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Predictive Analysis of Electric Vehicle Performance Parameters Using Random Forest Regression: A Comprehensive Study of Battery Capacity, Range, Charging Time, And Maximum Speed

Vijesh Malappurath Paramadam
Application Architect.
Vijesh.Paramadam@gmail.com

Abstract
This study presents a comprehensive analysis of electric vehicle (EV) technology, focusing on heavy-duty electric automobiles weighing more over 10,000 pounds gross vehicle weight. The research examines advanced electric powertrains with dual electric drive units for the front and rear axles, each incorporating electric motors, controllers, two-speed gearboxes, and locking differentials. The “high-torque avoidance control” system is highlighted, which dynamically adjusts transmission gear ratios to optimize motor rotation speed and maintain vehicle efficiency, while avoiding inefficient operating regions characterized by PWM over-modulation control. The study evaluates critical performance parameters including battery capacity (kWh), driving range (km), charging time (hrs), and maximum speed (kmph) across various EV configurations. The research addresses the evolution from traditional internal combustion engines to sustainable electric alternatives driven by environmental concerns, petroleum resource limitations, and rising fuel costs. Extended-range electric vehicles (EREVs) have been identified as promising solutions to address battery electric vehicle limitations. This method uses random forest regression for predictive modelling, using ensemble learning to analyse complex, nonlinear relationships between vehicle parameters. This approach provides robust predictions while managing high-dimensional datasets and reveals feature importance, making it particularly suitable for vehicle performance analysis and optimization of electric vehicle systems.

Keywords: Battery electric vehicle (BEV), electric vehicle (EV), Surge avoidance control, Random Forest regression, Electric powertrain, Battery capacity, Charging time, extended range electric vehicle (EREV), Motor control system.

1. Introduction

This study presents an electric automobile rated for gross vehicle weights exceeding 10,000 pounds. The car is equipped with an electric powertrain positioned under the frame and aligned with the central front axle, with the remaining drivetrain components located above the base of the powertrain. It includes two electric drive units, one for the front axle and one for the rear, each consisting Comprising a motor controller, an electric motor, a two-speed gearbox, a parking lock, and a locking differential. Power is supplied to internally mounted brakes connected to the wheel hubs by constant velocity driveshafts, where final gear reduction takes place. The vehicle also features a hydraulically adjustable suspension system that enables automatic levelling and ride height control. This configuration supports a variety of operating modes, including external power export. It is offered in SUV and pickup truck models, with two- or four-door options, all built on a shared powertrain and chassis platform [1]. This document outlines an electric vehicle system consisting of a motor, an inverter, and a transmission. The inverter is designed to power the motor with electrical energy from the battery, while the transmission adjusts the rotational output of the motor using a variable gear ratio. The central controller oversees both the motor control via the inverter and the gear ratio adjustment in the transmission. A unique feature of this system is its “high-surge avoidance control”, which modifies the transmission gear ratio to regulate the motor rotation speed, maintain vehicle speed, and move the operating point away from the high-surge region. This region is characterized by specific motor speed and torque conditions, where the inverter operates under PWM over modulation control [2]. This paper, published on June 27, 2019, discusses the electric vehicle and its control system, emphasizing advances in electric vehicle technology and control strategies. The primary components of the vehicle include a propulsion motor, a transmission system, and a battery. To power the motor, an inverter transforms the battery's direct current (DC) into alternating current (AC), with a capacitor connected to the input terminals of the inverter. A controller developed to change the gear position of the transmission is highlighted as a key innovation. Gear shifting is specifically triggered when two conditions are met: the motor's rotational speed is within a defined range, and its output exceeds a certain limit. This control strategy aims to enhance the vehicle's overall performance and efficiency [3]. This document outlines an innovative electric vehicle design with a modular support system. The vehicle frame consists of a central block and separate front and rear frame blocks, all constructed using a lattice-style construction. The structure includes two upper and two lower vertical longitudinal beams, which are connected by cross members for additional stability. The front block is specifically designed to house the entire front suspension system, including the wheel supports and swing arms. It also includes a front electric motor assembly consisting of two symmetrically spaced electric motors oriented with their axes perpendicular to the vehicle's longitudinal axis. In addition, two central gear reduction units are included, which transmit power to the wheel hubs via drive shafts [4]. Over the past decade, advances in battery technology, combined with increasing public and stakeholder interest in sustainable transportation, have led to performance improvements in electric vehicles that run on batteries (BEVs). But EREVs, or extended-range electric cars have become a viable substitute to alleviate some of the drawbacks related to with BEVs [5]. Since the rise of reliable and rapidly advancing internal combustion engine (ICE) technology, the share of electric vehicles in road transport has declined significantly. However, growing concerns about environmental pollution, limited petroleum resources, rising fuel prices, and the pursuit of energy independence have renewed interest in electric vehicles as a potential alternative mode of transport [6]. Through analysis and comparison of more than 75 market and technology-specific parameters for each vehicle, the study identifies current developments and emerging trends in hybrid and battery electric vehicle technologies. The findings highlight key patterns in the development of these vehicles, focusing on design stages, vehicle types and powertrain configurations [7]. The task force also chose to serve as an initial platform to address the diverse perspectives and interests of stakeholders in the hybrid electric vehicle (HEV) sector. The group aimed to explore potential strategies and partnerships to support the development, commercialization, and infrastructure needed for hybrid propulsion systems and vehicle alternatives. Ultimately, its efforts aimed to enhance public and private awareness and, where appropriate, promote all aspects of HEV system advancement [8]. Using our estimated demand model, we conducted counterfactual simulations that yielded three important insights. First, electric vehicles tend to replace relatively fuel-efficient conventional cars because households that switch to EVs also prefer gasoline vehicles with higher fuel efficiency. This implies that emissions benefit estimates should consider balanced substitution patterns among conventional vehicles [9].

