ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940
www.ijasem.org
Vol 18, Issue.2 April 2024

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

Nallapothula Hari Prasad [1],Sulthan Arvind Reddy [2],
Reddy Shreekar Narayan [3], Mrs.A. Padma Priya[4]
[1,2,3] UG Student, Dept. of ECE, CMR Institute of Technology, Hyderabad
[4] Assistant Professor, Dept. of ECE,
CMR Institute of Technology, Hyderabad

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

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 powertrain 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).

LITERATURE REVIEW

''Gasoline compression ignition approach to efficient, clean and affordable future engines,''

The worldwide demand for transport fuels will increase significantly but will still be met substantially (a share of around 90%) from petroleum-based fuels. This increase in demand will be significantly skewed towards commercial vehicles and hence towards diesel and jet fuels, leading to a probable surplus of lighter low-octane fuels. Current diesel engines are efficient but expensive and complicated because they try to reduce the nitrogen oxide and soot emissions simultaneously while using conventional diesel fuels which ignite very easily. Gasoline compression ignition engines can be run on gasoline-like fuels with a long ignition delay to make low-nitrogen-oxide low-soot combustion very much easier. Moreover, the research octane number of the optimum fuel for gasoline compression ignition engines is likely to be around 70 and hence the surplus low-octane components could be used without much further processing. Also, the final boiling point can be higher than those of current gasolines. The potential advantages of

ISSN2454-9940
www.ijasem.org
Vol 18, Issue.2 April 2024

gasoline compression ignition engines are as follows. First, the engine is at least as efficient and clean as current diesel engines but is less complicated and hence could be cheaper (lower injection pressure and after-treatment focus on control of carbon monoxide and hydrocarbon emissions rather than on soot and nitrogen oxide emissions). Second, the optimum fuel requires less processing and hence would be easier to make in comparison with current gasoline or diesel fuel and will have a lower greenhouse-gas footprint. Third, it provides a path to mitigate the global demand imbalance between heavier fuels and lighter fuels that is otherwise projected and improve the sustainability of refineries. The concept has been well demonstrated in research engines but development work is needed to make it feasible on practical vehicles, e.g. on cold start, adequate control of exhaust carbon monoxide and hydrocarbons and control of noise at medium to high loads. Initially, gasoline compression ignition engines technology has to work with current market fuels but, in the longer term, new and simpler fuels need to be supplied to make the transport sector more sustainable.

‘‘Routing a mixed fleet of electric and conventional vehicles,’

We present a vehicle routing problem with load capacity and time windows for a fleet of electric vehicles (EVs) and internal combustion vehicles (ICVs). Different charging technologies, including Level 1, 2, and 3 chargers and swapping batteries, are considered in this research. Given the location of the depot, the existing customers, and the set of charging stations, this problem aims to minimise the overall cost of constructing the routes over the vertices that need to be visited by either an ICV or EV. We develop a mixed-integer linear programming (MILP) model for this problem, and we solve small samples using a CPLEX solver. In addition, we develop two metaheuristic solution approaches by combining Adaptive Large Neighbourhood Search (ALNS) with Simulated Annealing (SA) and Tabu Search (TS). Using a set of locations from Scarborough, Ontario, Canada, we investigate the delivery routing problem with a fleet of ICVs and EVs. By solving the problem for different scenarios, we observed that EVs often require partial recharging and faster chargers (Level 3) when traveling in the city.

‘‘Computing the hazard ratios associated with explanatory variables using machine learning models of survival data,’’

The application of Cox proportional hazards (CoxPH) models to survival data and the derivation of hazard ratio (HR) are

ISSN2454-9940
www.ijasem.org
Vol 18, Issue.2 April 2024

well established. Although nonlinear, tree-based machine learning (ML) models have been developed and applied to the survival analysis, no methodology exists for computing HRs associated with explanatory variables from such models. We describe a novel way to compute HRs from tree-based ML models using the SHapley Additive exPlanation values, which is a locally accurate and consistent methodology to quantify explanatory variables' contribution to predictions.

‘‘Driving cycle prediction model based on bus route features,’’

Bus fuel economy is deeply influenced by the driving cycles, which vary for different route conditions. Buses optimized for a standard driving cycle are not necessarily suitable for actual driving conditions, and, therefore, it is critical to predict the driving cycles based on the route conditions. To conveniently predict representative driving cycles of special bus routes, this paper proposed a prediction model based on bus route features, which supports bus optimization. The relations between 27 inter-station characteristics and bus fuel economy were analyzed. According to the analysis, five inter-station route characteristics were abstracted to represent the bus route features, and four inter-station driving characteristics were abstracted to represent the driving cycle features between bus stations. Inter-station driving characteristic equations were established based on the multiple linear regression, reflecting the linear relationships between the five inter-station route characteristics and the four inter-station driving characteristics. Using kinematic segment classification, a basic driving cycle database was established, including 4704 different transmission matrices. Based on the inter-station driving characteristic equations and the basic driving cycle database, the driving cycle prediction model was developed, generating drive cycles by the iterative Markov chain for the assigned bus lines. The model was finally validated by more than 2 years of acquired data. The experimental results show that the predicted driving cycle is consistent with the historical average velocity profile, and the prediction similarity is 78.69%. The proposed model can be an effective way for the driving cycle prediction of bus routes.

