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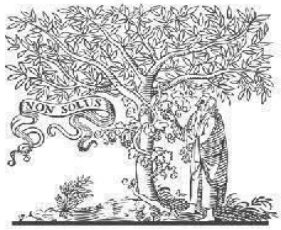

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DATA DRIVEN ENERGY ECONOMY PREDICTION FOR ELECTRIC CITY BUSES USING MACHINE LEARNING

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ABSTRACT

The electrification of transportation, particularly city buses, presents significant opportunities for sustainability. Understanding real-world driving data driving data is crucial for efficient vehicle design and fleet management, as energy demand uncertainties often lead to inefficient and costly conservative design. Both industry and academia face challenges in addressing this issue due to the complexity and interdependence of various parameters.Accurate energy demand prediction is crucial for overcoming these obstacles can greatly reduce costs through optimized operations.This paper enhances the understanding of battery electric buses'(BEB) energy efficiency through machine learning models.

I.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 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.

The public bus operator in Seville brought up a problem that served as the basis for this

investigation. In other words, they intended to switch out their fleet of diesel cars for all-electric cars, but first they needed to figure out how big the batteries would be in the cars and where in the city would be the ideal places to charge them. This entails employing computers to forecast consumption on each route in real life [12]. Regretfully, as present, this is limited to employing intricate physical models that necessitate extended simulation durations, or data-driven models that, once trained, require less computing but demand copious driving, mechanical, and road measurements as inputs (see to Section I-A). This is where the current study is useful. In this research, we create data-driven models that anticipate the energy requirements of the vehicles using a physics-based model of soon-to-be-deployed electric buses and the bus operator's database. Among other things, our contribution differs from earlier data-driven methods in that we demonstrate that, in order to use machine learning to predict consumption on a route with accuracy, we only need to know the vehicle's instantaneous speed and the bus's passenger count. In particular, there are three steps in our approach:

1) We utilize a physics-based model, approved by the bus manufacturer, to determine the energy consumption of the bus on each route. The model takes as inputs mass and speed, which includes the weight of the bus and its payload. The operator's database is the source of both variables.

2) From the speed signal, we extract an extensive set of temporal and frequency information.

3) Using the bus payload mass and the previously listed variables, we train machine learning regression models to estimate energy usage. We then determine which models have the highest predictive value. It's interesting to note that this field of study has not yet addressed the feature that ends up being the most important: the spectrum entropy of velocity.

In the end, our findings are helpful for organizing the switch from a conventional to a green bus fleet and even for incorporating new features that planners will find helpful. For instance, the algorithms may be applied to battery management systems to offer a different method of keeping an eye on the batteries' current state of charge.

The format of the paper is as follows. In section I, we first outline the difficulties in this field and examine the current state of the art. Second, Section II provides an explanation of our materials, methodology, and techniques. In part III, the experimental results are shown and discussed. Section IV wraps up our work and highlights potential directions for future research.

II. EXISTING SYSTEM

The forecast of energy consumption for battery electric vehicles (BEVs) in general, and battery electric buses (BEBs) in particular, have been widely explored. This is not surprising, as [13] reveals that BEBs are a feasible replacement for conventional vehicles and are also less susceptible to fluctuations in mission profiles than diesel buses. It is crucial to note however that the duty cycle and driving conditions of a BEB are substantially different from those of other BEVs, changing the focus from kinematic connections to route, timetable, and passenger load.

The majority of past studies utilize complicated physics based vehicle models, albeit they differ in focus and purpose [14]–[21]. In [14], for example, the authors analyze the impact of power train efficiency, rolling resistance, and auxiliary power on the energy consumption of battery electric vehicles (BEVs). While drive train efficiency and rolling resistance are relevant to the physical movement of the vehicles, auxiliary power demand is especially important at the lower speeds (< 40 km/h) where city buses typically operate, motivating the need for accurate knowledge of auxiliary power to predict overall energy consumption. The work by De Cauwer et al. [15] incorporates a physical model of the vehicle with a data-driven technique with the purpose to find and quantify connections between the kinematic parameters and the vehicle's energy usage. Commonly used kinematic parameters are reinforced by other elements such as the journey distance and duration or the temperature.

