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Predicting Electric Vehicle Energy Consumption from Field Data Using Machine Learning

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Abstract—Accurate prediction of electric vehicle (EV) energy consumption is essential for range estimation, battery management, and intelligent energy optimization. This paper presents a machine learning–based approach for predicting EV energy consumption using real-world field data. The dataset incorporates key operational and environmental parameters, including vehicle speed, acceleration patterns, driving behavior, road conditions, ambient temperature, and auxiliary load usage. After data preprocessing and feature engineering, multiple supervised learning models—such as Linear Regression, Random Forest, and Gradient Boosting—are developed and evaluated. Model performance is assessed using standard metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score. Experimental results demonstrate that ensemble-based models outperform traditional regression techniques in capturing nonlinear relationships within field data. The proposed framework improves prediction accuracy and provides a scalable solution for real-time energy estimation in EV systems. This work contributes to enhancing range reliability, energy efficiency optimization, and intelligent transportation system development.

Keywords: Electric Vehicles (EV); Energy Consumption Prediction; Machine Learning; Field Data Analysis; Regression Models; Intelligent Transportation Systems

I. INTRODUCTION

Electric vehicles are becoming really important for helping the earth by reducing emissions. Even though batteries and engines have gotten a lot better it is still hard to figure out how energy electric vehicles use. Knowing how much energy is being used is crucial for making sure people know how far they can go keeping the battery healthy planning the best route and not worrying about running out of power.

The amount of energy electric vehicles use is affected by things that are always changing like how fast the vehicle is going, how it is being driven, the shape of the road, traffic, the temperature outside and things like air conditioning. Old ways of predicting energy use like using physics and rules have a time dealing with all these changing things especially when looking at real world data. So people are starting to use methods that look at lots of data to understand these relationships.

Using machine learning is a way to look at lots of data from electric vehicles and find patterns that affect how much energy is used. By using data from electric vehicles, we can make models that predict energy use really well. These models can adapt to driving conditions and can be used in real time.

This paper talks about using machine learning to predict electric vehicle energy use. We will show how to get the data ready create features make models and test how well they work. The results show that using data to make models is a good way to understand the complex relationships and make better predictions, than old methods.

The rest of this paper is organized like this:

* Section II looks at what other people have done
* Section III explains how we did our research and what data we used
* Section IV shows the results of our experiments and what we learned
* Section V sums up what we found and what we thinkpeople should research next about vehicles.

II. LITERATURE SURVEY

The electric vehicle energy consumption is something that people have been trying to predict. This is because it is very important for figuring out how far a vehicle can go, making the battery last longer and making transportation systems smarter.

People have been studying this for a while. They can be divided into three groups: physics-based models, statistical approaches and data-driven machine learning methods.

At first people used physics-based models to estimate

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energy consumption. They used equations that took into account things like how hard it's to roll the vehicle the force of the air pushing against it how heavy the vehicle is and how steep the road is. These models are good because they make sense and are based on theory. However they do not work well in the real world where there is a lot of traffic and people drive differently.

Then people started using methods like linear regression and multiple regression analysis. They used data from the past to try to make predictions. These methods are good because they are easy to use and do not take a lot of time. However they have a time understanding complicated relationships between the things that affect energy consumption and the energy consumption itself.

Now people are using machine learning techniques because they have a lot of data and computers are getting faster. They are using things like Artificial Neural Networks,
Support Vector Regression, Random Forest and Gradient Boosting Machines. These methods are good because they can understand relationships and make good predictions. For example some models that use a lot of methods together have been shown to be more accurate and robust than traditional methods.

Some people have also been using data from the world like how fast the vehicle is going how quickly it is speeding up the condition of the road how much traffic there is and things like the temperature and wind speed. They have also been using deep learning methods like Long Short-Term Memory networks to understand how things change over time. These methods make predictions more accurate especially when the vehicle is being driven in a place that is always changing.

