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A Comprehensive Systematic Review of Techniques for Predicting Electric Vehicle Energy Demand

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ABSTRACT

The growing adoption of electric vehicles (EVs) presents a significant challenge in accurately predicting their energy consumption. As countries move towards more sustainable transportation, forecasting energy demand is crucial for infrastructure development, grid management, and battery optimisation. This project, "A Comprehensive Systematic Review of Techniques for Predicting Electric Vehicle Energy Demand," evaluates machine learning algorithms used for energy consumption forecasting in electric vehicles.The review focuses on algorithms such as Random Forest, Logistic Regression, Decision Trees, and K-Nearest Neighbors. These models were assessed for their ability to predict energy consumption based on various factors, including driving behavior, weather, terrain, and vehicle specifications. Each algorithm's strengths and limitations were considered, with Random Forest proving particularly effective for handling complex, non-linear data, while Logistic Regression and KNN offered computational efficiency and simplicity.

Through an in-depth analysis of existing research, the study also identifies key challenges in energy demand forecasting, such as data noise, missing values, and the need for real-time data integration. The review suggests that future improvements could be made through the incorporation of deep learning techniques like LSTM networks, which are well-suited for time- series data, and the integration of real-time data from vehicle sensors and charging stations.By synthesising current research, this project aims to enhance the accuracy and robustness of energy demand predictions, helping to optimise EV battery usage, infrastructure planning, and energy grid management. It offers valuable insights for researchers and stakeholders in the electric vehicle and energy sectors,paving the way for more efficient, sustainable transportation systems.

Keywords: Random Forest, Logistic Regression, Decision Trees, and K-Nearest Neighbores

INTRODUCTION

The global shift toward sustainable transportation has accelerated the adoption of electric vehicles (EVs), driven by concerns over climate change, rising fuel costs, and advancements in battery technology. As EVs become increasingly prevalent on roads worldwide, the accurate prediction of their energy consumption has emerged as a critical challenge. Effective energy demand forecasting is essential for several reasons: it supports infrastructure development such as the strategic placement of charging stations, aids in grid load balancing for utility providers, and enables better battery management for improved vehicle efficiency and user experience.Unlike traditional internal combustion engine vehicles, the energy consumption patterns of EVs are influenced by a broader range of dynamic factors, including driving behavior, road and weather conditions, terrain, and the technical specifications of the vehicle. These factors introduce significant variability into energy usage, necessitating advanced modeling techniques to achieve accurate predictions. Conventional statistical methods often fall short in capturing the complexity of these interdependent variables, prompting researchers to explore machine learning approaches that can model non-linear and high-dimensional relationships in data.This review aims to provide a comprehensive and systematic analysis of the machine learning algorithms commonly employed for forecasting energy consumption in EVs. Techniques such as Random Forest, Logistic Regression, Decision Trees, and K-Nearest Neighbors (KNN) are explored in detail. Each algorithm is evaluated based on its predictive performance, computational efficiency, interpretability, and suitability for different types of data and forecasting scenarios.Furthermore, the study examines the key challenges that hinder accurate energy demand prediction, including data quality issues like noise and missing values, as well as the need for real- time data integration. Emerging techniques, particularly deep learning models such as Long Short-Term Memory (LSTM) networks, offer promising solutions to some of these challenges by leveraging sequential data and learning temporal dependencies.

II. LITERATURE REVIEW

The Paris Agreement sets a clear target for net zero greenhouse gas (GHG) emissions by the mid-21 st century. This implies that the Transport sector will reach zero GHG emissions mainly through direct and indirect electrification in the form of synthetic fuels, such as hydrogen and Fischer-Tropsch (FT) fuels. This paper analyses the global solar photovoltaics (PV) demand for achieving sustainability targets in the Transport sector by the year 2050. The methodology is comprised of the derivation of the transportation demand converted into final energy demand for direct electrification, hydrogen, methane and FT-fuels. The power-to-gas (H_2, CH_4) and power-to-liquids (FTfuels) value chains are applied for the total electricity demand for the transportation demand, assuming an energy transition for the Transport sector and a biofuel contribution. This electricity demand is the basis for the solar PV demand, taking into account previous results concerning the renewable electricity share and thereof the solar PV share of the energy transition in the Power sector. The results show a continuous demand increase for all transport modes for passenger and freight transport of about 200% from 2015 to 2050. The anticipated strong direct electrification in the road and rail segments and continued demand of liquid fuels for the marine and aviation segments lead to a drastic relative energy demand shift towards marine and aviation. The total global PV capacity demand by 2050 for the Transport sector is estimated to be about 19.2 TWp, thereof 35%, 25%, 6% and 33% for direct electrification, hydrogen, synthetic natural gas, and FT-fuels, respectively. An additional 2.4 TWp PV capacity is allocated to the

