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

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ABSTRACT

Electrification of transportation systems is increasing, in particular city buses raise enormous potential. Deep understanding of real-world driving data is essential for vehicle design and fleet operation. Various technological aspects must be considered to run alternative powertrains efficiently. Uncertainty about energy demand results in conservative design which implies inefficiency and high costs. Both, industry, and academia miss analytical solutions to solve this problem due to complexity and interrelation of parameters. Precise energy demand prediction enables significant cost reduction by optimized operations. This paper aims at increased transparency of battery electric buses' (BEB) energy economy.We introduce novel sets of explanatory variables to characterize speed profiles, which we utilize in powerful machine learning methods. We develop and comprehensively assess 5 different algorithms regarding prediction accuracy, robustness, and overall applicability. Achieving a prediction accuracy of more than 94%, our models performed excellent in combination with the sophisticated selection of features. The presented methodology bears enormous potential for manufacturers, fleet operators and communities to transform mobility and thus pave the way for sustainable, public transportation.

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.

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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 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. 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:

1) 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.

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

3) 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.

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.

The paper is structured as follows. First, we identify the challenges in this field and review the state of the art in section I. Secondly, our material, methodology and methods are explained in Section II. Experimental results are presented and discussed in section III. Finally, section IV concludes our paper and shows possible future developments.

II. EXISTING SYSTEM

The prediction of energy demand for battery electric vehicles (BEVs) in general, and battery electric buses (BEBs) in particular, have been thoroughly investigated. This is not surprising, as [13] shows that BEBs are a viable replacement for conventional vehicles and are also less sensitive to variations in mission profiles than diesel buses. It is important to note also that the duty cycle and driving conditions of a BEB are very different from those of other BEVs, shifting the focus from kinematic relationships to route, schedule, and passenger load.

The majority of previous studies utilize complex physics based vehicle models, though they vary in focus and objective [14]–[21]. In [14], for example, the authors examine 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 study of De Cauwer *et al.* [15] integrates a physical model of the vehicle and a data-driven methodology with the aim to detect and quantify correlations between the kinematic
parameters and the vehicle's energy consumption. Commonly used kinematic parameters are complemented by additional factors such as the travel distance and time or the temperature.

Wang et al [17] studied the influence of rolling resistance, which depends on the road surface, as well as various weather conditions, on power demand. The prediction model in [18] consists of a longitudinal dynamics model complemented by additional dedicated measurements from a dynamometer, as well as coastdown tests, to reduce the model's uncertainty. Similarly, in [21] the authors introduce a novel and computationally efficient electro-mechanical model of a BEB to study the influence of factors such as payload mass, temperature and rolling resistance on consumption. All these approaches provide valuable insight on the interrelation of factors of
influence; nevertheless, they involve intricate equations and require accurate modeling of the vehicles and their components to generate results. Like all physics-based models, they are of limited practical use due to the long simulation times. In addition, most previous research has focused primarily 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 and real-world driving data, or even mixed data-driven and physics-based approaches, can be found in [22]–[35]. For example, Chen et al. [22] review state of the art energy-consumption estimation models (rulebased vs. data-driven) for electric vehicles and study the case of electric buses using logistic regression and neural networks on real-world data. Additionally, they identify the research gap for energy consumption models of heavy duty vehicles e.g. city buses, buttressing the motivation of our work. Pamula et al. [23] used both deep learning and classical neural networks to forecast the energy demand of electric buses.

These prediction models utilized actual data obtained from various bus lines. The models are based on input variables that fleet operators can easily measure, 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] investigate factors of influence such as the route and driver characteristics. Ericsson [25] studied the effects of different driving patterns collected in real traffic on consumption and emissions of internal combustion vehicles. Starting with 62 features, a factorial analysis allows them to reduce this number to only 16. This work demonstrates, on the one hand, the influence of common kinematic driving pattern parameters, such as speed, acceleration, and deceleration, on energy consumption and, on the other, the paper evaluated the usefulness of feature analysis and selection. Simonis and Sennefelder [26] accurately describe the behavior of drivers as a function of a set of selected characteristics, which can be used next to predict energy demand of BEVs.

Interestingly, Abdelaty *et al.* [27], [28] used a Simulink model to estimate the energy consumption of BEBs, where the inputs were carefully selected from a mix of operational, topological, vehicular and external variables using machine learning algorithms and statistical models. They found that the battery state of charge and the road gradient were the most significant factors, while the vehicle's drag coefficients appeared to have a relatively minimal effect. However, temperature and thus auxiliary power demand are not well covered, which is one of the most important factors as Ji *et al.* demonstrate in their paper [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% increased energy consumption compared to optimum working condition. Expanding on this important topic, in another recent study by Perugu *et al.* [37] in Lancaster, California, BEBs energy consumption and charging behavior are examined: the vehicles face significant daily and seasonally varying temperatures from −9◦ C up to 46◦ C and thus the variability in energy consumption can be attributed to the use of heating, cooling, venting and air conditioning (HVAC).

Their results show the existence of relevant operational costs for the operator, which can increase up to 18% during summer. Anyway, this cost analysis might be different in other situations (location, terrain, traffic etc.) as cost assessment of BEBs is generally a vast field as can be seen in [4], [6], depending on a magnitude of factors (production numbers, development costs, public grants, energy price etc.). In [38], Goehlich *et al.* perform a technology assessment for BEBs in Berlin, Germany. They use an energy simulation model to forecast the consumption in daily service and finally analyze the system's economics in terms of total costs of ownership (TCO). Using a thermal model of the cabin, they find that heating by Positive Temperature Coefficient (PTC) elements is generally more critical than cooling, and discover a worst case additional HVAC consumption of up to 1.1 kWh/km, which is almost a third of the overall energy consumption.

