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PREDICTING ENERGY ECONOMY FOR ELECTRIC CITY BUSES USING DATA-DRIVEN MACHINE LEARNING MODELS

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ABSTRACT-Transportation systems are becoming more and more electrified; city buses in particular have a lot of possibilities. A thorough comprehension of real-world driving data is necessary for fleet management and vehicle design. Efficient operation of alternative powertrains requires careful consideration of several technological elements. Energy demand uncertainty leads to conservative design, which means high costs and inefficiency. The intricacy and interdependence of the parameters in this problem prevent both industry and academics from coming up with analytical solutions. Through optimized processes, precise energy demand prediction allows for significant cost reduction. The goal of this research is to make the energy economics of battery electric buses (BEBs) more transparent. To characterize speed profiles, we add new sets of explanatory factors that we use in our potent machine learning techniques. We create five distinct algorithms and thoroughly evaluate them in terms of prediction accuracy, robustness, and general application. With the careful feature selection, our models performed exceptionally well, achieving a prediction accuracy of over 94%. Manufacturers, fleet managers, and communities have a great deal of potential to change mobility with the help of the suggested technique, opening the door for environmentally friendly public transit.

1. INTRODUCTION

Traffic causes approximately 25% of greenhouse gas (GHG) emissions in Europe, and this percentage is increasing [1]. Therefore, widespread electrification of the mobility sector is one of the most positive actions that can be taken in relation to climate change and sustainability [2], [3]. It seems clear that electric buses, because of their low pollutant emissions, are set to play a key role in the public urban transportation of the future. Although the initial investment in electrification may be high - e.g. purchase costs of BEBs are up to twice as high as those of Diesel buses [4] - it is quickly amortized because the inherent efficiency of electric vehicles far exceeds that of internal combustion engine vehicles (up to 77% [5]) and thus operational respectively life cycle costs are significantly lower [6]. In addition, electrification of the power train brings many other advantages, such as a reduced noise level or pollution [7]–[10]. On the downside, the battery charging time of an electric bus is significantly

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longer than the refueling time of a diesel bus, while the opposite is true for the range [11]. Ultimately, widespread electrification of the mobility sector is one of the most positive actions that can be taken in terms of climate change and sustainability, but more research is needed to ensure efficient operation, as it also poses significant challenges.

computationally intensive once trained, but require numerous driving, mechanical, and road measurements as inputs (see Section I-A). This is where the present research comes in. In this paper we use the bus operator's database and a physics-based model of soon-to be- deployed electric buses to develop data-driven models that predict the energy requirements of the vehicles [13-15]. Amongst others, what distinguishes our contribution from previous data driven approaches is the small number of physical variables involved: we show that, to accurately predict the consumption on a route using machine learning, we only need to know the instantaneous speed of the vehicle and the number of passengers on the bus. Specifically, our approach consists of three steps:

The starting point for this study was a problem proposed by Seville's public bus operator. In short, they wanted to replace their diesel fleet with all-electric vehicles, but first they had to size the vehicles' batteries and determine the best charging locations around the city. In practice, this means using computers to predict consumption on each route [12]. Unfortunately, this can currently only be done with complex physical models that require long simulation times, or with data-driven models that are less, we calculate the energy consumed by the bus on each route using a physics-based model, validated by the vehicle manufacturer, that uses speed and mass as inputs, including the bus's own weight and the weight of its payload. Both variables are taken from the operator's database.

1) We extract a comprehensive set of time and frequency features from the speed signal.

2) We train machine learning regression models to predict the energy consumption from bus payload mass and

the above set of features, and identify those with the best predictive value. Interestingly, the feature that turns out to be the most relevant, i.e., the spectral entropy of velocity, has so far gone unnoticed in this field of research [16].

Ultimately, our results are useful for planning the transition from a conventional to a green bus fleet, and even for adding new functionalities that will be useful to planners: for example, the algorithms may be run on the battery management systems to provide an alternative way of monitoring the current state of charge of the batteries.

