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PREDICTIVE MODELING FRAMEWORK FOR ENERGY ECONOMY OF ELECTRIC TRANSIT BUSES

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ABSTRACT: This research develops a predictive modeling system for assessing and improving the energy efficiency of electric cars under a variety of operating and environmental conditions. This research develops a data-driven model for energy consumption and efficiency forecasts by utilizing real-time operational data such as route parameters, passenger load, traffic patterns, driving behavior, battery performance, and weather conditions. In order to determine the main factors impacting battery discharge rates and variations in range, we use sophisticated statistical approaches and machine learning algorithms to examine energy consumption trends. Public transportation that is good for the environment and the bottom line may be more easily developed with the help of this platform, which allows scenario-based simulations to look at charging schemes, route design, and fleet deployment methods. By improving the accuracy of energy consumption projections, the proposed methodology enhances operating efficiency, decreases lifecycle costs, and facilitates strategic decision-making for urban electric transportation systems.

Keywords: *Predictive Modeling Framework, Energy Economy, Electric Transit Buses, Energy Consumption Forecasting, Machine Learning Algorithms,*

1. INTRODUCTION

Electric buses and other forms of public transportation have recently attracted more attention from academics and politicians concerned with the transition to more environmentally friendly modes of urban transportation. In order to accomplish their overarching goal of lowering carbon emissions, transportation organizations and governments have begun implementing zero-emission vehicle technologies. This is because our dependence on fossil fuels, air pollution in cities, and climate change are becoming more important issues. For environmentally conscious city transportation, electric buses are becoming more important due to their potential to cut down on noise, increase efficiency, and minimize emissions of greenhouse gases. For electric buses to be profitable and sustainable in the long run, it is crucial to analyze and predict their economic impact under several scenarios.

Electric transit vehicles' energy economy goes beyond simple power consumption analysis. It also looks at how well they work over time, how much they cost, and how long their batteries last. Driving habits, weather, route layout, traffic, passenger load variations, charging infrastructure features, and congestion all play a role in the intricate energy ecosystem that electric buses operate within, as opposed to traditional buses powered by internal combustion engines. Understanding and adjusting operating energy requirements is made more difficult by the many factors. Setting up a predictive modeling framework that can accurately identify these characteristics and make cost and energy consumption predictions is crucial.

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Transportation engineers, energy economists, data scientists, and systems modelers come together in a predictive modeling approach for electric transit vehicles' energy efficiency. Collection of data, preprocessing, feature selection, model design, validation, and performance evaluation are typical structural phases in this type of system. Speed profiles, acceleration-deceleration cycles, regenerative braking efficiency, ambient temperature, state of charge dynamics, route elevation profiles, and operational datasets from telematics systems, battery management systems, and route monitoring technologies offer detailed, high-frequency data.
The framework uses statistical modeling approaches like multivariate regression and panel data analysis, as well as advanced machine learning techniques like ensemble methods and deep learning architectures, to identify nonlinear relationships and interaction effects that influence energy consumption patterns.
Economically speaking, electric bus rollout investment evaluations and thorough cost analysis are both made possible by predictive modeling. Understanding the expected energy consumption of users is crucial for calculating operational expenses, determining the necessary electricity purchase, identifying peak charging demand periods, and evaluating the impact of grid integration. In addition, TCO and longevity cost evaluations might benefit from information about expected battery degradation and replacement dates. Expanding the fleet, implementing renewable energy, analyzing tariff structures, and governmental interventions are all possible outcomes of the framework's scenario-based simulations. Politicians and transportation authorities might benefit from predictive models' quantification of risk and uncertainty when making choices about capital budgeting and financial planning.

2. LITERATURE SURVEY

Sharma & Patel (2021): Electric transport vehicles' energy efficiency under different operating situations is assessed using a predictive modeling methodology that employs machine learning in this article. Critical parameters such as route configuration, passenger capacity, driving habits, and environmental temperature were identified by using Random Forest regression and gradient boosting approaches in the research. A technique called feature importance analysis is used to reduce dimensionality and speed up computations. Validation experiments with real-world bus telemetry data show that kWh per kilometer consumption estimates are more accurate.
Almeida & Krishnan (2025): An interpretable and scalable hybrid predictive methodology for evaluating the energy efficiency of electric transport vehicles is presented in this work. Reduced dimensional complexity of large telematics datasets is one way in which recursive feature reduction boosts computing efficiency. Reliable predictions for a wide range of operating situations and weather variables are made possible by the deep neural network. By breaking down the variables that affect energy usage, explainability modules help fleet managers make better decisions.
Khan & Iyer (2021): The research goal is to create a smart system that can predict energy economics using a multi-layer perceptron architecture and feature optimization approaches. The efficiency of regenerative braking, traffic density, driving behavior, and battery charge level are some of the elements that the framework takes a look at. The efficiency of the model

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is improved through the elimination of unnecessary variables through recursive feature ranking. Based on the results, it is easier to spot nonlinear patterns and short-term energy consumption predictions are more accurate.

