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Influence of temperature on consumption of electric bus. Analysis of the case with midibuses in Brussels

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Executive Summary

Previous work [1] have shown that consumption of electric buses is poorly documented and not well known. The main parameters impacting energy consumption are driving cycle (speeds, stops, acceleration), bus length and passenger load, temperature and heating/cooling. The aim is to characterise the impact of the temperature on the energy consumption. According to the highest figures found in the literature, the consumption could increase by 32% for a cold day and increase by 12% for a hot day compared to a temperate day. This paper improves the previous model by adding a more accurate model of the impact of climate-related energy consumption of midibuses (8.9 meters). This is based on measurements taken in Brussels, by STIB/MIVB (the local bus operator) at an interval of 5 seconds from January to mid-april and also for June 2021.

The results obtained in this study is that at 2.5 °C the energy consumption for a round trip increases by 16% and at 25 °C increases by 30% compared to the lowest energy consumption registered at a reference temperature of 12 °C.

1 Introduction

The number of battery electric buses (BEB's) is growing quickly, for example, 3282 BEB were registered in Europe in 2021 [2], this number increased by 48% compared to 2020. This is driven by more stringent local and national environmental level, improvement in battery density and cost with more return of experience. The EU 2019/1161 directive imposes EU countries to have a minimum target for the share of clean light-duty vehicle (e.g., 38.5% in Belgium) [3]. From 2026, only zero emission at tailpipe (i.e. battery electric and fuel cell) will be considered as clean vehicles.

It is important to know the energy consumption (also referred as energy demand in this paper) of electric buses for two reasons:

1/ for the bus operator to avoid paying more than necessary for a bus with limited number of passengers or having not enough range to complete the journey;

2/ for the bus operator and grid operator to have a smoother grid connection of the charger and avoid negative grid impact.

From an extensive literature review of more than 100 sources, it appeared that data for climated impact are limited, especially for midibuses [1]. A better knowledge will help the bus operator avoiding oversizing the battery, size properly the charging infrastructure in function of the bus schedule and local climate.

This paper fills these gaps by analyzing the impact of the temperature on the energy demand decoupled from the other parameters that could influence the energy demand.

2 Literature review

ViriCiti, a company providing data analytics for vehicles acquired by charging station manufacturer ChargePoint, investigated the impact of cold and hot temperatures on the consumption [4]. Data was gathered from 100+ electric buses in the Netherlands. Due to the flat landscape, the assumption was made that the average temperature during the shift is the only influencing parameter for the average energy demand of the shift. Shifts selected for the study are at least 40 km long to be representative. These shifts are divided in three temperature classes in function of the average temperature of the shift. The boundaries of the classes are the following, cold between [-10 ; 14] °C, normal between [15;19] °C and hot between [20;29] °C. Cold temperatures increase the energy demand by 14% for 12m buses and 21% for 18m buses. Hot temperatures increase the energy demand by 9% for 12m buses and 12% for 18m buses.
Another study in collaboration with public sector transit agency SARTA used data from four transit agencies in the US [5]. Similar to the previous study, the assumption was made that the average temperature during the day is the only influencing parameter for the average energy demand of the day. The four locations of the transit agencies are Washington DC (DDOT); Duluth Minnesota (DTA); Worcester Massachussets (WRTA) and Seneca South Carolina. The modelling of the impact of the temperature on the energy demand is done with reference to a base temperature that is defined as the outdoors temperature where the lowest energy consumption for heating and cooling are registered. The function of the daily average energy demand depending on the daily average temperature is assumed to be in V-shape. The slopes and base temperature are obtained with a best-fit piecewise linear regression model and the results are available in Table 1.

Transit Agency	Data collection period	Daily Average Temp. Range [°C]	Base Temp [°C]	Increase in energy demand when below base temp [%/°C]	Increase in energy demand when above base temp [%/°C]
DDOT	MAR 2018 – JUN 2019	-10.3 ; 30.3	18	3.8	2.1
DTA	NOV 2018 – JUN 2019	-30.5 ; 20	12.2	1.5	Not enough hot data
Seneca	SEPT 2014 – JUL 2018	-9.4 ; 28.9	18.3	0.6	1.3
WRTA	SEPT 2013 – AUG 2017	-17.8 ; 27.2	13.7	2.7	2.6

Table 1 - Summary of the main results [6] (adapted in °C from °F)

Results are also computed in a format that can somehow be compared with the study of ViriCiti. The cold temperature interval is between [-5.5;0] °C, normal between [10;15.5] °C and hot between [21;26.5] °C. When operating in cold conditions the energy consumption increases by 32.1% and in hot conditions by 6.4 %.