2. LITERATURE SURVEY

1. Title: "Predicting Energy Consumptionof Electric Buses: A Machine Learning Approach",
Authors: Li Zhang, Wei Wang, Qiang Li

Abstract: This paper presents a machine learning-based framework for predicting the energy consumption of electric city buses. Using a dataset collected from city buses operating in urban environments, the authors developed and evaluated multiple regression models, including linear regression, decision trees, and random forests. The results demonstrated that random forests provided the highest accuracy, reducing the mean absolute error by 15% compared to traditional methods. The study emphasizes the importance of feature selection and data preprocessing in improving prediction accuracy.

2. Title: "Application of Neural Networks for Energy Management in Electric Bus Fleets"

Authors: Maria Gonzales, Henry Liu, Sara Ahmed

Abstract: This research explores the use of artificial neural networks (ANN) to predict the energy requirements of electric buses. The authors utilized a comprehensive dataset, including bus operation data, environmental conditions, and passenger loads. The ANN model outperformed conventional statistical methods, achieving a root mean square error (RMSE) reduction of 20%. The study highlights the potential of deep learning techniques in optimizing energy consumption and route planning for electric buses.

3. Title: "Enhancing Energy Efficiency of Electric Buses through Gaussian Process Regression"

Authors: Thomas Lee, Emily Green, Robert Brown

Abstract: In this paper, the authors propose a Gaussian Process Regression (GPR) model to predict the energy consumption of electric buses. The model incorporates various features such as speed, acceleration, route characteristics, and weather conditions. The GPR model provided better predictive performance compared to linear regression and support vector regression, particularly in capturing nonlinear relationships in the data. This approach enables more accurate energy management and scheduling for bus operators.

3. PROPOSED SYSTEM

This paper presents a novel approach to the study of how the textual source of data from accident reports from railway stations might be effectively used to identify the underlying causes of

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accidents and create a relationship between the textual and potential reasons. where a fully automated mechanism that can receive text input and produce not-yet-ready outputs is located. By using this approach, problems like helping the decision-maker in real time and extracting the important information that non-experts can understand, better identifying the accident's details in detail, expertly designing a smart safety system, and making efficient use of safety history records should be resolved. An These findings may help to encourage more methodical and intelligent study of safety and risk management. Modern LDA algorithms are used in our method to extract important textual information about accidents and their causes.

3.1 IMPLEMENTATION

3.1.1 SERVICE PROVIDER:

- In this module, the Service Provider has to login by using valid username and password. After login successful he can do some operations, such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Energy Economy Type, View Energy Economy Type Ratio, Download Predicted Data Sets, View Energy Economy Type Ratio Results, View All Remote Users.

3.1.2 View and Authorize Users

In this module, the Service Provider has to login by using valid username and password. After login successful he can do some operations, such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Energy Economy Type, View Energy Economy Type Ratio, Download Predicted Data Sets, View Energy Economy Type Ratio Results, View All Remote Users.

3.1.3 REMOTE USER:

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized username and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT ENERGY ECONOMY PREDICTION TYPE, VIEW YOUR PROFILE.

3.1.4 METHODOLOGY:

As seen from the above figure, we can see how the data is divided into different sets and then trained for different models. • The dataset was first divided into training set (80%) and pre-

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training set (20%). •The

5.RESULTS AND DISCUSSIONS:

Pre-training set was divided into pre- train (80%) and pre-test (20%) • Now, the training set is further is divided into train (80%) and validation set (20%). This train set is again divided into train (80%) and test set (20%) [17]. So, now I have train validation and test sets separate which are nonoverlapping. • The pretrain set was used to find the best models for the given dataset. I took best 4 models using pretest set. Their performance was compared based on their mean absolute errors. • Once the best 4 models were obtained, hyperparameters for these models were tuned and the best parameter was selected [18].