2. Materials and methods

Measured in kilowatt-hours, battery capacity (kWh) is the quantity of electrical energy that a battery can store and provide. It refers to how much energy the battery can deliver over time, for example, a 60 kWh battery can deliver 60 kilowatts of electricity per hour. In electric vehicles, higher battery capacity generally means longer driving range. It is a key factor in determining performance, range, and energy efficiency. Range (km) refers to the farthest distance, expressed in kilometres that an electric vehicle (EV) can cover on a single full charge. It depending on elements including vehicle performance, driving circumstances, topography, battery capacity, and speed. A higher range means more travel without the need for frequent recharging. Range is an important performance metric for EVs, influencing consumer choice and overall usability for daily commuting or long-distance travel. Charging time (hours) refers to the total amount of time required to recharge an electric vehicle (EV) battery from a depleted state to full capacity, measured in hours. This time varies depending on factors such as battery size, state of charge, charger type (Stage 1, Stage 2, or DC fast charging), and power output. Fast charging options reduce downtime and improve convenience, making charging time a key factor in EV usage and adoption. Top speed (kmph) refers to the maximum speed an electric vehicle (EV) can achieve under optimal conditions, measured in kilometres per hour (kmph). It is determined by factors such as motor power, aerodynamics, drivetrain design, and weight. While top speed is not always a primary concern for EV buyers, it is an important performance indicator, especially for high-performance models or for highway driving. Manufacturers often limit top speed electronically for safety and efficiency.

Random Forest Regression: An ensemble learning technique is called random forest regression designed to predict continuous values. Using randomly chosen subsets of the data and features, it constructs several decision trees and then aggregates their results by averaging the results. This method lowers the possibility of over fitting and enhances the generalizability of the model. The randomness between trees introduces heterogeneity, which leads to more reliable and accurate predictions than a single tree. Random forest regression is well suited to capturing complex, nonlinear relationships and managing high-dimensional datasets. It is resilient to noise and outliers and offers insightful information about the significance of features, revealing the most influential variables. Its reliability, flexibility, and high accuracy make it a popular choice for predictive modelling in fields such as finance, healthcare, and engineering.

3. Results and discussions

This dataset provides specifications for a variety of electric vehicles, highlighting four key performance metrics: battery capacity, range, charging time, and top speed. Battery capacities range from 30.4kWh to 99.1kWh, which directly impacts driving range, which varies from 182km to 629km. charging the durations vary from 1.74 hours to 7.47 hours at most, depending on battery size and charger type. Top speeds range from 120kmph to 195kmph, reflecting performance differences across models. The data shows how larger battery capacities generally correlate with greater range and faster top speeds, while more efficient models offer a balance between performance and charging efficiency.

Table.1. Descriptive Statistics

	Battery Capacity (kWh)	Range (km)	Charging Time (hr)	Top Speed (kmph)
count	100.0000	100.0000	100.0000	100.0000
mean	62.9180	377.1800	4.7568	153.0600
std	20.8272	125.7593	1.7353	21.1573
min	30.4000	182.0000	1.7400	120.0000
25%	43.5000	270.2500	3.2375	134.7500
50%	62.5000	378.5000	4.7900	153.0000
75%	81.1250	489.2500	6.3775	170.0000
max	99.1000	629.0000	7.4700	195.0000

Table 1 provides descriptive statistics for 100 electric vehicles based on four key parameters. The average battery capacity is 62.92kWh, the average driving range is 377.18km, the average charging time is 4.76 hours and the maximum speed is 153.06kmph. The data shows significant variation, as indicated by the standard deviations, especially in the range (125.76km). Battery capacities range from 30.4 to 99.1kWh, and the range is from 182 to 629km. charging times vary widely, from 1.74 to 7.47 hours. The maximum speed drops from 120 to 195kmph. Overall, the dataset reflects a wide range of EV performance capabilities.

