Battery Monitoring System for Ensuring Safety

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*Abstract*— The proposed solution delves into the world of Electric Vehicles (EVs) and their capabilities through a combination of linear regression and multivariate analysis techniques. The dataset includes data of 100 Electric vehicle brands and their specifications, such as acceleration, range, top speed, efficiency, and prices. An algorithm for determining the EV State of Charge and making decisions related to charging and discharging is proposed. This algorithm utilizes data loading, feature selection, model training, evaluation, range prediction, energy consumption estimation, SoC calculation, and predefined thresholds to enhance understanding and decision-making in real-life EV usage scenarios. The model's accuracy in estimating the remaining range is assessed using metrics like MAE, MSE, and R-squared. The proposed system has a higher R-squared (0.9835) and lower MAE (8.9550) and MSE (137.56) values, indicating superior performance compared to other systems.

Keywords— Machine learning, electric vehicles, range, linear regression, state of charge

# Introduction

Along with other problems, humanity is currently dealing with an energy shortage, severe worldwide warming, and pollution of the environment. Using Electric Cars (EVs) instead of conventional cars would be one of the most notable approaches to reducing global warming and other issues. Many developed countries, like the USA and China, have already established measures for subsidies for hybrid electric vehicles, offering energy savings, emission reduction, and reduced air pollution. Vehicle speed prediction methods, including Model-based parametric Methods (MBPM) and Data-driven non-parametric Methods (DDNPM), are used to improve energy management in hybrid electric buses [1].

The development of Plug-in Hybrid Electric Vehicles (PHEVs) offered an alternative to the typically used internal combustion engines, but finding the best energy management strategy (EMS) has been a challenge. Heuristic strategies have been cost-effective and are available for online use, but their real-time application is limited [2].

In recent years, a wealth of studies has unveiled a plethora of highly effective reinforcement learning techniques to maximize computational speed and fuel efficiency in plug-in hybrid electric cars. These cutting-edge techniques utilize model-free online RL approaches, which seamlessly integrate intricate powertrain modeling with intuitive heuristic planning strategies to achieve maximum real-time fuel savings. While these advancements offer clear advantages, one notable disadvantage remains [3]. The introduction of hybrid electric vehicles (HEVs) has brought about new and complex challenges in terms of energy management. Despite the use of traditional techniques such as Reinforcement Learning (RL), achieving optimal fuel efficiency while maintaining a charged battery remains a constant struggle. There is no one solution that can perfectly balance these competing objectives, leaving researchers and engineers in a constant state of conflict [4].

Through the use of advanced neural networks, EMS knowledge was successfully transferred between various types of HEVs with a remarkable increase in convergence efficiency by 69.5%. The cutting-edge technology of Deep Transfer Reinforcement Learning (DTRL) allowed for improved generalization capabilities under driving cycle 2. However, further research is required to fully comprehend the extent of its potential impact. The possibilities are endless and exciting for the future of electric vehicle development and optimization [5].

# Literature Survey

The EV technology includes main categories: Three types of electric vehicles are Hybrid, Plug-in, and Battery (BEV). BEVs and PHEVs can be externally recharged, however, the concept of vehicle-to-grid (V2G) is briefly explored for utilizing EV batteries to store energy during extended parking. The paper acknowledges challenges and advancements in EV technology and emphasizes the importance of charging EV batteries from renewable energy sources to achieve zero emissions [6]. Determining the State of Health (SOH) and State of Charge (SOC) of the battery is the primary function of the BMS for Electric Vehicles.

The BMS comprises five blocks: Measurement, battery algorithm, Capability estimation, Cell equalization, and Thermal management. SOC can be accurately calculated by using the 'Coulomb Counting method' [7].

Machine learning techniques for BMS, focus on Remaining- Useful-Life (RUL) prediction and fault detection. It categorizes methods by principles, types, structures, and performance evaluation. Three ML groups using SOH data are supervised, unsupervised, and reinforcement learning. Gaussian Naïve Bayes (GNB) operates well with non-linear curves, while Neural Networks (NN) achieves high scores but requires substantial training data for efficiency improvement [8]. Multi-agent multi-objective reinforcement learning is used in multi-agent selfish-collaborative architecture (MASCO). Acquiring the ability to manage the charging of electric vehicles while avoiding transformer overloads and reducing energy expenses. MASCO adapts to tariff types, accommodating consumer preferences. It addresses the issue of EV grid congestion by proposing a solution where EVs autonomously decide when to charge.