The values from the two studies are consistent. Unfortunately the energy demands in the literature are only averages certain temperature windows: specific energy demands for specific given temperatures are missing. The values are only given for a daily average and there is room for improvement regarding the precision. The hypothesis of considering the temperature as only influencing factor on the energy demand has to be verified given that ridership of public transport might increase during the winter months. This could be due to a shift of bike and walking commuters to public transport. This is a complex topic and shows that having ridership data offers an added value [6].

3 Statistical analysis of data

The dataset at our disposal is the daily operation measurements logs of seven battery electric buses in Brussels. Data are available for January to mid-April 2021 and also for June 2021. Data are logged every 5 seconds. In total, there are approximately 1 million useful samples.

These seven buses serve the bus line 33 operated by STIB/MIVB [7]. The terminals of this bus line are called "Dansaert" and "Louise". The trip from "Dansaert" to "Louise" is 4 km long and has a net elevation gain of 48m. The trip in the other direction is 2.5 km long. The length difference between the two directions are due to one-way streets and the choice of placement of the bus stops.

All buses are the same model, Solaris Urbino 8.9 LE electric fitted with 160 kWh battery [8]. The bus has a capacity for 22 seats and 20 standing places. The empty vehicle weights 10.7 tons. Figure 1 gives an example of retrieved parameters for one trip and one shift. Ambient temperature is also available in the dataset.

Previous studies ([4], [5]) used the time scale of a day or a shift. Since we have a data point every 5 second,

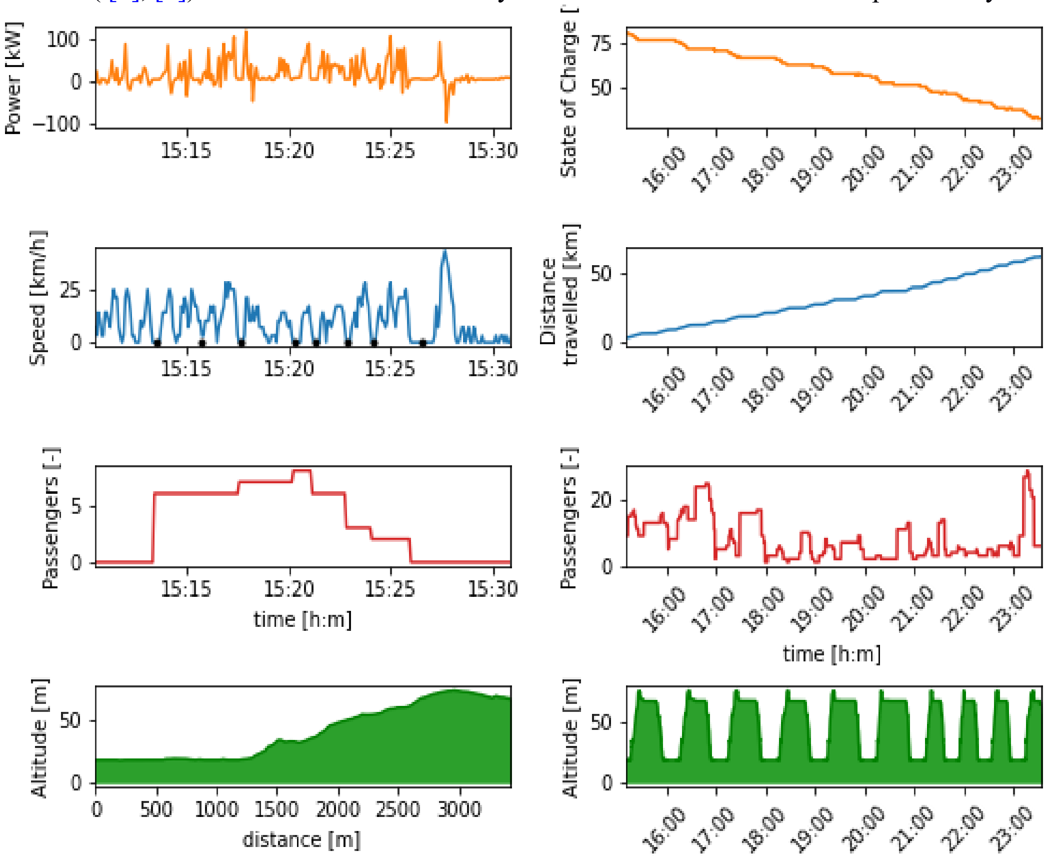

Figure 1 - Example for one trip and shift (Friday 14th January)

we can aggregate to get larger time scales. We filtered data to get information for end stops (i.e., Dansaert, Louise and depot), this is referred as a "trip" in the paper. We obtain four categegories of trips 1\ from the depot, 2\ from Dansaert to Louise, 3\ from Louise to Danseart and 4\ to the depot. The average times for these travels are respectively 25 minutes, 35 minutes, 20 minutes and 15 minutes. This allows to smooth the measurements and improve accuracy while remaining more specific than for a whole day and have similar routes. The trips from and to the depot could vary slightly.

