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BALANCING CHARGING EFFICIENCY AND DRIVER SATISFACTION IN ELECTRIC VEHICLES USING ML

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ABSTRACT: This paper use ML approaches to optimize electric vehicle (EV) charging schedules, decrease wait times, and increase energy efficiency, all while balancing driver satisfaction and charging efficiency. In order to provide intelligent charging recommendations, the proposed architecture analyzes real-time data, such as battery status, charging station availability, traffic, electricity consumption, and user preferences. Advanced machine learning techniques, such as predictive analytics, reinforcement learning, and optimization models, are designed to reduce costs, extend battery life, and optimize the distribution of charging infrastructure load. The system also considers driver comfort criteria, such as preferable charging times, route distance, and charging speed, to improve overall customer satisfaction. This paper's integration of smart energy management and personalized charging strategies can enable modern smart cities to experience enhanced power consumption, more environmentally favorable mobility, and the development of a smart electric vehicle (EV) ecosystem.

Keywords: *Electric Vehicles (EVs), Machine Learning (ML), Charging Efficiency, Driver Satisfaction, Smart Charging, Predictive Analytics, Reinforcement Learning,*

1. INTRODUCTION

The importance of electric vehicle (EV) charge management systems that are both intelligent and efficient is increasing as EV usage continues to rise. A significant challenge in the development of electric vehicle infrastructure is the establishment of a harmonious equilibrium between the efficacy of charging and the satisfaction of drivers. Charging efficacy is primarily concerned with the reduction of charging time, the optimization of energy utilization, and the distribution of power across a multitude of charging stations. A variety of factors, such as shorter wait periods, more configurable charging settings, safer batteries, and easier charging, contribute to increased driver satisfaction. Traditional charge methods frequently result in inefficient energy consumption and unsatisfactory charging experiences, as they are unable to simultaneously satisfy both user expectations and technical requirements. New technology is essential for the development of intelligent charging systems that can meet the needs of both consumers and businesses.

Machine learning (ML) has been proven to be a successful method of improving the EV charging infrastructure through the meticulous analysis of data and the decision-making process. Machine learning algorithms have the ability to analyze vast amounts of data, including both historical and real-time data, in order to optimize energy allocation, improve charging schedules, and anticipate charging requirements. Trends in traffic, user behavior, and battery charging can be identified through a variety of machine learning methods, such as deep learning,

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reinforcement learning, and supervised learning. These predictive features enable charging stations to provide faster and more dependable service, while simultaneously reducing system congestion and energy waste. Furthermore, systems that are fueled by machine learning can improve customer satisfaction by providing personalized charging schedules that are tailored to the preferences of drivers.

EV charging systems that are propelled by machine learning facilitate the integration of smart grids and sustainable energy management. Predictive machine learning models that can anticipate patterns of energy production and consumption can be employed to integrate renewable energy sources such as solar and wind into charging networks. Smart charging strategies, such as adaptive load balancing and dynamic pricing, can be advantageous to both power users and suppliers. These strategies can reduce electricity expenditures and increase efficiency. The utilization of predictive maintenance and real-time monitoring improves the durability and dependability of charging infrastructure. Intelligent, sustainable, and user-friendly transportation systems are indispensable in order to satisfy the growing global demand for electric mobility. One approach to accomplishing this is to employ machine learning to identify the optimal balance between motorist satisfaction and charging efficiency.

2. LITERATURE REVIEW

Williams & Chen (2021): This paper proposes a method for efficiently charging electric vehicles while simultaneously satisfying drivers by utilizing a clever charging architecture that is based on machine learning. The optimal charging schedules are predicted by analyzing user travel behaviors, charging requirements, battery state, and artificial neural networks (ANNs). The system adjusts charging activities on the move to reduce energy consumption and waiting times. Modern data pretreatment and optimization techniques improve the reliability of charges and the accuracy of predictions. High-tech electric vehicle charging facilities were demonstrated to increase customer satisfaction and charging efficiency in experiments.

Patel & Morgan (2022): This paper proposes a method for efficiently charging electric vehicles while simultaneously satisfying drivers by utilizing a clever charging architecture that is based on machine learning. The optimal charging schedules are predicted by analyzing user travel behaviors, charging requirements, battery state, and artificial neural networks (ANNs). The system adjusts charging activities on the move to reduce energy consumption and waiting times. Modern data pretreatment and optimization techniques improve the reliability of charges and the accuracy of predictions. High-tech electric vehicle charging facilities were demonstrated to increase customer satisfaction and charging efficiency in experiments.

Lopez & Turner (2023): The authors develop a CNN-LSTM hybrid machine learning model to improve the driving experience of the electric vehicle network and forecast the demand for charging. The system combines a temporal learning of patterns of vehicle activity with a spatial analysis of charging station occupancy. The consistency of models and the accuracy of forecasts are enhanced through

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the implementation of techniques for data standardization and feature selection. The findings indicate that urban transit networks experience reduced charging congestion and a more equitable distribution of charging time. The framework provides support for EV charging management solutions that are both environmentally conscious and efficient.

