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SMART ENERGY FORECASTING FOR ELECTRIC BUSES THROUGH MACHINE LEARNING TECHNIQUES

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ABSTRACT

Transportation systems are becoming more and more electrified; city buses in particular offer tremendous possibilities. Designing vehicles and managing a fleet requires a thorough grasp of real-world driving data. To operate alternative powertrains effectively, a number of technical factors need to be taken into account. When energy consumption is uncertain, cautious design is used, which suggests inefficiency and high prices. Because of the intricacy and interdependence of the factors, both industry and academics fail to find analytical answers to this challenge. By optimising processes, accurate energy demand forecast allows for considerable cost savings. The purpose of this study is to make the energy economy of battery electric buses (BEBs) more transparent. To describe speed profiles, we provide new sets of explanatory variables that we use in effective machine learning techniques. We create and thoroughly evaluate five distinct algorithms in terms of their general applicability, robustness, and prediction accuracy. When combined with the careful feature selection, our models demonstrated exceptional performance, achieving a prediction accuracy of over 94%. The suggested approach has the potential to revolutionise mobility and open the door for sustainable public transportation for municipalities, fleet operators, and manufacturers.

I. INTRODUCTION

In Europe, traffic is responsible for around 25% of greenhouse gas (GHG) emissions, and this number is rising [1]. Thus, one of the best things that can be done to combat climate change and promote sustainability is to electrify the transportation sector on a large scale [2], [3]. Given their minimal emissions of pollutants, it is certain that electric buses will be a major part of the public transport system in cities in the future. Even though the initial investment in electrification may be high—for example, the purchase costs of BEBs can be up to twice as high as those of diesel buses [4]—it is quickly recouped because electric vehicles are inherently more efficient than internal combustion engine vehicles (up to 77% [5]), which results in significantly lower operational and life cycle costs [6]. There are several other benefits of electrifying the power train, including lower pollution and noise levels [7]–[10]. The drawback is that an electric bus's battery charge time is much longer than a diesel bus's refuelling time, while the range is the reverse [11]. In the end, extensive electrification of the mobility sector is one of the best things that can be done to combat climate change and promote sustainability, but it also presents a number of difficulties that need more study to assure effective operation.

The public bus operator in Seville came up with the issue that served as the basis for our investigation. Simply said, they intended to switch out their fleet of diesel cars with all-electric ones, but first they needed to figure out how big the batteries were and where the best places to charge them were in the city. In actuality, this entails forecasting consumption on each route using computers [12]. Regretfully, this is now limited to data-driven models that, once trained, need a large number of mechanical, road, and driving measures as inputs, or complicated physical models that require lengthy simulation durations (see Section I-A). This is where the

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current study is useful. In this work, we create data-driven models that forecast the energy needs of the vehicles using a physics-based model of soon-to-be-deployed electric buses and the bus operator's information. We demonstrate that, among other things, we only need to know the instantaneous speed of the vehicle and the number of passengers on the bus in order to use machine learning to accurately predict the consumption on a route. This sets our contribution apart from earlier data-driven approaches. In particular, there are three phases in our approach:

1) We utilise a physics-based model, verified by the vehicle manufacturer, that takes into account the bus's own weight as well as the weight of its cargo to determine how much energy the bus needs on each trip. The operator's database contains both variables.

2) From the speed signal, we extract a complete set of time and frequency information.

3) Using the aforementioned set of parameters and bus payload mass, we train machine learning regression models to estimate energy consumption and determine which models have the greatest predictive value. It's interesting to note that the trait that proves to be most significant—the spectrum entropy of velocity—has not yet been identified in this area of study.

In the end, our findings can be used to plan the switch from a conventional to a green bus fleet, as well as to add new features that planners will find helpful. For instance, the algorithms can be used to monitor the batteries' current state of charge using battery management systems.

The structure of the paper is as follows. In part I, we first evaluate the state of the art and identify the obstacles in this subject. Second, Section II provides an explanation of our materials, approach, and techniques. Section III presents and discusses the experimental outcomes. Section IV wraps up our work and outlines potential directions for further research.

