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Impact of the Velocity Profile on Energy Consumption of Electric Vehicles

A. Desreveaux, A. Bouscayrol, *Member, IEEE*, R. Trigui, E. Castex and J. Klein

Abstract— The driving range of electric vehicles is an important issue. The velocity profile can have an important impact on their energy consumption and thus their driving range. In this paper, a commercial electric vehicle is studied. The model of its traction subsystems is developed using a forward approach. A specific driving cycle generator is then coupled with this model. A feedback from the model to the generator allows for recalculation of the velocity reference in case of a limitation due to the electrical drives, for a more accurate estimation of energy consumption. Different trips are then studied with this method. The maximal velocity has a strong impact on the energy consumption while the maximal acceleration has a low impact.

Index Terms—Electric Vehicles, Driving Cycle, Road Planning Software, Energy Consumption

I. INTRODUCTION

Air pollution and global warming are major challenges for the transport sector. A short-term solution is to reduce the maximal velocities on roads. This solution has a valuable impact on air pollution [1] [2], fuel consumption [3] and reduces the traffic flow [4]. Other governments have used variable speed limits [5] [6]. Furthermore, policies aim to introduce velocity limitations for safety reasons [7]-[9].

Most previous studies about velocity impact on energy consumption deal with conventional cars. However the electric vehicle (EV) is an increasing part of the vehicle market [10]. In fact, reducing the velocity limitations can also have a positive impact on EV range, which is a real issue for drivers. Nevertheless, the effect of velocity limitation on electric and conventional car's consumption cannot be transposed in an easy way. Indeed, most of EVs have no gearbox and can have regenerative braking. Moreover the efficiency of an internal combustion engine is very different from those for electric drives [11] [12].

Driving cycles such as NEDC, WLTP are used to evaluate the energy consumption of different vehicles. But these driving cycles do not reflect real use of vehicles [13] [14] and in particular electric vehicles because they are not developed specifically for these vehicles [15].

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More generally, traffic conditions have an impact on energy consumption and real driving cycles are of interest. [16] [17]. But when a driving cycle is measured on a real vehicle, it cannot reflect the random characteristics of different cycles. Statistical methods can be used to express this variability, but they required a lot of measurements [18] [19]. In another approach, probabilistic models are developed using Markov chain or other methods [20]-[23]. But the effect of the characteristics of the driving profile (maximal and average velocity, maximal and average acceleration) is difficult to derive from these driving cycles. Indeed all parameters are linked and a scaling factor on the driving cycle will impact all parameters at the same time.

Driving cycle generators have been developed to select independently the characteristics of the cycles, mainly the maximal velocity [24]-[28]. The driving cycle generators have been used for autonomous vehicle [26] or for energy consumption evaluation of EVs [24]-[25]. They are generally based on a vehicle model in a backward approach. In this case, there is no feedback between the vehicle model and the driving cycle generator. In case of limitation due to the traction system (e.g. torque limitation), the velocity calculated by the driving generator cannot be followed. Because there is no feedback in this approach, the velocity is considered as not disturbed. The simulated energy composition is thus different from the real one. A new method based on a forward approach has been developed for a subway system [27]. In this case, a feedback is given from the vehicle model to the driving cycle generator. In case of limitation, the generator can thus recalculate the velocity reference to reach the final position. It has been demonstrated that this method lead to a more accurate estimation of energy consumption. This method has been extended to a 2-seat electric vehicle for very simple trips without stops and traffic lights [28].

The objective of this paper is to determine the effect of the maximal velocity and acceleration of a driving cycle on the energy consumption of an EV. To that end, the forward approach developed in [27]-[28] couples a traction simulation model with a specific driving cycle generator. A Renault Zoe and more realistic trips are now considered for validation of the developed method and for the study of the impact of the velocity profile. Furthermore, the Energetic Macroscopic Representation (EMR) formalism [29] is used to organize all the models.

The principle of the study is described in Section II. The model of the studied EV is presented and validated in section III. The driving cycle generator is developed and validated in section IV. Finally, the impact of the velocity and the

acceleration are presented in section V.

