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## Vehicle fleet electrification: electric energy consumption assessment at the scale of an urban area.

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### Introduction

In the field of transportation, one of the European strategies being considered to mitigate climate change is the deployment of electric vehicles (EVs). In France, fleet electrification is rather slow, but it seems to be intensifying: EVs and Plug in HEV account for 22% of new car sales in France in 2022. Indeed, electric mobility has proven to be a powerful technology for decarbonization of the transportation sector (Kouridis, 2022). In comparison to conventional vehicles, EVs have either zero or lesser tailpipe greenhouse gas emissions. However, their carbon emissions are shifted from the exhaust pipe to the electric generators. Therefore, EVs are more eco-friendly the lower the carbon intensity of the electricity generation mix (De Angelis, 2020).

As more electric vehicles are introduced into the fleet, the consumption of electric energy increases. The amount of electric energy consumed is often simply assessed by considering that a typical personal electric car consumes 20kWh per 100km on average. However, some papers focus on the evaluation of EVs electric consumption (EC): (Zhang, 2015) proposes an estimate from driving cycles, (Al-Wreikat, 2021) analyses experimental data to understand the relevant factors that influence EC during operation, (Fiore, 2019) looks at impact of traffic conditions on fuel and electric consumption by modelling it from various speed profiles.

In this paper, the issue is to assess EC at the scale of an urban network with a fleet of vehicles including an increasing share of EV. Is a flat rate estimate sufficient? What is the appropriate description of traffic conditions in order to provide a more accurate estimate? Our objective is to compare on a large urban area, namely L63V (3 districts in the metropole of Lyon) (i) an estimate using detailed speed profiles directly derived from simulated trajectories and (iii) an estimate using average flow velocity per road section, (ii) an estimate using average flow velocity per Iris zone.

### Case study: Lyon63V

The case study is the Lyon63V<sup>1</sup> network, a 15 km<sup>2</sup> urban area divided into 75 sub-areas (fig.1). The supply specification covers the various transportation modes: light, heavy vehicles, and public transport (metro, tram and bus). The demand specifications are defined dynamically on morning peak hour (from 6.30 am to 10.30 am), for each vehicle category and each OD pair. This baseline demand profile has been calibrated on loop detectors measurements.

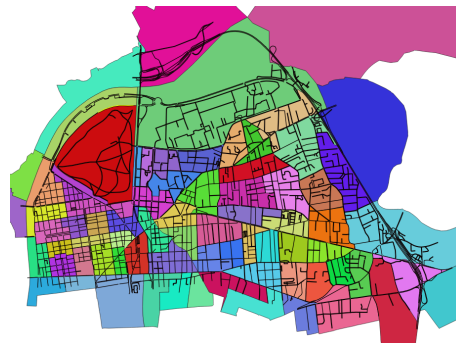


Figure 1. L63V network : road sections and 75 IRIS areas (uniform subdivision of the population for statistical purposes, INSEE<sup>2</sup>)

<sup>1</sup> 3<sup>rd</sup> and 6<sup>th</sup> districts of Lyon and Villeurbanne

<sup>2</sup> French national institute of statistics and economic studies

The traffic microsimulation was implemented in the SYMUVIA platform<sup>3</sup>. Vehicle movements at the microscopic scale are governed by a set of rules, including car-following modelling (Leclercq, 2007a, 2007b), lane-changes (Laval and Leclercq, 2008) and specific movements at intersections (Chevallier and Leclercq, 2007). The platform also copes with the cohabitation on the network of vehicles with different kinematics, including passenger cars, buses and heavy-duty vehicles.

In this first study, we have decided to focus on passenger cars. We will consider three levels of information in order to study the impact of traffic dynamics level of description on the evaluation of electricity consumption: (i) vehicle trajectories, (ii) traffic variables at link scale and (iii) at IRIS zone scale. In the first case, we consider each individual vehicle, so the output of the traffic simulation is characterized by its instantaneous speed profile. In the other cases, a spatio-temporal element is considered (i.e., the road section for 10min or the zone for 10min) and the micro-simulation outputs are aggregated to obtain the associated average speeds and distance travelled.

