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REVIEW

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A Review for Remaining Driving Range Prediction of Electric Vehicles Using Machine Learning Algorithms

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Abstract: With the widespread use of electric vehicles, greenhouse gas emissions can be reduced. Thus, a solution can be proposed to minimize the environmental impact of transportation. However, one of the most important obstacles to the widespread use of electric vehicles is the limited driving range and the accompanying challenges such as range anxiety. Researchers have proposed various methods and algorithms to accurately predict the remaining driving range of electric vehicles to address these challenges. The study is aimed at analyzing and comparing studies that focus on remaining driving range estimation using mathematical-based methods, statistics, and machine learning algorithms. The study includes a comprehensive exploration of the datasets, methods, algorithms, and performance metrics used in the selected studies. It was found that machine learning algorithms, especially Extreme Gradient Boosting and Random Forest, are frequently used for remaining driving range estimation, followed by statistical models such as multiple linear regression. In addition, most of the datasets used are obtained from real-time electric vehicle data. This highlights the importance of real-time data for developing accurate prediction models. In addition, performance metrics such as Root Mean Square Error, Mean Absolute Error, and Coefficient of Determination are widely used metrics to evaluate the performance of the models. The findings obtained within the scope of this study provide valuable information about the current status of remaining driving range estimation research for electric vehicles and suggest potential future studies in this area.

Keywords: electric vehicles, machine learning, mathematical-based approaches, remaining driving range, statistical models

1. Introduction

The development of industrialization has benefited humanity, but it has also brought harm to the natural ecosystem. Damage to the natural ecosystem can be measured by the carbon footprint. Carbon footprint can be defined as a certain quantity of gaseous emissions that are related to changes in climate and relevant to human consumption and production [1]. It has gained widespread usage in the public discussion about sustainability and prevention strategies against threats caused by climate change. At this point, various international regulations have been made to minimize damage to the natural ecosystem. One of them is the International Environmental Policy which covers various issues, including biological variety preservation, forests, oceans, and soil conservation, as well as climate protection and sustainable energy policy. Furthermore, with the coming into force of the Kyoto Protocol, industrialized countries have committed to decreasing greenhouse gas emissions, leading to significant progress in reducing environmental pollution [2]. When it comes to OECD countries whose aim is decreasing greenhouse gas emissions, different countries have different sources of emission changes. Austria, France, Italy, Spain, the Czech Republic, and the Slovak Republic have greenhouse gas emission reductions due to the composition effect, which can be done by increasing the portion of clean sectors. The method effect, which is brought about by the technical advancement in emission intensities, helps the mitigation of greenhouse gases in Denmark, Latvia, Poland, Sweden, and the UK. For differential emission reduction, these findings have important consequences [3].

The transportation sector is responsible for a significant amount of greenhouse gas emissions within the European Union, accounting for 25% of total emissions, and this percentage is consistently rising [4]. To address this issue, electric vehicles (EVs) are a practical and efficient alternate for conventional vehicles in the transportation sector. EVs produce minimal noise and emit no exhaust gas, thanks to their use of electric motors and battery energy [5]. Undoubtedly, EVs will benefit the world's ecosystem by reducing carbon emissions compared with conventional internal combustion engines [6]. However, it is important to note that there are also some disadvantages associated with EVs. When the studies addressing the disadvantages of EVs are examined, according to Bedogni et al. [7], in a recent report conducted by the US Department of Energy, approximately 70% of the human population would not purchase an EV because of the term called driver range anxiety, which is a doubt about not having decent charging stations close to users whenever they want and since Li-ion batteries offer significantly less range than conventional vehicles [8]. Increasing battery capacity will be key to overcoming range anxiety but will also result in bigger, heavier, and more expensive batteries due to the relationship between battery capacity and maximum range [9]. Ultimately, according to the research conducted in reference [10], electric car batteries are highly sensitive to temperature changes. This means that extreme temperature variations can significantly reduce the performance of EVs.

In order to overcome many of these challenges mentioned above, there is a need for accurate "remaining driving range (RDR) estimation." As shown in Figure 1, the methods proposed in the

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Figure 1
EV range prediction approaches

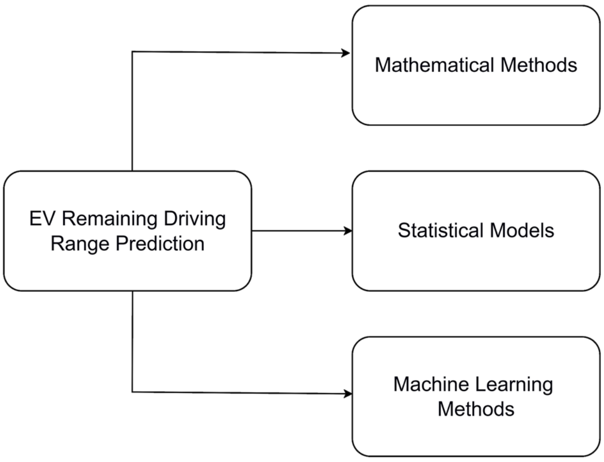
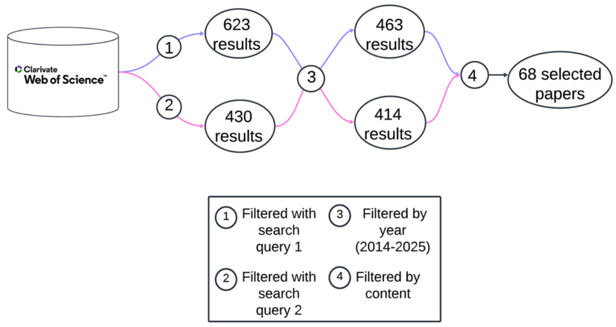


Figure 2
Outline of the steps involved in conducting a literature search



literature for RDR estimation can be given in three categories: mathematical methods, statistical models, and machine learning methods. To give a superficial definition of these approaches, statistical models are one of the approaches used to establish a mathematical relationship with given values. Linear regression, one of the statistical models, is practical for predicting a computable output. Machine learning methods train models how to use data more effectively and efficiently. Nevertheless, the data input enters the algorithm and outputs a prediction.

Other reviews in the literature were examined to identify and improve the deficiencies in their narratives and to present a more comprehensive review. In this context, in the reviewed papers, Chen et al. [11] and Gurusamy et al. [12], energy prediction models for EVs are categorized into two main categories: rule-based and data-driven models, framing them in a general structure. The approach used for classification focuses on how the models work. Rule-based models perform the prediction process using fixed rules, while data-driven models rely on learning processes from datasets. In this context, this classification method helps in understanding the basic structure of the models but it does not provide sufficient insight into the details of their functionality and inner workings. Marzbani et al. [13] classify energy consumption prediction models into linear, nonlinear, and hybrid categories. This classification method focuses on the mathematical structure of the models. However, similar to the previous method, it is also insufficient in explaining the inner workings of the models. Our classification, based on mathematical, statistical, and machine learning models, offers a deeper and more comprehensive perspective. With this approach, the mathematical foundations of the model, as well as its learning processes and interactions with data, are taken into account.

The contributions of our study are as follows:

- Providing RDR researchers with detailed information about the datasets to give them an idea of where they can access them, which features they can use, or which dataset they can use by providing detailed information.
- To give researchers an idea about the method they will use by examining the methods used in the literature.
- To give an idea about the performance metrics that can be used to evaluate the methods presented by the researchers by examining the performance metrics used in the studies.

In light of this information, we aim to guide and facilitate researchers working on range estimation in EVs.