After pre-processing, around 3500 trips are extracted from all the raw data and put into a new Python dataframe ready to use for machine learning. The nine selected parameters for each trips are the following average energy consumption in kWh/km; average and standard deviation of the speed to give an idea of the smoothness of the ride; altitude gain; passengers average, maximum and minimum; day of the week and average ambient temperature. It is acceptable to take the average temperature as it does not vary much over the time of the trip compared to a whole day.

4 Climate modelling

The aim is to model the impact of the temperature on the energy demand in kWh/km. An histogram shows the diversity of temperatures within the useful trips from our dataset in Figure 2.

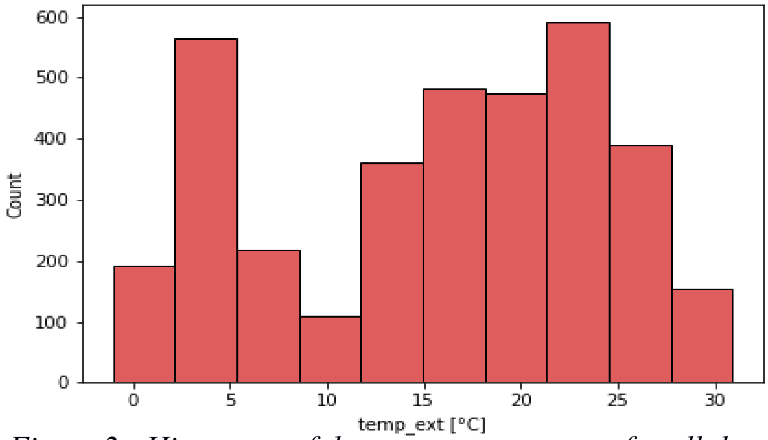

Figure 2 - Histogram of the mean temperatures for all the travels

A polynomial regression and other machine learning algorithms (linear, ridge regression and K-Nearrest neighbours) are used to quantify and predict the impact of temperature on the energy demand. The performance of each algorithm and scaling method is investigated with cross-validation. A grid search is performed for some algorithms to find the value of the hyperparameters. 70% of the dataset is used for training and 30% for testing. The best performing model is the polynomial regression of degree 2 with a ridge regression. The test score obtained has an R square score function is 88%. The other test scores are 80% for the linear model, 82% for the ridge regression model.

The impact of the temperature on the energy consumption (see Figure 3) is represented thanks to the partial dependence plots from scikit-learn [9]. The base temperature according to the model is 12 [°C]. This corresponds to the lowest energy consumption in function of outdoors temperature. At 2.5 °C the energy consumption increases by 16% of the energy consumption at base temperature and at 25 °C the energy consumption increases by 30%.

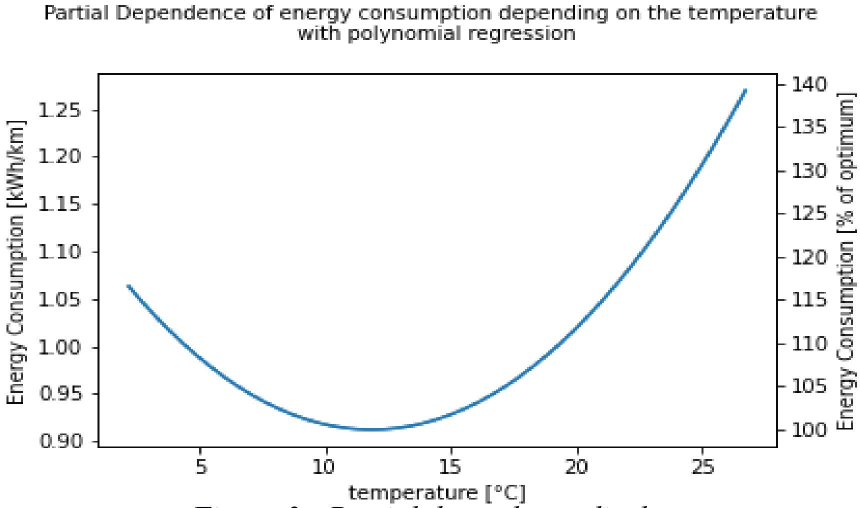

Figure 3 - Partial dependence display

$$Energy\ Consumption\ [\%\ of\ optimum] = 0.18 * (T[°C] - 12)^2 + 100$$

5 Discussion

Litterature shows that the function of the daily average energy demand depending on the daily average temperature is assumed to be in V-shape.