II. LITERATURE SURVEY

"The market for electric vehicles is booming and expanding globally,"

T. Wu, S. Schenk, N. Müller, and P. Hertzke,

The high dynamics of the growth of supply and demand for electric cars in both domestic and international economies make the study of the electric car market relevant. The article's objective is to examine the unique features of Ukraine's electric vehicle market's growth and government regulation in comparison to other countries, and to generalise suggestions for maximising the market's contribution to the country's economy. By using a methodical approach, it was possible to analyse the dynamics of changes in the number of electric cars in recent years, the nature of competition, and the structure of supply and demand for these vehicles. The degree of institutional support and market size for electric vehicles in Ukraine and outside were compared using comparative analysis. The fundamental components of the electric vehicle market, namely the characteristics of the electric car as an economic product, are disclosed, together with the theoretical underpinnings of the market study. Clarified are the benefits and drawbacks of electric vehicles in comparison to conventional vehicles. The elements impacting the growth of the electric vehicle industry in both national and international economies are grouped. The primary growth trends of the global electric vehicle market as well as the characteristics of the development of the domestic market are examined. The primary growth paths in Ukraine under contemporary circumstances are disclosed, as is the international experience of governmental control of the electric vehicle sector.

"A gasoline compression ignition method for future engines that are economical, clean, and efficient,"

B. Johansson and G. Kalghatgi,

Even while the need for transportation fuels will rise dramatically globally, petroleum-based fuels will still account for a significant portion of this demand—roughly 90%. There will likely be an

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excess of lighter low-octane fuels as a result of this demand growth being heavily skewed towards commercial vehicles and, thus, towards diesel and jet fuels. Because they employ standard diesel fuels that ignite quickly and attempt to minimise nitrogen oxide and soot emissions concurrently, current diesel engines are efficient but costly and complex. Low-nitrogen-oxide, low-soot combustion is greatly facilitated by gasoline compression ignition engines, which may be powered by gasoline-like fuels with a lengthy ignition delay. Additionally, the excess low-octane components might be utilised without any additional processing since the research octane number of the ideal fuel for petrol compression ignition engines is probably about 70. Additionally, it may have a greater ultimate boiling point than modern gasolines. The following are some possible benefits of gasoline compression ignition engines. Initially, the engine is as clean and efficient as existing diesel engines, but it is simpler and may be less expensive since it uses less injection pressure and controls emissions of hydrocarbons and carbon monoxide instead of nitrogen oxide and soot. Second, compared to existing petrol or diesel fuel, the ideal fuel would be simpler to produce and have a reduced greenhouse gas footprint since it needs less processing. Third, it offers a way to decrease the anticipated worldwide demand imbalance between heavier and lighter fuels and enhance refinery sustainability. The idea has been clearly shown in research engines, but more work is required to make it workable in real-world cars. Examples of this work include cold start, proper regulation of exhaust hydrocarbons and carbon monoxide, and noise reduction at medium to high loads. Technology for petrol compression ignition engines must first function with the fuels already available on the market, but in the long run, new and easier fuels must be provided to make the transportation industry more sustainable.

"Economic evaluation of battery-powered electric transit buses,"

L. Eudy, M. Jeffers, C. Johnson, and E. Nobler,

Based on the average or typical characteristics of current battery electric bus (BEB) fleets, a baseline bus fleet and battery electric bus investment scenario was created. The baseline fleet had a net present value of $785,000 and a simple payback of 3.3 years, according to a discounted cash flow analysis. After determining their proportional impact on NPV, the 33 primary factors were prioritised based on a ±50% swing. The range of observed values was then divided by the baseline value to determine parameter volatility. Fleet managers should concentrate on the most significant and erratic factors when assessing whether BEBs are a viable investment choice for them. These primary criteria are 1) BEB purchase price, 2) foregone diesel bus purchase price, 3) grant amount, 4) foregone diesel bus maintenance expenses, and 5) yearly vehicle kilometres driven.