2. Literature Review

The literature search was conducted utilizing the extensive resources available in the Web of Science database. Careful selection of keywords was made to optimize the search query, ensuring that all relevant articles available were captured. After compiling a list of potential candidates as shown in Figure 2, filtering was performed to ensure that only the most appropriate articles were selected for further analysis. TS represents title search, and TI represents title inclusion. The search queries utilized were as follows:

1. Search query for RDR: (TS= (EV OR electric* vehicle) AND (TS= (estimation OR prediction OR forecast OR model OR measurement))) AND (TI=(range)) AND (TS= (Machine learning OR ML Deep learning OR DL Artificial neural network OR AI Regression analysis OR Statistical modeling OR Predictive modeling OR Data-driven modeling OR Data analysis OR Time series analysis OR Forecasting OR Optimization OR Simulation OR Stochastic modeling OR Statistical modeling OR Mathematical modeling)).
2. Search query for energy consumption: (TS=(EV OR electric* vehicle) AND (TS=(estimation OR prediction OR forecast OR model OR measurement))) AND (TI=(energy consumption)) AND (TS=(Machine learning OR ML Deep learning OR DL Artificial neural network OR AI Regression analysis OR Statistical modeling OR Predictive modeling OR Data-driven modeling OR Data analysis OR Time series analysis OR Forecasting OR Optimization OR Simulation OR Stochastic modeling OR Statistical modeling OR Mathematical modeling)).

Figure 2 shows the specific actions taken during the literature search. After the search queries were executed, the articles that were found were filtered by year in step 3 to get more recent results. Then, the articles that passed this filtering process were examined based on their titles and abstracts. After conducting a detailed and comprehensive review, a total of 68 articles were carefully selected based on their relevance, quality, and suitability for the study. The selection process involved a thorough analysis of each article's content, methodology, and conclusions to ensure that they meet the required standards.

Figure 3 provides information on the publishers of the 68 selected articles. To ensure a comprehensive study, articles were selected from various academic publishers. Most of the selected articles were published by Elsevier, one of the world's leading academic publishers. The majority of articles were also published by IEEE, which specializes in electrical engineering, computer science, and related technical fields. In addition, some articles were selected from MDPI, which follows an open-access publishing model and publishes scientific journals across various disciplines, and Wiley, which operates in academic research, professional development, and information services.

Some of the journals that have selected articles were published, as presented in Figure 4. To ensure the reliability and precision of

Figure 3
The distribution of publishers for the articles selected through literature research

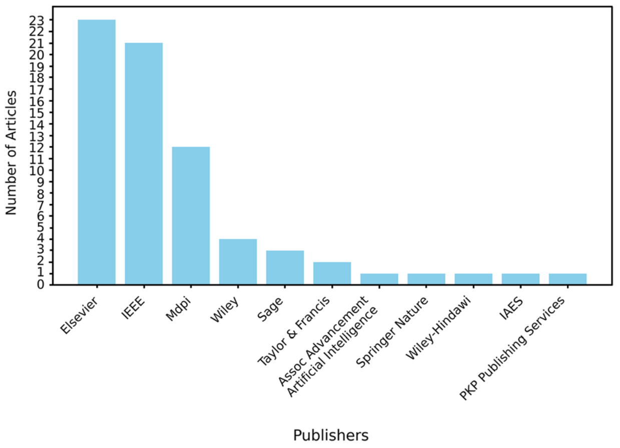
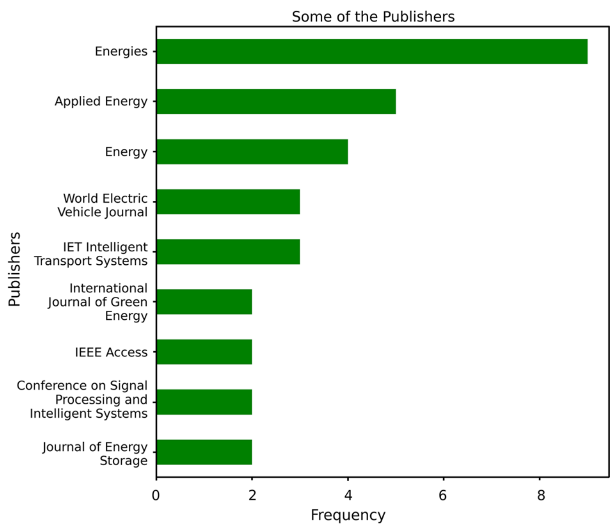


Figure 4
The journals that some of the selected articles published



the research, articles were primarily selected from journals with Q1 (Energy, Applied Energy) and Q2 (Energies) scores. This selection criterion ensures that the articles are from journals with high-impact factors and have experienced strict peer review processes, thereby increasing the validity of the research findings.

Predicting the driving range accurately is crucial for EVs, as it combines energy consumption and battery capacity. Therefore, the studies in the literature related to the prediction of energy consumption were also analyzed besides the studies related to the prediction of the driving range of EVs. After a comprehensive review of the studies, the highlights of these studies are summarized. These summaries are classified into four categories: mathematical approaches, statistical models, machine learning methods, and hybrid approaches. Initially, studies that use machine learning methods will be discussed, followed by mathematical and statistical approaches proposed in the literature related to the same task.

Various approaches in the literature use machine learning algorithms in terms of RDR or energy consumption prediction of EVs. The study conducted by Achariyaviriya et al. is aimed at examining the actual energy consumption rate of commercial Battery Electric Vehicles (BEVs) in Thailand. The research includes real-world driving tests in both urban and rural modes. Employing various machine learning techniques such as Extreme Gradient Boosting (XGBoost), Random Forest (RF), Multilayer Perceptron (MLP), and Support Vector Regression (SVR), they analyzed the dataset to forecast energy consumption and identify influential factors. The most important factors affecting the energy consumption of BEVs were determined to be battery current, speed, state of charge (SOC), acceleration, and road slope [14].

Nabi et al. [15] used a neural network-based machine learning technique to estimate the energy consumption of EVs, which is consistent with the results obtained from GT-SUITE software. The one-dimensional model for eight different driving cycles was estimated by the developed neural network scheme. The proposed energy consumption model performed successfully with an accuracy rate of 89%.

Hua et al. [16] developed an energy consumption model that takes both vehicle and environmental data into account. The prediction accuracy was improved by using trajectory segmentation, Bidirectional Recurrent Neural Network (BiRNN), and transfer learning. The proposed model used real-time speed, vehicle exterior temperature, and GPS coordinates to calculate the estimated energy consumption rate based on trajectory data.

Ullah et al. [17] estimated the energy consumption of EVs with a training model built using 68 trip data collected in Japan. They considered various factors such as distance, speed, lighting, heater, air conditioner, and road slope to improve the prediction accuracy. The proposed model has been shown to outperform commonly used models such as Decision Trees (DT), RF, and K-Nearest Neighbors (KNN).

Fukushima et al. [18] developed a data-driven model to accurately predict real-world EV trips. They concluded that the prediction error rate was improved by 30% with the proposed transfer learning method when compared with traditional methods.

Witvoet et al. [19] utilized a platform called AutoMl, which simplifies each step of the machine learning process, from handling raw data to deploying machine learning models. Their study is aimed at predicting the range and SOC. They used models generated using AutoGluon for SOC and range prediction. The input data included battery voltage, battery current, battery power, current average, and voltage average.

Qiu et al. [20] conducted a study on predicting energy efficiency based on range prediction. They used a dataset that included medium- and heavy-duty battery-electric vehicles (MHD EVs) Data Collection (CALSTART, 2023) and ZETI Database (CALSTART, 2023). The dataset consisted of duty cycle features, such as average driving speed, total distance, total run time, driving time, and idling time percentage, and vehicle configuration features, such as manufacture, model name, model year, weight, class, vehicle platform, body style, rated energy, nominal range, and estimated payload. The researchers used various algorithms such as XGBoost, Gradient Boosted Trees, Lasso, and Ridge to predict energy efficiency. The most accurate algorithm was found to be XGBoost.

Yavasoglu et al. [21] proposed a DT to predict the road type and driver profile. The metrics used for range prediction were the driver profile, road type, auxiliary loads, environmental factors, constant vehicle parameters, and dynamic vehicle parameters. For the known road type, the proposed estimation rate was 97.79%. For the unknown road type, the proposed estimation rate was 94.33%.