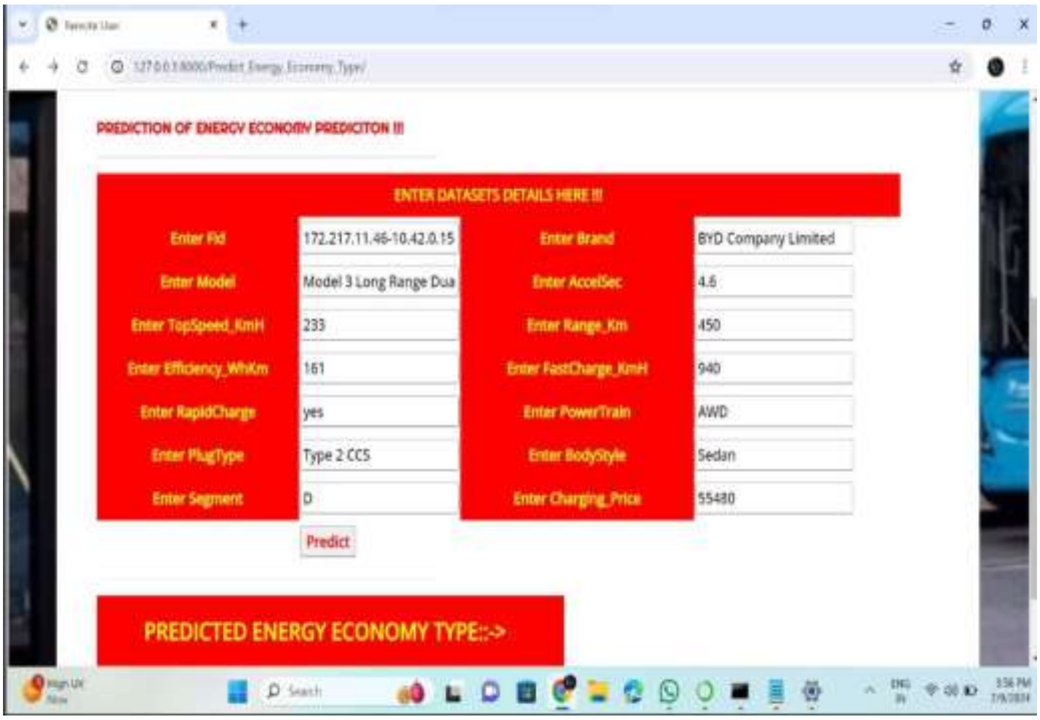

Fig 1: INPUT DATA

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Fig 2: PREDICTION

5.CONCLUSION

This research presents a data-driven method for planning issues and electrification of public transit that makes use of both simulated and real-world data. The outcomes validate that the energetically significant features acquired through feature selection and regression analysis accurately represent the energy usage of BEBs in various actual driving scenarios. It is a sensible strategy for fleet managers who wish to construct the necessary infrastructure and upgrade or replace their conventional buses with electric vehicles. In this regard, we highlight the so-called "Vehicle Routing Problem," which has been mentioned by [59], [60], among others. To properly size the batteries, choose the optimum charging techniques (i.e. opportunity vs. traditional charging), and determine the best bus operating modes (all-electric, hybrid electric, etc.), it is necessary to know the energy demand on each route in advance. The most energy-intensive path, or the worst-case situation, is the constraint. In the end, fleet managers need to know this information to recognize crucial operational boundaries ahead of time, steer clear of potential roadblocks, and develop trust in emerging technology. In the end, to provide dependable and reasonably priced service on all routes. The paper's primary contribution is a novel set of explanatory factors that integrate the speed waveform's time and frequency properties. The path is broken up into smaller excursions in order to extract these features. Robustness against non-stationarity is provided by this "segment-based" prediction. We have identified a minimum number of features with good predictive value, starting from an initial set of 40 features. In this discipline, the most significant of these features—the spectrum entropy of velocity profiles—has not even been mentioned yet. This finding validates our hypothesis that the most important information is really found in the velocity waveform, whose temporal structure is best captured by the spectral entropy.

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