"Energy consumption of an internal combustion and electric passenger car." a comparative case study using actual data on the German Erfurt circuit,

W. Rid and A. Braun,

By lowering energy use and CO2 emissions, for example, electric cars offer to help create a more sustainable transportation system. Information on the energy consumption of electric cars in comparison to conventional vehicles is required for the evaluation of their environmental effect and for choices regarding their operational deployment. This study compares and contrasts the energy usage of internal combustion and battery-electric passenger cars under different driving conditions. Several gadgets were installed in the cars to measure and record energy data while they were in use. In December 2016, a team of drivers performed test drives on a 42-kilometer test route in and around the German city of Erfurt. To get comparable statistics, each driver operated both cars in succession. The impacts of peak-hour traffic and driving style on energy usage are also investigated via certain driving scenarios. Particularly, the impacts on the BEV and the ICV differ depending on the kind of route. Our

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findings confirm that compared to conventional cars, electric vehicles' energy usage is less sensitive to speed dynamics in urban settings. In the baseline scenario, the relative efficiency advantage of electric cars is 68 percent; however, in urban driving, it is 77 percent. The relative consumption benefits of BEVs for aggressive and calm driving, as well as during peak hours, did not vary significantly, according to our analysis.

"Lifecycle cost analysis and carbon dioxide emissions of electric, fuel cell hybrid, diesel and natural gas transit buses,"

T. Lipman and A. Lajunen,

The lifespan costs and carbon dioxide emissions of several city bus models are assessed in this article. The Autonomie vehicle simulation program was used to create the simulation models of the various powertrains. Both the bus operation and the fuel and energy paths from well to tank have their carbon dioxide emissions computed. The main energy sources, Finland and California (USA), were subjected to two distinct operational environment case scenarios. The operational environment was taken into consideration while choosing the fuel and energy paths. Purchase, operating, maintenance, and potential carbon emission expenses are all included in the lifetime costs. According to the modelling findings, alternative engine technologies may greatly increase the energy efficiency of city buses. While fully-electric buses have the potential to drastically cut carbon dioxide emissions by up to 75%, hybrid buses have somewhat lower carbon dioxide emissions over the course of their service life than diesel buses. According to the lifetime cost study, natural gas and diesel buses are already comparable with diesel hybrid buses. The main obstacle to lowering lifespan costs to more competitive levels for fuel cell hybrid buses is the high cost of the battery and fuel cell systems.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM

Battery electric buses (BEBs) and battery electric vehicles (BEVs) in general have had their energy requirements predicted in great detail. Given that [13] demonstrates that BEBs are a feasible substitute for traditional vehicles and are less susceptible to changes in mission profiles than diesel buses, this is not surprising. It's also crucial to remember that a BEB's duty cycle and driving circumstances vary significantly from those of other BEVs, which causes the emphasis to change from kinematic correlations to route, timetable, and passenger load.

Although they differ in emphasis and goal, most earlier research uses intricate physics-based vehicle models [14]–[21]. For instance, the authors of [14] investigate how rolling resistance, auxiliary power, and power train efficiency affect battery electric vehicles' (BEVs') energy use. Even though rolling resistance and drive train efficiency affect how the vehicles move physically, auxiliary power demand is particularly significant at the slower speeds (less than 40 km/h) where city buses usually travel. This makes precise knowledge of auxiliary power necessary to forecast total energy consumption. In order to identify and measure relationships between the vehicle's energy usage and its kinematic characteristics, De Cauwer et al.'s research [15] combines a data-driven technique with a physical model of the vehicle. Other variables like the temperature or the trip duration and distance are added to commonly used kinematic parameters.

The impact of rolling resistance, which is dependent on the road surface and different weather conditions, on power consumption was investigated by Wang et al. [17]. In order to lower the uncertainty of the prediction model in [18], extra dynamometer observations and coastdown tests are added to the longitudinal dynamics model. Similar to this, the authors of [21] provide a brand-new, computationally effective electro-mechanical model of a BEB in order to investigate how variables like rolling resistance, temperature, and payload mass affect consumption. All of these methods provide insightful information on how various influencing elements interact, but in order to produce useful results, they need precise modelling of the vehicles and their parts as well as complex equations. The lengthy simulation periods make them practically useless, as is the case with all physics-based models. Furthermore, light-duty vehicles have been the primary focus of the majority of prior research, and scaling to the heavy-duty class is challenging because of the vastly different driving dynamics and profiles.

