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Evaluation of EVs energy consumption influencing factors,

driving conditions, auxiliaries use, driver's aggressiveness

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Abstract

This paper presents a simulation study dealing with the influence of different factors on the energy consumption of an electric vehicle (EV). Due to the limited quantity of energy embedded in the battery, EVs are very sensitive to parameters which can influence their energy consumption and then can induce huge variations in their actual range. Among all these factors, driving conditions, auxiliaries' impact, driver's aggressiveness and braking energy recovery strategy are to be considered as the main factors influencing the EV energy consumption. The objective of this paper is thus to simulate and quantify the influence of each factor independently. For this, a virtual EV simulator has been created and validated through EVs experiments on a climatic 4WD chassis dyno in the frame of a project sponsored by the French ADEME and with the help of PSA, Renault and Tazzari car manufacturers. This simulator, validated thanks to a limited number of experimental results, has been then used on a very large range of operating conditions and hypotheses to extrapolate experimental results and help the analyses of influencing factors.

Keywords: EVs, energy consumption, auxiliaries, simulation, passenger cars

1 Introduction

Electric Vehicles (EVs) enable to avoid local nuisances (atmospheric pollutant emissions and noise) together with a possible decrease in greenhouse gases (GHG) and fossil primary energy use. However, a widespread diffusion of EVs in the market is still difficult due to their high price, limited range and high sensitivity of this range to the operating conditions such as driving schedule and auxiliaries use. This paper deals with the influence of the main parameters on EV energy consumption which are the type of driving conditions, the use of on board auxiliaries, the driver's aggressiveness and the influence of brake energy recovery strategy. EV energy consumption is on every continent evaluated through a standard procedure implementing a specific driving schedule with no use of A/C ; this last point has a limited effect for IC engine vehicles due to the their large range and capacity to refill, and also due to the fact that cabin heating is coming free from the engine heat losses. The situation is completely different for EVs because the range is limited and is affected in both cabin heating and air conditioning use. Consequently, the French ADEME and IFPEN decided to carry out an experimental study in order to assess the influence of driving conditions and A/C use on EVs energy consumption

(CONSOVEX, a 2010 – 2012 cost shared program). In the frame of this program, 3 EVs have been tested on IFP Group 4WD climatic chassis dyno, with the help of the French car manufacturers PSA, Renault and Tazzari. Six specific driving schedules together with 3 ambient temperature and hygrometry conditions have been considered.
The complexity and the cost of the experimental tests have led IFPEN to develop a generic simulation model of an EV, validated through the measurements and implemented in order to cover a large type of situations or even access the potential of in-progress technologies on the EVs energy consumption. Such an approach is particularly interesting in evaluating the potential of new optimized A/C systems developed by car manufacturers and OEMs.

2 Methodology

2.1 Vehicle simulator presentation

To evaluate the influence of different factors on the energy consumption, a representative electric vehicle simulator has been developed on the LMS.IMAGINE.Lab AMESim platform, based on component models available in the IFP-Drive and ESS libraries (Figure 1). Such models have been developed for a long time by IFPEN researchers and adapted to different cases such as EVs and PHEVs [1, 2, 3]. The different electric vehicle parameters are based on available data in the literature (Table 1). It is to be noticed that for simulator validation (§ 2.6), the vehicle characteristics used in simulation were similar to the rolling test bed coefficients taken into account on experimental facilities in order to make a relevant and accurate comparison.

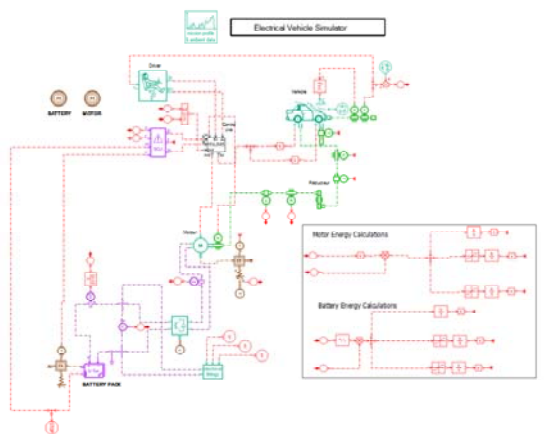

Figure1: Electric vehicle simulator

Table1: Electric vehicle specifications

Vehicle characteristics	Value
Total vehicle mass	1,250 kg
Wheel inertia	0.7 kg.m^2
Wheel radius	0.2848 m
Aerodynamic coefficient S Cx	0.706 m^2
Rolling resistance coefficient	0.007

The characteristics of the simulated EV are representative of a large part of EVs available on the market with a permanent magnet electric machine, a reducer and a Li-ion battery. The powertrain characteristics are shown in Table 2. Limitations on regenerative braking strategy are taken into account in order to be representative of existing EVs (§ 3.4). The different models used for the powertrain are described in the following sections.

