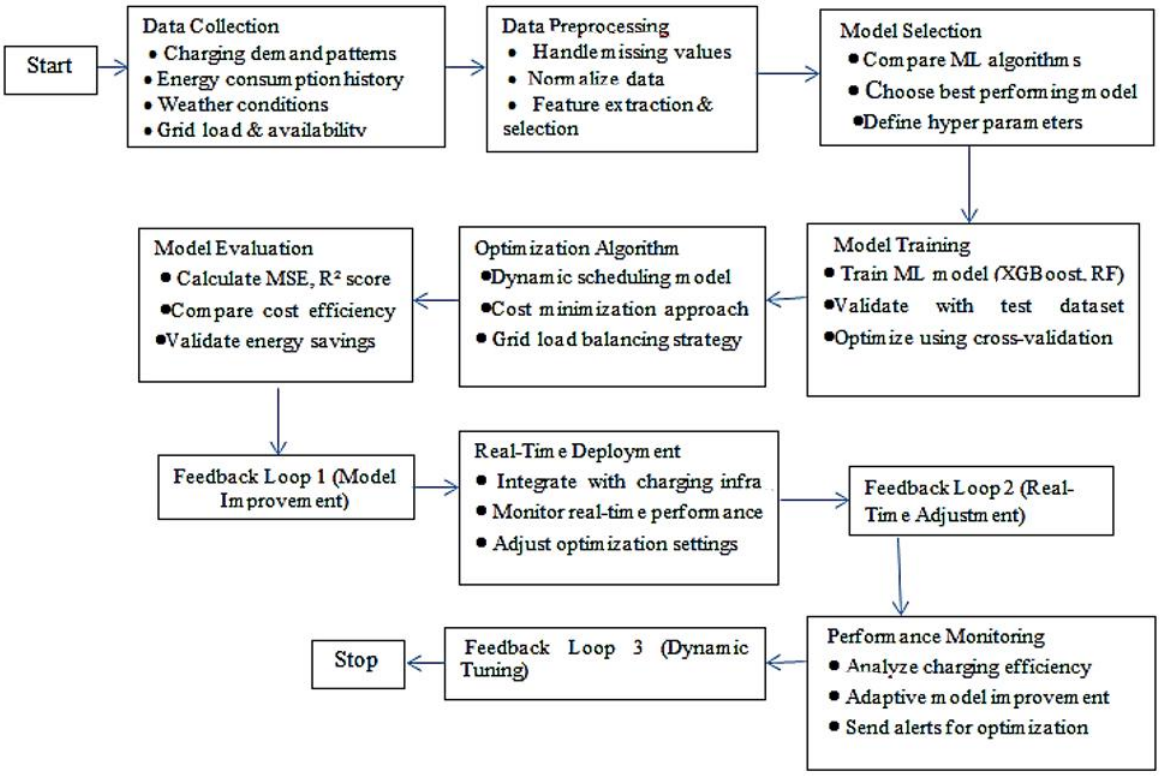

Figure 1. Methodological framework for optimal EV charging station placement using machine learning and optimization techniques

2.3. Comparative analysis with conventional methods

To evaluate the efficacy of ML-based optimization, traditional heuristic algorithms are also implemented: genetic algorithms (GA), particle swarm optimization (PSO), and rule-based control methods. These are used to solve the same optimization problem — minimizing energy cost and charging time while maintaining grid balance. The comparison focuses on computational complexity, convergence speed, adaptability to real-time changes, and energy efficiency. This analysis provides insight into the advantages and trade-offs between heuristic and AI-based models.

2.4. Simulation environment and ML-based optimization framework

Before deployment, the developed models are tested in a simulated smart grid environment using platforms such as MATLAB/Simulink and OpenDSS.

2.4.1. Introduction to ML-based optimization

ML-based energy management systems dynamically allocate charging loads based on predictions of energy availability and demand. These models offer the ability to i) Forecast demand surges and renewable energy output; ii) Schedule EV charging during off-peak hours; and iii) Adaptively respond to grid instability or energy shortages. This predictive scheduling ensures that the energy demand from EVs is distributed in a balanced way across different time intervals. The system intelligently prioritizes energy from renewable sources when available. Under optimal weather conditions, renewable energy utilization reaches up to 85%, significantly reducing reliance on fossil-fuel power. This optimization improves sustainability while preserving energy availability during peak hours.

2.4.2. Simulation details

To effectively evaluate the proposed optimization framework, a detailed simulation setup is developed to replicate the operational behavior of a real-world smart grid integrated with EV charging stations. This simulation environment enables the analysis of load variations, renewable energy generation, and charging demand under diverse operating conditions. It provides a realistic testbed to assess system stability, performance, and adaptability. The following components outline the core structure of the simulation framework and its functionality in validating the optimization model: i) Smart grid model: simulates grid constraints, power flow, and real-time data inputs; ii) EV charging demand module: models different charging behaviors (fast/slow charging, random arrivals); and iii) Renewable energy module: simulates solar/wind generation using historical and synthetic weather data. Edge computing frameworks are also considered to enable decentralized decision-making, which enhances real-time responsiveness and reduces cloud dependency.