Zhao et al. [22] collected data from the NDANEV platform through the EV CAN bus. The study utilized several features, including the maximum and the minimum temperatures of the cell, the difference between the maximum and minimum temperatures, the braking ratio, the stopping ratio, the acceleration ratio, and the driving time. The researchers merged XGBoost and LightGBM, to analyze the collected data.

The study by Topić et al. [23] is aimed at predicting the All-Electric Range (AER) of EVs using deep neural network (DNN) models.

They preprocessed driving cycles into three input types (IT1, IT2, and IT3) to serve as static inputs for neural networks. They considered two neural network architectures: Multi-Layer Perceptron (MLP) and Convolutional Neural Network (CNN). Due to its effectiveness in feature extraction from 2D matrix inputs, similar to the representation of driving cycles, they emphasized CNN. The CNN model with IT3 input showed superior performance, achieving accuracy in predicting AER for most points within a ±1-km interval.

Sagar et al. [24] used cloud computing and the RF machine learning algorithm to estimate the remaining range of EVs. By leveraging cloud computing, massive volumes of real-time data, such as weather conditions, traffic status, and road gradients, were collected, analyzed, and continuously updated. Due to the multiple DTs in Random Forest Regression, overfitting was prevented, resulting in a system capable of making consistent predictions under various conditions. This model achieved an accuracy of approximately 92%, outperforming conventional methods.

Mishra et al. [25] used various machine learning algorithms to estimate the remaining range of EVs. In the data preprocessing step with Exploratory Data Analysis (EDA) approach, they identified anomalies, detected missing and outlier values, and examined the relationships between different parameters. Then, they estimated the energy consumption rate with linear regression, RF, and Deep Multilayer Perceptron (Deep MLP) models. The performance of these models was compared using Root Mean Square Error (RMSE), Mean Square Error (MSE), and R^2 metrics. The best estimation results were achieved with Deep MLP.

Ozkan et al. [26] proposed a data-driven approach to estimate the energy consumption in Plug-and-Play Hybrid Electric Vehicles. They integrated driver behaviors in the proposed model. They modeled the uncertainty in fuel consumption using LightGBM and Harmonized Quantile Regression (CQR). They used data generated using a driver-cycle simulator with 26 participants and Monte Carlo simulations to evaluate the model performance. The experimental results show that the proposed model provides statistically valid prediction intervals and detects changes in driver behavior, route conditions, and vehicle dynamics.

Kim et al. [27] present a machine learning-based technique including real-time traffic and route data for enhancing EV range prediction. The proposed method combines a DNN that models the energy balance relation with Long Short-Term Memory (LSTM) networks to interpret time series data (speed and acceleration). Hyundai Kona EV driving data (160,000 km, 1000 hours) were used to train the model. It was then tested with various data partitions according to driving situations (Normal Load vs. High Load). The findings show that the LSTM-DNN mixture model significantly outperforms conventional physics-based techniques, achieving an error rate of only 2–3 kilometers in a 40-minute prediction window. By adjusting to current traffic circumstances, the method improves the accuracy of EV range predictions while lowering driver anxiety.

Zhu et al. [28] propose a machine learning-based framework that incorporates physics-informed features and online adaptation for real-time enhancements. The dataset includes 91,932 trips from 55 Beijing-based electric taxis in 2017 and 2018. With an average error rate of 6.30%, the Quantile Regression Neural Network was the pioneering model. However, its online adaptation drastically improved the prediction accuracy by lowering the error rate to 5.04%. Trip features (distance, time), road parameters (elevation, road grade), vehicle states (speed, acceleration), and environmental factors (wind speed, temperature, and humidity) were all considered in the feature selection process. To increase prediction reliability, the study also added uncertainty estimation utilizing Quantile Extreme Gradient Boosting Regression (QEGBR) and Quantile Regression Forests (QRF). The findings show that combining machine learning with physics-based features can greatly improve the prediction of energy usage for fleets of EVs.

In addition to the discussed machine learning algorithms, mathematical approaches that produce more precise results with high computational costs have also been used in the literature to solve the problem addressed in the study. Pei et al. [29] conducted a study on predicting the state-of-power for batteries with the help of an Extended Kalman Filter (EKF)-based approach. The objective of the study was to improve the accuracy of power predictions by taking into consideration the battery voltage, current, and SOC limits. The Parameter and State Estimation implemented an online method for real-time identification of battery parameters and states, ensuring accurate predictions.

Fiori et al. [30] proposed the VT-CPEM model to predict the energy consumption rate of EVs. An error rate of 5.86% was obtained for field data with the proposed model. Experimental results showed that EVs consume significantly less energy than conventional vehicles. In addition, energy consumption differences for different EV models were presented. The study also found that under certain conditions due to the use of auxiliary systems, energy consumption can increase by up to 32% and the range of EVs can decrease by up to 24%.

Liu et al. [31] used an improved Seagull Optimization method and an updated Recursive Least Squares (RLS) method to predict and optimize the energy consumption rate of EVs. Neural networks were used to analyze the effect of air conditioning (A/C) usage on energy consumption. Variable Forgetting Factor was added to RLS to improve the energy consumption prediction accuracy. In the experimental results, an error rate of 5.1% was obtained with the proposed VEC prediction model.

Hybrid approaches have also been proposed in the literature to improve the performance of the energy consumption prediction model. Eissa et al. [32] used a hybrid approach combining LSTM and CNN. They collected data from real-life behaviors of about 50 users over the last 2 weeks. They found small prediction errors ranging from 1.07 km to 5.34 km.

Varga et al. [33] considered driver behavior, ambient temperature, route, and traffic parameters to estimate the SoC of a battery. The experimental results show that the traditional methods have an average of ±2%–8% estimation error, the Adaptive Filter Algorithm has an average of ±1%–4% error, the Learning algorithms have an average of ±2%–5% error, the Nonlinear Observer has an average of ±1%–4% error, and the Hybrid methods have an average of ±1–8% estimation error.

Wang et al. [34] proposed a new method to estimate the range of an EV using a least squares support vector machine (LSSVM) model. The model is optimized by particle swarm optimization (PSO). Real-time EV data collected in Beijing for 1.5 years, including parameters that take into account real-world conditions such as day, temperature, and battery discharge depth, were used. The accuracy of the LSSVM algorithm optimized with PSO was evaluated using statistical parameters such as Relative Error (RE) and Mean Absolute Relative Error (AARE). The AARE rates for training and testing data were determined as 1.99% and 5.99%, respectively. The study found that temperature changes, especially at low temperatures, significantly affected the prediction accuracy.

Chen et al. [35] conducted a study that involved gathering real-world driving data from a large fleet of EVs. They proposed an improved nonlinear regression model to estimate energy consumption based on density-based classification. The study classified driving behaviors according to their characteristics using the improved DBSCAN method. A comparison of various methods, such as SVR, MLR, and DBC-SVR, was made to determine the most appropriate method for predicting energy consumption. The study revealed that DBC-MLR is the most suitable method for predicting energy consumption.

Zhang et al. [36] developed a machine learning-based hybrid framework for predicting the energy consumption of EVs. They extracted various factors related to the vehicle, the environment, and the driver. Monte Carlo was employed for driving condition prediction, and the resulting parameters were used to train and test the XGBoost machine learning model. Compared with the conventional method, this framework achieved 32.05% lower RMSE and 30.14% lower Mean Absolute Percentage Error (MAPE).

The study conducted by Pokharel et al. [37] involved collecting data from Spritmonitor, a German open-source website. The data were preprocessed to extract relevant features using Python and Scrapy for web scraping. The study implemented machine learning models, including multiple linear regression (MLR), SVR, and XGBoost, using Python libraries like scikit-learn. The data were divided into training (80%) and test (20%) sets for model evaluation. The independent variables used in the study include trip distance, tire type, driving style, power, odometer, EV model version, city, motorway, country roads, A/C usage, and park heating. The dependent variable was the total energy consumption (TEC) in kWh. Among the machine learning models, XGBoost demonstrated the highest accuracy (91.86%) and the lowest error (RMSE = 9.490 kWh) in predicting TEC.