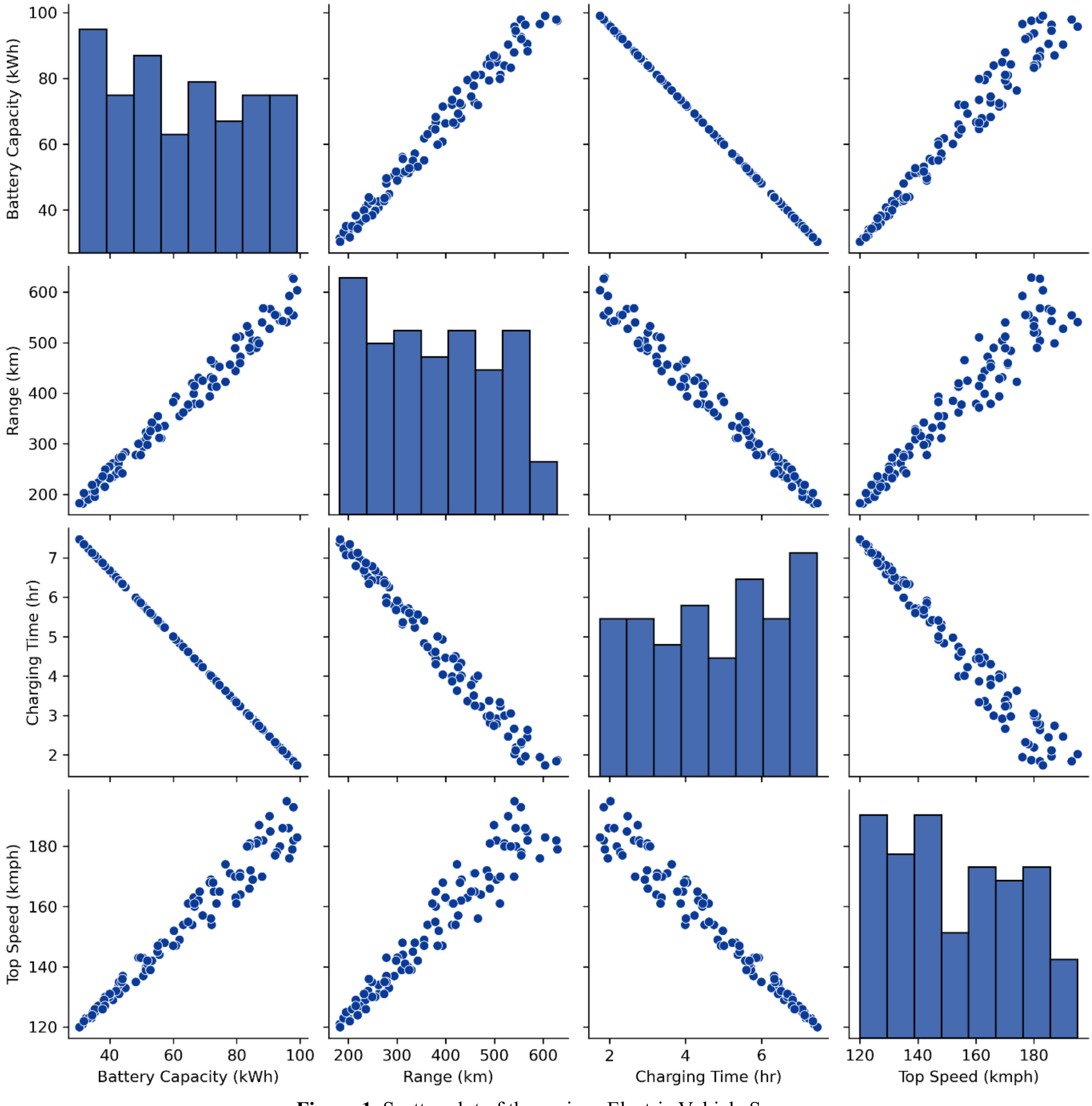

Figure.1. Scatter plot of the various Electric Vehicle Specs

Figure 1 presents a scatterplot matrix that visualizes the relationships between various electric vehicle (EV) specifications, including battery capacity, range, charging time, and top speed. Strong positive correlations are evident between battery capacity and range, and between range and top speed. In contrast, charging time shows a strong negative correlation with these variables.