According to the fleet composition published by Citepa<sup>4</sup> in December 2022, the share of electric vehicles is 0.64% of passenger cars in France. However, this share is constantly growing. In 2023, 23.5% of new vehicle registrations were for electric vehicles (European Alternative Fuels Observatory<sup>5</sup>). For the purposes of this study, we assume that all vehicles are electric, in order to avoid introducing biases by randomly selecting vehicles. We will therefore focus on the relative differences between the proposed options. The passenger car electric fleet considered is composed of Tesla model 3, Renault Zoe and Citroën C0, three EVs with different sizes and autonomy ranges. For more realistic case study, one must consider the actual French EVs share.

Finally, two different simulations are used to evaluate and compare the energy consumption of the EV fleet in the considered area. In the first option, accurate EV simulation energetic models are used based on VEHLIB software description and the different generated trajectories (Vinot, 2008), while for the second and the third options, a curve of EC in function of the average speed has been previously built using the same models and speed profiles databases.

## Electrical consumption assessment

Energy consumption of electric vehicles depends on several internal (vehicle features) and external (environment) parameters. The most impacting vehicle characteristics are the weight, the aerodynamic drag, the frictions and the efficiency of the components such as the battery and the electric drive systems. The environment parameters that influence the energy consumption are related to the infrastructure (road type, slopes, lights), the traffic and the weather conditions. Consequently, a precise calculation of the consumed energy during a trip is a complex task.

### The Accurate Dynamic Model (ADM)

For more than two decades, LICIT-ECO7 lab has been developing VEHLIB, an energy consumption software dedicated to all types of vehicles, including EVs. VEHLIB is now an open-source software available on the Gitlab platform (Jeanneret & al, 2021). Two types of simulation are possible, namely forward simulation and backward simulation. The first is based on Simulink blocks and allows to simulate in a causal way the power flow in each component of the vehicle using speed control and a driver model. The second uses Matlab scripts and an inverse causality, i.e upstream from the effect to the cause (e.g. from the speed to the forces that cause it). Both need the instantaneous speed profile as input and allow the calculation at each time of the power going through the different systems of the vehicle. As no driver model and control loop is needed in the backward model, this makes it faster and fairer for comparison as the speed profile is supposed to be exactly followed. The forward model is on the other hand more adapted to develop components and vehicle controls and is often used in real time experiments such as hardware in the loop tests. We suggest in this paper to use the backward model for the “microscopic”

<sup>3</sup> <https://github.com/licit-lab/Open-SymuVia>

<sup>4</sup> <https://www.citepa.org/en/>

<sup>5</sup> <https://alternative-fuels-observatory.ec.europa.eu>

simulations (first option) and this will be considered as the reference for the energy comparison of the different simulation options because of its proven validity when compared to vehicle test.

### The pre-processed interpolated model (PIM)

The previous model requires as input the instantaneous speed profile, at least second by second, and the detailed vehicle parameters data. For a global calculation of a whole fleet of vehicle in a given area and during significant period of time this imposes two constraints that are firstly the availability of the huge amount of instantaneous data and secondly the computation time that can exceed the capacity of standard computers.

Therefore, one solution to accelerate simulation, in order to consider larger spatial and time scales, could be the use of the accurate model to generate pre-processed consumption results for each vehicle. The approach is to use ADM VEHLIB based model of the EV and a representative set of speed profiles (here we considered data from Hyzem, Artemis and WLTC speed profiles). The speed data so gathered is divided into sequences, each one represents an elementary speed profile from the vehicle start until the next stop. The ADM model of the EV is then executed on each sequence to calculate the corresponding EC. In this paper, the described method is applied to the three electric vehicles considered (Tesla, Zoe and C0). The EC of each sequence is plotted in blue function of the average speed of the sequence for the three vehicles (fig 2). To obtain a mathematic function of the EC to be used in the aggregated options (option 2 and 3), we considered an exponential interpolation function plotted in red on the same figures.