Huang et al. [38] proposed a method to predict the RDR of an EV using SVR. The datasets were recorded from real-world data of EVs. This dataset included features such as driving range, driving motor temperature, total voltage, and driving motor speed. Looking at their algorithm design, they first started with feature extraction using RF. The calculation method used in RF is the out-of-pocket data error rate. In the second step, the model was trained using SVR. Finally, they optimized the model and compared the changes with the MSE to obtain an optimal model of driving range.

In the following subsections, studies that have been analyzed will be compared by datasets, algorithms, methods, and performance metrics. After thorough research, studies related to the prediction of energy consumption and driving range of EVs have been analyzed. Studies that have detailed information about related topics have been selected.

2.1. Comparison by dataset

In this section, studies have been compared by their dataset features, accessibilities, and details. There are various features specific to each study, such as battery status, average speed, and consumption. All the features used in the studies and their frequency of use will be discussed later in this section. The accessibility of the studies was categorized into two types: private and public. A private dataset means that you are not allowed to access the dataset. A public dataset means that the dataset is already an open source or may be available upon request. In the details section, a summary of how these datasets were acquired is given. The details section includes information such as if it was obtained from a website, which website it was obtained from, if it was real-time data, or which vehicle it was obtained from.

As shown in Table 1, the datasets have been compared by their attributes, accessibility, and some brief details about where these data were collected. Twelve of the datasets were public, and 10 of the datasets were private. A major amount of private datasets were collected by real-time data of EVs. To collect all the data, they used the EVs' CAN channel to log the real-time data of the EVs. There are several public datasets available that contain data related to EVs. One such dataset is collected by a website called "spritmonitor.de," which provides information on various EVs such as their consumption, range, and temperature. CALSTART, an organization that offers data from different electric cars during specific years from various regions of America, also provides a public dataset. Another public dataset is obtained from NDANEV, the National Big Data Alliance of New Energy Vehicles, which provides data through its open laboratory to monitor and manage new EVs [22]. Additionally, some studies use datasets that are available on GitHub.

The graph shown in Figure 5 displays the distribution of attributes used in various models. The graph is arranged in a way that attributes with the same frequency are represented by the same color, while those with different frequencies are arranged in different colors. The legend located below the graph explains the attributes that correspond to those colors. For example, it can be seen that attributes such as charging habits, humidity, and cloud amount, which correspond to the green columns on the far right of the chart, all have a frequency of 1. The most commonly encountered attribute is vehicle speed, which plays a significant role in the RDR estimation models. After that, attributes such as slope, vehicle mass, SOC, air resistance, temperature, rolling resistance, and auxiliaries are observed with considerable frequency.

2.2. Comparison of algorithms and methods

In this section, the algorithms and methods used will be compared. Machine learning algorithms, statistical models, and mathematical models will be compared according to their frequency and types of use. For instance, machine learning algorithms have variations such as XGBoost, MLP, and support vector machine (SVM). Statistical models have variants such as MLR, SVR, and DT. Ultimately, mathematical-based methods have variants such as the Bellman-Ford algorithm and EKF.

In Table 2, studies have been compared by the algorithms and methods that they used. These algorithms and methods have been classified into three categories: machine learning, statistical models, and mathematical-based approaches.

In Table 2, studies have been compared by the algorithms and methods that they used. These algorithms and methods have been classified into three categories: machine learning, statistical models, and mathematical-based approaches.

Machine learning algorithms are the most commonly used, followed by statistical models, with physics- and model-based approaches appearing last, as shown in Figure 6.

In Figure 7, algorithms used in machine learning are shown by algorithm types. XGBoost is leading with 13.0% of the usage rate. Then, RF follows with 11.6% of the usage rate. MLP, deep MLP, and NN follow with 8.7% of the usage rate.

In Figure 8, algorithms used in statistical models are shown by their usage percentage. MLR is leading with 46.2% of the usage rate. Then, linear regression follows with 15.4% of the usage rate. After searching the algorithms used in the literature, it was found that the physics-based approach is the most commonly used mathematical approach. In addition to this, other models such as the Digital Twin Model, FastSim's Model, VT-CPEM, and Adaptive Filter Algorithm are also being utilized.

2.3. Comparison by performance metrics

Some performance metrics are needed to evaluate the results of the experiment. In light of these metrics, an evaluation can be made to decide whether the experiment is effective or not. For example, Mean Absolute Error (MAE), RMSE, and Coefficient of Determination (R^2) are generally used to determine whether a regression algorithm is effective or not. Each metric is calculated with its mathematical formula. The formulas of performance metrics frequently used in the literature are listed below.

RMSE measures the average difference between the predicted value $(\hat{y}_i)$ and the actual value (y_i). It estimates model accuracy and is given as follows:

Table 1
Datasets used in literature, their features, and accessibility

Accessibility	Study	Features	Details
Public	[14]	Battery current, speed, SOC, acceleration, and road slope.	The data presented in this study are available upon request from the corresponding author.
	[15]	Motor power, SOC of the battery, vehicle speed, distance travelled, and energy consumption.	Data will be made available upon request.
	[16]	Longitude, latitude, temperature, and real-time speed.	https://github.com/gsoh/VED.
	[17]	Trip distance, travel speed, nighttime lighting, usage of the heater and A/C, and road gradient.	https://www.nrel.gov/transportation/secure-transportation-data/tsdc-puget-sound-traffic-study.html.
	[20]	Average driving speed, total distance, total run time, driving time, idling time percentage, and vehicle configuration features: manufacturer, model name, model year, weight, class, vehicle platform, body style, rated energy, nominal range, and estimated payload.	Composed by MHD EV Data Collection (CALSTART, 2023), ZETI Database (CALSTART, 2023).
	[22]	Longitudinal speed, motor voltage, motor current, battery pack voltage, battery pack current, SOC, maximum cell temperature, minimum cell temperature, odometer value, and timestamp.	Collected from NDANEV.
	[25]	Distance, route type, auxiliaries, and vehicle speed.	Collected from Spritmonitor.
	[28]	Distance, time, slope, vehicle speed, acceleration, wind speed, temperature, and humidity.	National Monitoring & Management Platform for New Energy Vehicles in China driving trips from 55 battery electric taxis in Beijing.
	[31]	Distance, slope, air resistance, and acceleration	Environmental Protection Agency, EXCEEDDATA working condition data.
	[35]	Velocity, accelerated velocity, and temperature.	Data will be made available upon request.
	[36]	Driving factors, traffic factors, and environmental factors.	N/D.
	[37]	EV model, tire type, power (kW), odometer (miles), trip distance (km), city, motorway, country roads, A/C, park heating, and TEC (kWh).	Collected from Spritmonitor.
	[39]	Manufacturer, power (kW), fuel date, odometer, distance (km), quantity (kWh), tire type, motor-way roads, city streets, country roads, driving style, consumption (kWh/100km), A/C, parking heating, and avg speed (km/h).	Collected from Spritmonitor.
	[40]	Traffic, road segment context, vehicle context, weather context, and driver profile context.	https://github.com/bewiv/DB_EMEC_EV_UML.
	[41]	Vehicle-related factors (velocity, acceleration, braking energy regeneration, and auxiliary system energy consumption), environment-related factors (ambient temperature, wind speed, road condition, and traffic condition), and driver-related factors (driving patterns, charging habits, and route planning).	National Monitoring and Management Platform for New Energy Vehicles (NEVs) https://rp5.ru/.
Private	[18]	Trip distance (km), trip time (h), average speed (km/h), accumulation of up incline (m), accumulation of down incline (m), maximum battery capacity (kWh), and temperature (°C) based on information from the SoC, timestamp, rest area, road topology, and ambient temperature.	Data on EV trips are collected through smartphones.