[22]–[35] include data-driven methods that combine physics-based and data-driven methods, or even machine-learning or deep learning algorithms with real-world driving data. Chen et al. [22], for instance, examine the most recent energy-consumption prediction models for electric vehicles (rule-based vs. data-driven) and investigate the case of electric buses using logistic regression and neural networks using actual data. The motivation for our study is further supported by their identification of the research need for energy consumption models of heavy-duty vehicles, such as city buses. In order to predict the energy consumption of electric buses, Pamula et al. [23] used both deep learning and traditional neural networks.

These prediction models made use of real data from different bus routes. In addition to operational data such bus routes and stop locations, travel times between bus stops, timetables, and peak hour information, the models are based on input factors that fleet operators can readily monitor. Kontu and Miles [24] look at influencing elements including the driver's traits and the route. Ericsson [25] investigated how various driving behaviours gathered in actual traffic affected internal combustion car emissions and consumption. A factorial analysis enables them to decrease the initial 62 characteristics to only 16. In addition to evaluating the value of feature analysis and selection, this study shows how basic kinematic driving pattern characteristics, such as speed, acceleration, and deceleration, affect energy usage. Driver behaviour as a function of a few chosen parameters is correctly described by Simonis and Sennefelder [26], and this information may then be used to forecast the energy consumption of BEVs.

Remarkably, Abdelaty et al. [27], [28] estimated the energy consumption of BEBs using a Simulink model. Using machine learning methods and statistical models, the inputs were carefully chosen from a variety of operational, topological, vehicular, and external characteristics. They discovered that the road gradient and the battery's level of charge were the most important variables, whereas the vehicle's drag coefficients seemed to have a little impact. However, as Ji et al. show in their study [36], which examines real-world data from a fleet of 31 BEBs in Meihekou City, China, temperature and consequently auxiliary power consumption are not well addressed, despite the fact that they are one of the most crucial elements. The temperature rises from -27°C to 35°C, resulting in a 47% increase in energy usage above optimal operating conditions. Expanding on this crucial subject, a recent study conducted in Lancaster, California by Perugu et al. [37] looks at the energy consumption and charging behaviour of BEBs. The vehicles are subjected to significant daily and seasonal temperature variations, ranging from -9°C to 46°C. As a result, the use of heating, cooling, venting, and air conditioning (HVAC) can be blamed for the variability in energy consumption.

Their findings demonstrate that there are pertinent operating expenses for the operator, which may rise by as much as 18% in the summer. In any case, this cost analysis may change based on several parameters (output numbers, development expenses, governmental grants, energy price, etc.) since the cost evaluation of BEBs is typically a broad subject, as shown in [4], [6]. Goehlich et al. conduct a technology evaluation for BEBs in Berlin, Germany, in [38]. They anticipate daily

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service consumption using an energy simulation model, and then they examine the system's economics in terms of total costs of ownership (TCO). They determine that heating by Positive Temperature Coefficient (PTC) components is often more important than cooling using a thermal model of the cabin. In the worst scenario, they find that extra HVAC consumption may reach 1.1 kWh/km, or almost a third of the total energy consumption.

Disadvantages

• The majority of methods make use of information that typical cars are often unable to measure, including the placement of bus stops or the incline of the road. Furthermore, factors like trip duration that are heavily reliant on the specific circumstances of the experiment are often considered. It is clear how the latter relates to vehicle energy efficiency; for example, the further you drive, the more energy your car uses. It must be utilised carefully for prediction, however, since machine learning algorithms could concentrate on it and ignore other important aspects. In contrast, our algorithms just need the mass (calculated by adding the number of passengers to the curb weight) and the vehicle speed as initial inputs, which the user can readily get. Additionally, we extract 40 characteristics in the frequency and temporal domains at various levels of abstraction to characterise speed profiles. In this manner, we unearth buried but important information that improves generalisation, increases prediction accuracy, and, thus, increases application relevance. Furthermore, we use a clever route segmentation technique that strengthens the prediction against data non-stationarity, increasing the final framework's applicability and transferability.