II. CALCULATION OF ENERGY CONSUMPTION OF AN EV

A. Classical backward approach

In a classical approach, a backward model is generally used to compute the energy consumption of the vehicle from travel (Fig. 1). In this case, the velocity is assumed to be achievable by the vehicle ($v=v_{ref}$). The advantage is that no control loop is required to compute the energy. The drawback is that no limitation can be taken into account. For example, a torque limitation leads to violations of the velocity reference, and thus induces an error on the energy consumption estimation.

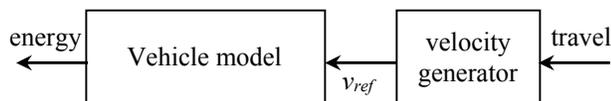


Fig. 1: Classical backward approach

B. Forward approach

A new approach has been proposed in [27] for calculation of subway energy consumption. In this case, a forward model of the vehicle is considered including its control (Fig. 2). The drawback is that a control algorithm must be defined. Moreover the computation time will be longer. The advantage is that the vehicle limitations can be considered. In case of limitations, when the velocity cannot follow its reference, the velocity generator has to recalculate a new velocity reference to reach the final position. An adaptation of the velocity generator is thus required.

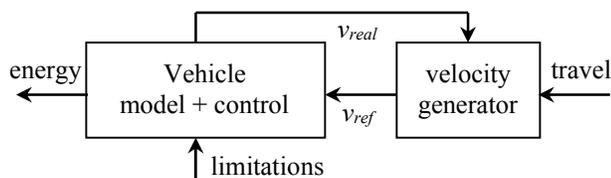


Fig. 2: Forward approach

C. Comparison of both approaches

The studied EV is the Renault Zoe (Fig. 3, parameters in Appendix). Its simulation model is presented in section III. A simple trip is considered to compare both approaches. In this trip, a torque limitation occurs due to the maximal torque of the electrical machine (Fig. 4).



Fig. 3: Renault Zoe [30]

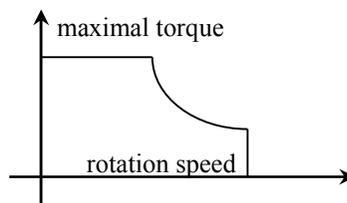


Fig. 4: Maximal torque vs. rotation speed of the electric drive

In the backward approach, the driving cycle is considered achievable. But due to the limitation, the real velocity is not achieved all the time (Fig. 5). The final distance is thus not reached. The total energy consumption is 1.19 kWh.

In the forward approach, the velocity reference is recomputed to reach the final distance. The total energy is 1.25 kWh. An error of about -5% is thus obtained in the backward approach.

It can be noted that the limitation is not reached in deceleration mode. Indeed, as only the front wheels are driven, only half of the total braking torque is required for the electric drive (see Fig. 5). The mechanical brakes produce half of the total braking torque on the rear wheels.

Other limitations can also be considered as supplementary masses or slopes, which lead to stronger torques for the same velocity. These effects can also not be considered in a classical backward approach.

In this paper, a variation of the velocity and/or acceleration is studied. Thus, limitations can be reached by increasing acceleration (i.e. torque) and velocity (reduction of the torque limitation of the electric drive). In these cases, a forward approach is required for a more accurate energy calculation.

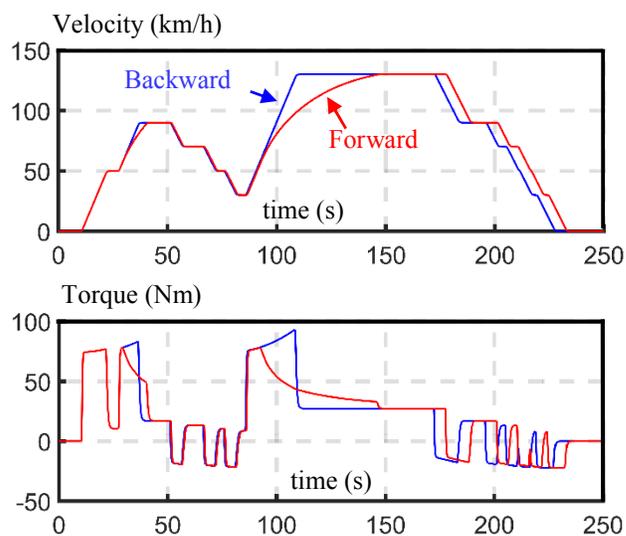


Fig. 5: Backward vs Forward approaches a) velocity b) torque

III. FORWARD SIMULATION OF THE STUDIED EV

A. Modeling of the studied vehicle

The studied EV is the commercial Renault Zoe using a Li-ion NMC battery of 22 kWh, an electric drive of 65 kW, a differential and two driven wheels in the front.

