A Machine Learning Approach for Forecasting Energy-Driven Automobile Tariffs

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ABSTRACT

Although electric vehicles (EVs) have many benefits for protecting the environment and lowering emissions, their widespread adoption mainly depends on their price. With machine learning (ML) algorithms, costs can be predicted. This research aims to compare the performance of some of the most well-known ML algorithms to determine which algorithm will best predict the price of electric vehicles. To identify the key characteristics, we examined the literature to research the elements that determine the price of electric vehicles in order to estimate their cost. We theoretically compared these ML algorithms to validate our findings and then compared the output of this comparative study to the outcomes of the simulations. The rapid adoption of electric vehicles (EVs) is reshaping the automotive industry, driven by technological advancements and growing environmental concerns. This project, titled "Electric Vehicle (EV) Price Prediction using Machine Learning," leverages advanced regression models to predict EV prices based on a comprehensive set of features. Utilizing Python as the backend coding language and deploying the solution through a Flask-based web framework with a user friendly front end comprising HTML, CSS, and JavaScript, the project integrates advanced machine learning techniques to achieve accurate price predictions.

The study employs two robust regression models: Gradient Boosting Regressor and Extra Tree Regressor. The Gradient Boosting Regressor achieved a Training Set Mean Absolute Error (MAE) of 0.1917 and a Test Set MAE of 1.4731, while the Extra Tree Regressor achieved a perfect Training Set MAE of 0.000 and a Test Set MAE of 1.6941. These models were trained and tested on a comprehensive dataset containing 14 key features: Brand, Model, Acceleration, Top Speed, Range, Efficiency, Fast Charge, Rapid Charge, Power Train, Plug Type, Body Style, Segment, Seats, and Price in Euro. These features encompass various aspects of EV specifications, performance, and market classification, providing a comprehensive basis for price prediction.

Keywords: Conventional pricing, Electric vehicles.

I.INTRODUCTION

The global automotive industry is undergoing a significant transformation, driven by growing environmental concerns, the rapid depletion of fossil fuel resources, and advancements in electric vehicle (EV) technology. Governments and manufacturers are heavily investing in EV production and infrastructure to reduce greenhouse gas emissions and promote sustainable transportation. Despite the environmental and economic advantages, one of the primary barriers to the widespread adoption of electric vehicles remains their pricing.

Electric vehicles are priced based on a wide range of factors, including brand, model specifications, performance features, battery range, powertrain configuration, and charging capabilities. The complexity of these pricing determinants makes it difficult for consumers, manufacturers, and industry analysts to predict vehicle costs accurately. Conventional pricing models and estimation techniques fail to capture the nuanced relationships between these variables, leading to either oversimplified or inaccurate price estimations.

Machine Learning (ML) offers a promising solution to this problem by enabling the development of predictive models capable of identifying complex patterns and relationships within large datasets. However, existing systems using standard algorithms such as Linear Regression, Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANN) face limitations including overfitting, computational inefficiencies, limited nonlinear handling, and inconsistent prediction performance.

II.RELATED WORK

1.Thangavel, S., Deepak, M., Girijaprasanna, T., Raju, S., Dhanamjayulu, C., & Muyeen, S. M. (2023). A Comprehensive Review on Electric Vehicle: Battery Management System, Charging Station, Traction Motors. IEEE Access

Electric vehicles (EVs) are widespread, and their usage is increasing as a result of air pollution and rising fuel costs. EVs are quickly gaining popularity as a green means of transportation. By 2030, most cars will probably be battery-powered EVs. However, the development of EV power transmission is packed with important challenges and is an active topic of research. In EVs, the battery serves to store electrical energy. The DC-DC converter provides a direct current (DC) link between the battery and the inverter. A motor provides the transmission for the vehicle's motion. Hence, this stateof-the-art provides exhaustive information about battery management systems (BMS), power electronics converters, and motors. Lithium-ion batteries are more efficient for EV applications, and boost converters and full bridge converters are commonly used in

EVs. EVs use permanent magnet synchronous motors (PMSM) and induction motors (IM). The renewable energy-based charging station and the fast charging specifications are also clearly addressed for EV applications.