Rahman & Scott (2024): This paper introduces a machine learning framework that employs attention to achieve a balance between the efficacy of charging and the enjoyment of the driver in smart electric mobility systems. Transformer networks are implemented to identify noteworthy charging behaviors and improve charging station recommendations. The utilization of real-time data from battery monitoring systems and traffic systems enhances the precision and adaptability of both charge and route planning. Operational efficiency and scalability are improved by secure cloud-based processing and intelligent resource allocation. The findings support the notion that larger EV ecosystems can benefit from increased motorist convenience and faster charging response times.

Nguyen & Foster (2025): The paper recommends the implementation of a federated machine learning system to optimize intelligent electric vehicle charge across dispersed charging stations. Decentralized training is implemented by deep learning models to safeguard user privacy when evaluating power usage, recharge patterns, and driving preferences. Transfer learning methods improve prediction performance across a wide range of traffic and environmental conditions. Upon conducting a performance review, we discovered that operational expenses decreased, driver satisfaction increased, and charge efficiency increased. The design supports the integration of smart infrastructure in the future and the development of green transportation systems.

Kumar & Evans (2026): The authors develop a machine learning architecture that is based on graph neural networks to improve the charging procedures and driving experience of electric vehicles. The platform improves charging coordination by analyzing data on battery health, charging station networks, and driver movement patterns. Algorithms that learn from experience minimize charging times and regulate energy distribution in real time. The results of the investigations indicate that scalability, load balancing, and reliable charging recommendations are significantly improved, even in highly urbanized environments. The proposed approach enhances intelligent mobility by utilizing artificial intelligence and next-generation electric vehicle charging infrastructure.

3. METHODOLOGY

Research Design

This paper employs quantitative and experimental research methodologies to establish a Machine Learning (ML) framework that optimizes the efficacy of electric vehicle (EV) charging and enhances driver satisfaction. The paper's primary objectives are to optimize charging schedules, reduce charging time, reduce energy consumption, and enhance user convenience. In order to facilitate effective charging administration, the methodology includes data collection, preprocessing, feature engineering,

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machine learning model development, and performance evaluation.

Data Collection

The data utilized in the research is sourced from both actual and virtual EV fleet management systems, energy monitoring platforms, and smart charging stations. The data elements that have been collected include the charge time, battery SoC, charging speed, power cost, wait time, availability of charging stations, driver preferences, route distance, and traffic conditions. The accuracy of predictions is improved by considering a variety of environmental parameters, such as the energy system demand and temperature.

Data Preprocessing

Preprocessing is implemented to enhance the consistency and quality of the acquired data. Duplicate and unnecessary entries are eliminated, and mean and median imputation methods are implemented to address missing data. Min-max scaling is implemented to guarantee uniformity among variables and to normalize numerical attributes. For instance, categorical data such as the varieties of charging stations and the preferences of drivers can be rendered machine-readable through the use of one-hot encoding and label encoding.

Feature Selection and Engineering

Feature engineering is a potent instrument for pinpointing the most critical attributes that influence the efficacy of charging and the enjoyment of the driver. You should consider factors such as the duration of the battery, the frequency with which it must be recharged, the capacity of the charging stations, the cost of energy, the duration of the delay, and the time of day at which you prefer to charge. Principal component analysis (PCA) and correlation analysis are employed to enhance model performance while simultaneously minimizing complexity. Additionally, data such as the estimated delay length and the anticipated charging completion time are generated.

Machine Learning Model Development

The most effective model for refining electric vehicle charging systems is identified through the comparison and contrast of numerous machine learning algorithms. Driver satisfaction and charge demand can be predicted through the implementation of supervised learning models, including Random Forest, Decision Tree, Support Vector Machine (SVM), and Gradient Boosting. Deep learning algorithms, such as ANN and LSTM networks, can be employed to forecast energy consumption and charging behaviors.

Charging Optimization Framework

A smart framework for optimizing charges has been devised with the assistance of reinforcement learning (RL) and predictive analytics. The framework dynamically assigns charging places based on user preferences, grid circumstances, and battery capacity. The system ensures that the grid is not overloaded by balancing energy distribution and promoting rapid recharge during periods of low demand. The optimization system considers metrics such as cost-effectiveness, reduced wait times, and simple charging as factors that contribute to driver satisfaction.

Model Training and Testing

A smart framework for optimizing charges has been devised with the assistance of reinforcement learning (RL) and predictive analytics. The framework dynamically assigns charging places based on user preferences, grid circumstances, and battery capacity. The system ensures that the grid is not overloaded by balancing energy distribution and promoting rapid

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recharge during periods of low demand. The optimization system considers metrics such as cost-effectiveness, reduced wait times, and simple charging as factors that contribute to driver satisfaction.

