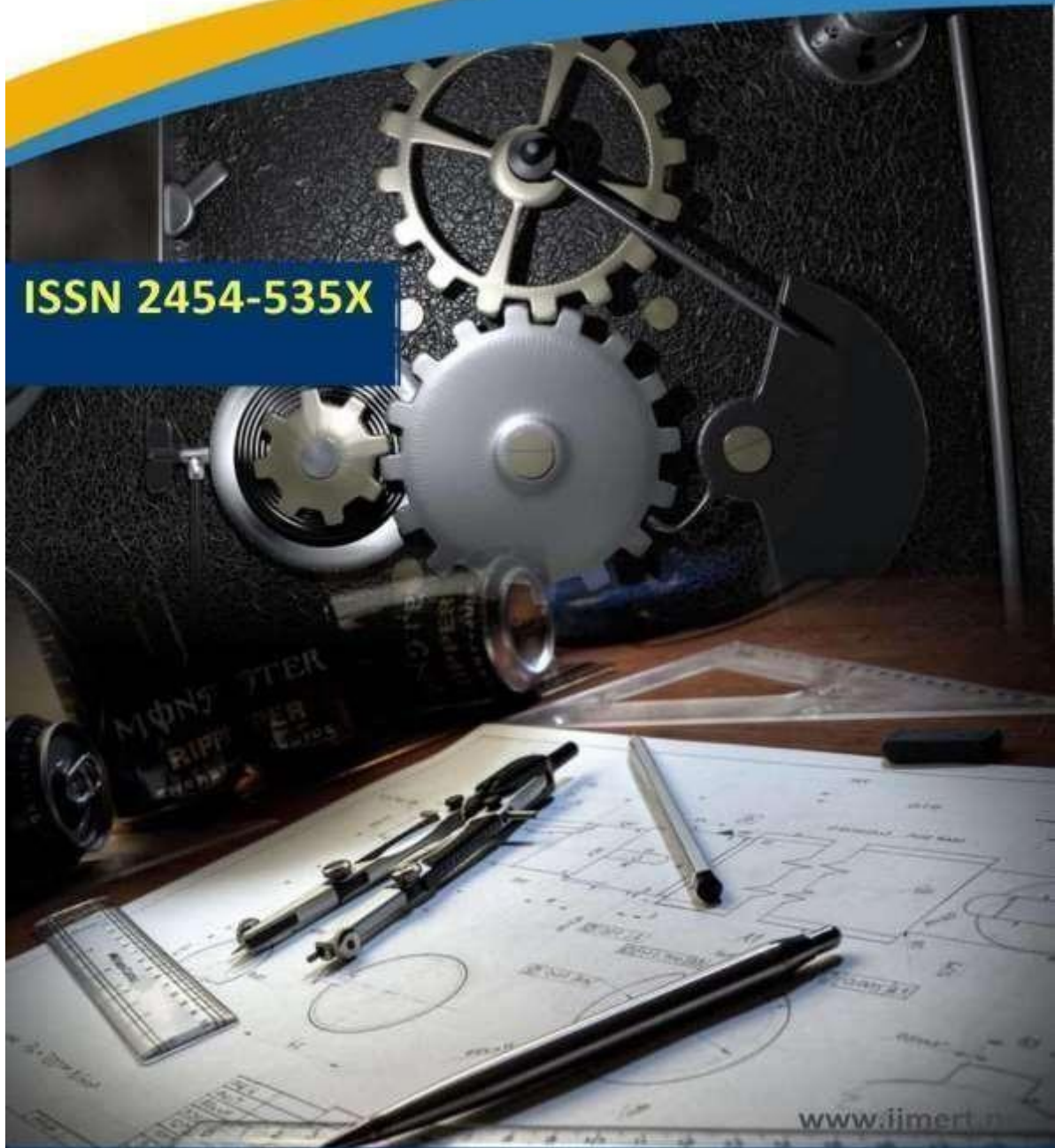




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DATA-DRIVEN ENERGY ECONOMY PREDICTIONS FOR-ELECTRICITY BUSES USING MACHINE LEARNING

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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.

