DATA DRIVEN ENERGY ECONOMY PREDICTION FOR ELECTRIC CITY BUSES

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ABSTRACT

The electrification of transportation systems is increasing rapidly, and city buses offer significant potential in this transition. A deep understanding of real-world driving data is essential for improving vehicle design and optimizing fleet operations. Several technological factors must be considered to operate alternative powertrain systems efficiently. Uncertainty in energy demand often leads to conservative vehicle design, which can result in inefficiencies and higher operational costs. Due to the complexity and interdependence of various parameters, both industry and academic researchers have faced challenges in developing analytical solutions for this problem. Accurate prediction of energy demand can enable cost reduction and improved operational planning. This paper focuses on increasing transparency in the energy consumption behavior of battery electric buses (BEB). A new set of explanatory variables is introduced to describe speed profiles, which are then applied within machine learning models for prediction. The study develops and evaluates five different algorithms in terms of prediction accuracy, robustness, and practical applicability. The proposed models achieved prediction accuracy of more than 94%, showing strong performance when combined with carefully selected features. The presented methodology offers valuable potential for manufacturers, fleet operators, and urban communities to support the transition toward efficient and sustainable public transportation systems.

Keywords: Battery Electric Buses, Energy demand prediction, Feature extraction, Machine learning, Meta modeling

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 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.

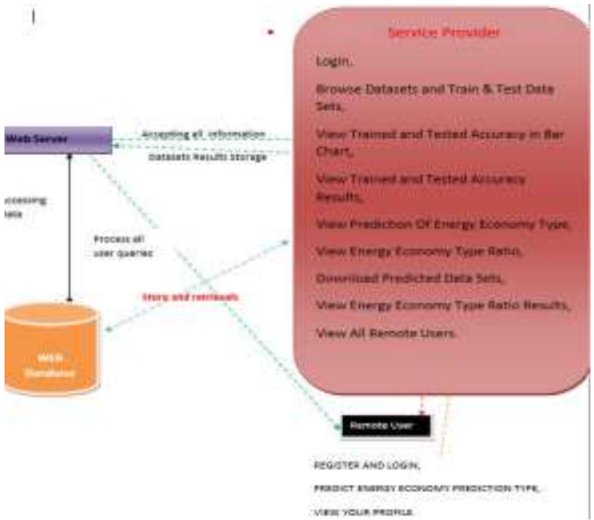

Fig 1: System Architecture

II RELATED WORK

Electrification of Public Transport

Electrification of transportation in cities is a matter of focus for a large number of studies. City buses are one of the essential parts in this process that help in lowering carbon emissions and increasing the mobility in urban areas. As more people become interested in using battery electric buses, there has been increased attention on analyzing their energy usage and developing ways to operate them as efficiently as possible. Many studies have underscored the need to develop precise models for predicting energy demand since uncertainties in energy consumption result in inefficient system designs and higher operational costs.

Energy Demand Prediction Models

Most of the early researches on BEB energy demand prediction were based on simple models that used route information, vehicle characteristics, and historical data. Liu et al. (2019) proposed a prediction model for energy consumption, using historical driving data and characteristics of routes. Though it provided useful insights, the approach did not take into account real-time variations like traffic conditions and driver behavior. In time, advanced models, including machine learning approaches, have been developed to overcome such shortcomings.

Machine Learning Models for Energy Prediction

The central idea behind the current development of more accurate models for energy prediction is techniques in machine learning. Zhang et al. (2021) employed support vector machines (SVM) and achieved promising results in controlled conditions for energy consumption prediction but faced issues in terms of scalability and adaptability under dynamic real-world conditions. Similarly, Lee et al. (2020) applied deep learning methods in controlled settings to accurately predict energy demand but showed poor robustness in terms of predictability in the urban environment. These studies reflect the great potential of machine learning, but at the same time, show a need for more robust and adaptive models.

Feature Selection and Speed Profiles

Selecting the appropriate features is an important aspect of improving the accuracy of energy prediction. For instance, research such as Ríos et al. (2020) has demonstrated that including various explanatory variables such as speed profiles, weather conditions, and vehicle load in the model can improve the performance of the prediction model considerably. Such variables give a better understanding of the factors that are affecting energy consumption and will result in more accurate energy demand predictions.

Current Gaps and Challenges

Despite the progress in energy demand prediction for BEBs, there are still large gaps in providing practical, scalable solutions for fleet operations. Most of the existing models either are too simplistic or lack robustness to handle the dynamic nature of urban environments. The lack of effective integration of real-time data and accurate feature selection continues to limit the applicability of these models in real-world settings.