Table2: Electric vehicle drivetrain specifications

Powertrain characteristics	Value
Motor peak power	43 kW
Motor peak torque	180 Nm
Motor Max speed	8,000 rpm
Motor shaft inertia	0.0685 kg.m^2
Axle ratio	6.066
Auxiliaries power (if no A/C use)	250 W
Axle efficiency	98 %

2.2 Electric machine modelling

The electric machine and power electronics efficiency maps have been generated with a home made tool developed at IFPEN (EMTool) able to size and to characterize electric machines (EM) from basic EM requirements (maximum power and torque, maximum motor speed, input voltage) [4]. This tool is based on analytical models allowing to design an electric machine that meets the required specifications. Electromagnetic parameters are then calculated from the geometry and are associated to quasi-static control strategy to evaluate electric machine performances and efficiency. A complete efficiency map can then be determined and integrated in the vehicle simulator. This tool, validated through measurements on IFPEN test bench (Figure 2), can be used in system simulation at an early stage of the new concept development, while data on the electric machine are not available yet. The characteristic of the electric machine considered is illustrated in Figure 3.

Figure2: IFPEN electric machine test bench

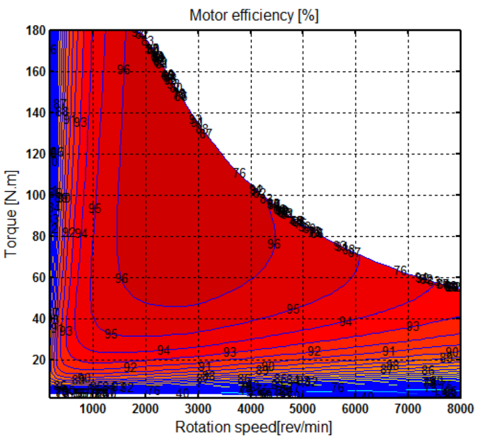

Figure3: Efficiency Map of the electric motor generated with EMtool

2.3 Battery modelling

The considered cell for our EV is a cylindrical 41 Ah high energy element with a NCA/graphite chemistry. The battery pack is composed of 88 cells in series whose characteristic are indicated in Table 3.

Table3: Electric vehicle battery pack specifications

Battery characteristics	**Value**
Nominal voltage	317 V
Maximum voltage	352 V
Minimum voltage	237 V
Nominal energy	13 kWh
Maximum discharge power	75 kW
Continuous charge current	82 A
Pulse – Continuous discharge current	300 A (30s) – 150 A
Weight of the cells	94 kg

IFPEN battery modelling is being made following several approaches from equivalent electrical circuit quasistatic models to physical electrochemical dynamic models calibrated on experimental data from IFPEN test benches. Quasistatic models are well suited for EV system simulations since they are fast and have good predictions during short power solicitations [5, 6]. Electrochemical modelling is better suited for applications with long constant current solicitation (eg. battery charge or vehicle to grid, V2G operations) since transient effects are taken into account as can be seen in Figure 4a and 4b). As a consequence the quasistatic model approach has been used during charge depleting EV simulations and the electrochemical model has been used to evaluate the charging efficiency of the battery.

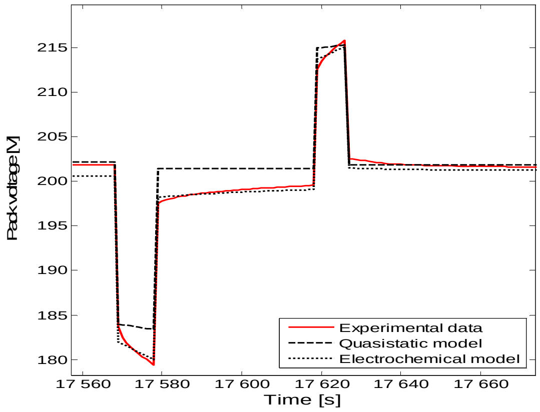

Figure4a: Comparison between model results and experimental data during a 10s current pulse of a HPPC procedure at 23°C

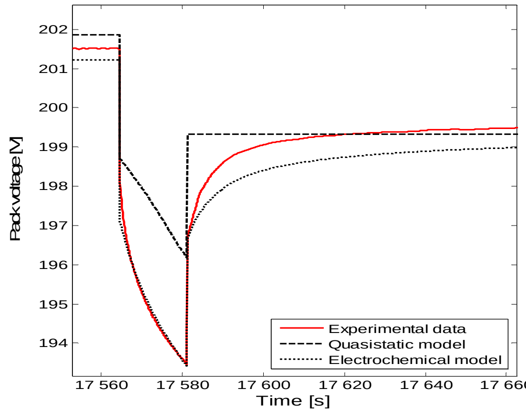

Figure4b: Comparison between model results and experimental data during a 200s discharge of a HPPC procedure at 23°C

Both models have been integrated in the AMESim software using the ESS library components for the quasistatic model and an in-house component for the electrochemical model. The necessary lithium-ion safety operation is ensured using a Safety Control Unit (SCU) computing the maximum charge and discharge currents. This component limits the electric machine torque command in order to maintain the battery pack in both current and voltage limits.