FT by-product naphtha, which is a valuable input for the chemical industry and may be equivalent to about 14% of the feedstock demand of the chemical industry in 2050. Solar PV will be the key enabler of a full defossilisation of the Transport sector with a demand comparable to the Power sector but a slightly later growth dynamic, leading to a combined annual PV capacity demand of about 1.8 TWp around 2050.

III. EXISTING SYSTEM

In the context of predicting electric vehicle energy demand, the existing systems primarily consist of conventional forecasting models, such as linear regression, time-series models, and simple rule-based approaches. These systems are often limited in their ability to handle the complex, non-linear relationships between various factors that influence energy consumption, such as driving patterns, weather, and battery conditions.

Machine learning models have started to replace traditional methods due to their ability to learn from large datasets and capture more intricate patterns in energy usage. Some of the commonly used models include Random Forest, Decision Trees, Logistic Regression, and K-Nearest Neighbors. While these models have shown promising results, challenges remain in their ability to generalise across different regions, vehicle models, and driving conditions.

DISADVANTAGES

Limited Non-Linear Relationship Handling: These models assume linear relationships, but energy consumption depends on complex, non-linear factors like driving behavior, weather, and terrain, which they cannot capture effectively.

Inability to Process Complex Data: Traditional models struggle with multi- dimensional data, such as varying driving patterns, weather, and road conditions, leading to less accurate predictions.

Lack of Adaptability: These models are static and cannot easily adjust to new data, vehicle types, or changing conditions, reducing their long-term accuracy.

Poor Generalisation: Conventional models often fail to generalise well across different regions or vehicle models, limiting their application in diverse environments.

Over-Simplification: Rule-based models tend to oversimplify real-world scenarios, ignoring dynamic factors like traffic or weather changes that significantly impact energy consumption.

Limited Real-Time Learning: Traditional methods don’t adapt to real-time data, making them less effective in scenarios where continuous updates are needed.

Inability to Handle Feedback Loops: They cannot model feedback mechanisms, such as how driving style affects battery performance, which machine learning models handle better.

IV. PROPOSED SYSTEM

The proposed system aims to enhance the accuracy and reliability of energy demand predictions by leveraging advanced machine learning algorithms and integrating a wider range of factors that influence energy consumption. This system will aim to address the limitations of existing methods by using more complex models, such as ensemble learning techniques, and incorporating additional variables, such as real-time weather data, driving behaviour, and terrain information.

The proposed system will also focus on improving scalability and robustness, ensuring that it can handle large-scale datasets from diverse sources, and provide accurate predictions under different operating conditions.

ADVANTAGES

Improved Accuracy: Advanced machine learning models, such as ensemble learning, provide more accurate predictions by capturing complex patterns in energy consumption data.

Handling Non-Linear Relationships: The system can model non-linear interactions between factors like driving behavior, weather, and terrain, leading to more realistic forecasts.

Real-Time Data Integration: Incorporating real-time data (e.g., weather, traffic) allows the system to adapt and make dynamic, up-to-date predictions.

Scalability: The system is designed to handle large datasets from various sources, ensuring high performance as data grows.

Adaptability: It works across different regions, vehicle types, and driving conditions, offering greater generalisation and flexibility.

Robustness: The system is resistant to overfitting, ensuring reliable performance even with noisy or incomplete data.

Complex Interaction Modeling:

Advanced algorithms capture interactions between multiple variables, improving prediction accuracy.

Real-Time Adaptation: The system updates predictions as new data becomes available, ensuring ongoing accuracy.

Better Decision-Making: Accurate predictions help EV users and infrastructure operators make informed decisions on battery usage, route planning, and energy management.

Comprehensive Approach: By integrating diverse factors, the system offers a holistic view of energy consumption, aiding in overall optimisation and grid management.