As neither curve nor wheel slip are considered, an equivalent

wheel is assumed. Energetic Macroscopic Representation (EMR) is used to interconnect the models [29]. A more detailed description can be found in [28].

The battery model (green oval) delivers a voltage u_{bat} from the state-of-charge SoC derived from the current i_{ed} as input.

$$u_{bat} = u_{ocv}(SoC) - R_{bat}i_{ed} \quad (1)$$

with R_{bat} the battery resistance and u_{ocv} the open circuit voltage. The electric drive (inverter and electrical machine) is modelled by a static model [31] (orange circle) with a look-up table efficiency map [32]. Its inputs are the battery voltage, the reference torque T_{ed-ref} and the rotation speed Ω_{gb} . The outputs, the current i_{ed} and torque T_{ed} , are obtained from the inputs and the efficiency η_{ed} of the look-up table.

$$\begin{cases} T_{ed} = T_{ed-ref} \\ i_{ed} = \frac{T_{ed}\Omega_{gb}}{u_{bat}}\eta_{ed} \end{cases} \quad (2)$$

The mechanical transmission is composed of the gearbox, the differential and the wheel (orange square). Its model links the torque to the traction force F_{wh} , and the vehicle velocity v_{ev} to the rotation speed:

$$\begin{cases} F_{wh} = k_{tm}\eta_{tm}^k T_{ed} \\ \Omega_{gb} = k_{tm}v_{ev} \end{cases} \text{ with } \begin{cases} k = 1 \text{ for } F_{wh}v_{ev} > 1 \\ k = -1 \text{ for } F_{wh}v_{ev} < 1 \end{cases} \quad (3)$$

With k_m , the equivalent gain and η_m the equivalent efficiency of 92%. An ideal mechanical brake is considered (green oval): the braking force F_{mb} is equal to its reference:

$$F_{mb} = F_{mb-ref} \quad (4)$$

The chassis (overlapped squares) combines the traction and the braking force in a total force F_{tot} :

$$F_{tot} = F_{mb} + F_{wh} \quad (5)$$

Moreover, Newton's laws (crossed orange rectangle) links the velocity v_{ev} to the total and the resistive force, F_{res} :

$$M \frac{d}{dt} v_{ev} = F_{tot} - F_{res} \quad (6)$$

with M the vehicle mass. The road (green oval) will lead to a resistive force to the motion.

From the EMR, an inversion-based control scheme can be obtained [29]. Relation (6) is inverted by a closed-loop control:

$$F_{tot-ref} = C(t)(v_{ev-ref} - v_{ev-meas}) + F_{res-meas} \quad (7)$$

with $C(t)$ a controller to be defined. Relation (5) is inverted using a distribution input $k_D(t)$ to distribute the forces:

$$\begin{cases} F_{mb-ref} = k_D F_{tot-ref} \\ F_{wh-ref} = (1 - k_D) F_{tot-ref} \end{cases} \quad (8)$$

In the traction mode, $k_D=0$ (no braking force). In the braking mode, $k_D=0.5$ to distribute the braking force between the rear and the front wheels. Only half of the energy is thus recovered. Moreover, a limitation curve of the electric drive is used to limit its torque as a function of the rotation speed (see Fig. 4). Relation (4) is directly inverted to obtain the drive torque reference:

$$T_{ed-ref} = \frac{1}{k_{tm}} F_{wh-ref} \quad (9)$$

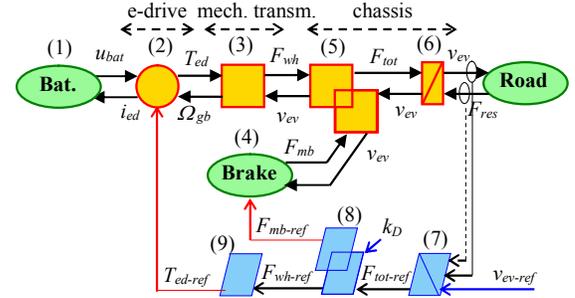


Fig. 6: EMR of the studied vehicle

B. Validation of the vehicle model

A 17 km driving cycle is performed with the real vehicle (Fig. 7). This suburban trip has sections with speed limits from 30 km/h to 110 km/h. Different variables are measured using the CAN bus: battery voltage, electric drive current, SoC and vehicle velocity. The energy consumption is calculated as follows:

