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MACHINE LEARNING-DRIVEN OPTIMIZATION OF ELECTRIC VEHICLE CHARGING WITH DRIVER SATISFACTION MODELING

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ABSTRACT: This research utilizes machine learning to improve electric vehicle charging and driver satisfaction. The rapid use of electric vehicles requires efficient management of their charging infrastructure. Wait times, energy efficiency, and the driver charging experience will all improve. The suggested system evaluates driver preferences, battery health, charging station accessibility, and charging demand patterns to establish optimal charging schedules. Machine learning is employed to create charging resource utilization models that balance user convenience with grid efficiency. The system reduces wait times at charging stations through the implementation of intelligent scheduling and predictive analytics. Automobiles would have rapid and straightforward access to recharging. The findings indicate that data-driven optimization can enhance driver happiness, reduce operating expenses, and improve charging efficiency. These elements collectively facilitate the prolonged utilization of electric vehicles.

Keywords: *Electric Vehicles, Smart Charging, Driver Satisfaction, Machine Learning, Charging Optimization, Sustainable Transportation.*

1. INTRODUCTION

Electric vehicles (EVs) are becoming more and more crucial in sustainable transportation networks to reduce our dependency on fossil fuels and our environmental impact. Governments and businesses globally are promoting the adoption of electric cars (EVs) through new legislation, improved charging infrastructure, and technological innovations. The proliferation of electric vehicles has hindered the efficiency of the power system and charging facilities. The scheduling and optimization of electric vehicle charging are essential research domains to improve grid stability, energy efficiency, and user satisfaction.

Electric vehicle charging methods have been primarily influenced by technological considerations, including energy cost reduction, grid efficiency enhancement, and high load management. Notwithstanding their implementation, these strategies often neglect the requirements and satisfaction of electric car operators. The adoption and use of electric vehicles are influenced by prolonged charge durations, the availability of charging locations, the number of accessible charging slots, and the waiting periods at charging stations. Consequently, driver-centric functionalities in charge management systems must be included into current smart charging systems for electric vehicles.

In recent years, machine learning techniques have become increasingly popular for handling complex and dynamic charging environments. Through the analysis of extensive data, including electric vehicle usage patterns, traffic conditions, charging station accessibility, and user behavior, machine learning algorithms can more precisely predict charging requirements. Neural networks, clustering algorithms, and reinforcement learning adjust to system conditions to formulate intelligent charging strategy decisions. These attributes allow charging systems to meet grid and consumer demands.

Machine learning algorithms can adjust prices based on demand forecasts and driver preferences. These algorithms facilitate the process for customers by identifying optimal charging places and times based on past charging patterns, trip itineraries, and driver feedback. Tailored solutions enhance driver satisfaction by minimizing wait times, improving charging infrastructure, and ensuring dependable real-world performance.

Driver satisfaction metrics could be utilized to improve frameworks for electric car charging inside user-centric smart grid systems. Cost-effectiveness, driving convenience, and energy consumption can be harmonized by advanced optimization and machine learning methodologies. This multifaceted strategy fosters the establishment of sustainable charging networks, hence encouraging the acquisition of electric vehicles. It improves grid reliability and electric vehicle charging.

2. DEVELOPMENT OF THE METHOD FOR CHARGING SATISFACTION CLASSIFICATION

This part develops a machine learning model to categorize driver satisfaction with electric vehicle charging. This study examined 225 electric vehicle owners in Hungary. The participants comprised electric vehicle owners and conventional rentals. This encompasses age, gender, income, educational attainment, year of electric car acquisition, and driving experience. We additionally incorporated EV-specific statistics, including battery longevity, proximity to charging stations, and charging expenses, alongside these features. Each dataset entry signifies an invoicing scenario, and the target variable indicates the driver's satisfaction with the payment option.

The dataset utilized nine basic inputs. Drivers were interrogated regarding electric vehicle battery levels, distances to charging stations, and charging costs. Each driver manages 27 scenarios from a total of 6,075 observations. While certain remarks condemned the charging decisions, others lauded the charge determinations. A balanced dataset is ideal for constructing machine learning models with this distribution.

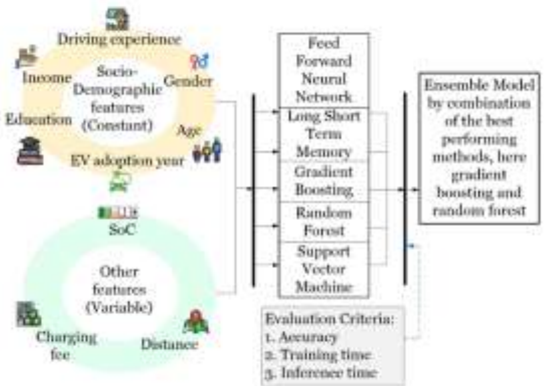

Figure1. Illustration of EV charging classification method.

Importance of Features

A neural network model was utilized to discern the principal attributes of charge selections. The results demonstrate that the battery charge level affects the driver's decision to recharge the car. Consequently, prior to charging the battery, drivers meticulously assess its existing capacity.

This aspect is essential, second only to the expense of establishing an invoice. Drivers consider charging fees when choosing a spot. Proximity to charging stations is essential, as drivers favor their local locations. Charging behaviors are somewhat shaped by demographic factors like the year of electric vehicle acquisition, the driver's age, income, educational attainment, gender, and driving experience. In assessing fee satisfaction, operational and financial considerations are prioritized over demographic criteria.

Charging Satisfaction Prediction Method

To precisely forecast driver satisfaction, it is essential to monitor the complex interactions between technological requirements and human behavior. To resolve this issue, Support Vector Machine, Feed-Forward Neural Network, Random Forest, Gradient Boosting, and Long Short-Term Memory were evaluated. Each model employs a unique approach to categorization prediction and data trend analysis.