Contribution of Current Work

The current study aims to fill these gaps by introducing novel sets of explanatory variables to characterize speed profiles and assessing five different machine learning algorithms. The proposed methodology achieves a prediction accuracy of over 94%, offering significant improvements in prediction robustness and scalability. This approach presents a promising solution for manufacturers, fleet operators, and municipalities, helping optimize BEB operations and contribute to sustainable public transportation.

The findings from this study offer a comprehensive, data-driven approach to energy demand prediction, paving the way for more efficient, cost-effective, and environmentally friendly public transportation systems.

III IMPLEMENTATION

The Service Provider module is implemented for authorized users to perform a variety of key operations related to the prediction system of the energy economy. After logging in using their valid username and password, these service providers get the capability to browse datasets, to use training and testing data sets and to view the accuracy of a trained model. They can view the accuracy of the models in bar charts and also review detailed accuracy results. In addition, the service provider can view the predicted energy economy types, including the energy economy type ratio, and download the predicted datasets for further analysis. The other feature of this module is that the service provider can view the energy economy type ratio results, which help gain deeper insights into energy consumption patterns. In addition, the service provider can view all the registered remote users and monitor their activities in the system.

The View and Authorize Users module is managed by the Admin, who has full control over user management. The admin can view a list of all registered users and access their details, such as their username, email, and physical address. The admin also gives permission to users, making sure that only the people with valid credentials are allowed to log in and use the functionalities of the system. This module is vital in maintaining the security and integrity of the system since it ensures that only authorized people are accessing the system.

In the Remote User module, a user first needs to register, giving their personal details, including their name, email, and address. Once the registration procedure is done, users can log in using their authorized username and password. After successful login operation, they can predict the energy economy type and view their profile. The remote user module keeps the system's prediction accessibility to only registered and approved individuals, thus adding to the comprehensive security and functionality of the system.

Together, these modules form a coherent system that supports the economic and efficient use of management tools for energy economy prediction whilst maintaining user authorization and security.

IV ALGORITHM

Decision tree classifiers

Decision tree classifiers are used successfully in many diverse areas. Their most important feature is the capability of capturing descriptive decision making knowledge from the supplied data. Decision tree can be generated from training sets. The procedure for such generation based on the set of objects (S), each belonging to one of the classes C1, C2, …, Ck is as follows:

Step 1. If all the objects in S belong to the same class, for example Ci, the decision tree for S consists of a leaf labeled with this class

Step 2. Otherwise, let T be some test with possible outcomes O1, O2,…, On. Each object in S has one outcome for T so the test partitions S into subsets S1, S2,… Sn where each object in Si has outcome Oi for T. T becomes the root of the decision tree and for each outcome Oi we build a subsidiary decision tree by invoking the same procedure recursively on the set Si.

Gradient boosting

Gradient boosting is a machine learning technique used in regression and classification tasks, among others. It gives a prediction model in the form of an ensemble of weak prediction models, which are typically decision trees.[1][2] When a decision tree is the weak learner, the resulting algorithm is called gradient-boosted trees; it usually outperforms random forest.A gradient-boosted trees model is built in a stage-wise fashion as in other boosting methods, but it generalizes the other methods by allowing optimization of an arbitrary differentiable loss function.

K-Nearest Neighbors (KNN)

- Simple, but a very powerful classification algorithm
- Classifies based on a similarity measure
- Non-parametric
- Lazy learning
- Does not “learn” until the test example is given
- Whenever we have a new data to classify, we find its K-nearest neighbors from the training data

Logistic regression Classifiers

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name logistic regression is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name multinomial logistic regression is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does.

This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

Naïve Bayes

The naive bayes approach is a supervised learning method which is based on a simplistic hypothesis: it assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature .

Yet, despite this, it appears robust and efficient. Its performance is comparable to other supervised learning techniques. Various reasons have been advanced in the literature. In this tutorial, we highlight an explanation based on the representation bias. The naive bayes classifier is a linear classifier, as well as linear discriminant analysis, logistic regression or linear SVM (support vector machine). The difference lies on the method of estimating the parameters of the classifier (the learning bias).While the Naive Bayes classifier is widely used in the research world, it is not widespread among practitioners which want to obtain usable results. On the one hand, the researchers found especially it is very easy to program and implement it, its parameters are easy to estimate, learning is very fast even on very large databases, its accuracy is reasonably good in comparison to the other approaches. On the other hand, the final users do not obtain a model easy to interpret and deploy, they does not understand the interest of such a technique.

