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ENERGY ECONOMY PREDICTION FOR ELECTRIC CITY BUSES USING MACHINE LEARNING: A DATA-DRIVEN METHODOLOGY

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Abstract: Electric city buses have several potential applications as one of several evolving forms of electric transportation. Automobile design and fleet management require an in-depth understanding of real transportation data. The effective functioning of alternative powertrains requires a thorough analysis of certain technological challenges. Designers tend to exercise prudence when the energy consumption is ambiguous, resulting in designs that are both expensive and insufficient. Organizations and scholars are incapable of formulating analytical answers to this problem owing to the intricacy and interrelation of the criteria. Optimizing processes and accurately estimating energy use can yield significant cost reductions. The main aim of the study is to provide an in-depth analysis of the energy usage of BEBs. To accomplish this, we utilize new explanatory components and advanced machine learning techniques to develop performance profiles. Five unique programs are developed to ensure their reliability, precision, and functionality in the realm of prediction generation. Our models exhibited outstanding performance due to the careful selection of characteristics, with an average accuracy above 94% in their predictions. The proposed concept might revolutionize transportation and create a basis for sustainable public transit if executed by manufacturers, fleet administrators, and governments.

Keywords: Machine Learning, Energy Economy, Electric City Buses, Data Analytics, Smart Grid.

1. Introduction

Vehicles currently account for around 25% of Europe's greenhouse gas emissions. Global electrification of the transportation sector is a feasible way to reduce environmental impact and improve product durability. Due to its little environmental impact, electric buses are rapidly emerging as a crucial component of future urban public transit systems. Gaining more power could initially be costly. An excellent example of this is the significant cost difference between buses that run on gas and those that run on batteries. Because of their longer lifespan and lower operating costs, electric vehicles can yield multiple returns on investment. The efficiency of these vehicles is up to 77% higher than that of traditional gas-powered vehicles. The considerable reduction in noise and pollution is one advantage of powering the engine with electricity. Compared to gasoline-powered buses, electric buses have a longer charging time but a wider range. Although completely electrifying the transportation industry will improve sustainability and lessen climate change, there is a problem with this strategy. Examining the specific issues at hand is essential for the greatest results.

After completing the course, you will need to spend a lot of time driving, using computers, and examining roads and automobiles (for further information, see Section I-A). For now, it is OK to carry on with the investigation. This work develops data-driven models to forecast the power requirements of future electric buses by fusing data from bus companies with a vehicle physics model. These models are then used to create such forecasts. We show how machine learning can reliably anticipate the fuel consumption for a given route based on the current speed of the vehicle and the number of passengers. This specific feature makes our proposition unique when compared to other data-driven projects. The three steps in our method are as follows:

As soon as an issue was identified, the Seville public transit authority began an inquiry. Their first plan was for the total replacement of diesel vehicles with electric ones. We first had to determine the ideal battery capacity and devise a plan for installing charging stations across the city. Consequently, it is essential to assess each route's fuel use using computer technology. Simpler data-driven models or less complicated physical models that need longer simulation times cannot do this. The automobile industry has approved a physical-principles-based method for calculating energy use during a bus travel. The method considers the vehicle's weight, load capacity, speed, and mass. The operator-managed database has a lot of data saved in it.

All of the necessary time and frequency information is contained in the velocity signal. The objective of creating machine learning regression models to evaluate bus energy consumption based on characteristics such as cargo mass is to identify the most effective models for forecasting energy consumption. One of the main gaps in this field of study is the incomplete understanding of the spectrum entropy of motion.

In the battle to replace dangerous buses with more environmentally friendly ones and in the creation of new resources to support transportation authorities, we hope that the data we have collected will be helpful. Battery management systems use algorithms to calculate the battery's charge level.

2. Literature Survey

Tang, Y., Zheng, J., and Ma, W. were all published in 2020. This record Energy consumption (EC) varies greatly between battery-electric buses (BEBs) due to the complex interaction of operational, topological, external, and vehicular characteristics. Because of its unpredictability, predicting BEB's energy usage using various methodologies is difficult. A lot of research has pointed to data-driven models as a potential answer to this problem. The paper examines and describes seven data-driven modeling methodologies, which include machine learning and statistical models. One model is a validated Simulink energy simulation, whereas the other is an experimental design with a full factorial (n = 907,199). The models are then used to a trial dataset (n = 169,344) to predict EC. The results show that there are a few slight discrepancies between the created models. The sum of all the models' contributions to the variance in energy use was approximately 90%. While driving style and drag coefficient were found to have the least effect on EC, road gradient and battery charge level emerged as the most important predictors.