$$E_{ec} = \int u_{bat} i_{ed} dt \quad (10)$$

The EMR-based model is implemented in Matlab-Simulink©. The velocity driving cycle is imposed as input to the simulation. Energy consumption in the simulation is equal to 2.9 kWh. The energy consumption on the real vehicle is was 3.0 kWh. The accuracy of the vehicle model is thus about 3%. Another driving cycle has also been tested, also leading to an accuracy of about 3% [33].

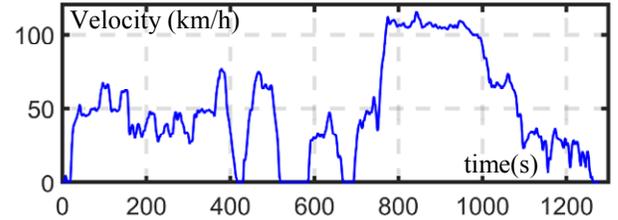


Fig. 7: Velocity measured during the test trip

IV. AUTOMATIC DRIVING CYCLE GENERATOR

A. Algorithm of the driving cycle generator

The driving cycle generator was developed initially for a subway application [27] and has been extended to an automotive application [28]. Only the main principle is described in this section. More details can be found in [28].

The driving cycle generator is composed of two control loops (Fig. 8). A first loop defines the velocity reference by controlling the vehicle position. In this loop, the velocity limitations are considered from the road and also from the vehicle. The second loop defines the vehicle acceleration by controlling the vehicle velocity. In this loop, the acceleration limitations are considered. The final velocity reference v_{ev-ref} is deduced from the acceleration reference γ_{ev-ref} .

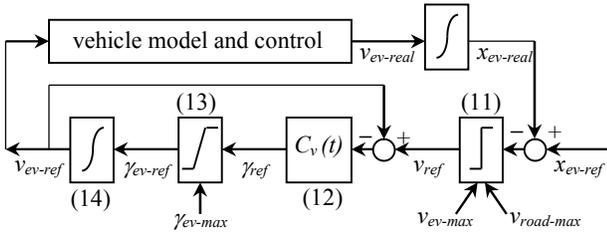


Fig. 8: Driving cycle generator

The first control loop imposes the maximal velocity until the vehicle reaches the final destination or position ($x_{ev-real}=x_{ev-ref}$):

$$v_{ref} = \begin{cases} 0 & \text{when } x_{ev-ref} = x_{ev-real} \\ v_{max} & \text{when } x_{ev-ref} < x_{ev-real} \end{cases} \quad (11)$$

As demonstrated in [27] such a hysteresis controller is sufficient. The maximal velocity v_{max} is the minimal value between the maximal velocity of the car and the maximal velocity authorized in the actual road section. It is assumed that the driver follows these limits in this paper. If any limitation occurs, this reference will not be achieved, and the final position will be not obtained. Thus, the feedback from the real position of the car enables it to continue to deliver the maximal velocity until it reaches the final destination.

The second control loop leads to definition of an acceleration reference γ_{ref} from the control of the velocity.

$$\gamma_{ref} = C_v(t)(v_{ref} - v_{ev-ref}) \quad (12)$$

As demonstrated in [27], a P controller is sufficient because a pure integral transfer function is considered between the velocity and acceleration. The optimal value of the parameter C_v is given in [34] depending on the maximal acceleration γ_{max} and the maximal jerk (derivative of the acceleration) J_{max} :

$$C_v = \frac{2J_{max}}{\gamma_{max}} \quad (13)$$

This acceleration reference is then limited by the maximal acceleration of the vehicle:

$$v_{ev-ref} = \begin{cases} \gamma_{ref} & \text{if } |\gamma_{ref}| \leq |\gamma_{ev-max}| \\ \gamma_{ev-max} & \text{if } |\gamma_{ref}| > |\gamma_{ev-max}| \end{cases} \quad (14)$$

Finally, the final velocity reference v_{ev-ref} is calculated from the acceleration reference taking into account all limitations at the road and vehicle level:

$$v_{ev-ref} = \int \gamma_{ev-ref} dt \quad (15)$$

The velocity is applied to the vehicle control. If a torque limitation occurs, this velocity will not be respected and the final distance will not be achieved. The position feedback will thus continue to provide velocity without stopping before the final point. A specific strategy for the calculation of the braking distance is proposed in [27] but it is not detailed in this paper.