• Only a small number of machine-learning methods are widely used, despite their availability. We examine the whole spectrum in this paper, ranging from supervised learning and probabilistic techniques to non-learning statistical approaches. Thus, the whole potential of innovative machine learning techniques for forecasting EV energy usage is shown and thoroughly compared in this paper. In the end, we examine the effectiveness of many potent machine learning models, from the most technical aspects to the long-term use.

• The majority of research employ speed profiles from Standardised Driving Cycles (SDCs) or data from a single vehicle travelling a single route. As a result, there is very little variation and variety in the data. The complexity of the interrelationships and the diversity of pertinent components provide a significant obstacle in this field, however. Therefore, machine learning predictions will be more accurate the more diverse the data. The underlying fleet data used in this study, on the other hand, comes from a total of thirty vehicles that travel different routes every day and have drivers who change regularly during the day. This enables us to record a vast range of traffic conditions and driving styles, yielding much more useful data.

• HVAC and other auxiliary power demands are seldom taken into account in detail and are often substituted with a constant term. Heating and cooling, however, have a major effect on energy consumption and, therefore, the range of BEBs, particularly in areas with very high and low temperatures. In order to address correct total energy consumption at the trip level, which is pertinent to transport operators, we have taken into account comprehensive energy profiles, including HVAC, recovery, etc.

PROPOSED SYSTEM

In this work, we create data-driven models that forecast the energy needs of the vehicles using a physics-based model of soon-to-be-deployed electric buses and the bus operator's information. We demonstrate that, among other things, we only need to know the instantaneous speed of the vehicle and the number of passengers on the bus in order to use machine learning to accurately predict the consumption on a route. This sets our contribution apart from earlier data-driven approaches. In particular, there are three phases in our approach:

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1) We utilise a physics-based model that has been verified by the vehicle manufacturer and takes into account mass and speed as inputs, including the weight of the bus and its cargo, to determine how much energy the bus needs on each trip. The operator's database contains both variables.

2) From the speed signal, we extract a complete set of time and frequency information.

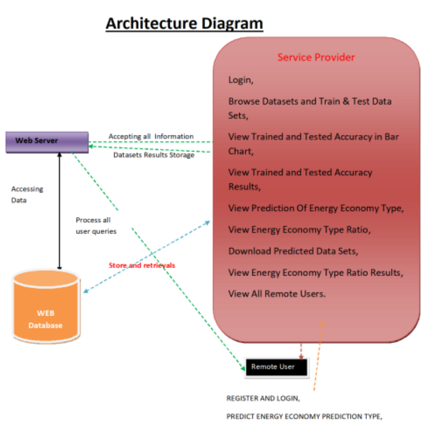
3) Using the bus payload mass and the aforementioned collection of characteristics, we train machine learning regression models to estimate energy usage and determine which ones have the greatest predictive value. It's interesting to note that the trait that proves to be most significant—the spectrum entropy of velocity—has not yet been identified in this area of study.

Advantages

1) For precise predictions, we suggest a hybridisation machine learning model that is both scalable and effective.

2) In order to enhance the performance of the Random Forest and Multivariate Linear Regression (MLR) prediction models, we carried out a number of hybridisations of genetic algorithms with filter and embedding feature selection techniques during the data pre-processing stage.

SYSTEM ARCHITECTURE



IV. IMPLEMENTATION

Modules

Service Provider

The Service Provider must use a working user name and password to log in to this module. Following a successful login, he may do various tasks including browsing datasets and training and testing datasets. View Results of Trained and Tested Accuracy, View Trained and Tested Accuracy in Bar Chart, View the Job Title Identification Type Ratio, View the Predicted Job Title Identification Type, Get Predicted Data Sets here. View All Remote Users and Job Title Identification Type Ratio Results.

View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

Remote User

A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. Following a successful login, the user will do tasks such as registering and logging in, predicting the job title and identification type, Examine your profile.