MASCO's approach balances multiple objectives, utilizing Reinforcement Learning and a Selfish Optimization procedure [9]. The new energy management strategy for HEVs uses reinforcement learning to estimate the costate. The strategy is divided into a pair of parts: a stochastic part that estimates the costate using Q-learning, and a deterministic part that uses the optimal control concept to calculate the control inputs. This allows it to make more informed decisions about the control inputs. The proposed strategy can improve fuel efficiency by 0.5 to 1.5% compared to the adaptive Equivalent Consumption Management Strategy (ECMS) [10]. The prominent ML models that are employed for evaluating and analyzing the effectiveness of the EVs are ANNs, SVMs, Linear Regression, Random Forest, and KNN. A few properties of the battery that can be used during data-driven SOH estimation are its voltage, current, temperature, and resistance. For predicting charging load at 15-minute intervals, a Long Short-term Memory (LSTM)-based model performed better than an Artificial Neural Networks (ANN) model, with lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) [11]. The challenges of data-driven SOH estimation include the need for large amounts of data, the non-linearity of the SOH degradation process, and the variability of the performance of batteries [12].

Recent advances in RUL prediction methods for Li-ion batteries. In the study thereafter, the effectiveness of ANNs and SVMs for SOC estimation in Lithium-ion Batteries was examined. ANNs outperformed Support Vector Machines (SVMs) in terms of both RMSE and MAE. ANNs could be used to develop a more accurate and reliable SOC estimation method for EVs [13]. The cell's SOC is approximately 0.2, which is consistent with the depth of discharge for electric car cells. They concluded that 2P4S has a higher charge/discharge capacity than 4S2P. The performance of parallel-then-series and series-then-parallel battery packs is compared in this research. The findings indicate that the parallel-then-series pack performs better in terms of charge/discharge capacity, efficiency, and cell utilization rate [14].

Artificial neural networks come in the form of multi-layer perceptrons, or MLPs. MLP’s are trained with the backpropagation for pattern classification, recognition, prediction, and approximation, learning algorithms are employed. A study was conducted to estimate the output current ripple in a power factor correction interleaved boost converter (PFC-IBC) converter using machine learning techniques. The results showed that the ANN model was the most successful, with the highest R-squared (R2), mean squared error (MSE), RMSE, and MAE values [15].

Study examines clever methods for electric vehicle (EV) battery management systems. It assesses battery state estimate techniques, temperature, equalisation, and protection controllers, and finds difficulties with computing complexity and execution issues. The goal of the evaluation is to increase battery performance, safety, and dependability, which will expand the market [16]. To guarantee the reliable and safe operation of lithium-ion batteries (LiBs), the study looks at battery thermal management systems (BTMS) in electric vehicles (EVs). It investigates design parameter optimisation techniques and air-cooled BTMS approaches. Naturally air-cooled BTMS techniques are straightforward and inexpensive, but they have limitations when it comes to providing sufficient cooling for high energy density LiBs. The work highlights that building effective battery-tracking module systems (BTMSs) requires precise numerical modelling and simulation of battery behaviour [17].

A clever bidirectional charging algorithm that considers the effects of temperature on lithium-ion batteries is suggested for electric vehicles to reduce charging expenses and increase customer profit. The system, which was tested in France, is more cost-effective and efficient than unregulated charging. Customers may make money by charging and contributing to the grid while adhering to SOCmini limitations thanks to the V2G feature, which also prolongs battery life [18]. Proteus, an intelligent and energy-efficient temperature control system for electric vehicles, is proposed in this research. Keep the battery compartment at the ideal temperature, this technique extends the life and efficiency of the batteries. The battery temperature is lowered and its lifespan is increased by the system's usage of a cooling fan to run at higher or lower temperatures [19].

To estimate the internal temperature of a LiFePo4 battery, the research provides a hybrid data-driven method that combines an extended Kalman filter with a linear neural network model. To choose input terms and save computational costs, the approach makes use of a quick recursive algorithm. For improved generalization, future research may make advantage of cutting-edge artificial intelligence techniques and actual loading circumstances [20].

# Research Gap

The evolution of electric vehicles (EVs) has undergone several advancements in the past few years. The research gaps in electric vehicle analysis, identified in the review of multiple studies, can be addressed by the current framework of the proposed system. Many systems as mentioned in the literature review consisted of models such as - ANNs, SVMs, KNN, LSTM, NN, etc. The reviewed papers evaluated the Dyna H algorithm and found that it was too slow for real-time applications, even when given more resources. It also produced less accurate results than other algorithms. Also, Neural Networks (NN) achieved high scores in accuracy but require substantial training data for efficiency improvement. Further, the mentioned systems were only designed to predict the price and estimation of batteries. However, none of the methods were able to optimize the charging and discharging of electric vehicle batteries in order to improve their lifespan and performance. None of the aforementioned methods is completely preferable, and every unique situation should consider the trade-off between generalisation, data sparsity, and accuracy. The proposed system would enact Linear Regression, SVM, and Random Forest to analyze electric vehicles based on their battery range, charging time, battery degradation, and other features.