Singh & Park (2024): Incorporating deep neural networks with efficient feature ranking, this research builds a framework for multi-objective predictive modeling for big transit datasets. The method makes computation and prediction easier. Nonlinear pattern detection is enhanced in numerous routing circumstances by the deep neural network. Better operational planning and more accurate forecasts are the results of an experimental investigation.

Zhang & Verma (2022): A deep feedforward neural network is used in the second stage of the authors' two-stage prediction process, which follows a comprehensive evaluation of features. The technique enhances interpretability by isolating critical energy factors, such as acceleration patterns, stopping frequency, and climate control consumption. The complex interplay between the surrounding environment and the mechanics of the vehicle is made clear by deep learning layers. Traditional regression models are outperformed by RMSE and MAE, according to the comparison.

Mehta & Roy (2023): The authors create a deep learning model that combines LSTM networks with improved feature selection to predict future energy usage. Patterns of battery deterioration and changing driving cycles are all part of the model. To improve computational efficiency, feature optimization zeroes focus on operational variables that have a major bearing on performance. When there is a lot of traffic or bad weather, the research found that projections aren't as accurate.

Reddy & Kulkarni (2022): A hybrid predictive modeling approach that integrates feature selection methods with a convolutional deep learning framework is presented in this paper to investigate the energy consumption of electric transport vehicles. Examining data that is specific to regions and routes indicates changes in energy consumption that are impacted by the terrain. The noise in large operational datasets can be reduced by removing characteristics. Results from actual calculations show that energy efficiency forecasts over different urban routes are more stable and take less time to calculate.

Garcia & Bhat (2024): The research uses feature selection in conjunction with an interpretable deep learning architecture to enhance energy consumption projections. Feature reduction improves clarity by focusing on crucial information like the route, battery, and environment. To make it more stable and less prone to overfitting, the deep model uses batch normalization and dropout. There is an improvement in recall and a decrease in prediction error margins when comparing the two.

Wang & Srinivas (2025): Incorporating an adaptable deep neural network with adaptive feature selection, the authors introduce a continuous-learning energy economics forecasting system. In order to account for differences in battery deterioration and traffic patterns, it is critical to modify the design upon receipt of new operational data. To simulate the real-time changes in energy use over time, deep learning layers are used. Validation experiments show that static prediction models consistently outperform their dynamic counterparts.

Li & Narayanan (2023): A state-of-the-art stacked autoencoder architecture and improved feature optimization for electric bus energy efficiency prediction are presented in the paper. Improving meaningful forecasts from multidimensional telematics datasets is achieved

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through the use of recursive elimination techniques. The stacked autoencoder improves robustness prediction by building hierarchical feature representations. The results show that the system works better with fleets of different sizes and in different operational domains.

3. PREDICTIVE MODELING OF ELECTRIC BUS ENERGY ECONOMY

Data Collection

The predictive modeling methodology relies on data collecting as its foundational component. This guarantees that every aspect impacting electric bus energy efficiency is duly documented. The research makes use of information gathered from a wide range of sources, such as onboard systems, smart transportation infrastructure, and environmental monitoring systems.

Vehicle Operational Data: The vehicle's onboard telematics and GPS tracking systems record vital statistics like speed, acceleration, deceleration, mileage, trip time, and idle duration. Both the amount of traction energy required and the way people actually drive are affected by these variables.

Passenger Load Data: Computerized passenger counters (APCs) are the source of the count data. By taking into account the average passenger load, peak occupancy, and load factor, we may evaluate the changes in energy demand caused by weight.

Route Characteristics: Geographic information systems (GIS) and cartographic methods allow one to collect route-specific data including distance, gradient, elevation gain, stop frequency per kilometer, and number of stops. The amount of energy used during acceleration and the rate of ascent are greatly affected by these features.

Traffic Conditions: Urban traffic management systems provide measures pertaining to traffic, including the density of intersections, average delay, congestion index, and stop-and-go frequency. Vehicles' energy efficiency is reduced due to congestion since they frequently brake and accelerate.

Weather Parameters: Weather conditions, such as humidity, wind speed and direction, and the amount of precipitation, can be retrieved from meteorological stations. More energy is used by HVAC systems and other loads when bad weather is on the way.