Performance Evaluation Metrics

A diverse array of statistical and classification metrics are employed to assess machine learning models. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are employed to evaluate regression models. The driver satisfaction prediction system's precision, recall, accuracy, and F1-score are evaluated. Charging efficiency is demonstrated by the reduction of operational expenses, the enhancement of energy consumption efficiency, and the reduction of charging times.

Simulation and Comparative Analysis

We employ EV charging scenarios that encompass varying grid load conditions, charging demands, and traffic densities to evaluate the system. In order to assess the efficacy and customer satisfaction enhancements of the proposed ML-based charging framework, it is contrasted with conventional charge management systems. The advantages of intelligent charging strategies in real-time scenarios are revealed through comparative analysis.

Ethical Considerations and Data Security

We employ EV charging scenarios that encompass varying grid load conditions, charging demands, and traffic densities to evaluate the system. In order to assess the efficacy and customer satisfaction enhancements of the proposed ML-based charging framework, it is contrasted with conventional charge management systems. The advantages of intelligent charging strategies in real-time scenarios are revealed through comparative analysis.

4. RESULTS AND PERFORMANCE EVALUATION

The proposed system is assessed using a variety of metrics, including driver satisfaction, reduced charge costs, accurate energy forecasts, and training time efficiency. We conduct a comparison between the model and two industry standards: regression-based methods and rule-based scheduling.

Table 1: Accuracy Comparison of Models

Model Type	Energy Prediction Accuracy (%)	Charging Decision Accuracy (%)
Rule-Based System	72.5	70.2
Linear Regression Model	81.3	78.6
Random Forest Model	88.7	86.4
Proposed ML + Reinforcement Model	94.8	92.9

In this table, a number of models are evaluated based on their ability to accurately predict energy requirements and charging alternatives. The ML + Reinforcement Learning model that has been recommended outperforms all others as a result of its capacity to learn from both current input and past data. The primary cause of the subpar performance of conventional rule-based systems is their rigidity. Ultimately, the precision of forecasts is significantly improved by powerful machine learning algorithms.

Table 2: Charging Cost Optimization Comparison

Method	Average Cost per Charge (₹)	Cost Reduction (%)
Traditional Scheduling	120	0%
Time-Based Pricing Strategy	105	12.5%
ML-Based Prediction Model	92	23.3%
Proposed Hybrid Model	78	35.0%

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In this table, you will observe how a variety of strategies reduce the cost of charging for EV purchasers. The proposed hybrid method achieves the greatest cost savings by using caution when invoicing during periods of reduced tariffs. Inadequate cost optimization in rule-based systems results in increased expenditures. Machine learning-based technology can be employed to optimize energy consumption patterns, resulting in increased financial efficiency.

Table 3: Driver Satisfaction Analysis

Model Type	Waiting Time (mins)	Satisfaction Score (1–10)
Rule-Based System	28	6.2
Regression Model	20	7.1
Reinforcement Learning Model	14	8.3
Proposed Hybrid Model	9	9.1

This table assesses user contentment by considering the overall charging experience and the waiting time. The most efficient scheduling and shorter wait periods of the proposed approach have resulted in the highest satisfaction rating. Conventional methods yield lower satisfaction and longer wait times. The user experience is improved by reinforcement learning's capacity to accommodate the distinctive preferences of each driver.

Table 4: Training and Computation Time Comparison

Model Type	Training Time (mins)	Prediction Time (ms)
Linear Regression	5	12
Random Forest	18	25
Deep Learning Model (DNN)	42	30
Proposed Hybrid Model	35	18

The time required to train and predict each model is compared in the table below. The hybrid model that is recommended requires slightly more time to train than complex deep learning models; however, it generates predictions at a faster pace. Deep learning models are computationally expensive and slow, in contrast to linear regression, which is rapid but inaccurate. The proposed solution satisfies both efficiency and performance requirements.

5. CONCLUSION

This paper introduces a machine learning-based framework for balancing the efficiency of EV charging and the enjoyment of drivers by taking into account critical factors such as battery state-of-charge, charging duration, station availability, and User preferences. The findings indicate that the user experience can be significantly improved, energy efficiency can be increased, and wait periods can be significantly reduced without compromising grid stability through the implementation of efficient charging methods. The proposed model enables data-driven and adaptive charging decisions that achieve a balance between operational efficiency and user convenience, thereby paving the way for smart transportation systems. Smart charging station scheduling, reduced charging station traffic, and simplified integration of renewable energy sources into urban energy management platforms, ride-sharing EV networks, fleet management systems, and smart charging stations are among the beneficial applications of this technology. Future research can focus on the following areas: personalizing driver behavior prediction, expanding multimodal data inputs such as weather and traffic conditions, incorporating real-time reinforcement learning models, and testing large-scale deployment in a variety of geographic regions. These initiatives are intended to

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enhance the system's scalability and robustness.

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