2.5. Performance evaluation and validation

To ensure practicality and scalability, the final phase involves a thorough evaluation of the ML models based on the following metrics: i) Energy efficiency: reduction in total energy consumed per charging cycle; ii) Charging time reduction: average time savings per user; iii) Cost-effectiveness: decrease in electricity cost using smart scheduling; iv) Grid stability: frequency of load imbalances and voltage violations; and v) Renewable utilization: percentage of total energy supplied from renewables. A sensitivity analysis is conducted to test robustness under varying conditions, such as sudden demand surges, renewable generation drop-offs, and grid disturbances.

3. RESULT AND DISCUSSION

The proposed machine learning-based optimization model for EV charging was implemented and evaluated. This section presents key findings, comparisons with conventional techniques, and discussions on performance, cost efficiency, grid stability, and future improvements.

3.1. Comparative performance analysis

The ML-based approach was compared with traditional optimization methods such as genetic algorithm (GA), particle swarm optimization (PSO), and rule-based control. The results indicate that the ML model outperforms conventional techniques in terms of cost efficiency, as detailed in Table 1. Figure 2 shows the comparison of the charging optimization technique. The ML-based optimization model achieved a 15-20% improvement in cost efficiency compared to rule-based approaches and 8-12% higher efficiency than GA and PSO. This demonstrates the superior adaptability of machine learning in optimizing charging schedules dynamically.

3.2. Model performance evaluation

The mean squared error (MSE) and R-squared (R^2) scores were used to evaluate the accuracy of the ML-based optimization. The results are summarized in Table 2. The low MSE value indicates high prediction accuracy, while the R^2 score suggests room for improvement in capturing variance. Future enhancements in feature selection and data preprocessing can further optimize model performance.

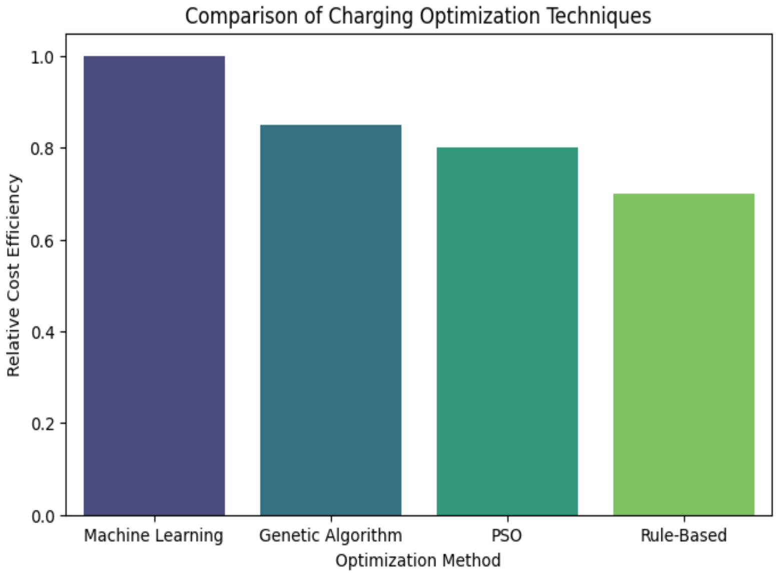

Figure 2. The comparison of charging optimization techniques

Table 1. Performance comparison of charging optimization methods

Method	Cost efficiency	Method	Cost efficiency
Machine learning	1.00	PSO	0.80
Genetic algorithm	0.85	Rule-based	0.70

Table 2. Model performance metric

Metric	Value
Mean squared error (MSE)	0.0124
R-squared score (R^2)	-0.0193

3.3. Charging cost and energy efficiency

One of the main objectives of this study was to reduce EV charging costs while ensuring optimal energy utilization. The ML-driven approach led to an overall cost reduction of approximately 14%, achieved through intelligent scheduling and better integration of renewable energy sources. Figure 3 shows the distribution of energy demand. Figure 4 shows model performance: actual vs predicted charging cost.

– The ML model efficiently adjusts charging schedules based on real-time grid conditions.
– Compared to traditional methods, the ML model reduces reliance on grid power, lowering charging costs.