Table 1
Continued

Accessibility	Study	Features	Details
	[19]	Current, voltage, total route speed, total route distance, and total route elevation change.	Real-world driving data from Chevy Bolt.
	[23]	N/D.	Driving data collected by using the vehicle tracking equipment based on GPS and GPRS technology.
	[24]	Weather, traffic, slope, temperature, humidity, vehicle speed, and distance.	Real-world driving data of EV.
	[27]	Vehicle speed, acceleration, SOC, temperature, and auxiliaries.	Collected from Hyundai Kona EV.
	[32]	SOC, battery current and voltage, battery temperature, motor torque and speed, vehicle GPS location, ambient temperature, vehicle speed, accelerator pedal position, and others.	2019 Nissan Leaf EV.
	[36]	Time, distance, vehicle speed, acceleration, temperature, traffic conditions, and driving patterns.	National Monitoring and Management Platform for NEVs, real-world operating EV.
	[38]	Distance, temperature, battery voltage, and vehicle speed.	Real-world driving data of EV.
	[42]	N/D.	A route in Cookeville, TN, using Nissan Leaf.
	[43]	GPS time, longitude, latitude, GPS speed, acceleration, pack current, pack total voltage, pack power, and SOC.	EV converted from a 1987 Nissan D21 pickup.
	[44]	GPS coordinates, motor torque and speed, battery states, and vehicle velocity.	Nissan Leaf EV, Cookeville, TN, USA.
	[45]	SOC start, All_v, All_i, Avg_T, V_diff, Max_V, and Min_V.	Wireless GPRS device.
	[46]	Driver behavior, exploitation environment, battery parameters, and auxiliary loads on the driving range.	N/D.
	[47]	Average speed and average power.	N/D.
	[48]	Wind, temperature, vehicle speed, acceleration, distance, and driver behavior.	Real-world driving data from five Type A Vehicles and five type B vehicles. Hourly updated temperature data were acquired from the weather website (https://www.visualcrossing.com).

*N/D: not defined

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_l\right)^2} \tag{1}$$

where n is the observation count.

MAE is the average difference between the actual and predicted values, and it is defined as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_l\right| \tag{2}$$

MAPE is used to evaluate the accuracy of models. MAPE calculates the average percentage difference between actual and predicted values, and it is calculated as follows:

$$\mathrm{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_l\right|}{y_i} \tag{3}$$

MSE is the average of the squared differences between the predicted and actual values, and it is given as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_l\right)^2 \tag{4}$$

R^2 represents the percentage of the variance in the dependent variable that can be explained by the independent variables included in the model. The formula for R^2 includes two parts: the total sum of squares (SST) and the residual sum of squares (SSR). SST is calculated by summing the squared differences between each data point and the mean of the dependent variable. And SSR is the sum of the squared differences between actual and predicted values of the dependent. The R^2 score can be calculated as $\mathrm{R}^2 = 1 - (\mathrm{SSR}/\mathrm{SST})$ or as follows:

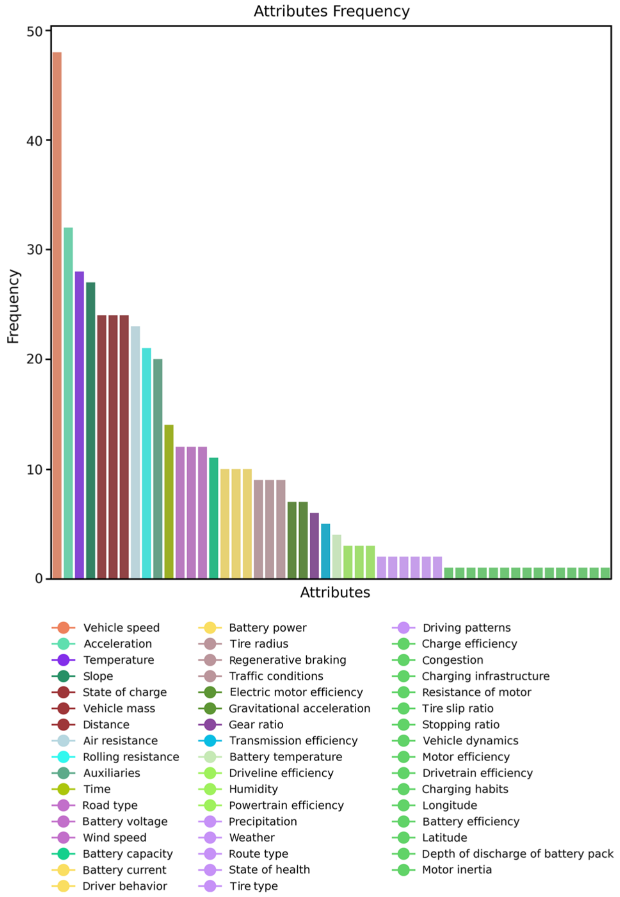
$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \widehat{y_l}\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{5}$$

where $\bar{y}$ is the mean of the dependent variable.

The absolute difference between the actual value and the predicted value is called Absolute Error, and it is calculated as follows:

$$\text{Absolute Error} = \left|y - \hat{y}\right| \tag{6}$$

Figure 5
Attributes used as input in models



RE is the ratio of the Absolute Error to the actual value, and it is calculated as follows:

$$\mathrm{RE} = \frac{|y_i - \hat{y}_l|}{y_i} \tag{7}$$

Accuracy is used to measure how close a prediction is to the actual value. And it is calculated by the difference between the predicted value and the actual value and then given the difference as a percentage of the actual value. It is calculated using the following formula:

$$\mathrm{Accuracy} = 100 * \frac{y - \hat{y}}{y} \tag{8}$$

As seen in Figure 9, the performance metrics applied in multiple studies, organized according to their frequency of use, are given in detail. Among the various performance metrics used in these studies, the three most commonly used metrics are RMSE, MAE, and R^2.

3. Conclusions

When the studies in the literature are examined, it is determined that there are many studies on the estimation of EV range. When machine learning methods are ranked according to their frequency of use, it is determined that algorithms such as XGBoost and RF are the most preferred. It is observed that statistical models such as MLR and linear regression follow these algorithms. Finally, in mathematical-based

Table 2
Approaches and algorithms used in literature

Approaches	Algorithms	Study
Machine learning	AutoML	[33]
	LSTM, Bi-LSTM	[27, 32, 41]
	SVM	[34, 49, 50]
	DT	[17, 21, 40, 51]
	Stochastic Model	[52]
	CNN	[23, 53]
	XGBoost	[14, 17, 20, 22, 36, 37, 41, 54]
	MLP, Deep MLP	[14, 23, 25, 39, 50, 55]
	RBF	[47]
	RF	[14, 17, 24, 25, 39, 48, 56]
	SVR	[14, 37, 48]
	NN	[15, 27, 42, 47, 50, 57]
	TL	[16]
	BiRNN, RNN	[16, 28, 41]
	KNN	[17]
	Robust Regression	[47]
	Gradient Boosted Trees	[20, 50, 51, 58]
	LightGBM	[17, 22]
	GRU	[41]
	BDT	[45]
	Pattern Recognition	[46]
	AdaBoost	[39, 56, 58]
	ANN	[49]
	QR, QEGBR, QRF	[28]
Mathematical approaches	Second-Order Mixed Estimator, Vehicle Longitudinal Model, Burckhardt Tire Model,	[53]
	FastSim's Model	[54]
	Physics-Based Approach	[58, 59]
	Transformer, Markov-Chain, Modified Intelligent Driver Model	[42]
	EKF	[29, 60]
	VT-CPEM	[30]
	Thevenin's Model	[60]
	Digital Twin Model	[61]
	Modular Vehicle Model	[62]
	RLS Algorithm Driving Behaviour Correction Algorithm	**[31, 63]**
	Conventional Methods, Adaptive Filter Algorithm, Learning Algorithms, Non-Linear Observer	[33]