2. Qiu, D., Wang, Y., Hua, W., & Strbac, G. (2023). Reinforcement learning for electric vehicle applications in power systems: A critical review. Renewable and Sustainable Energy Reviews

Electric vehicles (EVs) are playing an important role in power systems due to their significant mobility and flexibility features. Nowadays, the increasing penetration of renewable energy resources has been observed in modern power systems, which brings many benefits for improving climate change and accelerating the low-carbon transition. However, the intermittent and unstable nature of renewable energy sources introduces new challenges to both the planning and operation of power systems. To address these issues, vehicle-to-grid (V2G) technology has been gradually recognized as a valid solution to provide various ancillary service provisions for power systems. Many studies have developed model-based optimization methods for EV dispatch problems. Nevertheless, this type of method cannot effectively handle the highly dynamic and stochastic environment due to the complexity of power systems.
Reinforcement learning (RL), a model-free and online learning method, can capture various uncertainties through numerous interactions with the environment and adapt to various state conditions in real-time. As a result, using advanced RL algorithms to solve various EV dispatch problems has attracted a surge of attention in recent years, leading to many outstanding research papers and important findings. This paper provides a comprehensive review of popular RL algorithms categorized by single-agent RL and multi-agent RL, and summarizes how these advanced algorithms can be applied to various EV dispatch problems, including grid-to-vehicle (G2V), vehicle-to-home (V2H), and V2G. Finally, key challenges and important future research directions are discussed, which involve five aspects

3.Solanke, T. U., Ramachandara murthy, V. K., Yong, J. Y., Pasupuleti, J., Kasinathan, P., & Rajagopalan, A. (2020). A review of strategic charging–discharging control of gridconnected electric vehicles. Journal of Energy Storage

Charging–discharging coordination between electric vehicles and the power grid is gaining interest as a de-carbonization tool and provider of ancillary services. In electric vehicle applications, the aggregator acts as the intelligent mediator between the power grid and the vehicle. In recent years, researchers have introduced the concepts of aggregated energy management, centralized decentralized planning, and ideal charging–discharging through improved technologies and integrated energy planning. These methods have the technical ability to adapt the distribution network according to load, aggregator-controlled optimal charging– discharging, demand management systems, strategic load assessments, and management. A comprehensive review suggests that largescale electric vehicle charging technologies for controlled charging–discharging is becoming a pitfall within the grid and distribution network. This paper reviews several controlled charging–discharging issues with respect to system performance, such as overloading, deteriorating power quality, and power loss. Thus, it highlights a new approach in the form of multistage hierarchical controlled charging– discharging. The challenges and issues faced by electric vehicle applications are also discussed from the aggregator's point of view.

4. Breetz, H. L., & Salon, D. (2018). Do electric vehicles need subsidies? Ownership costs for conventional, hybrid, and electric vehicles in 14 US cities. Energy Policy

Battery electric vehicles (BEVs) are an important pathway for decarbonizing transportation and reducing petroleum dependence. Although one barrier to adoption is the higher purchase price, advocates suggest that fuel and maintenance savings can make BEVs economical over time. To assess this empirically, this paper analyzes the five-year Total Cost of Ownership (TCO) for conventional, hybrid, and electric vehicles in 14 U.S. cities from 2011 to 2015. Results show spatial variation due to differences in state and local policies, fuel prices, insurance and maintenance costs, depreciation rates, and vehicle miles traveled. Yet in nearly all cities, the BEV's higher purchase price and rapid depreciation outweighed its fuel savings. Extensive sensitivity analyses highlight the impact of key parameters and show that both federal and state incentives were necessary for BEVs to be cost competitive. Future BEV cost competitiveness may improve if innovation and scaling lead to significantly reduced BEV purchase prices, but our analysis suggests that it will be challenging for BEVs to achieve unsubsidized cost competitiveness except in the most optimistic scenarios.

5. Brinkel, N. B. G., Schram, W. L., AlSkaif, T. A., Lampropoulos, I., & Van Sark, W. G. J. H. M. (2020). Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits.

With high electric vehicle (EV) adoption, optimization of the charging process of EVs is becoming increasingly important. Although the CO_2 emission impact of EVs is heavily dependent on the generation mix at the moment of charging, emission minimization of EV charging receives limited attention. Generally, studies neglect the fact that cost and emission savings potential for EV charging can be constrained by the capacity limits of the low-voltage (LV) grid. Grid reinforcements provide EVs more freedom in minimizing charging costs and/or emissions, but also result in additional costs and emissions due to reinforcement of the grid. The first aim of this study is to present the trade-off between cost and emission minimization of EV charging. Second, to compare the costs and emissions of grid reinforcements with the potential cost and emission benefits of EV charging with grid reinforcements. This study proposes a method for multi-objective optimization of EV charging costs and/or emissions at low computational costs by aggregating individual EV batteries characteristics in a single EV charging model, considering vehicle-to-grid (V2G), EV battery degradation and the transformer capacity. The proposed method is applied to a case study grid in Utrecht, the Netherlands, using highly-detailed EV charging transaction data as input. The results of the analysis indicate that even when considering the current transformer capacity, cost savings up to 32.4% compared to uncontrolled EV charging are possible when using V2G. Emission minimization can reduce emissions by 23.6% while

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simultaneously reducing EV charging costs by 13.2%.