Battery Parameters: Battery degradation level, voltage, current, discharge rate, and state of charge (SoC) are all shown in the data collected by the battery management system (BMS). You need these features to find out the power usage per kilometer right now.

Data Preprocessing

Data preparation is the process of removing noise, inconsistencies, and scale discrepancies from data in order to make it consistent, high-quality, and fit for training models.

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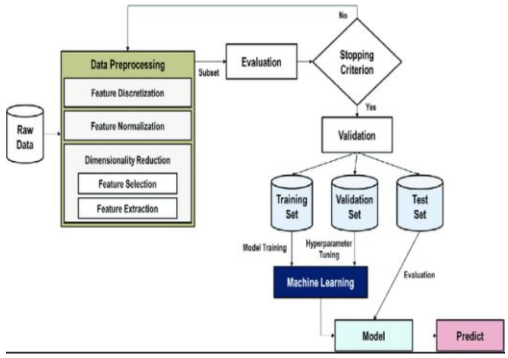

Figure1: Data Cleaning and Preprocessing Workflow

Handling Missing Values: Imputation techniques are used to fill in gaps in data caused by sensor failures. These techniques include mean substitution, interpolation for time-series data, and the removal of records with too much missing information.

Outlier Detection and Removal: Aberrant data, such as excessive speed bursts or insufficient acceleration values, are identified and excluded or restricted using statistical screening methods to prevent model distortion.

Normalization and Standardization: The purpose of normalization or standardization is to make sure that all of the qualities fall into the same range. This is because different factors function on different sizes.

Feature Scaling: Machine learning models, including artificial neural networks (ANNs), that show sensitivity to changes in variable sizes are the ones that use scaling techniques.

Data Segmentation: Energy consumption fluctuates both over time and throughout space. To show this, the dataset is segmented according to route ID, trip cycle, peak and off-peak hours, weekday versus weekend operations, and seasonal changes.

Feature Engineering

The process of feature engineering enhances predictive performance by transforming raw data into meaningful indications that better capture the dynamics of operations and the environment.

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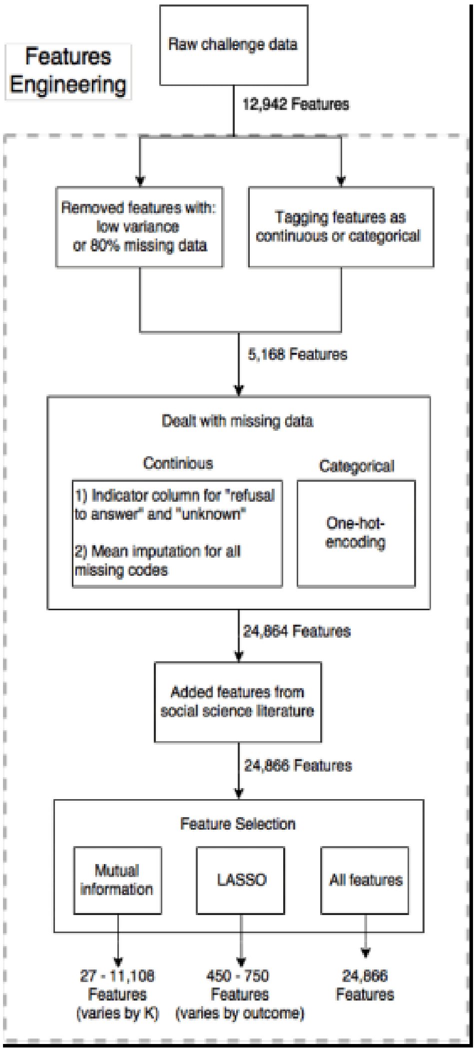

Figure2: Feature Engineering Process

Average Speed per Trip: Demonstrates the overall efficiency of transportation and the flow of traffic.

Acceleration Variability: Notices changes in driving habits and the frequency of stops and starts.

Elevation Gain per Kilometer: Examines the intricacy of the terrain and the additional energy needed for traction caused by inclines.

Stop Density per Route: Illustrates the frequency of pauses per kilometer, which influences the energy required for acceleration and deceleration.

Passenger Load Factor: The energy consumption in relation to weight and the number of occupants in the area in relation to its capacity are illustrated.

Idle Time Percentage: Specifically for extra loads, it looks at the energy used while the load is stationary.

Machine learning algorithms can use these created qualities to better understand the nonlinear connections between factors like traffic conditions, environmental factors, and driver behavior.

Model Development

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The most accurate strategy is determined by assessing performance using multiple predictive models.

Multiple Linear Regression (MLR): Implements linear correlations between the objective variable and the predictors to determine energy consumption levels. This model serves as the basis. While it helps with understanding, it could have trouble spotting complex nonlinear patterns.