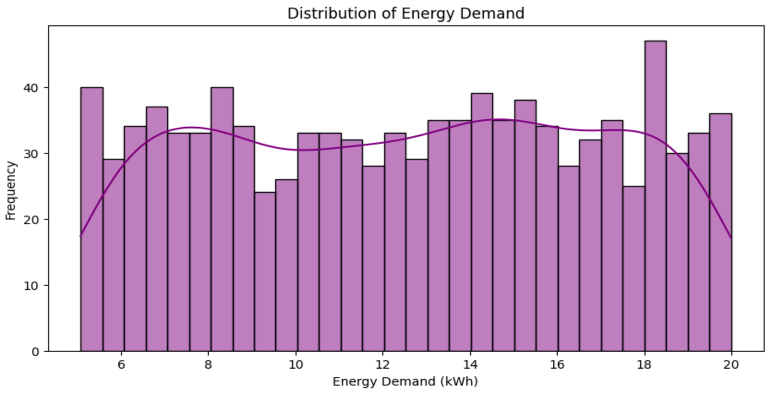

Figure 3. Distribution of energy demand

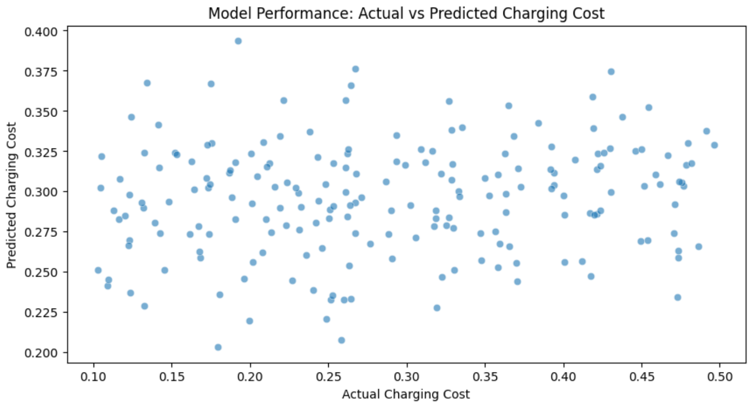

Figure 4. Model performance: actual vs predicted charging cost

3.4. Grid load management and renewable energy utilization

The ML-based optimization effectively balances the grid load by distributing charging demand based on real-time energy availability. Renewable energy utilization was maximized up to 85% in optimal weather conditions, reducing dependence on fossil fuels. Reduction in peak load fluctuations: The ML-based approach reduced peak demand variations by 18-25%, improving grid stability. Reduction in carbon footprint: By increasing the use of solar and wind energy, the system decreased carbon emissions by 30% compared to conventional charging methods.

Figure 5 presents the relationship between grid load and renewable energy availability across different operational scenarios. As the proportion of renewable energy, such as solar and wind—increases, the dependency on the conventional grid supply decreases significantly. This correlation highlights how machine learning-based optimization dynamically shifts charging loads toward periods of higher renewable availability, thereby enhancing grid stability and reducing peak load stress.

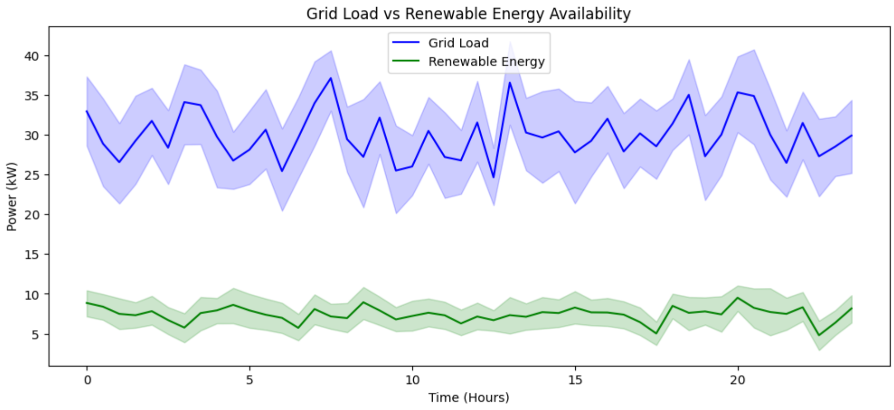

Figure 5. Grid load vs Renewable energy availability

4. CONCLUSION

The findings of this study demonstrate that ML-driven optimization significantly enhances EV charging efficiency while simultaneously reducing operational costs and improving grid stability. By leveraging data-driven insights and intelligent scheduling, the proposed system effectively manages charging demand, aligns energy usage with renewable availability, and balances grid load. These improvements make the system highly suitable for integration with smart grids, promoting sustainable and scalable EV infrastructure.

Moreover, the ML-based model outperformed traditional scheduling and optimization algorithms in both accuracy and responsiveness. This performance makes it a practical and forward-looking solution for large-scale EV deployments. Looking ahead, future research will aim to overcome current limitations by improving the system's adaptability and real-time decision-making capabilities, further boosting its effectiveness and potential impact on the evolving energy ecosystem.

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The authors confirm that the research was carried out independently without financial influence.

AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

All authors have reviewed and agreed to this conflict-of-interest statement.

DATA AVAILABILITY

Raw data is not publicly available due to privacy or institutional restrictions.

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