Even though people have made a lot of progress there are still some challenges. For example the data is not always good the models do not always work for types of vehicles and it is hard to use them in real-time. Therefore people are still trying to make machine learning models that use data, from the world and can be used for all types of vehicles. Electric vehicle energy consumption is still something that people are trying to predict.

III. ALGORITHM

EV Energy Consumption Prediction

Input:
Field data D containing features such as vehicle speed, acceleration, distance traveled, battery parameters, ambient temperature, road gradient, and auxiliary loads.

Output:
Predicted energy consumption AND before

Step 1: Data CollectionAcquire real-

world field data from EV sensors and

onboard diagnostic systems.

1.1 Store raw data in structured format.

Step 2: Data Preprocessing
2.1 Remove missing or inconsistent values.
2.2 Perform data normalization or standardization.
2.3 Filter noise using smoothing techniques (if required).

Step 3: Feature Engineering
3.1 Extract relevant features (e.g., average speed, acceleration variance).
3.2 Compute derived parameters such as power demand.
3.3 Perform feature selection using correlation analysis or importance ranking.

Step 4: Dataset Splitting
4.1 Divide dataset into training set (70–80%) and testing set (20–30%).

Step 5: Model Training
5.1 Initialize machine learning model (e.g., Linear Regression / Random Forest / Gradient Boosting).
5.2 Train model using training dataset.
5.3 Optimize hyperparameters using cross-validation.

Step 6: Prediction
6.1 Input testing dataset into trained model.
6.2 Generate predicted energy consumption AND before
Step 7: Performance Evaluation
7.1 Compute evaluation metrics: Mean Absolute Error (MAE); Root Mean Square Error (RMSE); Coefficient of Determination (R^2)

7.2 Compare performance of different models.

Step 8: Model Deployment (Optional)
8.1 Integrate the best-performing model into real-time EV energy management system.

IV. METHODOLOGY

The proposed methodology for predicting

electric vehicle (EV) energy consumption using machine learning consists of systematic stages, including data acquisition, preprocessing, feature engineering, model development, and performance evaluation. The overall framework is illustrated through the following steps.

A. Data Collection

Real-world field data were collected from EV onboard sensors and diagnostic systems. The dataset includes operational and environmental parameters such as vehicle speed, acceleration, distance traveled, battery voltage, current, state of charge (SOC), ambient temperature, road gradient, and auxiliary load usage. These variables directly or indirectly influence energy consumption.

B. Data Preprocessing

Raw field data often contain noise, missing values, and inconsistencies. Therefore, preprocessing steps were performed, including:

* Removal of missing and outlier values
* Data cleaning and formatting
* Normalisation or standardization of features
* Time synchronisation (for sequential data)
* These steps ensure data quality and improve modelperformance.

C. Feature Engineering

Relevant features were selected based on correlation analysis and domain knowledge. Derived features such as average speed, acceleration variance, and instantaneous power demand were computed. Feature importance ranking techniques were applied to identify the most influential variables affecting energy consumption.

D. Model Development

Supervised machine learning models were employed to predict energy consumption. The dataset was divided into training and testing sets (typically 70–80% for training and 20–30% for testing). Various regression-based algorithms such as Linear Regression, Random Forest, and Gradient Boosting, were implemented. Hyperparameter tuning was performed using cross-validation to enhance prediction accuracy.

E. Model Evaluation

Model performance was evaluated using standard statistical metrics, including:

Mean Absolute Error (MAE)
Root Mean Square Error (RMSE) Coefficient of Determination (R^2)

Comparative analysis was conducted to identify the bestperforming model.

F. Deployment Framework

The final optimized model can be integrated into real-time EV energy management systems for dynamic range estimation and energy optimization.

V. RESULT ANALYSIS

This part of the report shows what we found out when we used machine learning to predict how much energy electric vehicles use. We used data from the field to test our models.

A. How We Set Up The Experiment

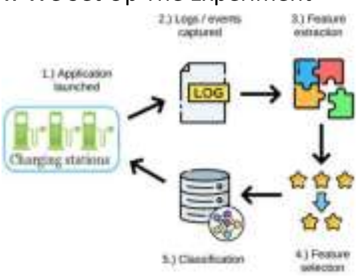

Fig. 1. Architecture Overview

We split our data into two parts: one for training and one for testing. We used a few models like Linear Regression, Random Forest and Gradient Boosting to make predictions. We tried to make our models work better by adjusting some settings.