The electrochemical model used to evaluate the charging efficiency [7] is based on the single-particle approach [8]. It takes into account the thermodynamic equilibrium potentials of the positive and negative electrodes, solid-phase mass balance within the spherical particles of the electrodes, liquid-phase mass balance within the electrolyte, and electrochemical kinetics at the electrodes/electrolyte interfaces. The charge efficiency, E_{charge}, has been calculated as follows (1):

$$E_{charge} = \frac{E_{stored}}{E_{received}} = \frac{C_{nom}\int_{t_0}^{t_{end}} U_0 \frac{dSOC}{dt} dt}{\int_{t_0}^{t_{end}} UIdt} \quad (1)$$

where U_0 is the open circuit voltage of the cell, U its voltage, I the current, SOC its state of charge and C_{nom} its nominal capacity.

In order to investigate the effects of charge parameters (C-rate, initial SOC) on the efficiency, CC/CV charges have been performed at various C-rates (from C/6 to 2C) and for several initial SOC (from 10 to 90%). The results are shown in Figure 5.

The faster and the deeper the charge is, the lower the charging efficiency will be. For instance a complete charge from 10 to 100% has a charging efficiency going from 99.5% at C/6 to 97.6% at C. Furthermore, a charge at C from 10% SOC has a 97.6% efficiency whereas the same charging method from 90% SOC has a 99% efficiency.

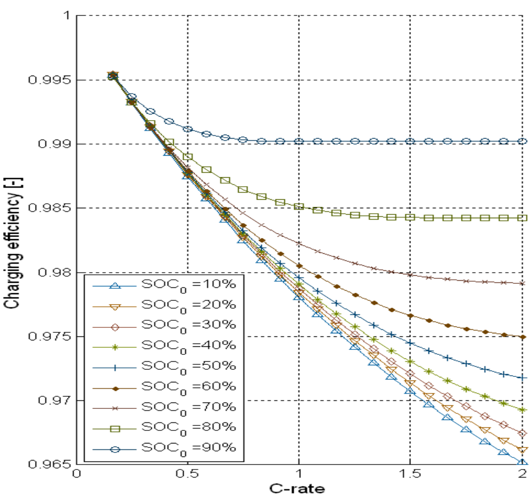

Figure5: Charging efficiency as a function of initial State of Charge (SOC_0) and C-rate

This can be accounted for by the losses occurring in the battery. At low C-rates (C/6) there are few losses due to resistive phenomena in the battery and the bigger the C-rates is the bigger the resistive phenomena are. Then, due to transient phenomena (eg. diffusion) the bigger the charge is the bigger resistive effects are. This effect is also more significant for higher C-rates since diffusion phenomena become more important. The battery pack cooling must then be sized for high power charges.

As a consequence, fast charging of 80% of a battery pack at 2C will lead to an efficiency close to 96.7%, to be compared with more than 99% at a 0.2 C rate.

2.4 Auxiliaries modelling

The model takes into account the electric auxiliaries connected to the 12 V DC network together with the electrically driven air conditioning and resistance for cabin heating. The electrical load applied for the high and low ambient temperature cases are directly coming from the experiments carried out on our climatic chassis dyno during the CONSOVEX program.

2.5 Driving condition modelling

The vehicle model is used to evaluate energy consumption according to vehicle use. Two different methods are implemented:

- A “conventional” method with the use of different driving cycles, representative of different vehicle driving conditions, from very congested urban cases to free flow conditions. These driving cycles are generated from actual use survey [9] or representative from standard conditions. A statistical method has been implemented in order to classify these driving cycles according to their characteristics [10].
- A method enabling to take into account the driver aggressiveness through the use of vehicle speed target according to distance. In this method the driving pattern is generated according to the speed targets and to the driver's behaviour (mainly acceleration and deceleration applied). The effect of driver's aggressiveness may then be highlighted for both acceleration and deceleration phases. Moreover, this method enables to create and follow driving patterns which are specific to EVs and not derived from IC engine vehicles surveys and then take into account specificities of EVs drivetrain.

2.6 Simulator validation with experimental results

Before performing an intensive use of the simulator on parametric simulation campaign, a first step of simulator validation and comparison to experimental results is necessary. This phase was performed on measurement results obtained through an experimental study on the influence of factors on EV energy consumption (CONSOVEX program described in section 1).

The vehicles have been equipped with sensors (current, voltage, temperature…) enabling to record the energy flows in the components (high and low voltage batteries, electric machine, auxiliaries…). Some additional recordings have been carried out from the CAN network when possible.

To limit the number of experiments, a method of driving cycles selection through statistical criteria was implemented [10] and allowed the selection of 6 driving cycles, each one being representative of specific operating conditions: urban congested conditions (UL1 cycle), urban flowing traffic conditions (Artemis Urban cycle), suburban conditions (SC03 cycle), rural road conditions (Hyzem Rural cycle) and highway driving conditions (A1 cycle). The last one is the European standard NEDC driving cycle, selected to have a reference on normative operating conditions.