In order to find the position of the velocity limitation of the road sections, the GraphHopperAPI [35] is used to call the OpenStreetMap database [36]. This API also includes the value of the slope at any position.

B. Validation of the driving cycle generator

1) Urban trip

An urban trip of 14 km is considered (Fig. 9). The velocity is limited between 30 and 50 km/h and there are many traffic lights. The maximal velocities of the different sections are derived from the API. The traffic stops are identified and added by hand (velocity limitation to 0 km/h). All these data are inputs for the simulation. The measured and generated velocities are plotted versus distance for a better comparison (Fig. 9). It is sure that traffic conditions impact the real velocity. The energy consumption is calculated to 2.4 kWh from simulation using the driving cycle generator. The energy consumption is calculated to 2.3 kWh from measurements on the real vehicle. Despite the velocity variations on the real driving cycle, the simulation has an error of only 3% in terms of energy consumption. Differences are, first, that the real velocity is lower than the velocity limits from the generator (per section), which decreases energy consumption. Second, the real velocity has more accelerations and decelerations, which increases energy consumption. These effects seem to compensate for each other.

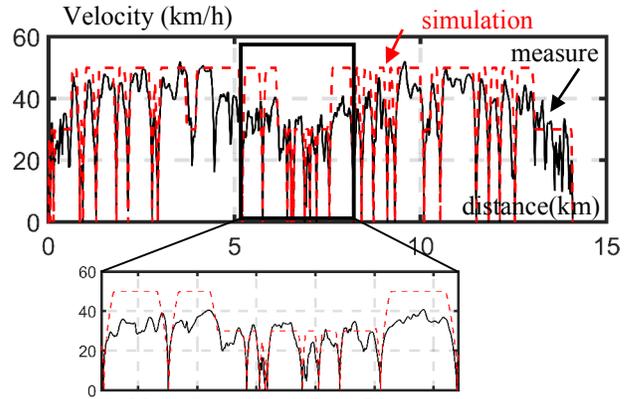


Fig. 9: Measured and generated velocities for the urban trip

2) Suburban trip

A suburban trip of 32 km is considered with maximal velocities of 50 km/h and 80 km/h for the different sections (Fig. 10). Only a few stops and roundabouts are observed. The velocity is less impacted by the traffic. The energy consumption calculated from the simulation and the driving cycle generator is 4.96 kWh. The energy consumption from the measurement on the real vehicle is 4.71 kWh. The error of simulation is about 5%. The real velocity is globally lower than the maximal velocity, but with less variation than the urban trip. This can explain the increase of the error.

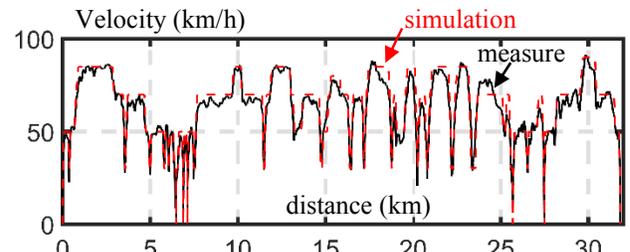


Fig. 10: Measured and generated velocities for the suburban trip

3) Highway trip

A highway trip of 19 km is considered with maximal velocities of 50 km/h and 130 km/h for the different sections (Fig. 11). The energy consumption calculated from the simulation and the driving cycle generator is 4.67 kWh. The energy consumption from the measurement on the real vehicle is 4.56 kWh. The error of simulation is about 3%. Most of the time both velocities are very close except some phase shift at the end of the trip.