# Methodology

The process begins with collection of dataset and preprocessing the dataset, on which the model is to be trained. Through linear regression, the analysis examines EVs based on their attributes, exploring relationships between factors like acceleration, range, top speed, efficiency, and EV price.

## System Architecture:

A diagram of a process

Description automatically generated

Fig. 1: Linear regression model

Fig. 1 presents a process flow diagram illustrating the steps involved in developing and applying a linear regression model for analyzing and predicting key parameters in energy storage or battery systems. It starts with data acquisition, followed by feature selection to identify relevant input variables. These selected features are then used to train a linear regression model. The trained model is employed to estimate the state of charge and predict the range and energy consumption of the battery or energy system. Finally, the model undergoes evaluation to assess its accuracy and effectiveness in making these predictions. This systematic approach leverages linear regression modeling techniques to gain insights and make informed decisions related to battery performance and energy management.

Additionally, multivariate linear regression is employed to predict the presence of rapid charging capabilities in these EVs.

## Dataset Details:

The data includes specifications of 100 brands of different models of Electric vehicles, such as Range, Acceleration, Top Speed, Total Power, Total Torque, Drive Battery Capacity, Charge Power, Charge Speed, and Fast Charge Speed, as well as price information.

Data preprocessing steps performed are primarily focused on data visualization rather than data cleaning or transformation.

Data splitting: The dataset was divided into training, testing, and validation sets in the proportion of 8:1:1.

*Features Selection:* The most relevant features for the predictive model are identified and the selected features are Acceleration 0 - 100 km/h, Top Speed, Total Power, Total Torque, Drive Battery Capacity, Charge Power, Charge Speed, Fast Charge Speed, these features are selected based on their coefficient values corresponding to each feature.

## System Design

Machine learning module:

Linear regression is a statistical method that can be used to model the relationship between a dependent variable (y) which is the remaining range of EV and independent variables (x1, x2, ...., xn) as shown in Fig 2.

y = β0 + β1x1 + β2x2 + ... + βnxn (1)

A graph showing the difference between a number of variables

Description automatically generated with medium confidence

Fig 2. Graphical Representation of Linear regression

The intercept (β0) is the value of y when all the independent variables are equal to zero. The coefficients (β1, β2, ..., βn) represent the slopes of the lines that relate the dependent variable to each of the independent variables.

In multivariate linear regression, the concept of simple linear regression is extended to model the relationship between a dependent variable (y) and multiple independent variables (x1, x2, ..., xn).

We implemented the multivariate linear regression model using a sci-kit-learn library in Python, and then trained the model on the training data using the selected features, making the remaining range the target variable.

In model evaluation, we have evaluated the linear regression model on the validation dataset using relevant regression metrics - MAE, MSE, and R-squared to make sure the model can accurately estimate the remaining range based on the current SOC and other factors.

MAE: MAE measures the average absolute difference between the predicted values (Ŷ) and the actual values (Y) of the remaining range for EVs.

MAE = (1 / n) \* Σ |Y - Ŷ| (2)

MSE: MSE measures the average of the squared differences between the predicted values (Ŷ) and the actual values (Y) of the remaining range for the EVs.

MSE = (1 / n) \* Σ (Y - Ŷ)² (3)

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Algorithm: Electric Vehicle SOC Estimation and Decision

Making

**Input:** Features: Select relevant features (X) and (y**)**

**Output:** Display the estimated SoC, charging and discharging status

1**. Training Phase**:

2. Initialize Model: model = LinearRegression()

3. model.fit(X\_train, y\_train)

4. **Evaluation Phase:**

5. y\_pred = model.predict(X\_test)

6. **Evaluate Model:**

7. mae = mean\_absolute\_error (y\_test, y\_pred)

8. mse = mean\_squared\_error (y\_test, y\_pred)

9. r2 = r2\_score (y\_test, y\_pred)

10. **SOC Estimation and Decision Making:1**

11**.** Predict Range: Use the trained model to predict the range

predicted\_range = model.predict(new\_features)

12. **Calculate Consumed Energy:**

consumed\_energy = predicted\_range / efficiency

13. **Estimate\_SoC**:

soc=(total\_capacity-consumed\_energy) / total\_capacity)

14. **Make Charging/Discharging** **Decision:**

**if** (estimated\_soc < min\_charge\_threshold) **then (**"Battery is Discharged")

**else if** (estimated\_soc > max\_charge\_threshold) **then**

("You are good to go!")

15.   return model

The approach for the proposed solution combines the strength of Multivariate Linear Regression with data visualization to accurately predict the range of Electric Vehicles, making it a reliable tool for understanding and optimizing electric mobility.

After predicting the range, SoC estimation and charging-discharging behavior of the battery are determined.