In a first step, the validation consists in comparisons of instantaneous data between experiments and simulations, for the 6 selected driving cycles. Figures 6 and Figure 7 show respectively a comparison on the battery current between simulation and experimental results for the NEDC driving cycle and a comparison on battery voltage between simulation and experimental results for the SC03 driving cycle. Results show a very similar behaviour between simulation and experiment. This level of accuracy was obtained in the 6 driving cycles.

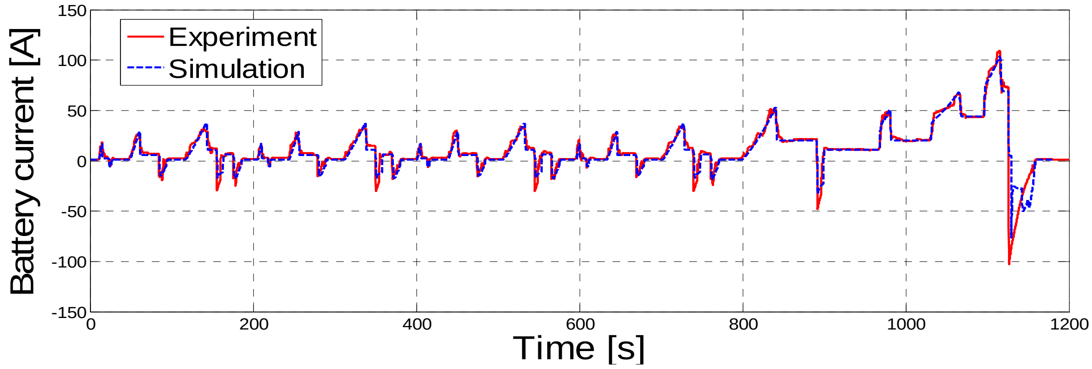

Figure6: Battery current comparison (NEDC simulation)

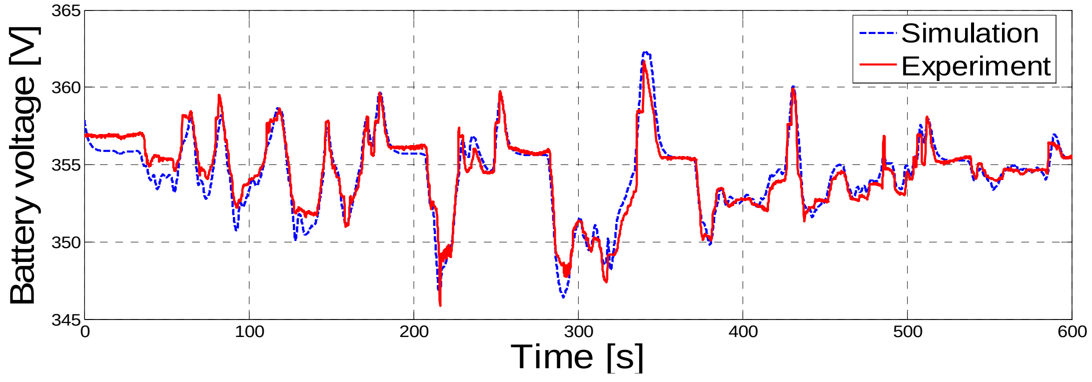

Figure7: Battery voltage comparison (SCO3 simulation)

In a second step, a comparison on the EV global energy consumption is performed and presented on Figure 8, showing very similar energy consumption for the whole driving cycles except for the UL1 one which presents some differences (max error : 18.5%, average error : 3.4%). It has to be noticed that UL1 is a very specific driving cycle representing city centre with traffic jam (average speed around 3.8 km/h). This driving cycle is exploring specific operating conditions on the powertrain, notably for the electric machine with an operating area focused on the very low speeds and relatively low torques. Taking into account that simulator data were built by homemade tools (no data from manufacturers), it is not surprising to find variations in a zone where an error on loss evaluation could have huge effects on efficiency prediction.

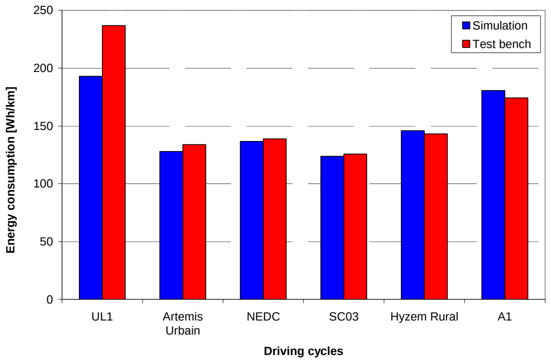

Figure8: Energy consumption from the grid on the 6 considered driving cycles

Nevertheless, this level of accuracy obtained on the different operating conditions enables us to validate the simulator to perform the following intensive simulation campaign.

