Data Driven Energy Economy Prediction For Electric City Buses Using Machine Learning

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Abstract:

The electrification of transportation is rapidly increasing, with city buses presenting significant potential for sustainable mobility. However, a deep understanding of real-world driving data is crucial for optimizing vehicle design and fleet operations. By leveraging powerful machine learning methods, five different algorithms were developed and rigorously evaluated in terms of prediction accuracy, robustness, and overall applicability. The efficiency of alternative powertrains depends on multiple technological factors, yet uncertainty in energy demand often leads to conservative designs, resulting in inefficiency and high costs. Due to the complexity and interrelation of parameters, both industry and academia lack analytical solutions to address this challenge effectively. This paper aims to enhance transparency in the energy economy of battery electric buses (BEBs) by introducing novel explanatory variables to characterize speed profiles. By leveraging powerful machine learning methods, five different algorithms were developed and rigorously evaluated in terms of prediction accuracy, robustness, and overall applicability. The best-performing model achieved over 94% accuracy, demonstrating the effectiveness of advanced predictive techniques combined with a sophisticated selection of features. The proposed methodology offers immense potential for manufacturers, fleet operators, and urban planners by enabling precise energy demand prediction, reducing operational costs, and improving efficiency. Ultimately, this research contributes to the transformation of public transportation towards a more sustainable and data-driven future.

Keywords: Road Electrification of Transportation, Battery Electric Buses (BEB), Energy Demand Prediction, Speed Profiles, Machine Learning, Energy Economy, Fleet Operations Alternative Powertrains, Prediction Accuracy.

1.INTRODUCTION

Traffic causes approximately 25% of greenhouse gas (GHG) emissions in Europe, and this percentage is increasing. 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 . 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 it is quickly amortized. downside, the battery charging time of an electric bus is significantly longer than the refuelling time of a diesel bus, while the opposite is true for the challenges. The starting point for this study was a problem proposed by Seville's public bus operator.

In addition, electrification of the power train brings many other advantages, such as a reduced noise level or pollution. On the 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. 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.

2. LITERATURE SURVEY

The electric vehicle (EV) industry has witnessed rapid growth over the past decade, with electric buses playing a crucial role in transforming urban public transport systems worldwide. One of the most significant areas of research in this field is optimizing energy usage, especially for electric buses. These buses are becoming the backbone of many cities' public transportation fleets, contributing to the reduction of carbon emissions and the promotion of cleaner urban mobility. However, for electric buses to become a truly sustainable option, there is a pressing need to optimize their energy consumption. Several studies have explored how machine learning, data analysis, and innovative technologies can be harnessed to improve the energy economy of these buses, ultimately making them more efficient, cost-effective, and sustainable in real-world conditions.

Roman Michael Sennefelder's 2024 study offers a major contribution to this area by incorporating machine learning algorithms to predict the energy consumption of battery electric buses. His approach is particularly groundbreaking because it integrates a wide range of variables that were previously overlooked in traditional models. In addition to the usual factors like bus speed and route length, Sennefelder's model also takes into account weather conditions, driving patterns, and the specific topography of the bus routes. Each of these factors can have a significant impact on energy consumption. For example, driving on a hilly route demands more energy than on a flat route, and adverse weather conditions, like heavy rain or cold temperatures, can increase energy usage as the bus needs more power to maintain speed or heat the interior. By incorporating these variables, Sennefelder's model achieved a remarkable prediction accuracy of over 94%. This high level of precision is essential for making real-time decisions about energy consumption and improving fleet management.

Sennefelder's work is valuable not just because of the high prediction accuracy, but also because it offers deeper insights into the factors that influence energy usage. These insights can be used to improve operational strategies for electric bus fleets. For instance, by analyzing the weather data alongside bus performance, transit authorities can anticipate energy demand and adjust routes or schedules accordingly. Buses can be optimized to operate more efficiently in adverse weather conditions, and specific routes that require higher energy consumption can be managed better through scheduling or vehicle allocation. This approach makes the transition to electric buses more viable, as it allows for the effective management of energy resources and reduces operating costs. Building on Sennefelder's work, Dimitar Trifonov's 2023 paper focuses on enhancing the precision of energy prediction models for electric buses. Trifonov emphasizes that to achieve more reliable predictions, it is necessary to incorporate additional features that reflect the complexities of real-world bus operations. One such feature is bus load, which refers to the number of passengers onboard. As the number of passengers increases, so does the total mass of the bus, requiring more energy to accelerate and maintain speed. Trifonov also highlights the importance of including passenger numbers, route-specific factors, and other dynamic conditions in the energy prediction models. These factors are especially important in urban environments, where routes may involve varying traffic patterns, stops, and turns.

3. PROPOSED METHODOLOGY

The proposed system aims to optimize the energy consumption and operational efficiency of electric city buses by leveraging data-driven insights through machine learning (ML). This system will predict energy needs, optimize routes, manage charging schedules, and enhance fleet management, all with the goal of reducing costs, improving sustainability, and enhancing operational efficiency. The system will be integrated into the existing urban infrastructure and will use real-time and historical data to provide actionable insights.