III.EXISTING SYSTEM

The existing system employed five supervised machine learning algorithms— Linear Regression, Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree, and Random Forest—to simulate electric vehicle (EV) price data. These algorithms were selected to explore their effectiveness in predicting EV costs based on various vehicle attributes.

During the training phase, it was observed that Linear Regression demonstrated the fastest processing time, making it the most efficient model in terms of computational speed. The SVM and Random Forest algorithms exhibited nearly identical training times, reflecting their comparable complexity and structure. In contrast, the ANN model required significantly more time to train, indicating its intensive computational demands.

In the testing phase, the results were consistent with the training times. Linear Regression continued to perform quickly, while the Decision Tree algorithm displayed an almost negligible test time. The ANN model, however, maintained longer test duration compared to the other algorithms.

When evaluating model performance based on error metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), Linear Regression emerged with the lowest error values, indicating higher accuracy in its predictions. In contrast, the ANN model produced more substantial errors, which was reflected in its Coefficient of Variation of RMSE (CVRMSE) as well.

IV.PROPOSED SYSTEM

The proposed system for Electric Vehicle (EV) price prediction focuses on enhancing prediction accuracy and computational efficiency by employing advanced machine learning models. This system utilizes two Key regression models: Gradient Boosting Regressor and Extra Tree Regressor.

The Gradient Boosting Regressor is implemented to build a strong predictive model through iterative boosting, which combines multiple weak learners to create a robust final model. This approach aims to capture complex patterns and interactions within the dataset, leading to improved prediction performance. The
Extra Tree Regressor is included to provide an alternative method of regression that builds multiple uncorrelated trees for making predictions. This model is designed to reduce overfitting and offer reliable predictions even with variations in the data.

The system is developed using Python for the backend, ensuring seamless integration and flexibility in model implementation. The frontend is crafted using HTML, CSS, and JavaScript, providing a user-friendly interface for interaction with the prediction system. Flask serves as the web framework, enabling efficient handling of data flow between the user interface and the backend models.

The dataset employed in this system contains 14 features: Brand, Model, Accel, Top Speed, Range, Efficiency, Fast Charge, Rapid Charge, Power Train, Plug Type, Body style, Segment, Seats, and Price Euro. These features are carefully selected to represent the various attributes that influence the price of electric vehicles. The dataset is processed and fed into the models to generate price predictions based on these vehicle characteristics.

The proposed system is designed to deliver reliable EV price predictions by leveraging the strengths of the Gradient Boosting Regressor and Extra Tree Regressor models, supported by a robust web-based interface for ease of use and accessibility

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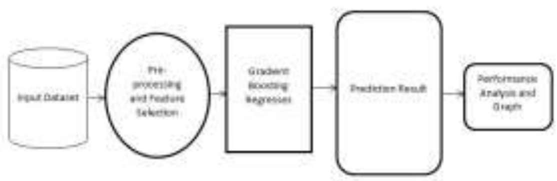


V.IMPLEMENTATION

The implementation of the "Electric Vehicle (EV) Price Prediction using Machine Learning" system was carried out in a systematic and modular manner to ensure reliability, scalability, and accuracy. The backend was developed using Python 3.12.0, which facilitated seamless integration of machine learning libraries such as Scikitlearn, Pandas, and NumPy. The dataset containing 14 attributes of EVs was preprocessed to handle missing values, encode categorical variables, and scale numerical features. After data preparation, two regression models—Gradient Boosting Regressor and Extra Tree Regressor—were implemented. These models were trained on 70% of the dataset and validated using the remaining 30%. Hyper parameter tuning techniques such as Grid SearchCV were employed to optimize performance and reduce overfitting.