3 Simulation campaign and results

With its capability to run exhaustive parametric numerical campaign, simulation can be considered as an interesting and complementary tool for experimental facilities, to extrapolate experimental results to a large range of operating conditions and to help their analysis. The objective of this part is thus to use the validated simulator presented above to investigate the influence of different factors on the energy consumption.

3.1 Driving cycle impact on energy consumption

As everybody knows, energy consumption and range of electric vehicle are significantly influenced by driving cycles. To quantify this impact, a database of forty driving cycles, representative of various operating conditions has been used with the simulator. Results of energy consumption, presented on Figure 9, show huge disparities between the different driving cycles, with a factor of 2.5 on the energy consumption in Wh/km between the least demanding driving cycle (around 90 Wh/km) and the worst one (around 240 Wh/km).

Driving cycles differ by different criteria, such as mean speed, acceleration, number of stop and start phases, stop phase duration… All these criteria influence the energy consumption. To facilitate result analysis, an analytic correlation has been fitted on the simulation results in order to create a realistic trend curve. This correlation depends on few selected cycle criteria: mean speed, mean positive acceleration, percentage of stop phases in total duration… Figure 9 shows energy consumption from the grid for the different simulated driving cycles in function of mean vehicle speed and the results of the correlation for a mean value of positive acceleration (0.613 m/s²) representative of what can be qualified as an 'ordinary' driver). This figure shows a minimum of energy consumption for the electric vehicle around 20 km/h. Below this value, energy consumption increases due to auxiliaries. Above 20 km/h, vehicle losses due to vehicle speed increase are responsible of this rise in energy consumption.

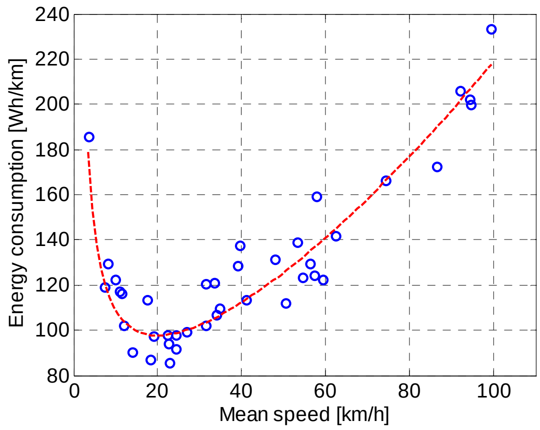

Figure9: Energy consumption from the grid versus mean speed

The differences between analytic correlation and simulation results are mainly due to two points:

- Positive mean acceleration representative of driver aggressiveness is specific of each of the driving cycles and is kept constant for the plotted correlation. The differences appearing on the figure indicate that driver aggressiveness may be considered as a major factor of influence on the energy consumption and this point will be illustrated further in the paper;

- Mean vehicle speed is a restrictive criterion to estimate energy consumption. For instance, vehicle speed distribution on a given driving cycle is a more appropriate criterion. Nevertheless, to facilitate the understanding and analysis, this criterion has been selected to represent energy consumption on parametric variations.

3.2 Auxiliaries impact

To quantify the auxiliaries' impact, a parametric variation of power accessories was performed. Three cases were simulated and presented in Figure 10 with 250W, 500W and 1000W of electric power accessories. The analytic correlation introduced just above, was also used to facilitate the analysis. As presented in Figure 10, auxiliaries' impact is important at low speeds (when vehicle speed is less than 40 km/h) and relatively limited at high vehicle speeds. An interesting result is that optimal mean vehicle (in terms of energy consumption) is around 20 km/h when power accessories is equal to 250W and moved to 30 km/h when power accessories is 4 times higher.

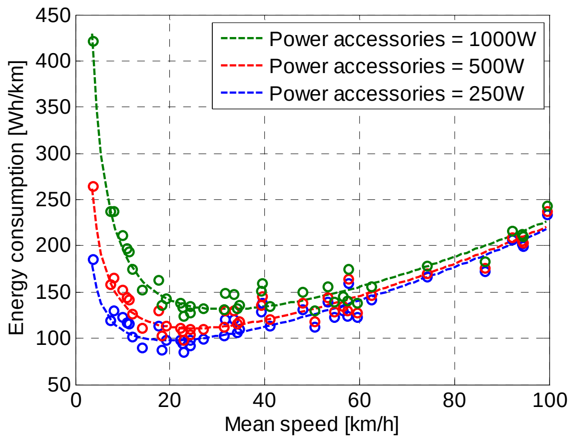

Figure10: Auxiliaries impact on energy consumption

3.3 Driver's aggressiveness impact

As already explained before, driver's aggressiveness has been evaluated with two methods.