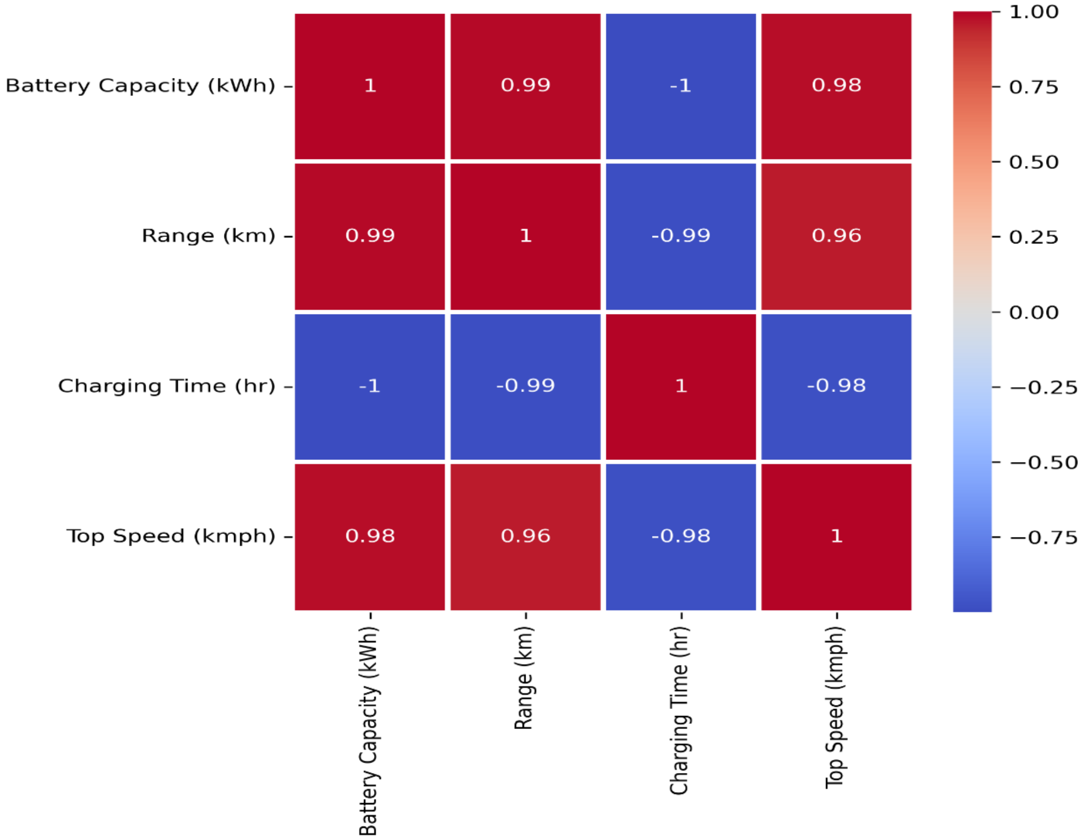

Figure.2. Heat map of the connection between process variables and outcomes

Figure 2 shows a heat map illustrating the relationship between electric vehicle parameters. Battery capacity, range, and maximum speed show strong positive correlations with each other, while charging time is highly negatively correlated with all three. These relationships highlight the trade-offs and interdependencies among key EV performance characteristics.

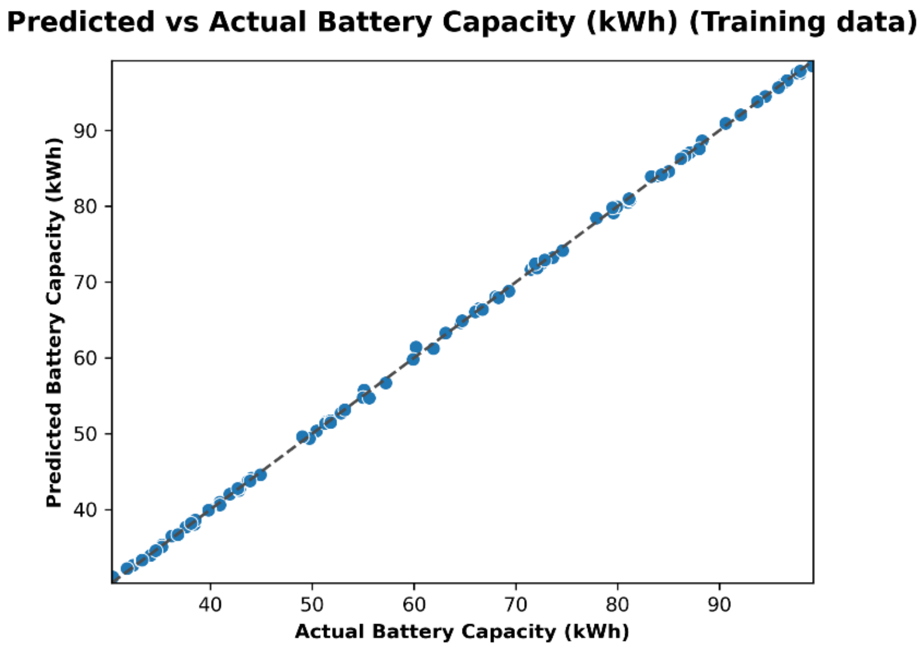

Figure.3. Random Forest Regression on Battery Capacity (kWh): training data

Figure 3 illustrates the performance of the random forest regression model in predicting battery capacity (kWh) using the training dataset. The almost perfect alignment of the data points on the diagonal line indicates high prediction accuracy, demonstrating the model's strong ability to capture the underlying relationship in the training data.