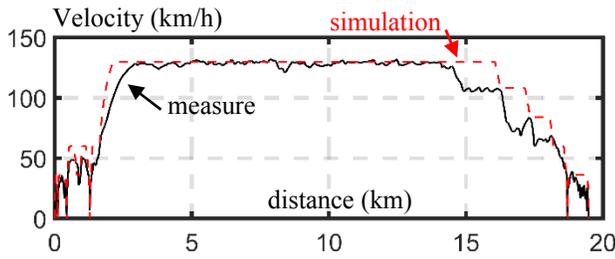


Fig. 11: Measured and generated velocities for the highway trip

V. IMPACT OF THE VELOCITY PROFILE

A new trip of 19 km combining urban, suburban and highway sections is considered (Fig. 12). It can be considered as a commuting trip for daily home-work travel. Only the generated driving velocity is used in this section for a fair comparison of the different cases (no impact of the traffic or the driver behaviour).

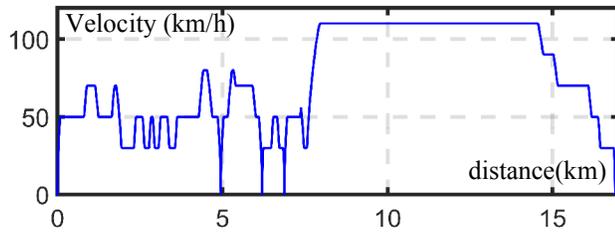


Fig. 12: Generated velocity for the mixed trip

A. Impact of the maximal velocities

In order to study the impact of velocity on energy consumption, the maximal velocities of the sections are changed without changing the acceleration. In case of limitations, the driving cycle generator adapts the travel to reach the final position.

All maximal velocities of the section are changed by -20%, -10%, +10% and +20% (Fig. 13). On one hand, decreasing the maximal velocities leads to increase travelling time (Fig. 14). In the base scenario, the trip duration is 19mn 08s while it is 22m 38s for the -20% of limitation. On the other hand, decreasing the maximal velocities leads to a decrease of the energy consumption of about the same percentage (Fig. 15). In normal operation, the energy consumption is 3.048 kWh, while it is 2.47 kWh for the -20% limitation.

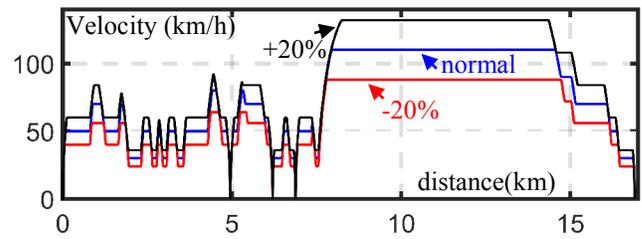


Fig. 13: Velocity for normal and -limitations for the mixed trip

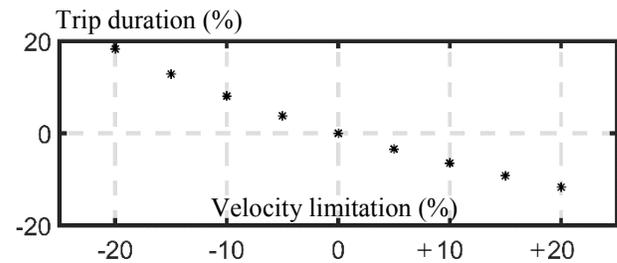


Fig. 14: Travelling time vs. velocity limitations

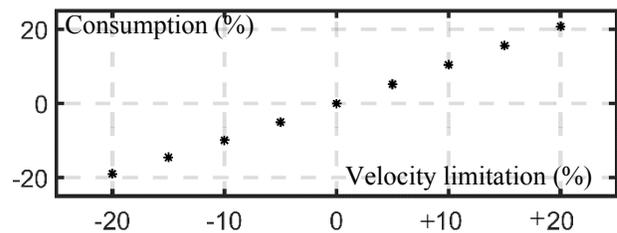


Fig. 15: Energy consumption vs. velocity limitations

B. Impact of the maximal accelerations

In order to study the impact of the acceleration on the energy consumption, the maximal acceleration is changed by a relative amount of -20%, -10%, +10% and +20%. Decreasing the maximal acceleration leads to a small increase in travelling time (Fig. 16). In the base case, the trip duration is 19mn 08s while it is 18mn 23s for the -20% limitation. In the same way, a decrease of the maximal acceleration has small impact on the energy consumption (Fig. 17). In normal operation, the energy consumption is 3.048 kWh, while it is 3.03 kWh for the -20% limitation.