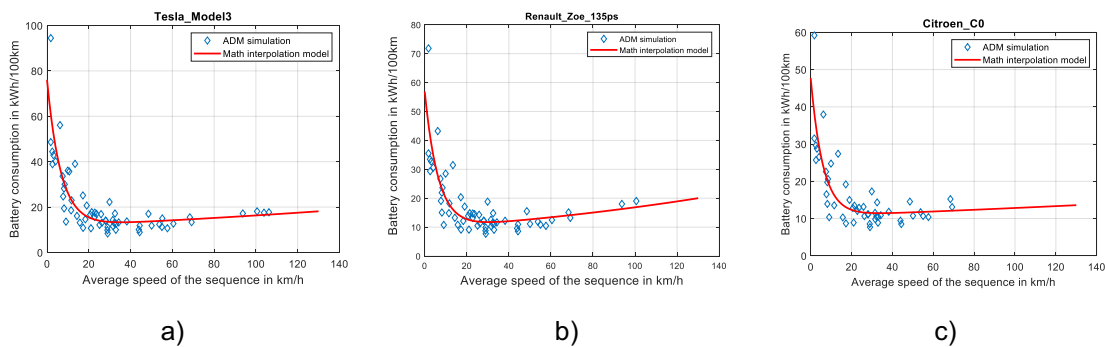


Figure 2. Energy consumption according to the average speed and the vehicle model: (a) Tesla model3, b) Renault Zoe, c) Citroen C0

## Results and discussion

### Global energy consumption

Using the traffic simulation software SYMUVIA and the two energy models (ADM for option1 and PIM for options 2 and 3) the total energy consumed during the simulation period (from 6.30 am to 10.30 am) is calculated for each vehicle then for the whole fleet. The vehicle fleet is supposed to be composed equally of Tesla, Renault Zoe and Citroen C0. The results are depicted in Table 1. As total energy consumption is the energy consumed by the battery, we add a column corresponding to the total energy need that includes the energy lost during charging with a charge efficiency value of 90%.

Table 1: Global Electric Energy Consumption of the three simulation options

[Simulation Options]	Distance (km)	Total EC (kWh)	Total Energy need (kWh)	Error in % Ref option1	Mean EC (kWh/100km)	Error in % Ref option1
Option 1	323202	47758	53 064	0	16.4	0
Option 2	326012	44742	49 713	-6	14.9	-9
Option 3	328754	42260	46 955	-11	14.3	-13

We can notice that the three options do not lead exactly to the same distance as this variable calculation method is different from an option to another (integral of speed for option 1 and sum of the length of different segments for option 2 and 3).

As shown in Table 1, options 2 and 3 underestimate the total energy requirement by 6 and 11% respectively. If we include the distance calculation effect, the average difference in energy consumption reaches 9 and 13% error compared to the reference option1.

In terms of computation time, option 1 runs in a parallel mode with 4 workers on a laptop I7-7820HQ CPU @ 2.90GHz processor and lasts almost 5 hours to achieve the whole simulation for the 3 vehicles. Options 2 and 3 need only one worker and last less than one second on the same computer.

As the PIM model is average speed dependant, and in order to understand the error origin for the options 2 and 3, we plotted in figure 3 the speed distribution according to the distance for the 3 options.

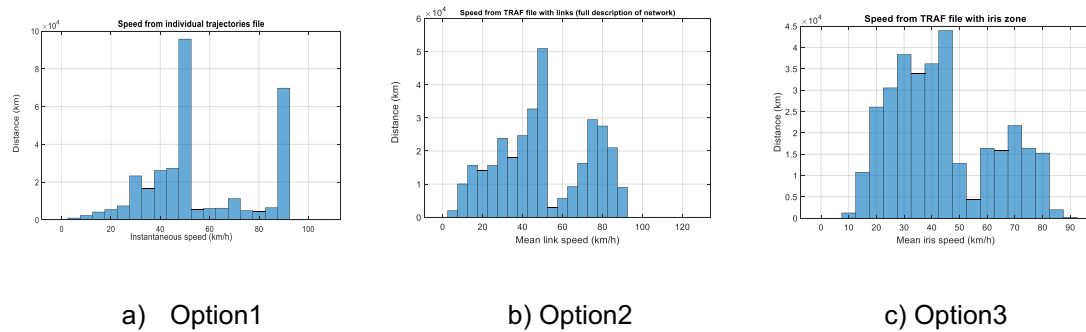


Figure 3. Speed distribution according to the distance for the three options of simulation

As shown in figure 3 a), the option 1 with instantaneous speed distribution includes two main classes around 50 and 90 km/h corresponding to the two speed limits encountered (urban and rapid loop speeds). These classes have less weight in option 2 and almost equal to the other classes in option 3. This is due to the average speed estimation on each link for the two options (full link and iris zone use respectively). As the PIM model uses these speeds to determine the energy consumption according to the mathematic model presented in figure 2, it seems coherent that EC is lower for option 2 and the lowest for option 3 (90 km/h has high EC).