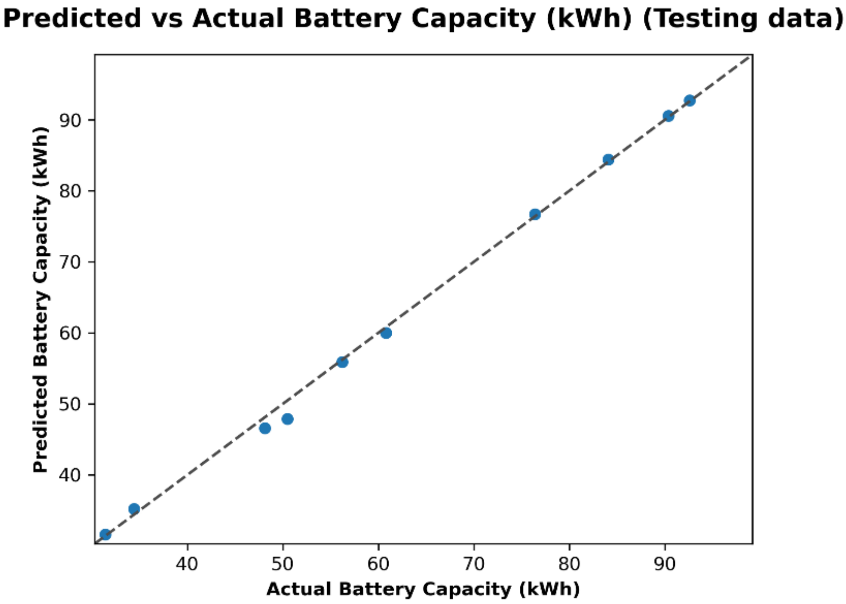

Figure.4. Random Forest Regression on Battery Capacity (kWh): testing data

Figure 4 presents the random forest regression results on the battery capacity (kWh) test data. The predicted values closely match the actual values on the diagonal, indicating good model generalization. This consistency demonstrates the reliability of the model in accurately predicting the unobserved data and confirms its strong predictive performance.

Table.2. Performance Metrics of Random Forest Regression on Battery Capacity (kWh) (Training Data and Testing Data)

Property	Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Battery Capacity (kWh)	Train	RFR	Random Forest Regression	0.99976	0.99976	0.10356	0.32181	0.23402	1.26450	0.00003	0.14950
	Test	RFR	Random Forest Regression	0.99763	0.99785	1.06518	1.03208	0.71770	2.60550	0.00044	0.32200

Table 2 summarizes the performance of the Random Forest Regression (RFR) model in predicting battery capacity (kWh) using both training and test data. The Excellent accuracy is demonstrated by the model, with an R2 value of 0.99976 in the training set and 0.99763 demonstrating high predictive power in the test set. Error metrics such as RMSE (0.32 train, 1.03 test) and MAE (0.23 train, 0.72 test) are low, showing minimum difference between the expected and actual numbers. The maximum error and mean absolute error are also within acceptable limits. Overall, the RFR model has been shown to be very reliable for estimating battery capacity.

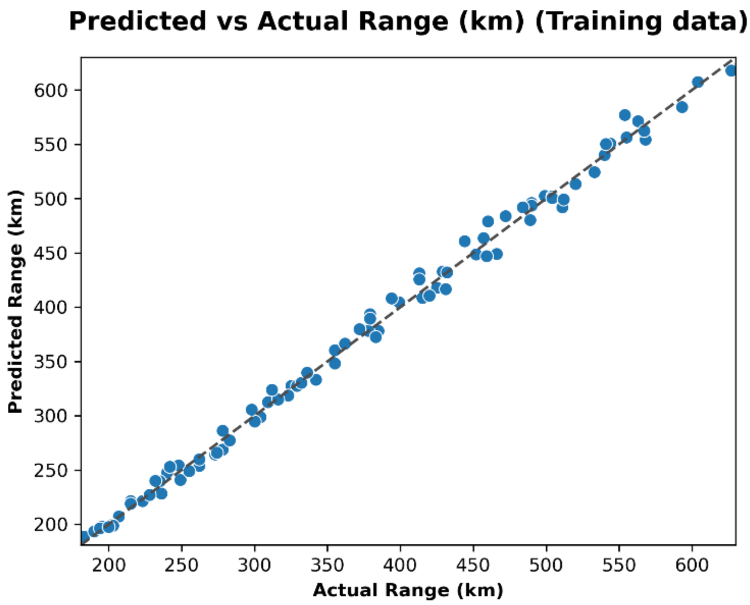

Figure.5. Random Forest Regression on Range (km): training data

Figure 5 shows the performance of the random forest regression model in predicting the range (km) of electric vehicles using training data. The close alignment of the actual and anticipated values on the diagonal indicates a strong model fit, indicating accurate learning of the relationship between features and vehicle range.