Wang et al [17] examined the influence of rolling resistance, which relies on the road surface, as well as varied weather conditions, on power demand. The prediction model in [18] consists of a longitudinal dynamics model reinforced by additional specific data from a dynamometer, as well as coastdown experiments, to lower the model's uncertainty. Similarly, in [21] the authors develop a unique and computationally efficient electro-mechanical model of a BEB to evaluate the influence of parameters such as payload mass, temperature and rolling resistance on consumption. All these approaches provide useful information on the interdependence of factors of influence; yet, they entail sophisticated equations and require proper modeling of the vehicles and their components to get results. Like many physics-based models, they are of limited practical value due to the extensive simulation timeframes. In addition, most past research has focused exclusively on light-duty vehicles, and scaling to the heavy-duty class is complex due to completely different driving profiles and dynamics.

Data-driven approaches, which use machine-learning or deep learning algorithms with real-world driving data, or even mixed data-driven and physics-based approaches, may be found in [22]–[35]. For example, Chen et al. [22] analyze state of the art energy-consumption prediction models (rulebased vs. data-driven) for electric vehicles and study the instance of electric buses using logistic regression and neural networks on real-world data. Additionally, they indicate the study gap for energy consumption models of heavy duty vehicles e.g. city buses, buttressing the motivation of our work. Pamula et al. [23] employed both deep learning and traditional neural networks to forecast the energy requirement of electric buses.

These prediction models employed actual data gathered from several bus lines. The models are based on input characteristics that fleet operators can easily monitor, but also operational information such as bus routes and stop locations, travel time between bus stops, schedules and peak hour information. Kontu and Miles [24] analyze aspects of influence such as the route and driver characteristics. Ericsson [25] examined the effects of different driving patterns recorded in real traffic on consumption and emissions of internal combustion automobiles. Starting with 62 features, a factorial analysis allows them to cut this number to only 16. This work showed, on the one hand, the influence of typical kinematic driving pattern characteristics, such as speed, acceleration, and deceleration, on energy consumption and, on the other, the research evaluated the usefulness of feature analysis and selection. Simonis and Sennefelder [26] accurately explain the behavior of drivers as a function of a set of specified variables, which can be utilized next to estimate energy demand of BEVs.

Interestingly, Abdelaty et al. [27], [28] developed a Simulink model to estimate the energy consumption of BEBs, where the inputs were carefully picked from a mix of operational, topological, vehicular and external characteristics utilizing machine learning methods and statistical models. They observed that the battery state of charge and the road gradient were the most significant influences, whereas the vehicle's drag coefficients appeared to have a relatively minor effect. However, temperature and thus auxiliary power consumption are not adequately addressed, which is one of the most crucial elements as Ji et al. demonstrate in their study [36], in which they investigate real world data from a fleet of 31 BEBs in Meihekou City, China. The ambient temperature expands from −27◦ C to 35◦ C which lasts in up to 47%

greater energy usage compared to optimum functioning state. Expanding on this essential topic, in another recent study by Data-driven approaches, which use machine-learning or deep learning algorithms with real-world driving data, or even mixed data-driven and physics-based approaches, may be found in [22]–[35]. For example, Chen et al. [22] analyze state of the art energy-consumption prediction models (rulebased vs. data-driven) for electric vehicles and study the instance of electric buses using logistic regression and neural networks on real-world data. Additionally, they indicate the study gap for energy consumption models of heavy duty vehicles e.g. city buses, buttressing the motivation of our work. Pamula et al. [23] employed both deep learning and traditional neural networks to forecast the energy requirement of electric buses.

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• Only a small number of machine-learning techniques are widely applied, despite their availability. We cover the whole gamut in this work, from probabilistic techniques and supervised learning to statistical approaches that don't require learning. As a result, the complete potential of cutting-edge machine learning techniques for forecasting EV energy usage is shown and thoroughly compared in this paper. In the end, we look into the functionality of several strong machine learning models, covering everything from minute technical details to long-term applications.

•Most studies use data from a single vehicle on a particular route or use speed profiles from Standardized Driving Cycles (SDCs). Therefore, the variety and diversity within the data is very limited. However, a key issue in this domain is that the important components are diverse and the interrelationships are complex. Thus, the more the variety in the data, the better the machine learning predictions will be. In contrast, the underlying fleet data for this work is measured from an entire fleet of 30 vehicles, which operate multiple routes a day

and drivers change frequently even during the day. This allows us to capture a wide variety of traffic situations and driving styles, containing much more valuable information.