ALGORITHMS

Naïve Bayes

The supervised learning technique known as the "naive bayes approach" is predicated on the straightforward premise that the existence or lack of a certain class characteristic has no bearing on the existence or nonexistence of any other feature. However, it seems sturdy and effective in spite of this. It performs similarly to other methods of guided learning. Numerous explanations have been put forward in the literature. We emphasise a representation bias-based explanation in this lesson. Along with logistic regression, linear

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discriminant analysis, and linear SVM (support vector machine), the naive bayes classifier is a linear classifier. The technique used to estimate the classifier's parameters (the learning bias) makes a difference.

Although the Naive Bayes classifier is commonly used in research, practitioners who want to get findings that are useful do not utilise it as often. On the one hand, the researchers discovered that it is very simple to build and apply, that estimating its parameters is simple, that learning occurs quickly even on extremely big datasets, and that, when compared to other methods, its accuracy is rather excellent. The end users, however, do not comprehend the value of such a strategy and do not get a model that is simple to read and implement.

As a consequence, we display the learning process's outcomes in a fresh way. Both the deployment and comprehension of the classifier are simplified. We discuss several theoretical facets of the naive bayes classifier in the first section of this lesson. Next, we use Tanagra to apply the method on a dataset. We contrast the outcomes (the model's parameters) with those from other linear techniques including logistic regression, linear discriminant analysis, and linear support vector machines. We see that the outcomes are quite reliable. This helps to explain why the strategy performs well when compared to others. We employ a variety of tools (Weka 3.6.0, R 2.9.2, Knime 2.1.1, Orange 2.0b, and RapidMiner 4.6.0) on the same dataset in the second section. Above all, we make an effort to comprehend the outcomes.

Random Forest

Random forests, also known as random decision forests, are ensemble learning techniques that build a large number of decision trees during training for tasks like regression and classification. The class chosen by the majority of trees is the random forest's output for classification problems. The mean or average forecast of each individual tree is given back for regression tasks. The tendency of decision trees to overfit to their training set is compensated for by random decision forests. Although random forests are less accurate than gradient enhanced trees, they often perform better than choice trees. However, their performance may be impacted by data peculiarities.

Tin Kam Ho[1] developed the first algorithm for random decision forests in 1995 by using the random subspace technique, which in Ho's definition is a means of putting Eugene Kleinberg's "stochastic discrimination" approach to classification into practice.

Leo Breiman and Adele Cutler created an algorithm extension and filed for a trademark in 2006 for "Random Forests" (owned by Minitab, Inc. as of 2019). The extension builds a set of decision trees with controlled variance by combining Breiman's "bagging" concept with random feature selection, which was initially proposed by Ho[1] and then separately by Amit and Geman[13].

Businesses often employ random forests as "blackbox" models since they need minimal setup and provide accurate forecasts across a variety of inputs.

SVM

The goal of a discriminant machine learning approach in classification problems is to identify a discriminant function that can accurately predict labels for newly acquired instances based on an independent and identically distributed (iid) training dataset. A discriminant classification function takes a data point x and assigns it to one of the several classes that are part of the classification job, in contrast to generative machine learning techniques that call for calculations of conditional probability distributions. Discriminant techniques are less effective than generative approaches, which are