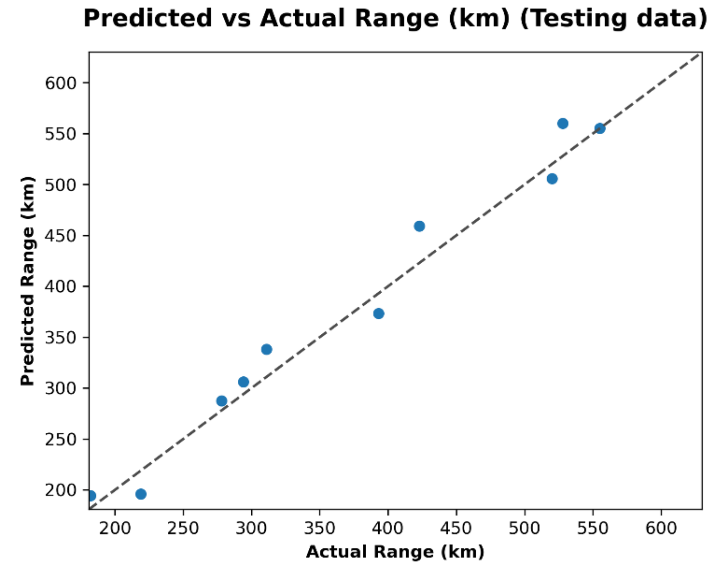

Figure.6. Random Forest Regression on Range (km): testing data

The outcomes of the random forest regression are displayed in Figure 6 for predicting EV range (km) using experimental data. Most of the Strong data points are found close to the diagonal line predictive performance. Although small deviations are observed, the model generalizes effectively to unobserved data, confirming its robustness and accuracy in estimating vehicle range.

Table.3. Performance Metrics of Random Forest Regression on Range (km) (Training Data and Testing Data)

Property	Data	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Range (km)	Train	0.99533	0.99534	72.84181	8.53474	7.07570	23.27000	0.00050	6.42500
	Test	0.97133	0.97470	461.24328	21.47658	18.72933	36.46500	0.00401	16.89250

Table 3 presents the performance metrics of the Random Forest Regression (RFR) technique to forecast an electric vehicle's range (kilometres). On the training data, the model performs exceptionally well with an R^2 of 0.99533 and a low RMSE of 8.53 km, indicating accurate predictions. The experimental results also show strong RMSE of 0.97133 and R2 of 0.97133 for performance 21.48 km. The mean absolute error (MAE) for training is 7.08 km and for testing is 18.73 km. Although the experimental errors are slightly higher, they are acceptable. Overall, the RFR model effectively predicts vehicle range with high reliability and generalization ability.

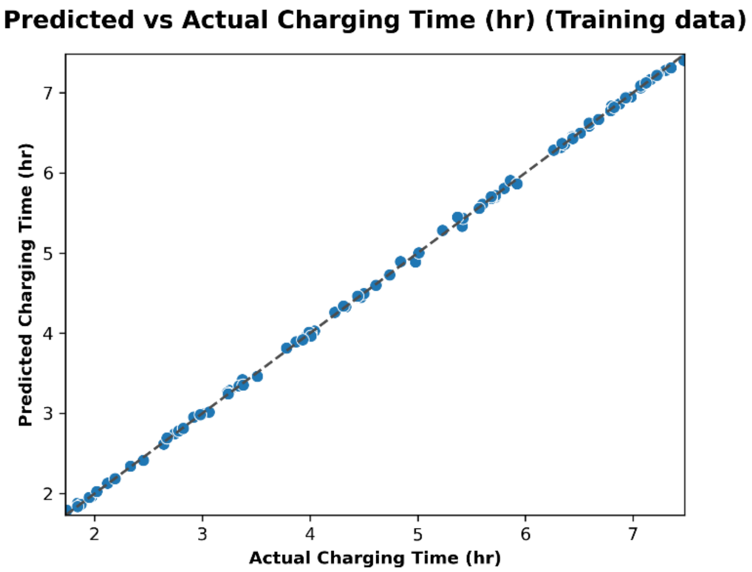

Figure.7. Random Forest Regression on Charging Time (hr): training data

Figure 7 illustrates the performance of the Random Forest Regression model in predicting charging time (hours) using the training dataset. The predicted values closely match the actual values on the diagonal, reflecting a very accurate fit. This strong agreement indicates that the model effectively captures the underlying pattern in charging time.