INTRODUCTION

In recent years, the global transportation sector has witnessed a paradigm shift towards sustainable and energy-efficient solutions, driven by the urgent need to mitigate environmental concerns and reduce dependence on fossil fuels.

Within this landscape, the electrification of public transportation, particularly through the adoption of electric buses, has emerged as a promising strategy to combat air pollution and greenhouse gas emissions while enhancing urban mobility. However, the successful

integration of electric buses into existing transportation networks hinges upon effective energy management and economic viability.

The "Data-Driven Energy Economy Predictions for Electricity Buses using Machine Learning" project aims to address these challenges by leveraging machine learning techniques to forecast energy consumption and optimize operational strategies for electric bus fleets. By harnessing large-scale datasets encompassing various factors such as weather conditions, route characteristics, passenger demand, and vehicle performance, this project seeks to develop predictive models capable of accurately estimating energy usage and identifying opportunities for efficiency improvements.

Through the analysis of historical data and real-time monitoring of electric bus operations, the project aims to generate actionable insights that enable transit agencies and fleet operators to optimize charging schedules, route planning, and vehicle deployment strategies. By predicting energy consumption patterns and optimizing resource allocation, the project aims to enhance the economic viability and environmental sustainability of electric bus operations, ultimately facilitating the transition

towards a cleaner and more efficient transportation ecosystem.

With the proliferation of smart sensors, telematics systems, and IoT devices in modern vehicles, the availability of high-quality data has become increasingly abundant, providing unprecedented opportunities for data-driven decision-making in the transportation sector. By harnessing the power of machine learning algorithms, this project seeks to unlock the potential of these datasets to drive innovation and optimization in electric bus operations, paving the way for a more sustainable and energy-efficient future in urban transportation.

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 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-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.

Advantages

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

The implementation of the "Data-Driven Energy Economy Predictions for Electricity Buses using Machine Learning" project involves several key steps. First, a comprehensive dataset encompassing various environmental, operational, and performance factors is collected and preprocessed. This dataset may include information such as weather conditions, route characteristics, passenger demand, vehicle telemetry data, and charging infrastructure specifications. Next, machine learning algorithms are trained on the preprocessed dataset to develop predictive models capable of forecasting energy consumption and optimizing resource allocation for electric bus fleets. These algorithms may include regression models, time series analysis techniques, or deep learning architectures such as recurrent neural networks (RNNs) or long short-term memory (LSTM) networks. Once trained, the predictive models are integrated into a software platform or decision support system, allowing transit agencies and fleet operators to input real-time data and receive actionable insights and recommendations for optimizing energy efficiency and operational performance. Continuous monitoring and evaluation of the

predictive models are conducted to ensure accuracy and reliability, with periodic updates and refinements made based on feedback and new data sources. Through iterative refinement and validation, the implemented solution enables data-driven decision-making and optimization of electric bus operations, ultimately leading to improved economic viability and environmental sustainability.

V.CONCLUSION

In conclusion, the "Data-Driven Energy Economy Predictions for Electricity Buses using Machine Learning" project holds significant promise in revolutionizing the efficiency and sustainability of electric bus fleets within urban transportation networks. By harnessing the power of machine learning techniques and leveraging vast datasets encompassing various environmental, operational, and performance factors, the project aims to develop predictive models capable of accurately forecasting energy consumption and optimizing resource allocation. Through the implementation of these predictive models, transit agencies and fleet operators can make data-driven decisions to optimize charging schedules, route planning, and

vehicle deployment strategies, thereby improving the economic viability and environmental sustainability of electric bus operations. By integrating data-driven insights into decision-making processes, this project contributes to the advancement of smart and sustainable transportation solutions, paving the way for a cleaner, greener, and more efficient urban mobility landscape.

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