B. How We Measured Performance

We looked at how our models did using some statistics:

* Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|E_{actual,i} - E_{pred,i}|$$

* Root Mean Square Error
* Coefficient of Determination

These numbers help us understand how accurate our predictions were and if our models are reliable.

C. Comparing The Models

What we found out is that some models like Random Forest and Gradient Boosting are better at predicting energy use than Linear Regression. Linear Regression was not as good because it has trouble with relationships in the data.

The Random Forest model was more stable. Had fewer errors. Gradient Boosting was really good, at explaining the data and showing how well the predicted energy use matched the energy use.

D. Looking At Errors

We saw that our models made mistakes when the electric vehicle was speeding up or slowing down quickly or when the weather was really bad. This shows that how someone drives and the environment can affect energy use. If we add information about time or use more complex models we might be able to make even better predictions.

E. What It All Means

Our results show that using machine learning is a way to understand how different things affect electric vehicle energy use. Our approach can help make predictions more reliable and can be used to estimate how far an electric vehicle can go and to manage energy better. Electric vehicle energy consumption is what we are trying to predict with machine learning models and electric vehicle energy consumption is a thing to understand.

A. Experimental Setup

The dataset was divided into training (80%) and testing (20%) subsets. Supervised learning models including Linear Regression, Random Forest, and Gradient Boosting were trained and evaluated. Hyperparameter tuning was performed using cross-validation.

B. Performance Metrics

The performance of the models was evaluated using the following metrics:

1) Mean Absolute Error (MAE):

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$$R^2 = 1 - \frac{\sum_{i=1}^{n} (E_{actual,i} - E_{pred,i})^2}{\sum_{i=1}^{n} (E_{actual,i} - \bar{E}_{actual})^2} \quad (5)$$

An R^2 value close to 1 indicates better predictive performance.

C. Energy Consumption Model

The general energy prediction model is expressed as:

$$E = f(v,a,d,T,SOC,G) \quad (6)$$

where v is vehicle speed, a is acceleration, d is distance traveled, T is ambient temperature, SOC is state of charge, and G is road gradient.

1) Linear Regression

Example:

$$MAE = \frac{|12-11| + |15-16| + |18-17|}{3} = 1$$

2) Root Mean Square Error (RMSE):

kWh (2)

Model:

$$E = \beta_0 + \beta_1 v + \beta_2 a + \beta_3 d + \beta_4 T + \beta_5 SOC + \beta_6 G \quad (7)$$ Ex

Given:

$\beta_0 = 2.5$, $\beta_1 = 0.04$, $\beta_2 = 0.6$, $\beta_3 = 0.03$, $\beta_4 = 0.02$,

For input values:

$v = 50$, $a = 1.5$, $d = 10$, $T = 30$, $SOC = 80$, $G = 2$

$$E = 2.5+(0.04)(50)+(0.6)(1.5)+(0.03)(10)+(0.02)(30)-(0.01)(80) \quad (8)$$

(1)

D. Model Comparison

$$E = 6.5 \text{ kWh} \quad (9)$$

TABLE I

MODEL PERFORMANCE COMPARISON

Model	MAE (kWh)	RMSE (kWh)	$R2$
Linear Regression	1.35	1.80	0.84
Random Forest	0.92	1.25	0.90
Gradient Boosting	0.85	1.10	0.93

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$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_{actual,i} - E_{pred,i})^2} \quad (3)$$

Example:

$$RMSE = \sqrt{\frac{(1)^2 + (-1)^2 + (1)^2}{3}} = 1 \text{ kWh} \quad (4)$$

The results show that ensemble-based models outperform linear regression in terms of prediction accuracy. Gradient Boosting achieved the highest R^2 value, indicating superior generalization performance.