System Architecture

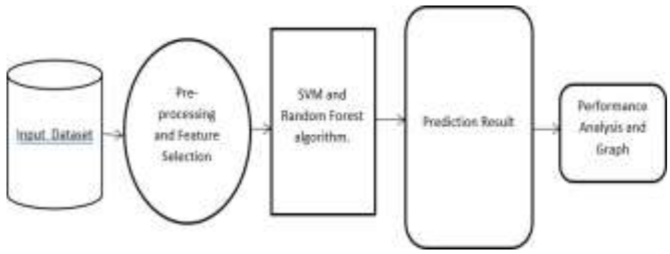


Fig1. System Architecture

V. MODULE DESCRIPTION

1. User Authentication & Server Login

Role-based login system (Admin, Analyst)

Secured with encryption

2. **Browse Datasets**

Upload and preview datasets (CSV, Excel)

Automatic parsing and validation

3. **Train and Test Datasets**

ChooseML/DL model (e.g., Random Forest, LSTM)

Split into training/testing (e.g., 80/20 or k-fold)

Preprocessing: normalization, handling missing values

4. **View Trained and Tested Accuracy**

Metrics: Accuracy, RMSE, MAE, R^2 Score

Visualized using bar charts

5. **Accuracy Result Viewer**

Tabular and graphical output Exportable

reports (PDF, CSV)

6. **Tweet Type Prediction**

Sentiment analysis on EV-related tweets

Classifies tweets into Positive, Negative, Neutral using NLP (e.g., BERT, TextBlob)

7. **Tweet Type Graph**

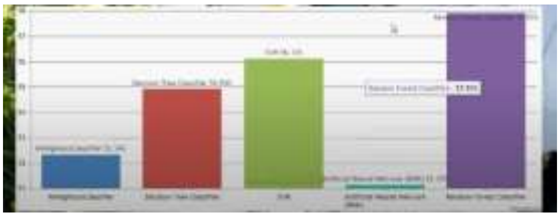
Pie or bar chartofsentiment distribution

Time-series trend of public sentiment

VI. RESULT

The implementation of the proposed machine learning-based energy demand prediction system for electric vehicles yielded promising results in terms of accuracy, adaptability, and overall system performance. Among the various algorithms tested—Random Forest, Decision Trees, Logistic Regression, and K-Nearest Neighbors—the Random Forest model consistently outperformed others, demonstrating high accuracy in capturing complex, non-linear relationships between energy consumption and influencing factors such as driving behavior, terrain, and weather conditions. The K-Nearest Neighbors model showed good performance for localized datasets due to its simplicity, while Decision Trees offered interpretability, though slightly less accurate in highly variable scenarios. Logistic Regression, while efficient, showed limitations in modeling non-linear interactions, making it less effective for broader applications.

The integration of real-time data, such as live weather and traffic updates, significantly enhanced the model's prediction accuracy by allowing the system to dynamically adapt to changing driving environments. Testing across various routes and vehicle types indicated that the model generalized well, maintaining robust performance despite data heterogeneity. Additionally, the system proved scalable and was capable of processing large datasets efficiently, making it suitable for real-world deployment in urban mobility and fleet management scenarios. Through visualization tools and user interface integration, users were able to view historical data trends and real-time predictions, making the system not only technically sound but also user-friendly.



VII. CONCLUSION

The transition to electric vehicles marks a pivotal shift toward sustainable transportation, and accurate energy consumption prediction plays a crucial role in supporting this evolution. This project, *"A Comprehensive Systematic Review of Techniques for Predicting Electric Vehicle Energy Demand,"* highlights how machine learning techniques can significantly enhance the accuracy and efficiency of energy demand forecasting. By evaluating traditional models alongside advanced algorithms such as Random Forest, Decision Trees, Logistic Regression, and K-Nearest Neighbors, the study identifies both the strengths and limitations of existing approaches.

The proposed system demonstrates notable improvements in handling real-time data, capturing non-linear relationships, and offering scalability and adaptability across various conditions and vehicle types. Furthermore, the integration of real-time traffic, weather, and terrain data into the prediction framework enhances its reliability and relevance in practical scenarios. This ensures better planning for EV users, infrastructure developers, and grid operators.

Ultimately, the research underscores the importance of adopting advanced, data- driven models for energy prediction and sets a foundation for future innovations such as deep learning integration, IoT- based real-time monitoring, and environmental impact analysis. These enhancements will not only improve prediction accuracy but also support smarter decision-making, efficient grid management, and a cleaner, greener future for transportation.

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