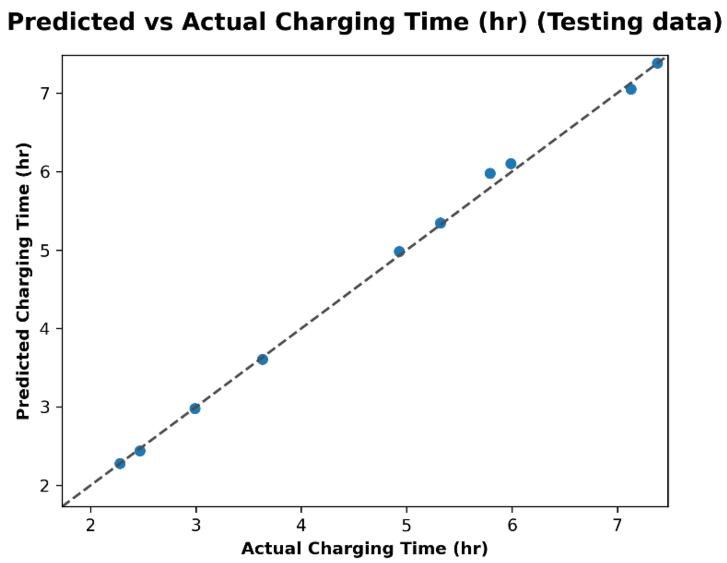

Figure.8. Random Forest Regression on Charging Time (hr): testing data

Figure 8 demonstrates the performance of the Random Forest Regression model in predicting charging time (hours) using experimental data. The predicted values closely follow the actual values on the diagonal line, indicating good generalization and prediction accuracy. The model reliably estimates the charging time for new data points with minimal deviation.

Table.4. Performance Metrics of Random Forest Regression on Charging Time (hr) (Training Data and Testing Data)

Property	Data	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Charging Time (hr)	Train	0.99974	0.99974	0.00079	0.02805	0.02015	0.09000	0.00003	0.01295
	Test	0.99815	0.99835	0.00577	0.07597	0.05205	0.18580	0.00013	0.02730

Table 4 presents the performance of the random forest regression (RFR) model in predicting the charging time (hours) for electric vehicles. The model shows excellent accuracy, with a test data R2 of 0.99815 and a training data R2 of 0.99974, indicating excellent predictive ability. The error measures are very low, with RMSE MAE values were 0.02015 and 0.05205, and values of 0.02805 (train) and 0.07597 (test), respectively. The maximum error and mean absolute error are also very low, reflecting the strong stability and accuracy of the model. Overall, the RFR model effectively estimates the charging time with high accuracy and generalizes well to unobserved data.

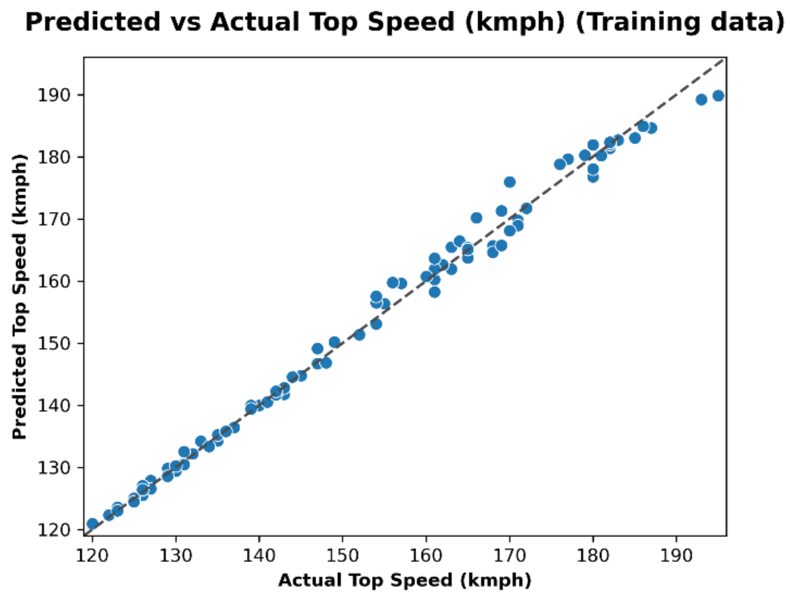

Figure.9. Random Forest Regression on Top Speed (kmph): training data

Figure 9 presents the results of the random forest regression for predicting the maximum speed (km/h) using the training data. The scatter points closely follow the diagonal line, indicating strong model accuracy. This alignment reflects the model's ability to effectively learn and predict the connection between maximum speed and input characteristics in electric vehicles.