Table 2
Continued

Approaches	Algorithms	Study
Statistical models	DBC-MLR, MLR	[35, 37, 50, 57, 64, 65, 66]
	Multiple Regression	[18]
	Linear Regression	**[25, 39, 56]**
	Hidden Markov Model	[55]
	Knowledge-Based	[64]
	Lasso and Ridge	[20]
	Accurate Computer-Based Model	[66]

Figure 8
Percentages of different statistical models used in literature

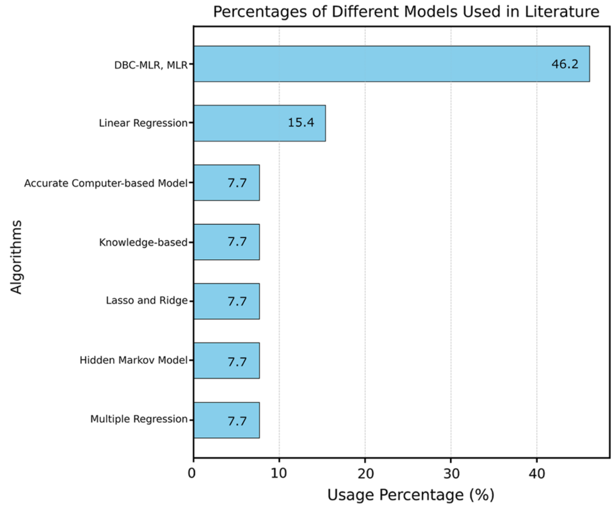


Figure 6
Percentages of machine learning, statistical models, and mathematical approaches used in literature

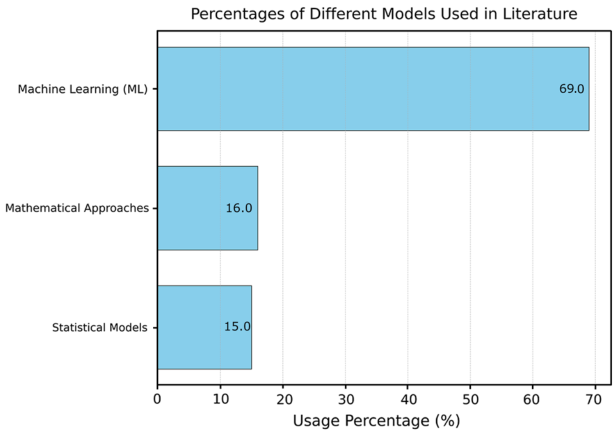


Figure 9
Performance metrics used in the literature

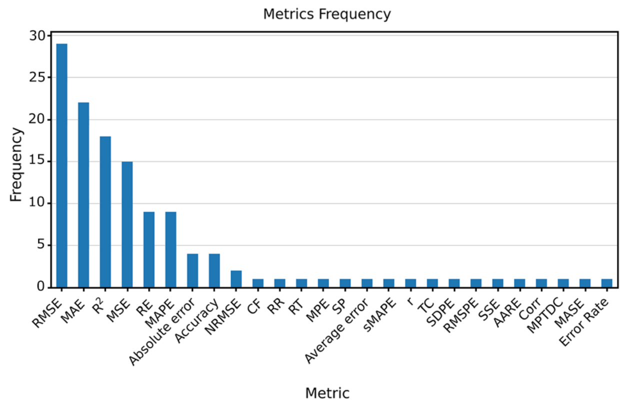
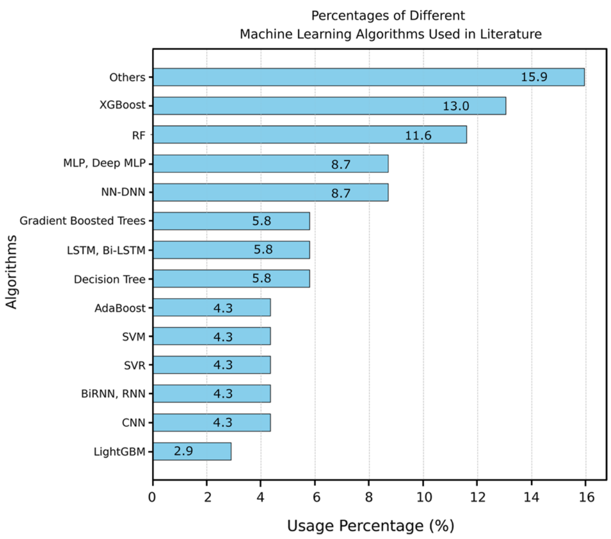


Figure 7
Percentages of different machine learning algorithms used in literature



models, physics-based approaches, EKF, and Belmann Ford algorithm are also among the frequently used algorithms. In addition, feature selection and engineering play an important role in developing accurate estimation models and increase estimation accuracy and robustness. It has been determined that factors such as speed, acceleration, and slope have a significant effect on energy consumption and have a performance effect on range estimation models. Performance metrics such as RMSE, MAE, and R2 are frequently used metrics in evaluating model performance. In addition to the findings obtained as a result of the literature research, it is also important to emphasize the importance of ongoing research in the field of range estimation of EVs.

However, despite the availability of various prediction techniques, several challenges remain in this area. One of the main challenges lies in the availability and quality of datasets. Generally, most of the datasets were created with real-time data of EVs. But of course, there is also the possibility to create dataset with public data. While real-time data from EVs offer valuable insights, obtaining comprehensive and reliable datasets is still a challenge.

Future research should focus on improving data collection methods and ensuring the quality and reliability of datasets used to train prediction models. As technology advances and more data become available, opportunities for further improvement and development of prediction approaches may arise. Prediction models that are adaptable to changing driving conditions and different driver behavior patterns in real time can be developed. Increasing user satisfaction and confidence is important to promote widespread adoption of EVs as a sustainable transportation option. Consequently, continued research and development in the field of EV range prediction are imperative. Addressing these challenges and conducting further studies in these areas will contribute to the development of more accurate and reliable methods for predicting the RDR of EVs.

Furthermore, to improve model transparency and user trust, it would be advantageous to integrate Explainable Artificial Intelligence (XAI) techniques into EV range prediction models. Open and service-oriented architectures for explainable AI can offer not only precise forecasts but also interpretable insights into the major elements impacting model outputs, as recent research [67, 68] has shown. To find important driving and environmental factors influencing range prediction, future research should investigate incorporating XAI tools like Shapley Additive exPlanations (XAI) and Local Interpretable Model-Agnostic Explanations into EV range prediction frameworks. Furthermore, as suggested by Wang et al. [67], the creation of cloud-based XAI services can provide replicable and scalable evaluation pipelines for model robustness and explainability, particularly in hostile and real-world scenarios. By implementing these strategies, consumer satisfaction, regulatory transparency, and the widespread use of EVs could all be greatly enhanced.

By providing a more thorough viewpoint based on mathematical, statistical, and machine learning techniques, this work enhances earlier classifications of RDR prediction models. Our approach offers deeper insights into model functionality, learning processes, and data interactions than previous research that only concentrates on general structures or mathematical features. We also provide helpful advice on feature selection, method selection, dataset accessibility, and performance evaluation measures. Our study intends to promote and facilitate future research in EV range estimation by organizing these crucial elements, resulting in prediction models that are more accurate and dependable.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Burak Caferler: Conceptualization, investigation, Writing—review & editing, and Visualization. **Aylin Ünal:** Conceptualization, Investigation, Writing—review & editing, and Visualization. **Sinem Bozkurt Keser:** Conceptualization, Investigation, Writing—review & editing, Visualization, and Supervision. **Ahmet Yazıcı:** Conceptualization, Investigation, Writing—review & editing, Project administration, and Funding acquisition.