Thus, we introduce in a new presentation of the results of the learning process. The classifier is easier to understand, and its deployment is also made easier. In the first part of this tutorial, we present some theoretical aspects of the naive bayes classifier. Then, we implement the approach on a dataset with Tanagra. We compare the obtained results (the parameters of the model) to those obtained with other linear approaches such as the logistic regression, the linear discriminant analysis and the linear SVM. We note that the results are highly consistent. This largely explains the good performance of the method in comparison to others. In the second part, we use various tools on the same dataset (Weka 3.6.0, R 2.9.2, Knime 2.1.1, Orange 2.0b and RapidMiner 4.6.0). We try above all to understand the obtained results.

Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.

The first algorithm for random decision forests was created in 1995 by Tin Kam Ho[1] using the random subspace method, which, in Ho's formulation, is a way to implement the "stochastic discrimination" approach to classification proposed by Eugene Kleinberg.

An extension of the algorithm was developed by Leo Breiman and Adele Cutler, who registered "Random Forests" as a trademark in 2006 (as of 2019, owned by Minitab, Inc.).The extension combines Breiman's "bagging" idea and random selection of features, introduced first by Ho[1] and later independently by Amit and Geman[13] in order to construct a collection of decision trees with controlled variance.

Random forests are frequently used as "blackbox" models in businesses, as they generate reasonable predictions across a wide range of data while requiring little configuration.

SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an independent and identically distributed (iid) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point x and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space.

SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to genetic algorithms (GAs) or perceptrons, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

RESULTS

Fig:1:User Login

Fig:2:Remote User

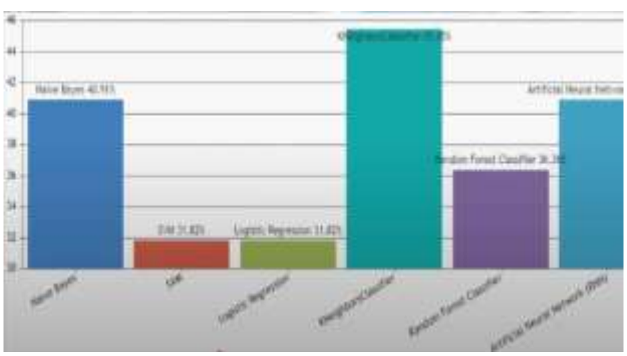

Fig:3:Accuracy Results

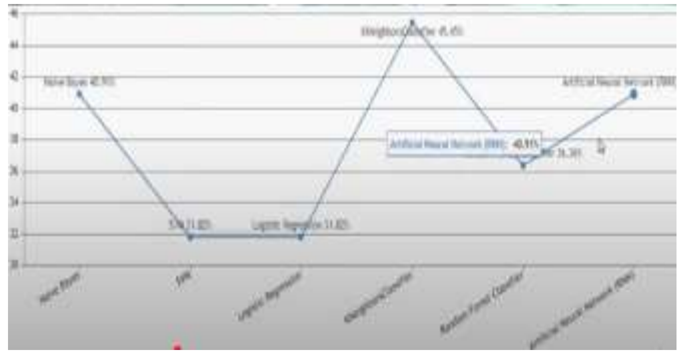

Fig:4:Algorithm Graph

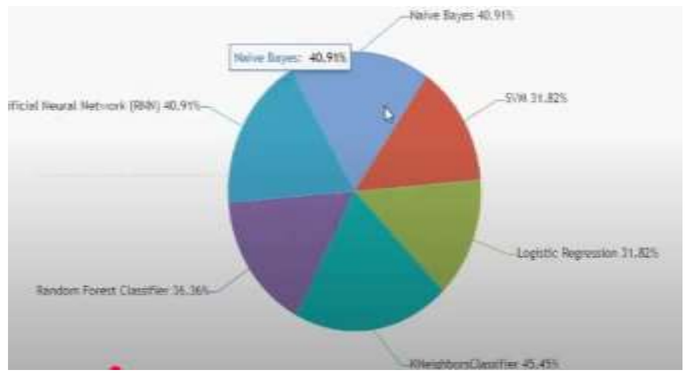

Fig:5:Pie Chart Algorithm Comparision

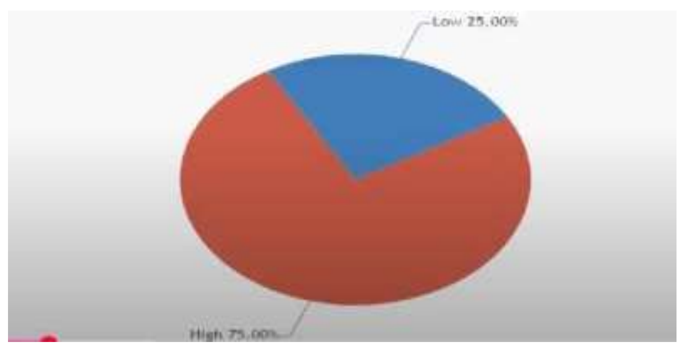

Fig:6:Pie Chart Prediction Comparision

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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