# Results

The experimental setup of the proposed system focuses on EV range prediction using a linear regression model. We have collected and visualized data encompassing the State of Charge (SoC), range, driving behavior, external factors, and linear regression-predicted range of the EVs. The approach for the proposed system combines rule-based decision-making for charging-discharging behavior with predictive modeling.

The Table I summarizes the performance of three machine learning models: Linear Regression, Decision Tree Regression, and Random Forest Regression, on both training and testing data.

Table I:  Model comparison with other Techniques

|  |  |  |  |
| --- | --- | --- | --- |
| Parameters | **Proposed System** | Decision Tree Regression | Random Forest Regression |
| R² (Training Data) | 0.9835 | 1.0 | 0.9949 |
| R²  (Testing Data) | 0.9807 | 0.9359 | 0.91530 |
| Mean Absolute Error (MAE) | 8.9550 | 14.5054 | 24.9029 |
| Mean Squared Error (MSE) | 137.56 | 470.51 | 620.15 |
| Root Mean Squared Error (RMSE) | 11.7286 | 21.6913 | 15.5241 |

The above models were evaluated using three regression metrics: R² (coefficient of determination), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The Linear Regression model is a good choice, as it has a high R² value and the lowest MAE value on the training data. The Decision Tree Regression model is the least accurate of the three models.

The MAE indicates that the average absolute difference between the predicted values and the actual values is 8.9550, while the RMSE indicates that the standard deviation between them is 11.7286. In summary, the proposed model shows moderate predictive power for the training data, with an R2 suggesting it explains about 98.35% of the variance. The model's performance is slightly reduced when applied to the testing data.

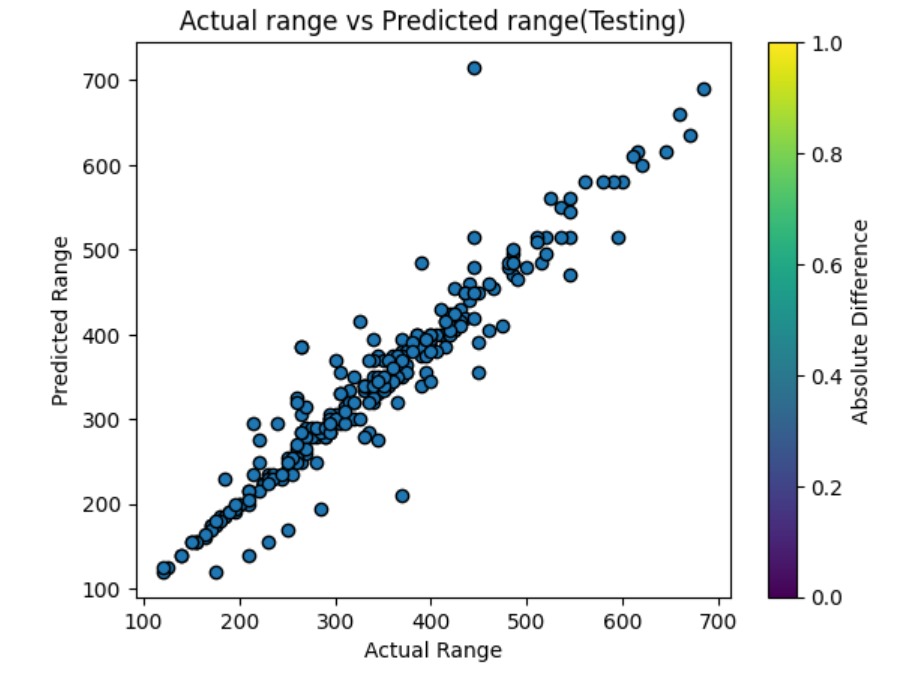


Fig. 3: Scatter-graph of Actual vs Predicted value for EVs Range

Above Fig. 3 shows the scatter plot indicating there is a positive correlation between the predicted range and the actual range, as it is seen from the line of regression and data-points associated with it. This means that the multivariate linear regression model can predict the range of EVs with good accuracy.

# Conclusion

This paper began with a comprehensive exploration of regression models, focusing on linear regression, decision tree regression, and random forest regression. The models were meticulously trained and evaluated to address the problem statement of predictive accuracy. Three noteworthy aspects of the proposed solution include the linear regression model's exceptional performance on both training and testing data, achieving R² values of 0.9835 and 0.9807, respectively. This model exhibits superior accuracy with lower Mean Squared Error (137.56) and Mean Absolute Error (8.96) on the testing set. However, limitations include the potential overfitting observed in the decision tree regression model. The project also implemented a decision-making system to determine whether to charge, discharge, or maintain the current battery state, considering user-defined SoC thresholds. While the project successfully addressed challenges and limitations, future enhancements could explore advanced machine-learning models and real-time sensor integration for more comprehensive and accurate results.

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