References

[1] Wiedmann, T., & Minx, J. (2008). A definition of carbon footprint. *Ecological Economics Research Trends*, *1*(2008), 1–11.

[2] Dogan, E., & Ozturk, I. (2017). The influence of renewable and non-renewable energy consumption and real income on CO2 emissions in the USA: Evidence from structural break tests. *Environmental Science and Pollution Research*, *24*, 10846–10854.

[3] Sun, X., Dong, Y., Wang, Y., & Ren, J. (2022). Sources of greenhouse gas emission reductions in OECD countries: Composition or technique effects. *Ecological Economics*, *193*, 107288.

[4] Andersson, Ö., & Börjesson, P. (2021). The greenhouse gas emissions of an electrified vehicle combined with renewable fuels: Life cycle assessment and policy implications. *Applied Energy*, *289*, 116621.

[5] Tan, K. M., Ramachandaramurthy, V. K., & Yong, J. Y. (2016). Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques. *Renewable and Sustainable Energy Reviews*, *53*, 720–732.

[6] Huang, C., Ou, Z., & Yu, X. (2023, June). Comparison of carbon emissions of gasoline vehicles and electric vehicles. In *Proceedings of the 6th International Conference on Economic Management and Green Development* (pp. 101–111). Singapore: Springer Nature Singapore.

[7] Bedogni, L., Bononi, L., D'Elia, A., Di Felice, M., Di Nicola, M., & Cinotti, T. S. (2014, November). Driving without anxiety: A route planner service with range prediction for the electric vehicles. In *2014 International Conference on Connected Vehicles and Expo (ICCVE)* (pp. 199–206). IEEE.

[8] Van, N. R. (2014). The rechargeable revolution: A better battery. *Nature*, *507*(7490), 26–28.

[9] Sankaran, G., Venkatesan, S., & Prabhahar, M. (2020). Range Anxiety on electric vehicles in India-Impact on customer and factors influencing range Anxiety. *Materials Today: Proceedings*, *33*, 895–901.

[10] Arora, N., & Raman, A. (2019). Beyond Nagpur: The promise of electric mobility. New Delhi: Ola Mobility Institute.

[11] Chen, Y., Wu, G., Sun, R., Dubey, A., Laszka, A., & Pugliese, P. (2020). A review and outlook of energy consumption estimation models for electric vehicles. *arXiv preprint arXiv:2003*. 12873.

[12] Gurusamy, A., Ashok, B., & Mason, B. (2023). Prediction of electric vehicle driving range and performance characteristics: A review on analytical modeling strategies with its influential factors and improvisation techniques. *IEEE Access*, *11*, 131521–131548.

[13] Marzbani, F., Osman, A. H., & Hassan, M. S. (2023). Electric vehicle energy demand prediction techniques: An in-depth and critical systematic review. *IEEE Access*, *11*, 96242–96255.

[14] Achariyaviriya, W., Wongsapai, W., Janpoom, K., Katongtung, T., Mona, Y., Tippayawong, N., & Suttakul, P. (2023). Estimating energy consumption of battery electric vehicles using vehicle sensor data and machine learning approaches. *Energies*, *16*(17), 6351.

[15] Nabi, M. N., Ray, B., Rashid, F., Al Hussam, W., & Muyeen, S. M. (2023). Parametric analysis and prediction of energy consumption of electric vehicles using machine learning. *Journal of Energy Storage*, *72*, 108226.

[16] Hua, Y., Sevegnani, M., Yi, D., Birnie, A., & McAslan, S. (2022). Fine-grained RNN with transfer learning for energy consumption estimation on EVs. *IEEE Transactions on Industrial Informatics*, *18*(11), 8182–8190.

[17] Ullah, I., Liu, K., Yamamoto, T., Zahid, M., & Jamal, A. (2021). Electric vehicle energy consumption prediction using stacked generalization: An ensemble learning approach. *International Journal of Green Energy*, *18*(9), 896–909.

[18] Fukushima, A., Yano, T., Imahara, S., Aisu, H., Shimokawa, Y., & Shibata, Y. (2018). Prediction of energy consumption for new electric vehicle models by machine learning. *IET Intelligent Transport Systems*, *12*(9), 1174–1180.

[19] Witvoet, K., Saad, S., Vidal, C., Ahmed, R., & Emadi, A. (2023, June). Electric Vehicle's Range and State of Charge Estimations using AutoML. In *2023 IEEE Transportation Electrification Conference & Expo (ITEC)* (pp. 1–6). IEEE.

[20] Qiu, Y., Dobbelaere, C., & Song, S. (2023). Energy cost analysis and operational range prediction based on medium-and heavy-duty electric vehicle real-world deployments across the United States. *World Electric Vehicle Journal*, *14*(12), 330.

[21] Yavasoglu, H. A., Tetik, Y. E., & Gokce, K. (2019). Implementation of machine learning based real time range estimation method without destination knowledge for BEVs. *Energy*, *172*, 1179–1186.

[22] Zhao, L., Yao, W., Wang, Y., & Hu, J. (2020). Machine learning-based method for remaining range prediction of electric vehicles. *IEEE Access*, *8*, 212423–212441.

[23] Topić, J., Škugor, B., & Deur, J. (2019). Neural network-based modeling of electric vehicle energy demand and all electric range. *Energies*, *12*(7), 1396.

[24] Sagar, B. S., Rajasekaran, M., Sakthisaravanan, B., Jyothi, R. L., Lalitha, K., & Murugan, S. (2024, November). Electric vehicle range prediction using random forest regression. In *2024 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 734–740). IEEE.

[25] Mishra, D. P., Kumar, P., Rai, P., Kumar, A., & Salkuti, S. R. (2024). Exploratory data analysis for electric vehicle driving range prediction: Insights and evaluation. *International Journal of Applied*, *13*, 474–482.

[26] Ozkan, M. F., Farrell, J., Telloni, M., Mendez, L., Pirvan, R., Chrstos, J. P., ... & Stockar, S. (2024). Data-driven personalized energy consumption range estimation for plug-in hybrid electric vehicles in urban traffic. *IFAC-PapersOnLine*, *58*(28), 162–167.

[27] Kim, D., Shim, H. G., & Eo, J. S. (2022, June). A machine learning method for ev range prediction with updates on route information and traffic conditions. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. *36*, No. 11, pp. 12545–12551).

[28] Zhu, Q., Huang, Y., Lee, C. F., Liu, P., Zhang, J., & Wik, T. (2024). Predicting electric vehicle energy consumption from field data using machine learning. *IEEE Transactions on Transportation Electrification*.

[29] Pei, L., Zhu, C., Wang, T., Lu, R., & Chan, C. C. (2014). Online peak power prediction based on a parameter and state estimator for lithium-ion batteries in electric vehicles. *Energy*, *66*, 766–778.

[30] Fiori, C., Ahn, K., & Rakha, H. A. (2016). Power-based electric vehicle energy consumption model: Model development and validation. *Applied Energy*, *168*, 257–268.

[31] Liu, C. (2024). Energy consumption prediction and optimization of electric vehicles based on RLS and Improved SOA. *IEEE Access*.

[32] Eissa, M. A., & Chen, P. (2023, June). An Efficient Hybrid Deep Learning Approach for Accurate Remaining EV Range Prediction. In *2023 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)* (pp. 430–435). IEEE.

[33] Varga, B. O., Sagoian, A., & Mariasiu, F. (2019). Prediction of electric vehicle range: A comprehensive review of current issues and challenges. *Energies*, *12*(5), 946.

[34] Wang, Z., Wang, X. H., Wang, L. Z., Hu, X. F., & Fan, W. H. (2017, June). Research on electric vehicle (EV) driving range prediction method based on PSO-LSSVM. In *2017 IEEE International Conference on Prognostics and Health Management (ICPHM)* (pp. 260–265). IEEE.