‘‘Advisor: A systems analysis tool for advanced vehicle modeling,’’

This paper provides an overview of Advanced Vehicle Simulator (ADVISOR)—the US Department of Energy’s (DOE’s) ADVISOR written in the MATLAB/Simulink environment and developed by the National Renewable

ISSN2454-9940
www.ijasem.org
Vol 18, Issue.2 April 2024

Energy Laboratory. ADVISOR provides the vehicle engineering community with an easy-to-use, flexible, yet robust and supported analysis package for advanced vehicle modeling. It is primarily used to quantify the fuel economy, the performance, and the emissions of vehicles that use alternative technologies including fuel cells, batteries, electric motors, and internal combustion engines in hybrid (i.e. multiple power sources) configurations. It excels at quantifying the relative change that can be expected due to the implementation of technology compared to a baseline scenario. ADVISOR's capabilities and limitations are presented and the power source models that are included in ADVISOR are discussed. Finally, several applications of the tool are presented to highlight ADVISOR's functionality.

Advanced Vehicle Simulator (ADVISOR) was first developed in November 1994 at the National Renewable Energy Laboratory. It was designed as an analysis tool to assist the US Department of Energy (DOE) in developing technologies for hybrid electric vehicles (HEV) through the Hybrid Electric Vehicle Propulsion System contracts with Ford, General Motors, and DaimlerChrysler. Its primary role is to highlight the system-level interactions of hybrid and electric vehicle components and their impacts on the vehicle performance and fuel economy.

EXITING 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.

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.

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.

References

[1] E. Commission, D.-G. for Mobility, and Transport, EU transport in figures : statistical pocketbook 2019. Publications Office, 2019. DOI: doi/10.2832/017172.

[2] P. Hertzke, N. Müller, S. Schenk, and T. Wu, ‘‘The global electric-vehicle market is amped up and on the rise,’’ EV-Volumes.com; McKinsey analysis, Apr. 18, 2018. [Online]. Available:https://www.mckinsey.com/industries/automotive-and-assembly/our insights/theglobal-electric-vehicle-market-is-amped-up-and-othe-rise(visited on 09/20/2022).

[3] G. Kalghatgi and B. Johansson, ‘‘Gasoline compression ignition approach to efficient, clean and affordable future engines,’’ Proceedings of the Institution of Mechanical Engineers, Part D: Journal of

Automobile Engineering, vol. 232, no. 1, pp. 118–138, Apr. 2017. DOI: 10.1177/0954407017694275.

[4] C. Johnson, E. Nobler, L. Eudy, and M. Jeffers, ''Financial analysis of battery electrictransit buses,'' National Renewable Energy Laboratory, Tech. Rep. NREL/TP-5400-74832, 2020, 45 pp. [Online]. Available: https://www.nrel.gov/docs/fy20osti/74832.pdf.

[5] A. Braun and W. Rid, ''Energy consumption of an electric and an internal combustion passenger car. a comparative case study from real world data on the erfurt circuit in germany,'' Transportation Research Procedia, vol. 27, pp. 468–475, 2017, 20th EURO Working Group on Transportation Meeting, EWGT 2017, 4- 6 September 2017, Budapest, Hungary, ISSN: 2352- 1465. DOI: https://doi.org/10.1016/j.trpro.2017.12.044. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352146517309419.

[6] A. Lajunen and T. Lipman, ''Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses,'' Energy, vol. 106, no. C, pp. 329–342, 2016. DOI: 10.1016/j.energy.2016.03..

[7] B. Propfe, M. Redelbach, D. Santini, and H. Friedrich, ''Cost analysis of plug-in hybrid electric vehicles including maintenance & repair costs and resale values,'' World Electric Vehicle Journal, vol. 5, pp. 886–895, Dec. 2012. DOI: 10.3390/wevj5040886.

[8] S. Trommer, V. Kolarova, E. Fraedrich, et al., ''Autonomous driving - the impact of vehicle automation on mobility behaviour,'' German Aerospace Center (DLR) / Institute of Transport Research, Tech. Rep., Dec. 2016. [Online]. Available: https : / / elib. dlr. de / 110337/1/ifmo_2016_Autonomous_Driving_2035_ en.pdf.

[9] Karne, R. K. ., & Sreeja, T. K. . (2023). PMLC- Predictions of Mobility and Transmission in a Lane-Based Cluster VANET Validated on Machine Learning. International Journal on Recent and Innovation Trends in Computing and Communication, 11(5s), 477–483. https://doi.org/10.17762/ijritcc.v11i5s.7109

[10] Radha Krishna Karne and Dr. T. K. Sreeja (2022), A Novel Approach for Dynamic Stable Clustering in VANET Using Deep Learning (LSTM) Model. IJEER 10(4), 1092-1098. DOI: 10.37391/IJEER.100454.

[11] Reddy, Kallem Niranjan, and Pappu Venkata Yasoda Jayasree. "Low Power

ISSN2454-9940
www.ijasem.org
Vol 18, Issue.2 April 2024

Strain and Dimension Aware SRAM Cell Design Using a New Tunnel FET and Domino Independent Logic." International Journal of Intelligent Engineering & Systems 11, no. 4 (2018).

[12] Reddy, K. Niranjan, and P. V. Y. Jayasree. "Design of a Dual Doping Less Double Gate Tfet and Its Material Optimization Analysis on a 6t Sram Cells."

[13] Reddy, K. Niranjan, and P. V. Y. Jayasree. "Low power process, voltage, and temperature (PVT) variations aware improved tunnel FET on 6T SRAM cells." Sustainable Computing: Informatics and Systems 21 (2019): 143-153.

[14] Reddy, K. Niranjan, and P. V. Y. Jayasree. "Survey on improvement of PVT aware variations in tunnel FET on SRAM cells." In 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC), pp. 703-705. IEEE, 2017