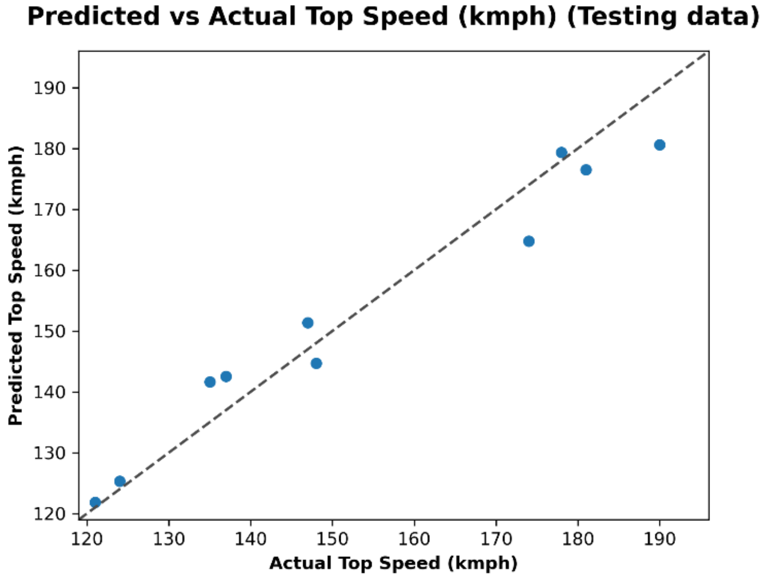

Figure.10. Random Forest Regression on Top Speed (kmph): testing data

Figure 10 shows the results of the random forest regression for predicting the maximum speed (km/h) using the experimental data. Although most of the predicted values closely match the actual values on the diagonal, small deviations are observed. Nevertheless, the model demonstrates strong generalization and effectively estimates the maximum speed for previously unseen electric vehicle data.

Table.5. Random Forest Regression Performance Metrics on Top Speed (kmph) (Training Data and Testing Data)

Property	Data	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Top Speed (kmph)	Train	0.99266	0.99266	3.14899	1.77454	1.28389	5.95500	0.00011	0.87000
	Test	0.94708	0.94777	30.28557	5.50323	4.65850	9.39000	0.00115	4.44250

Table 5 shows the performance of the Random Forest Regression (RFR) model in predicting the maximum speed (km/h) of electric vehicles. The model performs exceptionally well on the training data, with an R^2 of 0.99266 and a low RMSE of 1.77kmph, indicating high accuracy. On the test data, the model maintains even stronger performance, showing a 0.94708 R2 and an RMSE of 5.50kmph. The MAE values are 1.28 (train) and 4.66 (test), indicating an acceptable error, although slightly higher, in the test predictions. Overall, the RFR model reliably estimates the maximum speed with excellent training fit and good generalization to new data.

4. Conclusion

Based on a comprehensive analysis of electric vehicle technology and performance prediction using random forest regression, this study shows how well machine learning techniques work to comprehend and predicting key EV parameters. The research examined 100 electric vehicles across four key performance metrics: battery capacity, driving range, charging time, and maximum speed, revealing significant correlations and interdependencies among these variables. The random forest regression model proved to be highly effective across all predicted parameters, achieving exceptional accuracy with R^2 values consistently above 0.94 for all metrics. The model showed particularly strong performance in predicting battery capacity ($R^2 = 0.99763$), charging time ($R^2 = 0.99815$), and driving range ($R^2 = 0.97133$), with maximum speed prediction also showing strong results ($R^2 = 0.94708$). Combined with low error measures (RMSE and MAE), these high correlation coefficients confirm the model's reliability and generalizability to unobserved data. Correlation analysis revealed important insights into EV design trade-offs, showing strong positive relationships between battery capacity, range, and maximum speed, while charging time showed negative associations with these parameters. This understanding is crucial for manufacturers looking to improve vehicle performance and for consumers making informed purchasing decisions. The study's findings have significant implications for the continued growth and optimization of the electric vehicle industry. Predictive models can assist manufacturers in design optimization, help understand consumer performance expectations, and support infrastructure planning for charging networks. As the industry shifts from traditional internal combustion engines to sustainable electric alternatives, driven by environmental concerns and resource limitations, such analytical tools are becoming increasingly valuable. Future research should examine additional variables such as vehicle weight, aerodynamics, and real-world driving conditions to improve model accuracy. The integration of extended-range electric vehicles (EREVs) and advanced control systems, such as high-torque avoidance control, represent promising directions for addressing current BEV limitations while maintaining the environmental benefits of electric transportation.

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