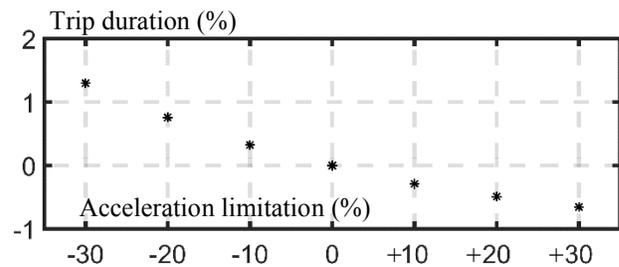


Fig. 16: Travelling time vs. acceleration limitations

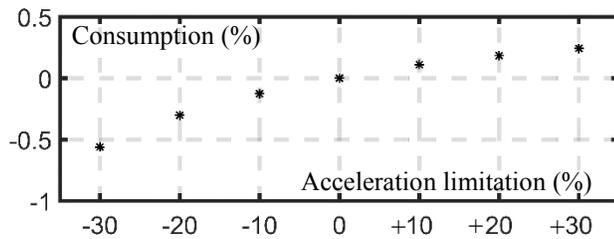


Fig. 17: Energy consumption vs. acceleration limitations

C. Study of the velocities limitation for all cycles

As only the maximal velocity has an important impact on the energy consumption, all the previous driving cycles have been studied only for velocity limitations of -20% and +20% (Table 1). It is difficult to compare the energy figures because of the difference of the distance and the number of stops. Only the percentage between the normal velocity limitation and the other limitations is of interest. It can be observed that the difference in energy consumption is lower for the urban use than the others. It can be explained by a lower average velocity. One part of the energy consumption is related to the drag force proportional to the square of the velocity. For higher velocity, this part will thus require more energy.

Table 1: Energy consumption for different cycles and velocity limitations

| Velocity limitation | Urban (kWh) | Suburban (kWh) | Highway (kWh) | Mix (kWh) |
|---------------------|--------------------|-----------------|----------------|------------------|
| -20% | 1.799 (-14.5 %) | 3.95 (-20%) | 3.57 (-24%) | 2.469 (-19%) |
| Ref | 2.105 | 4.96 | 4.67 | 3.047 |
| +20% | 2.439 (+16%) | 6.08 (+ 23%) | 5.79 (+24%) | 3.673 (+21 %) |

In order to highlight the interest of the developed generator, one case is also computed with a classical backward method (i.e without feedback). The highway trip and a velocity limitation of + 20 % is selected because of it leads to several limitations. In this case, the backward model leads to an energy consumption of 5.40 kWh. As the forward model has an energy consumption of 5.79 kWh (see Table 1), the backward model leads to an error of 6.7 %. This classical model will thus lead to underestimate the real energy consumption in this case.

VI. CONCLUSION

The impact of velocity profiles on energy consumption has been studied for electric vehicles. In order to have fair comparisons, a forward approach has been selected. In this case, any limitation can be taken into account and the driving cycle is recalculated to reach the final destination whatever the constraints are. In the classical backward approach, the limitations cannot be considered, which leads to an error in energy consumption.

First, a model of the traction of the Renault Zoe has been developed. The energy consumption has been validated by experimental tests on the real vehicle. Second, a driving cycle generator has been developed to adapt the speed profile for any

limitation to reach the final position. The generated cycles have also been validated by experimental test on the real vehicle.

Comparative studies have been achieved by coupling the traction model and the driving cycle generator. For the studied vehicle and the considered trips, the maximal velocity has a strong impact on the energy consumption. For a 20% increase of maximal velocity, an overconsumption of 15% to 25% is obtained. On the contrary, the maximal acceleration has a low impact on the energy consumption.

This method can be used to study the effect of other constraints such as the vehicle mass or the road slopes.

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APPENDIX: VEHICLE PARAMETERS

Table 2: Parameters of the simulation

| | |
|---------------------|------------|
| Weight of the car | 1468 kg |
| SCx | 0.75 |
| Wheel radius | 185/65 R15 |
| Gear ratio | 9.3 |
| Synchronous machine | 65 kW |
| Battery energy | 22 kWh |
| Battery voltage | 400 V |

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