• Auxiliary power demand, including HVAC, is rarely considered in detail and often replaced by a constant term. However, especially in extreme low and high temperature regions, heating and cooling have a significant impact on the energy consumption and thus the range of BEBs.We have considered complete energy profiles, including HVAC, recovery, etc., which allows this work to address accurate total energy consumption at the trip level, which is relevant to transit operators.

III. PROPOSED SYSTEM

In this study we combine the bus operator's database and a physics-based model of soon-tobe- deployed electric buses to construct data-driven models that anticipate the energy requirements of the vehicles. Among other things, our contribution differs from earlier data-driven methods in that we demonstrate that, in order to use machine learning to predict consumption on a route with accuracy, we only need to know the vehicle's instantaneous speed and the bus's passenger count. Our method specifically comprises of three steps:

1) We compute the energy spent by the bus on each trip using a physics-based model, approved by the vehicle manufacturer, that employs speed and mass as inputs, including the bus's own weight and the weight of its payload. The operator's database is the source of both variables.

2) From the speed signal, we extract an extensive set of temporal and frequency information.

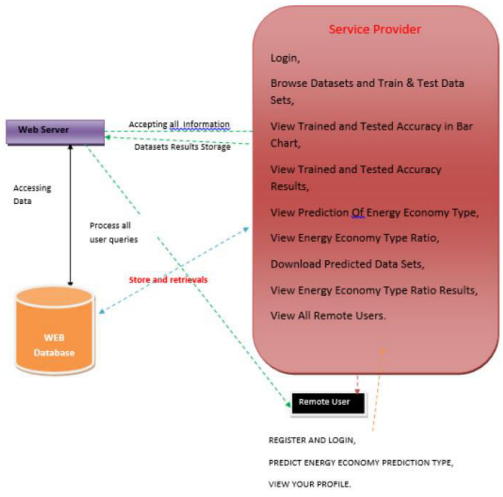
3) Using the bus payload mass and the previously listed variables, we train machine learning regression models to estimate the energy consumption. We then determine which models have the highest performance.

predictive value. Interestingly, the trait that turns out to be the most relevant, i.e., the spectrum entropy of velocity, has thus far gone unreported in this field of research.

Advantages

1) We offer a scalable and efficient hybridized Machine Learning models for exact predictions.

2) We conducted many hybridizations of genetic algorithm with filter and embedded feature selection methods, in the data pre-processing phase of Random Forest and Multivariate Linear Regression (MLR) prediction model, with the purpose of increasing its performance.



IV.MODULES

Service Provider: In this module, the Service Provider has to login by using valid user name and password.

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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.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

RemoteUser

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 user name and password. Once Login is successful user will do some operations like register and login, predict energy economy prediction type, view your profile.

V.CONCLUSION

This paper offers a data-driven approach that uses both simulated and real-world data for planning problems and electrification of public transport. The results confirm that the energetic relevant features obtained by feature selection and regression analysis perfectly characterize the energy consumption of BEBs under different real driving conditions. It is a practical approach for fleet operators who want to retrofit or replace their conventional buses with electric vehicles and build the corresponding infrastructure. We emphasize in this context the so-called ''Vehicle Routing Problem'', e.g. mentioned by [59], [60]. The energy demand on each route needs to be known *a priori* to correctly size the batteries, decide on the operating optimal modes , are

decide which charging techniques are most effective (i.e. opportunity vs. traditional charging). 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 verifies our notion that it is in the velocity waveform, whose temporal structure is well captured by the spectral entropy, that the most relevant information truly lies.

Our goal is to determine the performance of this methodology in many contexts, thus we intend to expand its application in future study. Transportation and logistics companies are particularly interested in the suggested approach. In particular, it is of importance to fleet operators that rely on heavy-duty trucks and typically fail to electrify their fleets because they lack a good framework for making the correct decisions for the right vehicles. It might even be used for other kinds of vehicles or transportation networks, including rail or passenger cars. On the other side, weather parameters, road type and operational features for instance might be explored more deeply. For this reason, we intend to look into situations that vary seasonally and geographically, and we advise choosing features carefully based on each use case. Lastly, predictive analytics of other target variables, such the system's peak power or the electric current demands on the batteries, are highly desirable and might be looked into using the approach that has been described.

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