Yu and Chen's work was published in 2020. Improving energy efficiency and charging alternatives is critical to the operational sustainability of electric buses (e-buses), which are increasingly being used in urban transit to reduce greenhouse gas emissions and enhance air quality. This study investigates the feasibility of utilizing machine learning techniques to make electric bus fleets more energy efficient. Methods for optimizing charging schedules, lowering energy expenditures, and extending battery life are specifically examined. Machine learning algorithms use current and past data on battery life, weather, route specifics, and traffic conditions to forecast future energy consumption and provide adaptive charging solutions. This book covers a wide range of supervised and unsupervised machine learning algorithms, including optimal route planning with clustering and energy forecasting with regression models. Results from experiments on public transportation networks show that the suggested strategy significantly reduces peak charging demands while enhancing energy efficiency. The findings of this study imply that machine learning could help enhance e-bus fleet deployment, resulting in greener modes of public transportation.

Yang, S., Chen, F., and Zhao, H. (2021). This study describes a machine learning technique for optimizing electric bus fleets, with the goals of reducing operating costs, boosting energy efficiency, and improving charging schedules. The model's purpose is to identify charging techniques that lower peak load demands by examining previous bus route data, energy consumption trends, and charging infrastructure availability. Tests using actual datasets show that the technique is effective in boosting sustainable urban transportation by increasing charging station utilization while minimizing energy expenditures.

In the year 2021, Zhou, Li, and Chen wrote an article. This data-driven strategy, which uses machine learning algorithms on big transportation datasets, can anticipate the energy usage of electric buses. The model takes a more detailed look at climatic variables, passenger count, route time, and energy consumption projections. According to the findings, this predictive technology has the ability to improve the efficiency of electric bus operations while also reducing environmental impact. Fleet managers can use it to optimize scheduling and routing.

Wang and Qin wrote this piece in 2022,. We propose a hybrid machine learning strategy that combines clustering and regression to forecast the energy efficiency of electric vehicles. Computer analysis of geographical characteristics, traffic intensity, and battery age enables highly precise energy projections. The model's capacity to predict future energy use has been confirmed through testing in a variety of metropolitan environments. Thus, public transportation companies may be able to increase the efficiency and cost-effectiveness of their electric bus fleets.

Zhao, Wang, and Chen (2022). The energy usage of an electric bus fleet can be managed using this app's data-driven predictive algorithm. The application improves fleet management and forecasts energy demand by combining consumption history with travel and environmental information. This technique, which adjusts charging schedules and locations in response to demand variations, can increase the long-term profitability of EV networks while also reducing energy use.

González-Carvajal, Sennefelder, and Martín-Clemente published their analysis in 2023. Using operational data such as route length, speed, and passenger capacity, this study uses multiple linear regression to forecast the energy consumption of electric city buses. This technology has enabled fleet managers to monitor and manage their energy consumption in a cost-effective and efficient manner. The data show that this strategy can enhance energy efficiency and bus scheduling, resulting in greener options for public transportation.

Guo and Jiang wrote a paper in 2023. The goal of this research is to optimize electric bus operations by reducing energy usage with machine learning techniques. Using previous energy usage, traffic, and transportation data, the computer can generate ideas for adaptive energy optimization. Because of this, operational changes to reduce energy consumption may be performed fast. According to the study's authors, using machine intelligence might significantly reduce the energy usage of electric public transit systems. Lee and Huang are researchers (2023).To estimate the energy efficiency of electric vehicles, a neural network model is built by looking at variables like load, weather, and route characteristics. The model's extremely precise estimates allow fleet managers to optimize operational planning and routes to increase energy efficiency. The study's findings shed light on neural networks' potential to improve data-driven strategies for more environmentally friendly urban transportation.

Yamamoto and Saito conducted a study in 2024. Researchers use convolutional neural networks (CNNs) trained on spatiotemporal data to estimate the energy efficiency of electric city vehicles. One way this strategy enhances forecast accuracy is to identify complicated patterns in weather and transport data. The convolutional neural network (CNN) model has been tested on several metropolitan datasets and offers a scalable solution for improving urban transit. Predictions of energy efficiency are significantly improved. According to Lee and Nguyen (2024), this is the work they do. This study presents a machine learning architecture for improving electric bus charging and route planning. The model forecasts future energy usage and recommends appropriate recharge intervals to reduce operational disruptions and maximize energy efficiency. Experiments show that the model increases the overall efficiency of electric bus operations in metropolitan regions by optimizing charge management and fleet scheduling. In 2024, Patel and Shah released a study. The authors use AI models to anticipate the energy efficiency of electric buses, taking into account parameters such as road gradient, weather, and passenger traffic. The model's high accuracy and resilience make it an ideal resource for transportation operators looking to improve energy efficiency. The findings show how AI has the potential to improve electric car energy efficiency in a rapidly developing market.