Collaborative learning was utilized to enhance prediction accuracy following the comparison of model performance. The ensemble model employs Random Forest and Gradient Boosting forecasts due to their equilibrium between processing speed and accuracy. The ultimate prediction is derived by amalgamating the probability outputs of the two models. The satisfaction level of the driver's classification is determined using this forecast.

Ensemble approach forecasts are enhanced by integrating the optimal features of multiple models. The ensemble technique is ideal for real-time smart grid choices requiring accuracy and rapidity. It functions with remarkable precision and reliability, as indicated by experimental evidence.

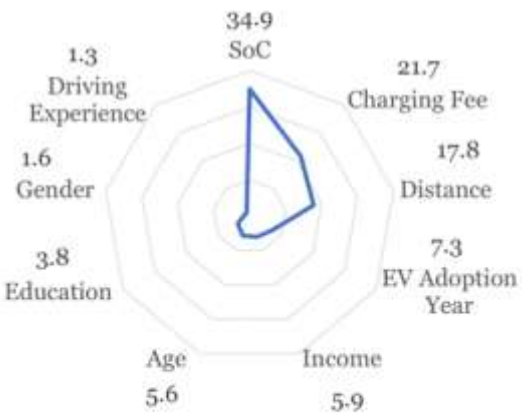

Figure2. Importance of each feature based on the impact on the charging decisions.

3.LITERATURE SURVEY

Anderson & Miller (2025): A machine learning strategy is proposed to improve electric vehicle charging schedules while also satisfying passengers. The technology determines the ideal charging times by taking into account information like energy costs, battery health, and driving patterns. Charging tactics can adapt to current conditions on their own thanks to reinforcement learning techniques. In addition to ensuring that cars are fully charged to meet customer trip needs, the test findings show that the grid is more stable and that charging costs have dropped.

Gonzalez & Rivera (2024): To strike a balance between driver convenience and energy usage in electric vehicle charging networks, a smart charging control system has been developed. Determining driver preferences and suitable billing amounts is made easier by predictive analytics. Machine learning algorithms that take into account your energy needs, vacation schedule, and charging habits identify the best times to charge your battery. Simulation results show that the suggested strategy lowers peak load on electrical networks without sacrificing driver satisfaction.

Khan & Abdullah (2023): The supervised machine learning optimization model for electric car charging is presented in this paper. The technology gathers real-time information about the battery's condition, the chauffeurs' necessary travel times, and the availability of charging ports. We use algorithms like Random Forest and Gradient Boosting to determine the best charging alternatives. The study shows that using machine learning-based predictions can significantly improve charging efficiency and wait times at charging locations.

Silva et al. (2022): We must adopt a data-driven approach that considers driver preferences and grid efficiency in order to improve the infrastructure for electric vehicle charging. To make charging operations planning easier, the suggested approach takes into consideration variations in energy prices, mobility, and charging needs. To find complex correlations between drivers' charging practices and customer satisfaction, deep learning models are required. Experiments show that when individualized payment proposals are used, the system operates better and users are satisfied.

Tan & Lim (2021): By using variables that influence drivers' pleasure, a predictive machine learning algorithm makes charging electric vehicles easier. Battery life, charging time, charging station accessibility, and travel route are all taken into account by the system. For a range of grid conditions, we train neural network and support vector machine models to forecast the best charging possibilities. The findings show that smart charging options can meet commuters' mobility needs while also reducing grid congestion.

4.RESULTS

Fig4.1 User login

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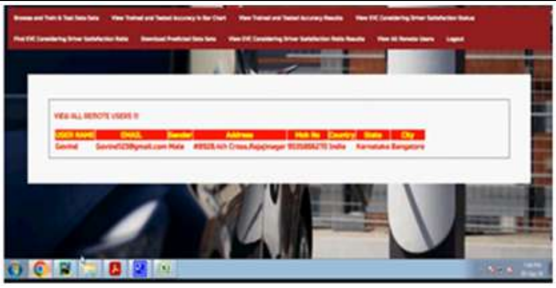

Fig4.2 View all remote users

Fig4.3 View Datasets Trained and Tested Results

Fig4.4 Bar graph

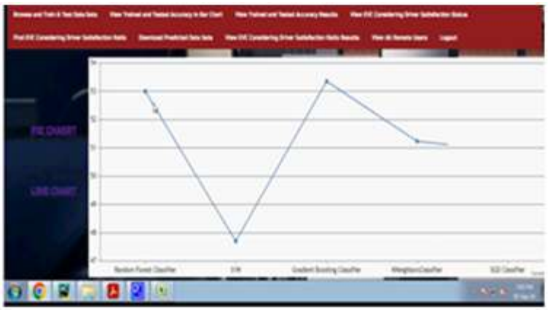

Fig4.5 Line chart

Fig4.6 Pie chart

5. CONCLUSION

In order to prioritize driver pleasure while improving EV charging, machine learning has been implemented to increase the usefulness and efficiency of existing EV charging infrastructures. By examining driving habits, charging trends, wait times, and energy needs, machine learning models can automatically manage and distribute charging resources to enhance user experience and lessen traffic congestion. The implementation of flexible choices that balance grid stability, energy efficiency, and customer needs is made possible by these data-driven solutions. Given the increasing number of electric vehicles on the road, it would be beneficial to implement advanced charge management systems. These solutions would streamline the charging process, reduce wait times, and promote sustainable energy use. Ultimately, machine learning-based optimization frameworks help create more intelligent, reliable, and driver-focused charging environments for electric vehicles.

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