[35] Chen, Y., Huang, M., & Tao, Y. (2022). Density-based clustering multiple linear regression model of energy consumption for electric vehicles. *Sustainable Energy Technologies and Assessments*, *53*, 102614.

[36] Zhang, J., Wang, Z., Liu, P., & Zhang, Z. (2020). Energy consumption analysis and prediction of electric vehicles based on real-world driving data. *Applied Energy*, *275*, 115408.

[37] Pokharel, S., Sah, P., & Ganta, D. (2021). Improved prediction of total energy consumption and feature analysis in electric vehicles using machine learning and shapley additive explanations method. *World Electric Vehicle Journal*, *12*(3), 94.

[38] Huang, J., Li, X., Zhou, T., Cai, B., He, J., & Hu, J. (2024, May). Prediction model of electric vehicle driving range based on support vector regression. In *2024 36th Chinese Control and Decision Conference (CCDC)* (pp. 875–880). IEEE.

[39] Amirkhani, A., Haghanifar, A., & Mosavi, M. R. (2019, December). Electric vehicles driving range and energy consumption investigation: A comparative study of machine learning techniques. In *2019 5th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS)* (pp. 1–6). IEEE.

[40] Mei, P., Karimi, H. R., Huang, C., Chen, F., & Yang, S. (2023). Remaining driving range prediction for electric vehicles: Key challenges and outlook. *IET Control Theory & Applications*, *17*(14), 1875–1893.

[41] George, D., & Sivraj, P. (2021, August). Driving range estimation of electric vehicles using deep learning. In *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)* (pp. 358–365). IEEE.

[42] Shen, H., Wang, Z., Zhou, X., Lamantia, M., Yang, K., Chen, P., & Wang, J. (2022). Electric vehicle velocity and energy consumption predictions using transformer and Markov-chain Monte Carlo. *IEEE Transactions on Transportation Electrification*, *8*(3), 3836–3847.

[43] Wu, X., Freese, D., Cabrera, A., & Kitch, W. A. (2015). Electric vehicles' energy consumption measurement and estimation. *Transportation Research Part D: Transport and Environment*, *34*, 52–67.

[44] Shen, H., Zhou, X., Wang, Z., Ahn, H., Lamantia, M., Chen, P., & Wang, J. (2022). Electric vehicle energy consumption estimation with consideration of longitudinal slip ratio and machine-learn-

ing-based powertrain efficiency. *IFAC-PapersOnLine*, *55*(37), 158–163.

[45] Adnane, M., Khoumsi, A., & Trovão, J. P. F. (2023). Efficient management of energy consumption of electric vehicles using machine learning—A systematic and comprehensive survey. *Energies*, *16*(13), 4897.

[46] Mao, L., Fotouhi, A., Shateri, N., & Ewin, N. (2022). A multi-mode electric vehicle range estimator based on driving pattern recognition. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, *236*(6), 2677–2697.

[47] Bi, J., Wang, Y., Shao, S., & Cheng, Y. (2018). Residual range estimation for battery electric vehicle based on radial basis function neural network. *Measurement*, *128*, 197–203.

[48] Feng, Z., Zhang, J., Jiang, H., Yao, X., Qian, Y., & Zhang, H. (2024). Energy consumption prediction strategy for electric vehicle based on LSTM-transformer framework. *Energy*, 131780.

[49] Padmavathy, R., Greeta, T., & Divya, K. (2023). A machine learning-based energy optimization system for electric vehicles. In *E3S Web of Conferences* (Vol. 387, p. 04008). EDP Sciences.

[50] Abdelaty, H., Al-Obaidi, A., Mohamed, M., & Farag, H. E. (2021). Machine learning prediction models for battery-electric bus energy consumption in transit. Transportation Research Part D: Transport and Environment, 96, 102868." Bi, J., Wang, Y., Sai, Q., & Ding, C. (2019). Estimating remaining driving range of battery electric vehicles based on real-world data: A case study of Beijing, China. *Energy*, *169*, 833–843.

[51] Sun, S., Zhang, J., Bi, J., & Wang, Y. (2019). A machine learning method for predicting driving range of battery electric vehicles. *Journal of Advanced Transportation*, *2019*(1), 4109148.

[52] Gebhardt, K., Schau, V., & Rossak, W. R. (2015, July). Applying stochastic methods for range prediction in e-mobility. In *2015 15th International Conference on Innovations for Community Services (I4CS)* (pp. 1–4). IEEE.

[53] Modi, S., Bhattacharya, J., & Basak, P. (2021). Convolutional neural network–bagged decision tree: a hybrid approach to reduce electric vehicle's driver's range anxiety by estimating energy consumption in real-time. *Soft Computing*, *25*, 2399–2416.

[54] Shamma, Z. S., Jones, B., Clark, M., Bailey, C., & Harper, M. (2022). Electric vehicle range prediction estimator (EVPRE). *Software Impacts*, *13*, 100369.

[55] Sun, T., Xu, Y., Feng, L., Xu, B., Chen, D., Zhang, F., ... & Zheng, Y. (2022). A vehicle-cloud collaboration strategy for remaining driving range estimation based on online traffic route information and future operation condition prediction. *Energy*, *248*, 123608.

[56] Ahmed, M., Mao, Z., Zheng, Y., Chen, T., & Chen, Z. (2022). Electric Vehicle Range Estimation Using Regression Techniques. *World Electric Vehicle Journal*, *13*(6), 105.

[57] De Cauwer, C., Verbeke, W., Coosemans, T., Faid, S., & Van Mierlo, J. (2017). A data-driven method for energy consumption prediction and energy-efficient routing of electric vehicles in real-world conditions. *Energies*, *10*(5), 608.

[58] Wang, Y., Lu, C., Bi, J., Sai, Q., & Zhang, Y. (2021). Ensemble machine learning based driving range estimation for real-world electric city buses by considering battery degradation levels. *IET Intelligent Transport Systems*, *15*(6), 824–836.

[59] Bailey, C., Jones, B., Clark, M., Buck, R., & Harper, M. (2022, October). Electric vehicle autonomy: Realtime dynamic route planning and range estimation software. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 2696–2701). IEEE.

[60] Sangeetha, E. P., Subashini, N., Santhosh, T. K., & Uma, D. (2024). Validation of EKF based SoC estimation using vehicle dynamic modelling for range prediction. *Electric Power Systems Research*, *226*, 109905.

[61] Zhang, Z., Zou, Y., Zhou, T., Zhang, X., & Xu, Z. (2021). Energy consumption prediction of electric vehicles based on digital twin technology. *World Electric Vehicle Journal*, *12*(4), 160.

[62] Dollinger, M., & Fischerauer, G. (2021). Model-based range prediction for electric cars and trucks under real-world conditions. *Energies*, *14*(18), 5804.

[63] Wang, J., Besselink, I., & Nijmeijer, H. (2018). Battery electric vehicle energy consumption prediction for a trip based on route information. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, *232*(11), 1528–1542.

[64] López, F. C., & Fernández, R. Á. (2020). Predictive model for energy consumption of battery electric vehicle with consideration of self-uncertainty route factors. *Journal of Cleaner Production*, *276*, 124188.

[65] Ye, F., Wu, G., Boriboonsomsin, K., & Barth, M. J. (2016, November). A hybrid approach to estimating electric vehicle energy consumption for ecodriving applications. In *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 719–724). IEEE.

[66] De Cauwer, C., Van Mierlo, J., & Coosemans, T. (2015). Energy consumption prediction for electric vehicles based on real-world data. *Energies*, *8*(8), 8573-8593.

[67] Wang, Z., Liu, Y., & Huang, J. (2024). An open api architecture to discover the trustworthy explanation of cloud AI services. *IEEE Transactions on Cloud Computing*.

[68] Wang, Z., & Liu, Y. (2024, July). Cloud-based xai services for assessing open repository models under adversarial attacks. In *2024 IEEE International Conference on Software Services Engineering (SSE)* (pp. 141–152). IEEE.

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