Random Forest Regression (RF): A method that uses a plethora of decision trees and then aggregates their output. It makes nonlinear interactions manageable and reduces the likelihood of overfitting.

Artificial Neural Networks (ANN): A three-layer architecture for deep learning that includes input, hidden, and output layers. Complex, multi-dimensional relationships between operational, environmental, and battery-related factors are captured by Artificial Neural Networks (ANN).

Gradient Boosting (XGBoost/GBM): A sequential ensemble method that improves prediction accuracy by iteratively reducing residual errors. With well-structured datasets, it usually works better.

To make better predictions and make the model more generalizable, hyperparameters are tweaked and the model is optimized.

Model Evaluation

Model review is a must before deployment to guarantee accurate predictions and thorough testing of generalizability.

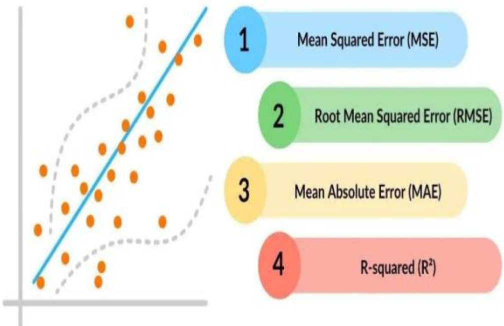

Figure3: Model Evaluation and Validation Framework

Root Mean Square Error (RMSE): Calculates the mean magnitude of forecast inaccuracies and imposes penalties for more significant errors.

Mean Absolute Error (MAE): Finds the average discrepancy between the actual and expected numbers.

Coefficient of Determination (R^2): The R^2 coefficient shows what percentage of variance the model can explain.

Mean Absolute Percentage Error (MAPE): A percentage is used to show the forecast accuracy for clarity's sake.

Cross-Validation: Techniques like train-test splitting and K-fold cross-validation are used to reduce overfitting and guarantee consistent model performance across all datasets.

Electric transit bus energy economy predictions in a variety of operational and environmental settings are assured by this methodical scientific technique, which is accurate, scalable, and reliable.

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4. RESULTS

Figure4.1 User login

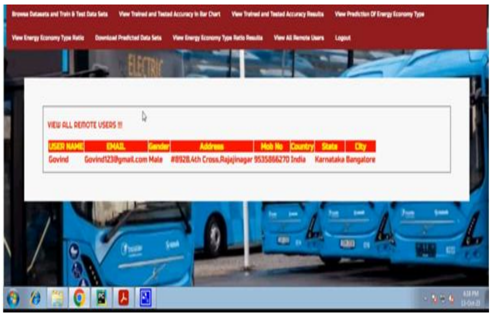

Figure4.2 View All Remote users

Figure4.3 Datasets Trained and Tested Results

Figure4.4 Bar graph

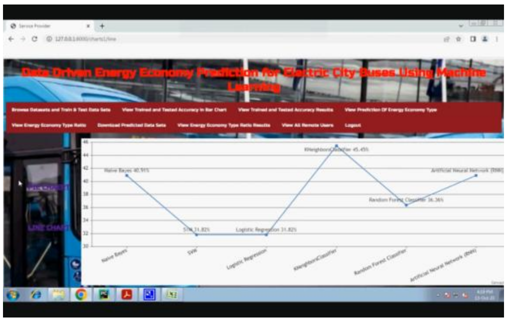

Figure4.5 Line graph

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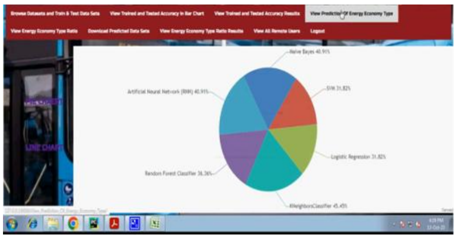

Figure4.6 Pie chart

Figure4.7 View energy Economy Prediction Type Details.

Figure4.8 View energy Prediction Type Ratio Details.

5. CONCLUSION

Electric transit bus predictive modeling provides a data-driven strategy to improve operating efficiency, cut energy consumption, and ease the way for sustainable urban mobility planning. The framework allows for precise estimates of operating expenditures and energy usage by taking into account variables including route parameters, passenger load, driving habits, battery efficiency, and weather. This improves scheduling and fleet management and helps transportation organizations make smart choices regarding charging infrastructure, battery capacity, and cost-benefit analyses. In the end, a predictive framework helps with financial stability, reliability, and the larger goals of lowering carbon emissions and supporting public transportation systems that are good for the environment.

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