Disadvantages

• Most approaches use data that standard vehicles are often not equipped to measure, such as the location of bus stops or road gradient. In addition, variables that are highly dependent on the particular conditions of the experiment are frequently taken into account, such as the length of the trip. The relationship of the latter with vehicle energy economy is obvious – e.g., the further you drive the more energy is consumed. However, it must be used with caution for prediction, as machine learning algorithms may focus on it and overlook other relevant factors. By contrast, our algorithms take as initial input only the mass (estimated from the curb weight plus number of passengers) and the vehicle speed, which can be easily obtained by the user. Furthermore, we characterize speed profiles by extracting 40 features at different levels of abstraction in the frequency and time domains. This way, we uncover hidden and valuable information that leads to higher prediction accuracy, improved generalization, and thus high application relevance. In addition, we implement an intelligent route segmentation algorithm that

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makes the prediction robust to data non-stationarity, making the final framework more transferable and even more applicable.

• Despite the abundance of machine-learning techniques, only a few of them are commonly used. In this work, we consider the full range, from non-learning statistical approaches to supervised learning and probabilistic methods. Consequently, this work presents and comprehensively compares the full potential of novel machine learning methods for predicting the energy consumption of EVs. Ultimately, we investigate the performance of various powerful machine learning models, from the very technical detail to the long-term application.

• Most studies use data from a single vehicle on a single route or use speed profiles from Standardized Driving Cycles (SDCs). Therefore, the variety and diversity within the data is comparatively low. However, a major challenge in this area is that the relevant factors are diverse and the interrelationships are complex. Thus, the larger 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 various 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 paper we use the bus operator's database and a physics-based model of soon-tobe- deployed electric buses to develop data-driven models that predict the energy requirements of the vehicles. 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:

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Advantages

1) We propose a scalable and efficient hybridization Machine Learning models for exact predictions.

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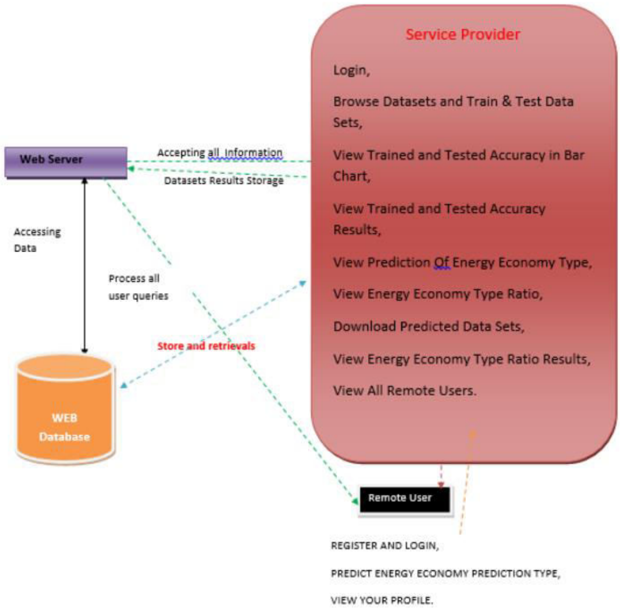
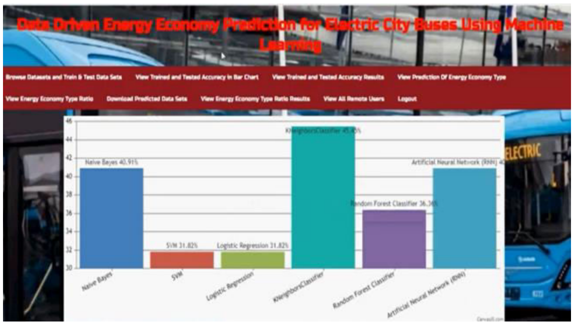
2) We conducted several hybridizations of genetic algorithm with filter and embedded feature selection methods, in the data pre-processing phase of Random Forest and Multivariate Linear Regression (MLR) predictive model, with the aim of improving its performance.



IV.MODULES

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

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.

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 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 optimal bus operating modes (all-electric, hybrid electric, *et cetera*), and select the best charging strategies (i.e. opportunity vs. conventional charging). The worst-case scenario – the most energy-intensive route – is the limiting factor. Ultimately, this knowledge is essential for fleet operators to identify critical operational limits in advance, avoid potential showstoppers, and gain confidence in new technologies. Thus, to achieve reliable and affordable service on all routes in the end .

As our main contribution, the paper presents a novel selection of explanatory variables that combine time and frequency characteristics of the speed waveform. To extract these features, the route is divided into micro trips. This 'segment-based' prediction provides robustness against non stationarity. Starting with an initial set of 40 features, we have found a minimum number of characteristics with high predictive value. The most relevant of these features, i.e., the spectral entropy of velocity profiles, has so far even gone unnoticed in this field. This result confirms our assumption that it is in the velocity waveform, whose temporal structure is well captured by the spectral entropy, where the most essential information actually resides.

In future research, we plan to extend this approach to other scenarios, as the challenge is to find out how this methodology performs under different circumstances. The proposed approach is of particular interest to companies in the transportation and logistics sector. In particular, it is of interest to fleet operators that rely on heavy-duty trucks and often struggle to electrify their fleets because they lack a solid framework for making the right choices for the right vehicles. It could even be applied to other classes of vehicles or transport systems, such as passenger vehicles or rail transport. On the other hand, meteorological characteristics, road type and operational features for instance could be investigated more deeply. This is why we plan to investigate seasonally and locally changing conditions and recommend careful feature selection according to each use case. Finally, predictive analytics of additional target variables, such as the peak power of the system or the electric current demands on the batteries are of high interest and could be investigated by the presented methodology.

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