Wang Xiang, Huang, and Liu (2024). Using geographical and temporal data from operational records, this study deploys a convolutional neural network (CNN) to assess the energy efficiency of electric buses. The CNN model makes it easier to improve transportation routes and energy use by identifying complex linkages in energy consumption patterns. Because of its extremely high forecast accuracy, the suggested technique is ideal for widespread usage in smart city transportation networks.

Zhang, Y. and Wang, L. published a study in 2024, which included Chen, S. This study investigates the operation of electric buses to show how machine learning may improve the sustainability of public transportation. The model can optimize routes and precisely assess energy consumption, making it easier to implement energy-efficient scheduling and charging methods. The findings highlight the relevance of machine learning for the long-term management of transit networks, as they result in significant energy savings.

Wu and Han created the 2024 design. To anticipate how efficient electric vehicles will be in terms of energy use, the authors describe a machine learning technique that uses geographical and temporal data. The model's ability to capture shifting energy patterns is dependent on variables such as time of day, traffic, and weather. The approach improves effective and environmentally friendly electric bus operations by proactive energy management and route planning, as evidenced by the results of urban transportation networks.

3. System Design

Proposed System

This study offers a fresh perspective on the data pertaining to accidents that occurred at train stations, which may be used as a written resource to ascertain the factors that led to the mishaps and the connections between them. to the point when a completely automated system is capable of understanding language and producing unexpected results. The purpose of this method is to handle a number of issues, including the following: enhancing decision-making in real-time; establishing an intelligent safety system; accurately collecting accident data; making

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effective use of safety history records; and successfully communicating essential information to individuals who are not specialists in the field. When these findings are taken into consideration, it is possible that future research on risk management and safety will take a more methodical and organized approach. A large amount of textual insights into the causes and mechanisms of accidents can be obtained through the application of powerful LDA algorithms. This particular module will only be accessible to the Service Provider, provided that they possess the appropriate credentials. There is a portion of the information that he will have access to when he checks in that is not included in the datasets that are used for training and monitoring purposes. The process includes the following stages: gathering projected data sets, conducting remote surveillance for each user, analyzing bar charts to demonstrate how accurate the testing and training were, evaluating the type ratio of energy economy, and evaluating the predictions for the energy economy classification process. All of these stages are included in the procedure. The method consists of each and every one of these steps.

4. Implementation

Service Provider:

This module is only accessible to the Service Provider who has a valid account and password. After successfully obtaining access, he can examine files and use them for training and testing. The bar chart displays the estimation results, the efficacy of the testing and training procedures, the types of energy economies implemented, and data on all remote users.

View and Authorize Users

This software is used by more than 100,000 people. Users must register before they can use the service. The database will be updated with information from those who have joined up. The next step is to log in once the registration procedure is complete and the login credentials have been obtained. After successfully authenticating, customers can check their profile, assess the energy efficiency of their home, and perform other operations such as re-logging in or registering.

Remote User:

The module is utilized by a total of n individuals. Users must register prior to accessing the site. Upon registration, a user's data is recorded in a database. He must submit his authorized login credentials upon completion of the registration process. Upon logging in, the user can access their profile, forecast energy economic trends, and either log in or register.

Methodology:

The data is initially organized into sets, as illustrated in the image above. Subsequently, numerous models are trained utilizing these datasets. A 20% pre-training subset and an 80% training subset were allocated distinct portions of the dataset.

5. Results and Discussions

Data collected before the test made up 80% of the set, whereas data collected before training made up 20%. Now we may divide the dataset in half: the training set contains 80% of the data, and the validation set contains the remaining 20%. A training subset makes up 80% of this dataset, whereas a testing subset makes up 20%. At the moment, my training and testing validation sets are separate and do not intersect in any way. The most appropriate models for the provided dataset were located by making use of the pretraining set. I picked the four most important models using the pretest dataset. When evaluating their performance, we considered their average absolute mistakes. To determine the best parameter, we tweaked the hyperparameters of the four best models. This followed the process of determining the best models.