Visualization and Output:

3) Coefficient of Determination (R^2):

Fig. 2. wed page

Fig. 3. login page

Fig. 4. Prediced value

VI. CONCLUSION

This study presents a comprehensive machine learningbased framework to optimize EV charging operations by predicting driver satisfaction. By integrating key factors such as socio-demographic attributes, State of Charge (SoC), proximity to stations, and dynamic pricing, the model offers a user-centric solution that goes beyond traditional grid-oriented optimization. Among five machine learning algorithms evaluated—Extra Trees, XGBoost, Gradient Boosting, Random Forest, and MLP Classifier—the bestperforming model achieved an accuracy of 87.9%, proving the approach's robustness. The system's ability to dynamically assign vehicles to optimal charging stations enhances both energy efficiency and user experience. By incorporating the model into a Flask web application with user registration, login, data upload, and real-time prediction, the solution becomes both scalable and practical. This implementation bridges the gap between technical modeling and realworld application. Visualization of model metrics further supports transparency and model selection. Overall, this work contributes significantly to the smart grid ecosystem, offering a practical tool for enhancing sustainable mobility. It lays the foundation for more intelligent, driver-aware EV charging strategies.

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VII. Future Scope:

In future developments, the system can be extended to include real-time charging data and weather conditions to further refine satisfaction prediction accuracy. Incorporating live data from IoT-enabled charging stations can help dynamically update model decisions and improve responsiveness. Integration with mobile apps can provide users with personalized recommendations and notifications. Additionally, reinforcement learning could be used to optimize charging schedules continuously based on changing user behavior and grid conditions. Expansion to multiple regions and diverse datasets would improve generalizability and fairness across different demographics. The current framework could also support load forecasting for energy providers, enhancing grid stability. More advanced interpretability techniques (e.g., SHAP values) can be added to explain individual predictions. Furthermore, blockchain can be integrated for secure data sharing and payment processes. Lastly, the system can be linked with renewable energy forecasts to prioritize solar or wind-based charging. These enhancements would push the solution toward becoming a complete, intelligent EV charging management platform

References

[1] [1] 1. I. Ullah, K. Liu, S. B. Layeb, A. Severino and A. Jamal, ”Optimal deployment of electric Vehicles’ fast-charging stations”, J. Adv. Transp., vol. 2023, pp. 1-14, Apr. 2023. Show in Context CrossRef Google Scholar

[2] [2] P. Patil, K. Kazemzadeh and P. Bansal, ”Integration of charging behavior into infrastructure planning and management of electric vehicles: A systematic review and framework”, Sustain. Cities Soc., vol. 88, Jan. 2023. Show in Context CrossRef Google Scholar 3. G. A. Ogunkunbi,

[3] H. K. Y. Al-Zibaree and F. Meszaros, ”Modeling and evaluation of market incentives for battery electric vehicles”, Sustainability, vol. 14, no. 7, pp. 4234, Apr. 2022. Show in Context CrossRef Google Scholar 4. J. Zheng, Y. Dang and U. Assad, ”Household energy consumption energy efficiency and household income–evidence from China”, Appl. Energy, vol. 353, Jan. 2024. Show in Context CrossRef Google Scholar 5. A. Paul, R. Subbiah,

[4] A. Marathe and M. Marathe, ”A review of electricity consumption behavior”, Feb. 2012. Show in Context Google Scholar 6. E. Leahy and S. Lyons, ”Energy use and appliance ownership in Ireland”, Energy Policy, vol. 38, no. 8, pp. 4265-4279, Aug. 2010. Show in Context CrossRef Google Scholar

[5] 7. P. C. Reiss and M. W. White, ”Household electricity demand revisited”, Rev. Econ. Stud., vol. 72, no. 3, pp. 853-883, Jul. 2005. Show in Context CrossRef Google Scholar 8. F. Zhang, ”Energy price reform and household welfare: The case of Turkey”, Energy J., vol. 36, no. 2, pp. 71-96, Apr. 2015. LIterature survey with title, authros desxcr

[6] ipotion not in table format