System Overview:

The proposed system is designed to use machine learning models and data from electric buses to predict energy consumption, optimize fleet operations, and improve charging infrastructure. The system will include data collection, preprocessing, predictive modelling, and optimization layers, which work together to provide real-time, actionable insights for bus operators. Key functionalities of the system include Energy Consumption Prediction: Using historical and real-time data to predict how much energy each bus will consume on a given route. Route Optimization: Finding the most energy-efficient routes for buses, considering factors like traffic, terrain, and weather. Charging Optimization: Optimizing the charging schedule for buses to ensure maximum efficiency, reduce downtime, and minimize electricity costs. Maintenance Prediction: Predicting the need for maintenance and identifying anomalies in energy consumption, such as battery degradation.

System Architecture and Components:

The architecture of the proposed system involves several key layers that enable data collection, processing, prediction, and optimization **Proposed System Workflow:**

Unlike traditional systems, the proposed solution continuously collects and analyses real-time cybersecurity discussions and reports. The system identifies emerging threats as they are being discussed in hacker forums, dark web platforms, and social media, allowing for faster detection and response. By categorizing threats using frameworks like MITRE ATT&CK, the system enhances situational awareness.

Key Benefits of the Proposed System

The system categorizes identified threats based on their severity, attack pattern, and potential impact. It uses AI-driven classification models to assign risk levels to each detected cyber threat, enabling security professionals to prioritize their mitigation efforts efficiently.

Energy Efficiency: By predicting energy consumption and optimizing routes, the system reduces unnecessary energy usage, contributing to significant cost savings.

Reduced Operational Costs: Optimized charging schedules and fleet operations reduce downtime and energy costs, making electric buses more cost-effective to operate.

Extended Battery Life: Predictive maintenance ensures that buses are serviced before issues occur, and optimized charging prevents overcharging, extending battery life.

Sustainability: The system helps reduce the carbon footprint of public transport by ensuring that electric buses operate more efficiently and integrate renewable energy sources during off peak hours.

Improved Fleet Management: The system provides actionable insights into the performance of individual buses, helping fleet managers improve operational efficiency and decision-making.

Future Enhancements and Considerations

Integration with Smart City Infrastructure: The system could be integrated with broader smart city technologies (e.g., smart traffic lights, autonomous vehicles) to further optimize urban transportation networks. Advanced Autonomous Features: As autonomous electric buses become more widespread, machine learning models could be adapted to optimize autonomous driving behaviors, further improving energy efficiency.

4. EXPERIMENTAL ANALYSIS

Figure 1: Home page

The Home Page serves as the main entry point of the platform, providing users with a clear and intuitive interface to navigate between different sections. It features a welcoming design with essential navigation options, prominently displaying buttons or links directing users to the Service Provider Login and User Login pages. The homepage typically includes a brief introduction to the platform's purpose, highlighting its key features and benefits. A responsive and user-friendly layout ensures accessibility across various devices, enhancing the overall user experience. With clear call-to-action elements, the homepage streamlines access to the respective login portals, allowing both service providers and users to proceed seamlessly.

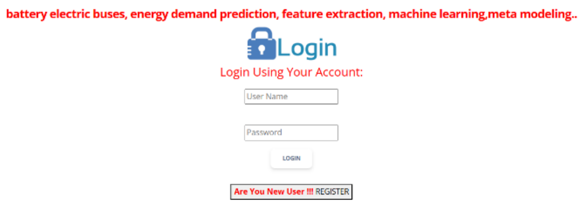

Figure 2: Landing page

The image depicts a login page for the system. There is a login section with a circular **"Login"** button that features a padlock icon, symbolizing security. The login form includes fields for "User Name" and "Password," along with a "sign_in" button, suggesting restricted access for authorized users.

Figure 3: Web page for the service provider login

There is a **login section** labeled **"Login Service Provider"** in red text, which includes a circular login button with a padlock icon, symbolizing security and restricted access. Below the button, there are input fields for **"User Name"** and **"Password,"** along with a **"Login"** button, indicating that only authorized users can access the system.

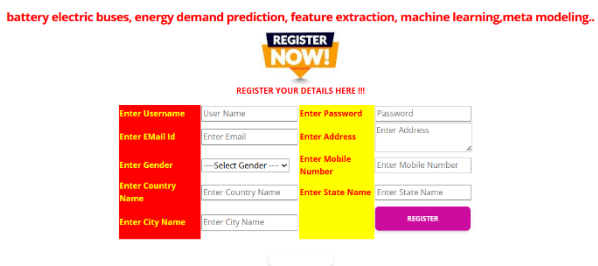

Figure 4: User Registration Page

A **User Registration Page** is an essential feature of web applications, allowing users to create accounts by providing details like name, email, phone number, and password. It includes form validation to ensure correct input formats, such as strong passwords and valid email addresses, enhancing security and usability. Secure password handling is crucial, often involving encryption techniques like **crypt hashing** to protect user data from breaches. Many registration systems also incorporate **email verification or OTP authentication** to confirm user identity before granting access. Additionally, integrating a database such as **MySQL, PostgreSQL, or MongoDB** ensures that user information is stored securely, enabling seamless login and authentication processes

5. 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". 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.

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