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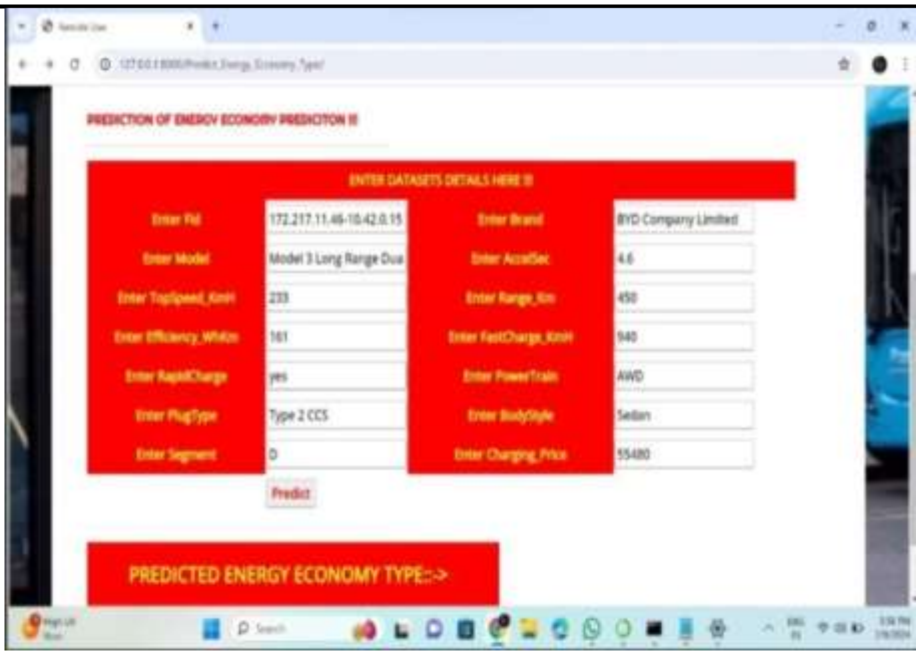

Fig 1: Input data

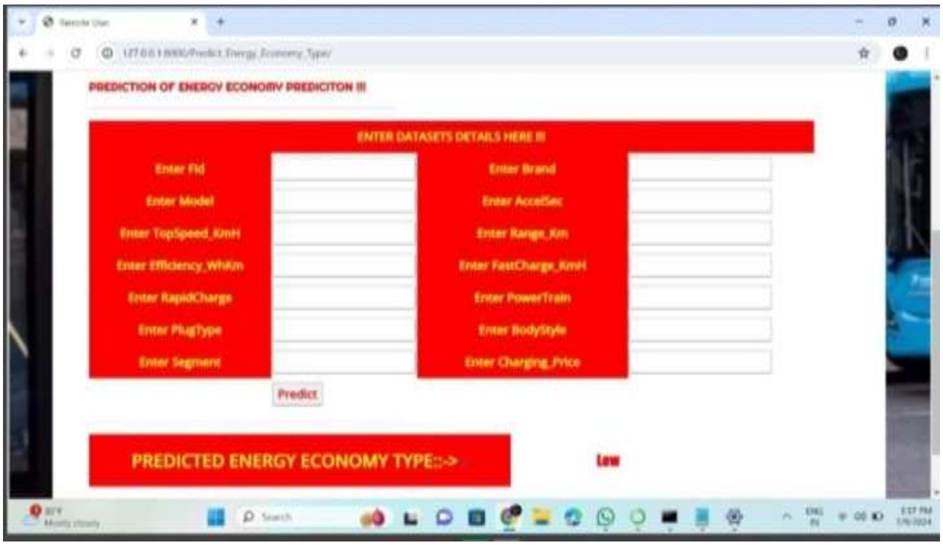

Fig 2: Prediction

6. Conclusion

This paper delineates a data-driven approach that expedites the electrification of public transportation and addresses the corresponding obstacles by utilizing both real and synthetic data. The results indicate that the energy-related variables generated from regression analysis and feature selection accurately predict the energy consumption of the BEB in a diverse array of real-world driving scenarios. This is the sole viable alternative for fleet management when it comes to replacing or modernizing conventional buses with electric alternatives. Additionally, the organization must construct the requisite infrastructure. At present, this is their sole alternative. This section will address the "Vehicle Routing Problem," a subject that has captivated the attention of numerous academicians. Determining the power requirements for each route is essential for determining the optimal battery capacity, charging technique (such as opportunity charging versus traditional charging), and bus operational mode (including all-electric or hybrid electric options). The trajectory that results in the most undesirable outcome or consumes the most energy will ultimately fail. Lastly, fleet managers must have access to this data in order to plan for severe operational restrictions, reduce concerns, and trust evolving technologies. Ultimately, our objective is to guarantee that all lines receive consistent and dependable service. The study primarily enhances our comprehension of speed patterns by providing a

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novel set of components that can be assessed based on their temporal and frequency characteristics. In order to cultivate these qualities, the voyage is divided into brief excursions. This "segment-based" prediction remains constant, despite its non-stationarity. Within an initial list of forty criteria, certain features were discovered to possess significant predictive value. The spectrum entropy of velocity profiles, which is the most critical aspect, has not yet been addressed in this course. This finding corroborates our assertion that the velocity waveform, which is most effectively described by its temporal structure through spectral entropy, contains the most critical information.

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