### Impact of the traffic

One advantage of the proposed model coupling (SYMUVIA+VEHLIB) is to evaluate the impact on the energy consumption of the traffic intensity according to the time of the day. Figure 4 presents a temporal simulation in the morning (from 6.30 am to 10.30 am) in the considered area (L63V) using option 2 methodology. Although the effect of a higher traffic density around the peak hours (8.40 to 9.40) is clearly registered on the energy consumption (without charging efficiency),

the difference between the peak value and the lowest value of the consumed energy is only about 3 %.

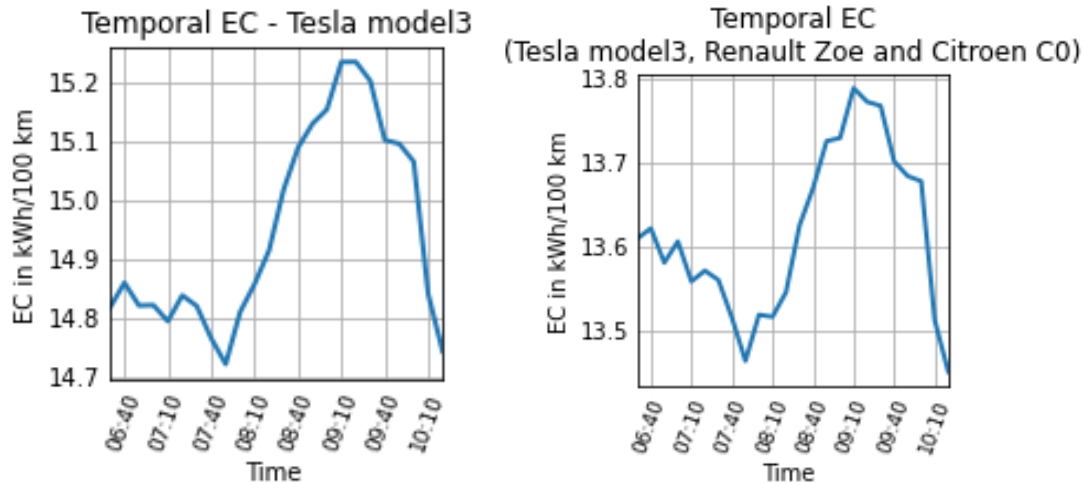


Figure 4. Electric Energy Consumption per vehicle and per 100km of the Evs fleet simulated on L63V according to the time. a) tesla model 3 vehicle b) average of the three vehicles

## Conclusion

In order to assess energy consumption in a large urban area considered infrastructure network and traffic constraints a new methodology based on traffic simulation tool and energetic vehicle modeling coupling is presented. Three options using this coupling have been set and compared. The first one, taken as reference, uses instantaneous description of the speed profile and a high-fidelity energetic vehicle model. It gives in theory the most reliable results. The second and the third option are derived from the traffic description with mean speed values for each segment. The third option, compared to the second, is based on area subdivisions to further reduce spatial description. The simulation results showed a deviation from the baseline of the total energy consumed with options 2 and 3 of 6 and 11% respectively. Depending on the objective of the various studies, these values could be considered satisfactory or not because, on the other hand, options 2 and 3 allow a drastic reduction in the calculation time. This opens up prospects for assessing energy consumption on a large scale as:

- Enlarging the spatial area to cover a whole town or metropolitan area and further study the scale effect.
- Using large scale traffic simulations or real census data.

However, studying power constraints on components is important for EVs. For example, the battery is a key component and its thermal behavior during use impacts its lifetime. In this case the option 1 is the only alternative to highlight and further control these phenomena.

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