In our dataset, the energy demand increase is higher for hot conditions than for cold conditions. Figure 4 displays the energy consumption of the subdatasets divided by destination and temperature range in form of boxplots. We can observe a minimum of energy consumptium in the temperature range between 9 and 12 °C. This consolidates the hypothesis of a base temperature where the energy consumption for heating or cooling is minimal.

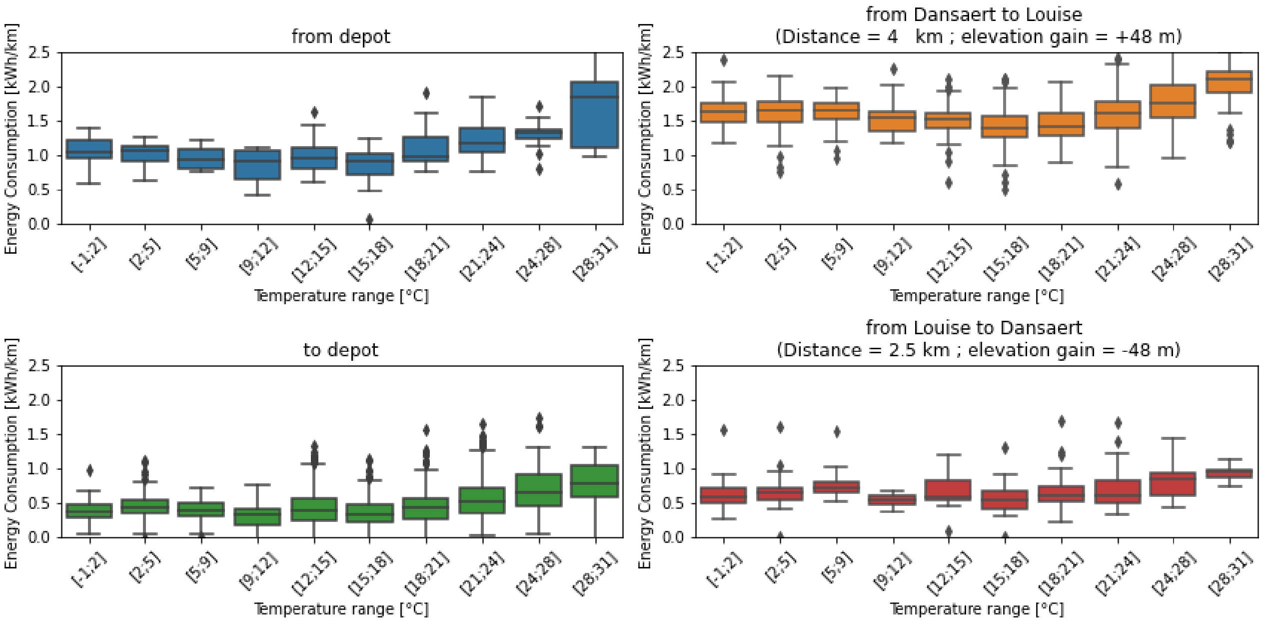

Figure 4 - Boxplots for EC [kWh/km] for different temperature ranges

Based on this observation, better modelling can be implemented. Some approaches were made by the authors. It finally appears that the V-curve can be advantageously replaced by the polynomial regression, with some limits. The limits of this model is that there seems to be a plateau for the cold temperatures. There is a lack of data for freezing temperatures to validate the model in cold conditions.

Temperature is not the only influencing parameter on the energy consumption certainly when considering small time scales. This can be confirmed for instance with the difference of approximately 1 kWh/km in energy consumption when going uphill or downhill. Taking a more global approach on energy consumption for battery electric buses allowed to better describe the influence of temperature on energy consumption.

Another methodology to confirm the model is by comparing energy demand of trips with the same parameters (terminus, speed distribution, passengers,..) and that the temperature is the only variable. This methodology was tried but did not provide conclusive results due to a lack of data under extreme conditions.