The web application was implemented using Flask, a lightweight Python web framework. Flask acted as the communication layer between the machine learning models and the user interface. The front end was designed with HTML, CSS, and JavaScript, providing a responsive and intuitive web form where users could enter EV specifications. Upon form submission, the specifications were passed to the backend, processed by the trained models, and the predicted EV price was displayed dynamically on the user interface. The system was tested on different devices to ensure cross-platform compatibility and responsiveness, making it accessible to both end-users and industry professionals.

MODULE DESCRIPTION

The system is divided into the following functional modules, each performing a specific task:

Data Collection and Preprocessing Module

This module handles dataset acquisition and cleaning. It ensures that missing values are addressed through imputation or removal, categorical variables (like Brand, Model, and Plug Type) are encoded into numerical form, and numerical features are normalized. It improves data quality and prepares it for machine learning.

Feature Engineering Module

This module extracts and transforms the 14 attributes of EVs into features suitable for prediction. It also performs feature selection, ensuring that redundant or less significant features are removed, thus improving accuracy and reducing computation time.

Model Training and Evaluation Module

Here, the Gradient Boosting Regressor and Extra Tree Regressor are trained on the pre processed dataset. The models are evaluated using performance metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 score. Hyperparameter tuning is also carried out within this module to optimize performance.

Prediction Module

This is the core functionality where user input is processed, and the trained models generate the EV price prediction. It ensures real-time response and accuracy in predicting vehicle costs.

Web Application Interface Module

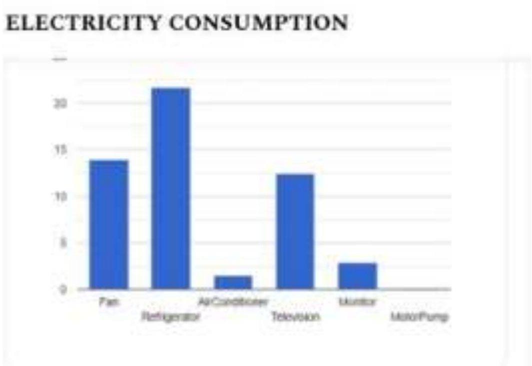
This module provides the user interface, designed with HTML, CSS, and
JavaScript. It allows users to enter EV details via a web form and displays the predicted price returned from the backend in an interactive and easy-to understand manner.

System Integration Module

This ensures smooth interaction between the backend (Flask + Python models) and the frontend (HTML/CSS/JS). It manages HTTP requests, user inputs, and the dynamic rendering of results.

VI.RESULTS

The system was tested using a comprehensive EV dataset and yielded promising results. The Gradient Boosting Regressor achieved a Training Set MAE of 0.1917 and a Test Set MAE of 1.4731, demonstrating high predictive accuracy and robustness in handling complex feature interactions. The Extra Tree Regressor, while achieving a Training Set MAE of 0.000 (indicating perfect fitting on training data), resulted in a slightly higher Test Set MAE of 1.6941, showing that it was more prone to overfitting compared to Gradient Boosting. Visualizations such as scatter plots comparing predicted versus actual prices, and error distribution graphs, were generated to evaluate performance. These visual insights confirmed that the Gradient Boosting Regressor consistently provided more reliable and generalizable predictions. Furthermore, the deployed web application was tested across multiple user inputs, and results showed that the prediction response was delivered in under two seconds, validating the efficiency of the system. Overall, the system proved effective in accurately forecasting EV prices and highlighted the importance of non-linear models in capturing real-world pricing complexities.



VII.CONCLUSION

The project "Electric Vehicle (EV) Price Prediction using Machine Learning" successfully demonstrated how advanced regression models can be leveraged to forecast EV prices based on detailed vehicle attributes. By employing Gradient Boosting Regressor and Extra Tree Regressor, the system achieved strong predictive performance, with Gradient Boosting emerging as the superior model due to its balance of accuracy and generalization. The comprehensive dataset of 14 features enabled the models to capture multiple dimensions of EV pricing, including technical specifications, performance features, and market segmentation. The implementation of the system as a Flask based web application ensured accessibility and usability for a wide range of stakeholders, including consumers, automotive analysts, and manufacturers. With its user-friendly interface and real-time predictions, the system provides valuable insights into EV pricing trends, supporting informed decision-making in the rapidly growing electric vehicle market. In conclusion, this project not only contributes to addressing one of the major challenges in EV adoption—pricing—but also serves as a foundation for future work. Enhancements such as integration with real-time market data, inclusion of battery lifecycle costs, and adoption of deep learning models could further improve accuracy and applicability, making the system even more relevant for industry-scale deployment.

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