The first method consists in analysing the impact of the mean positive acceleration on EV energy consumption. This analysis was facilitated by the use of the analytical correlation defined above. On the base of the correlation identified on Figure 9, a variation of mean positive acceleration is done to evaluate the influence of three types of driver we have qualified as 'ordinary' driver, 'economic' driver and 'aggressive' driver. Figure 11 shows the results with a mean positive acceleration varying between 0.38 m/s^2 (representative of an 'economic' driver) and 1.03 m/s^2 (representative of an 'aggressive' driver). These figures are extracted from the minimum and maximum values calculated on the whole database of driving cycles. As shown in Figure 11, energy consumption variation due to driver's aggressiveness is significant. Comparing the cases of economic driver and aggressive driver, this variation can range approximately from 40% at low speed to 10% at high speed. This remark illustrates the importance of the work performed on economical driving behaviour to reduce energy consumption and optimize electric vehicle range.

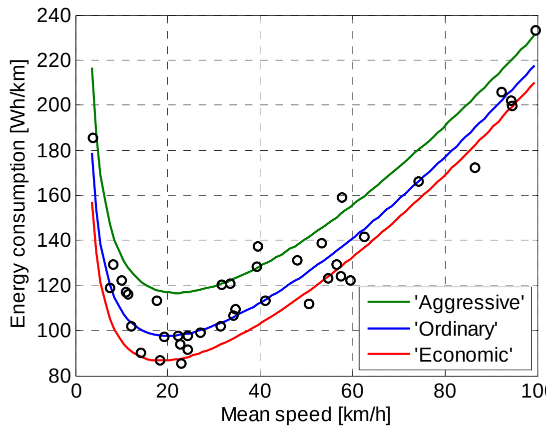

Figure11: Driver's aggressiveness impact on energy consumption (first method evaluation with analytic correlation)

To investigate driver's aggressiveness impact, the second method of driving condition modelling defined above is considered. This method takes into account the driver aggressiveness through the use of driving cycles defined by the vehicle speed target according to distance. With this method, each acceleration and deceleration is limited and a parametric variation is performed on this limited value (from a minimal value representative of our economic driver to a maximal value representative of our aggressive driver). Figure 12 presents the results obtained on four driving cycles (NEDC and Artemis driving cycles). For instance, on Artemis Urban driving cycle, driver aggressiveness is very influent, with a gap of 40 Wh/km for a difference in mean vehicle speed limited to 2 km/h. Once again, this type of results illustrates the importance of energy efficiency driving behaviour to optimize EV range on a mission profile.

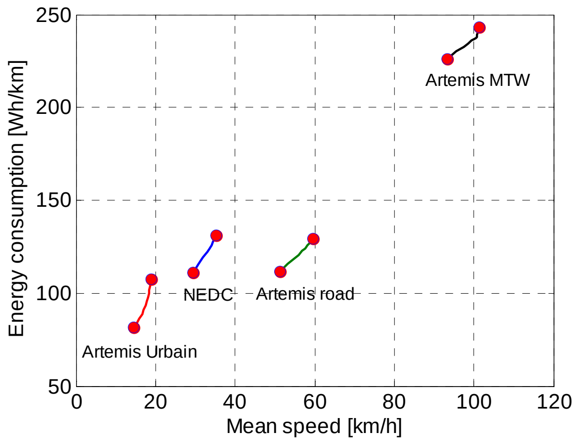

Figure 12 : Driver's aggressiveness impact on energy consumption (second method evaluation with a target speed driven methodology)

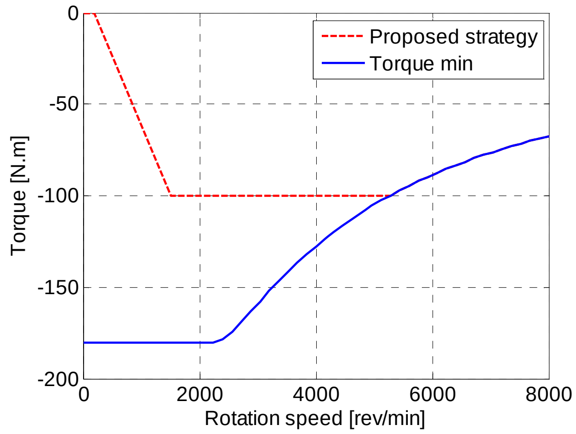

Figure 13 : Electric machine torque in generator mode and proposed regenerative braking strategy

3.4 Regenerative braking strategy impact

One important advantage of electric vehicles is its capability to recover energy during braking phases by using the electric machine in generator mode. This regenerative braking strategy is important to improve powertrain efficiency and thus optimize EV range. In order to guarantee passenger safety and comfort during braking, the regenerative strategy should be a compromise between maximizing the regenerative braking torque, while respecting the battery ability and vehicle driveability [11].

In this context, Figure 13 shows the characteristic of the electric machine in generator mode (blue solid line) and the proposed regenerative braking strategy (red dashed line). In fact, the illustrated strategy takes into account driver safety and comfort during braking, with a regenerative braking torque equal to zero when the rotation speed is less than 200 rev/min and a progressive increase of regenerative torque between 200 rev/min and 1500 rev/min. Setting the maximum regenerative torque to its maximum available may provide an unstable pedal feel as reported by Toyota with approximately 200 complaints and four accidents in both Japan and the United States as of February 2010 related to this strange braking feel [12]. The limitation in maximum braking torque is also established to respect the battery allowed envelope in current and voltage to avoid any damage or degradation of the battery total life [12]. This limitation may also be a function of battery temperature.