6 Conclusion and future work

The main qualitiative result is a quadratic equation for modeling energy consumption as a function of outdoors temperature. Future work will be carried to validate the prediction model by by splitting the dataset in different driving categories with parameters (excluding temperature) kept approximately constant.

It will also be interesting to compare the results with the literature and apply the same methodology to other types of battery electric buses and with other bus routes in order to generalise the results. This will help shape the charging strategy of the bus opeartor based on weather forecasts.

Acknoledgements

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References

[1] O. Y. ,. D. V. L. ,. D. J. E. Jadoul Frédéric, “Energy demand of Battery Electric Buses: an overview of the available values obtained with different approaches,” in *EVS34*, Nanjing, Jiangsu, China, 2016.

[2] E. Staff, Sustainable-bus, 10 February 2022. [Online]. Available: https://www.sustainable-bus.com/news/eu-electric-bus-market-2021/. [Accessed 20 March 2022].

[3] e. A. J. Vepsalainen, “Energy Uncertainty Analysis of Electric Buses, 11(12), 3267.,” *Energies,* November 2018.

[4] ViriCiti, “viriciti.com,” 28 July 2020. [Online]. Available: https://viriciti.com/reports/#E-Bus-Performance-Report. [Accessed 30 September 2021].

[5] H. M. S. A. Thomas Andrew, “An Analysis of the Association between Changes in Ambient Temperature, Fuel Economy, and Vehicle Range for Battery Electric and Fuel Cell Electric Buses,” Cleveland State University, Cleveland, 2019.

[6] C. K. A. Y. Abhishek Singhal, “Impact of weather on urban transit ridership,” *Transportation Research Part A: Policy and Practice,* vol. 69, pp. 379-391, 2014.

[7] “Ligne 33 vers DANSAERT - stib.be,” [Online]. Available: https://www.stib-mivb.be/horaires-dienstregeling2.html?l=fr&_line=33&_directioncode=V. [Accessed 21 February 2022].

[8] “A modern fleet to better serve our clients,” 2018. [Online]. Available: https://www.stib-mivb.be/irj/go/km/docs/guid/1055af2d-8999-3610-bfac-8d69ad91008f. [Accessed 5 February 2022].

[9] “4.1. Partial Dependence and Individual Conditional Expectation plots,” [Online]. Available: https://scikit-learn.org/stable/modules/partial_dependence.html. [Accessed 26 10 2021].

[10] R. a. K. K. a. E. L. Prohaska, “Fast charge battery electric transit bus in-use fleet evaluation,” *2016 IEEE Transportation Electrification Conference and Expo (ITEC),* pp. 1-16, 27-29 June 2016.

[11] “sustainable-bus.com,” [Online]. Available: https://www.sustainable-bus.com/news/bus-market-eu-2019-electric-bus-acea/. [Accessed 2 February 2021].

[12] “Sustainable and Smart Mobility Strategy,” [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52020DC0789&from=EN. [Accessed 22 February 2021].

Presenters Biography

Régis De Wilde was awarded a Bachelor of Engineering from Ecole Polytechnique de Louvain (2020). He is currently finishing a master of Engineering (Electro-mechanical and Energy) at the same place and he is doing an internship at Engie Laborelec.

Youssef Oualmakran has a master degree in industrial engineering with a major in power engineering from ISIB (Institut Supérieur Industriel de Bruxelles), Belgium. Since 2014, he works as an EV expert at ENGIE Laborelec. His work includes technology watch and assessment of electric vehicles, charging technologies and standards. As an expert in power grid and EV, he has performed assesment of grid impact of electric cars and buses from local level to national level. He contributed to several paper on smart charging and demand response, and also to ASSURED reports on grid constraints and specification of charging infrastructure.

Laurent De Vroey is an electromechanical engineer and PhD from UCLouvain (Belgium) and ENS Cachan (France). Laurent has been with the ENGIE utility group for more than 10 years as electric mobility expert. He has occupied several technical and management functions in the field and he is today heading the smart mobility business development for the ENGIE Group.

Emmanuel De Jaeger is Professor of Electrical Energy and Power Systems at the Université Catholique de Louvain (UCLouvain), Belgium, since 2012. He is currently Vice-Dean of the Louvain School of Engineering, in charge of the relationships with industry. His research interests include energy systems in general, electric power systems, power quality, electrical machines and power electronics in particular. Before holding his current academic position, he was Scientific Director and member of the Management Committee at ENGIE Laborelec (Research and Competence Centre in Electrical Power Technology). He worked for this company for more than 20 years. He holds M.Sc. and Ph.D. degrees in Electrical Engineering from UCLouvain.