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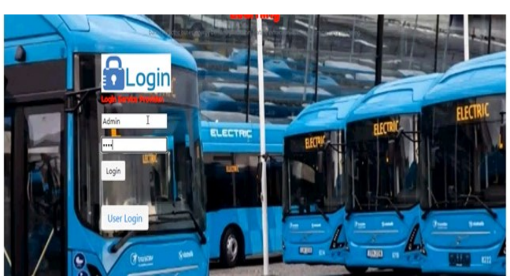
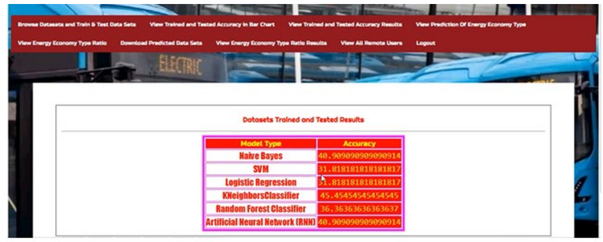
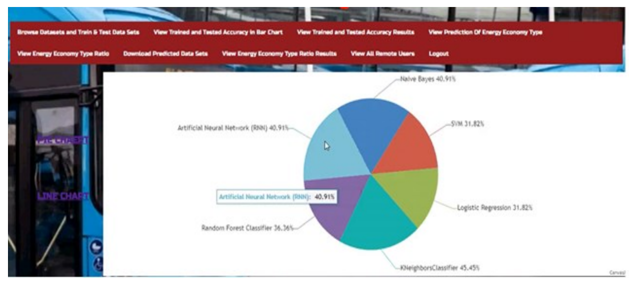
mostly used when prediction entails the identification of outliers. However, they need less training data and processing resources, particularly when dealing with a multidimensional feature space and when just posterior probabilities are required. Finding the equation for a multidimensional surface that optimally divides the various classes in the feature space is the geometric equivalent of learning a classifier.

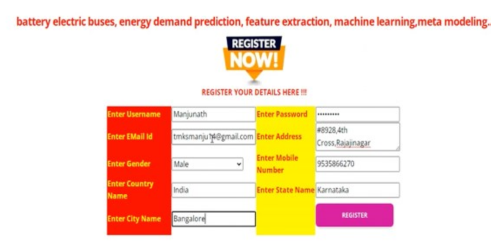
SVM is a discriminant approach that, unlike genetic algorithms (GAs) or perceptrons, which are both often used for classification in machine learning, always returns the same optimum hyperplane value since it solves the convex optimisation issue analytically. The initialisation and termination criteria have a significant impact on the solutions for perceptrons. While the perceptron and GA classifier models are distinct every time training is started, training yields uniquely specified SVM model parameters for a given training set for a certain kernel that converts the data from the input space to the feature space. The only goal of GAs and perceptrons is to reduce training error, which will result in several hyperplanes satisfying this criterion.

V. SCREEN SHOTS









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VI. CONCLUSION

This study presents a data-driven method for planning issues and public transport electrification that makes use of both simulated and real-world data. The findings verify that the energy consumption of BEBs under various actual driving situations is completely characterised by the energetic important characteristics that were acquired via feature selection and regression analysis. with fleet managers who want to upgrade or swap out their traditional buses with electric ones and provide the necessary infrastructure, it is a sensible strategy. In this regard, we highlight the so-called "Vehicle Routing Problem," as cited by [59], [60]. To properly design the batteries, choose the best bus operating modes (all-electric, hybrid electric, etc.), and choose the best charging methods (i.e. opportunity vs. traditional charging), it is necessary to determine the energy requirements on each route beforehand. The limiting element is the worst-case scenario, which is the most energy-intensive method. In the end, this information is crucial for fleet operators to anticipate important operating boundaries, steer clear of possible showstoppers, and develop trust in emerging technology. In order to ultimately provide dependable and reasonably priced service on all routes.

The paper's primary contribution is a unique set of explanatory factors that integrate the speed waveform's time and frequency properties. The tour is broken up into smaller excursions in order to extract these characteristics. This prediction is resilient to non-stationarity since it is "segment-based." We have identified a minimal number of features with good predictive value, starting with an initial collection of 40 features. To now, this discipline has even failed to discover the most important of these traits, which is the spectrum entropy of velocity profiles. This finding supports our hypothesis that the most important information is really found in the velocity waveform, whose temporal structure is best represented by the spectral entropy.

The problem is to determine how this technique works in other situations, thus we want to expand this approach to additional settings in future study. Businesses in the logistics and transportation industry are especially interested in the suggested strategy. Fleet operators that depend on heavy-duty trucks and often find it difficult to electrify their fleets due to a lack of a sound framework for selecting the appropriate vehicles are particularly interested in it. It could also be applicable to other vehicle classes or transportation networks, such rail or passenger cars. However, further research may be done, for example, on operating factors, road types, and weather conditions. For this reason, we want to look at circumstances that change regionally and seasonally and suggest carefully choosing features 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 also desirable and might be examined using the technique that has been described.

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