It is then interesting to evaluate the impact of the regenerative braking strategy on EV energy consumption according to vehicle type of use : to do so we considered our 40 driving cycles. Three different cases were tested: a first one with the proposed regenerative braking strategy, a second one without regenerative braking and a third one with a maximum regenerative braking without constraints. The results on these three cases are illustrated in Figure 14. The following remarks can be done on the results:

- There is a limited impact on energy consumption between the case using the proposed regenerative braking strategy and the case using maximum regeneration. Differences can be noticed on driving cycles with a mean vehicle speed under 20 km/h. Above this mean vehicle speed, it appears that the proposed strategy captures most of the recoverable energy while guaranteeing driver comfort and safety and optimized battery life time.

- Regenerative braking capability has a major influence on energy consumption of electric vehicle, with reaching a decrease of energy consumption of around 60% in urban conditions (mean speed inferior to 40 km/h). These results confirm the very good adequation of EVs with urban use, especially if we add their capability to be operated with no local air pollution and extremely limited noise level.

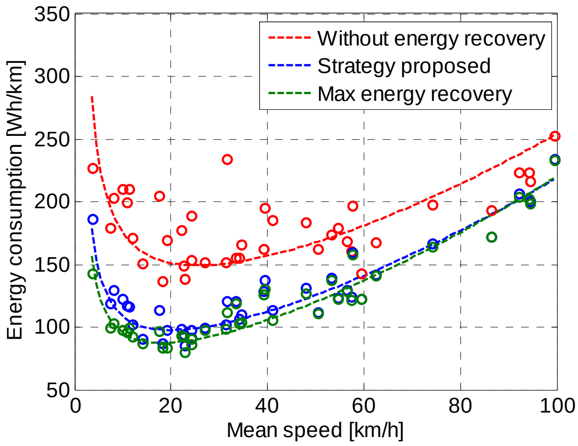

Figure 14 : Regenerative braking strategy impact on energy consumption

4 Conclusion

This paper illustrates a parametric study dealing with the main factors influencing an EV energy consumption and thus its in-use range. The evaluation has been performed thanks to a dedicated software which has been previously validated through chassis dyno experiments on a panel of EVs.

Our analysis, considering 40 different driving cycles covering a wide range of average speed, has highlighted huge disparities in vehicle grid energy consumption with a range laying from 90 to 240 Wh/km. To facilitate further analysis, an analytic correlation has been proposed, taking into account driving pattern criteria such as mean speed, mean positive acceleration, percentage of stop duration together with vehicle characteristics.

This correlation has been used in order to characterise the effect of various parameters on the vehicle energy consumption, ie:

Auxiliaries: Our results illustrate their high influence, especially at low speed with 15 to 40% for 20 km/h average speed and 5 to 15% for an average speed of 60 km/h (for resp. 250 W and 750 W additional aux power).

Driver's aggressiveness: The proposed criteria based on mean positive acceleration indicates that an increase of up to 40% may be encountered at 20 km/h and about 15% at 60 km/h.

Regenerative braking: This feature has a high influence on EV energy consumption with a maximum effect of more than 50% at 20 km/h and almost 30% at 60 km/h.

Such analytic approach is able to provide quickly orders of magnitude to access various parameters influence on vehicle energy consumption. The second method proposed, based on a vehicle target speed construction directly in the simulation, is more complex but enable a complete analysis of the vehicle behaviour according to the mission profile and to the driver's characteristics.

Both methods may be applied at different steps with the aim to characterise EVs energy consumption and range variations according to their conditions of use, this knowledge being of a high degree of importance to ensure a wide diffusion of EVs.

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Jean-Charles Dabadie is in charge of R&D in model and simulation in the Engine CFD and Simulation Department in the Energy Applications Techniques Division of IFP Energies nouvelles.

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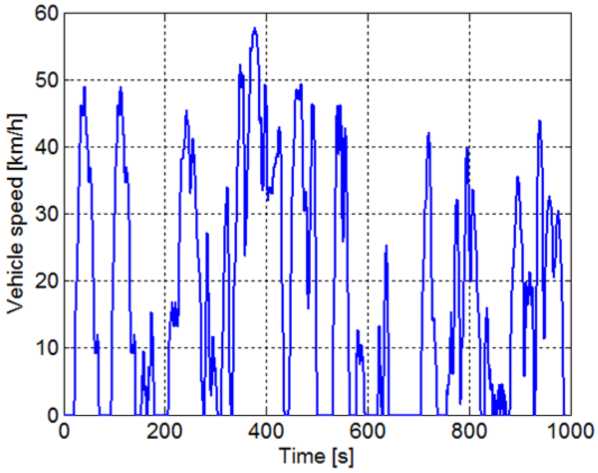
Sebastien Magand graduated from *Ecole Centrale de Marseille* Engineering school in thermal engineering and from Cranfield University (UK) in Motorsport Engineering and Management. He was engine test bed engineer since 2005 at IFP Energies nouvelles and turned into vehicle and transient test bed engineer in the field of calibration and benchmarking. In 2011, he became project leader of DEVICE collaborative project whose objective was to develop methodologies as well as tools to define new hybrid powertrains for urban car applications. Finally, in 2013, he is now the product development manager concerning innovative transmissions for hybrid applications and high efficiency engines at IFP Energies nouvelles.

Eric Condemine is project manager in Hybrid Vehicle at IFP Energies nouvelles, in charge of Vehicle integration synthesis. He has worked as vehicle system research engineer at PSA Peugeot Citroen from 1996 to 2009.

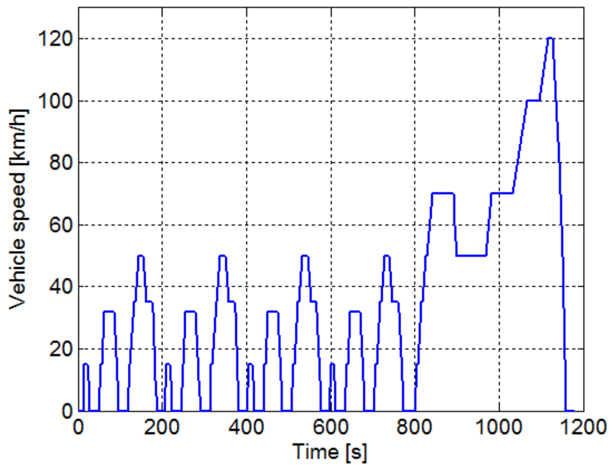
Appendix

Speed vs time profiles of the 6 selected driving cycles

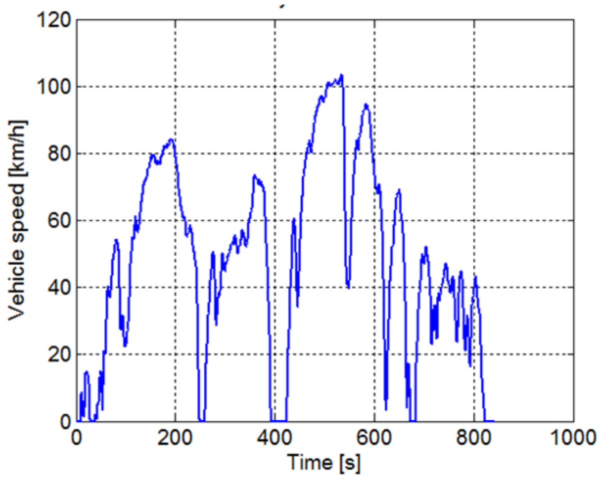
Artemis Urban (avg speed 17.6 km/h)



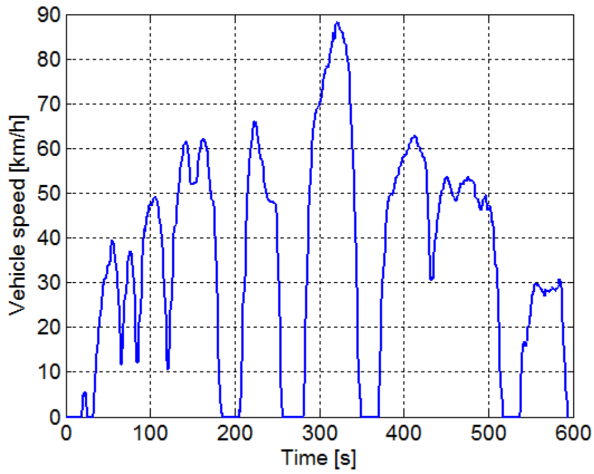
European Standard (NEDC)
(avg speed 33.6 km/h)



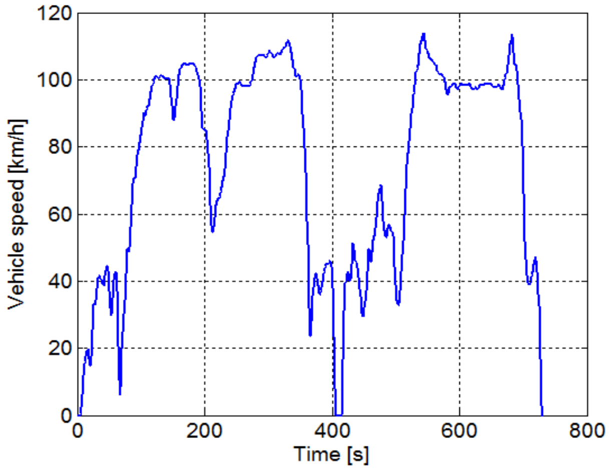
Hyzem rural (avg speed 48 km/h)



Sub Urban conditions SC03
(avg speed 34.8 km/h)



Highway driving conditions (avg speed 74.3 km/h)



Congested urban conditions (UL1)
(avg speed 3.8 km/h)