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Difference between constant efficiency and loss map of an electric drive on fuel saving on a P-HEV

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Abstract – Retrofit electrification of engine-powered vehicles to plug-in hybrid electric vehicles is growing. Different hybrid solutions exist, but all of them must compromise between integration constraints, cost and efficiency. Full vehicle simulation, including the powertrain subsystems is thus mandatory. During the pre-design step, some sub-systems are not available. Use a simplified model for some subsystems is then common, to initiate the sizing process. In this paper, two electric drive models are compared: one using a torque and speed dependent loss map and another with a constant efficiency. Using Dynamic Programming, the fuel consumption is estimated for both models. The simple average efficiency leads to only 3% of errors on fuel saving. Such simple model can thus be relevant for the comparison of solutions in terms of fuel saving.

Keywords - *Control, Energetic Macroscopic Representation, Hybrid Electric Vehicles, Energy Management Strategy, Dynamic Programming*

I. INTRODUCTION

The electrification of vehicles is a consistent solution in the reduction of greenhouse gases to limit global warming. In order to electrify the global vehicle fleet faster, it would be interesting to retrofit conventional engine-powered vehicles to full electric vehicles or plug-in hybrid electric vehicles. But it is a challenge because the required modifications must be efficient and cheap.

There are already different studies of retrofitted vehicles in the literature [1], [2]. This hybridization is usually based on the addition of an electrical buffer, such as a battery, and an electrical drive. The position of hybridization depends directly on the feasible modifications. Among these possible various solutions, it may be difficult to identify the best compromise (location...) of the hybridization system on the fuel saving. Three main topologies exist for Hybrid and Plug-in Hybrid Electric Vehicles (HEV and P-HEV): series, parallel and series-parallel [3]. The selection of one architecture is mostly function of integration constraints (space), cost and targeted fuel savings. The parallel topology is often considered to retrofit, because it only requires adding components to an existing powertrain, simplifying the vehicle integration [4].

Simulation is an important step in the retrofit process to observe the potential performances of the vehicle after modification. Dynamic programming can be used to benchmark the influence of the electric drive performances in terms of fuel savings [5], [6]. To compare the different solutions vehicle simulations with models of all the powertrain subsystems must be performed. These models must include at least the components limits (torque, power,

etc..) and a loss model. However, it is sometimes difficult to get accurate models of these subsystems, especially during the preliminary sizing steps. Losses are typically obtained from test bench measurements in function of the torque and speed range of each electric drive. Then an accuracy loss map may be deduced from these tests. In the case of it is not possible to obtain a loss map of the electric drive because it is not available or does not exist. There are several possibilities to deduce an equivalent loss map. One method often used is a scaling adaptation called homothety which can be quickly implementable [16]. It is based on an existing loss map that we adjust with a factor. Homothety could be a good approach when the scaling factor is small [16]. Still, the electric drive losses data is not always available to build this static model at the beginning. In that case, an even simpler losses model must be used. A second more simplistic method is to use a constant efficacy. Moreover, it is quickly implementable, the maximal power can be easily adjusted in the mathematical model and can reduce the time design phase avoiding the pre-calculation of different loss map. In most cases, the use of a static model for the electric drive modelling for energy analysis is enough, the inertia and dynamics are neglected [7], [8], [9].

The aim of this paper is to compare the two-static modelling. The 1st model uses a loss map (function of torque and speed) deduce by experimental tests. The 2nd model uses a constant efficiency. This 2nd model represents the simplified case, when data is not available. Both models will be used in the same vehicle model, and compared over the same speed profile to observe the impact on the fuel consumption.

Section II presents the model of the retrofitted vehicle. Section III describes the optimal energy management strategy. Section IV compares the simulation results between the different electric drive models.

II. MODELLING OF THE STUDIED VEHICLE

A. The studied P-HEV and Modelling

The studied vehicle is a Peugeot 308 SW break converted to a P-HEV (Fig. 1). The global hybrid system is composed by: a 48V battery, 2 electrical machines (25 kW on the rear axle, 4 kW on the belt), a double stage gearbox with a dog-clutch for the rear machine and an on-board charger.

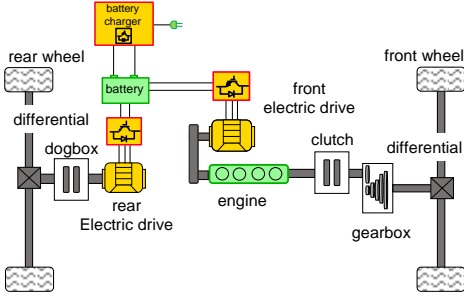


Fig. 1: Structural scheme of the studied P-HEV vehicle

This choice of this hybridization is based on the structure of the vehicle. Compared to other parallel hybrids typologies, the rear axle is easier to modify, and there is space in the trunk for the battery. A second 48V electric drive takes the place of the alternator and is always connected to the engine by the accessories belt. The 48V system is powerful enough to maximize fuel consumption benefits on WLTC, and using 48V instead of high voltage limits the need for specific safety systems. It simplifies the retrofit and lowers the hybridization cost.

The vehicle model is organized using Energetic Macroscopic Representation (EMR) [10]. EMR is a graphical formalism to organize the model interconnection of multidisciplinary energy systems such as one finds in a P-HEV. EMR is based on the principle of interaction. It respects the physical causality and a control structure can be systematically derived [10]. The formalism is based on four basic pictograms: 1) source element, 2) accumulation element, 3) element conversion element and, 4) coupling element (see appendix)

B. Front electrification model

Only the front hybridization equations is presented in this paper. All equations concerning the rear transmission are available in [11]. The DP includes front and rear modelling.

1) Parallel connection of the battery

A common battery supplies both electric drives. A simple model is used for the battery (an open voltage circuit and constant resistance). The total current is the sum of the currents of each electric drive.

$$\begin{cases} U_{bat} = U_{bat_re} = U_{bat_fr} \\ i_{bat} = i_{bat_re} + i_{bat_fr} \end{cases} \quad (1)$$

2) Front Electric Drive

The Front Electric Drive (F-ED) uses a static model. Losses are calculated based on the efficiency. The efficiency is either constant (case n°1) or function of the torque and speed of the machine (case n°2). The same modeling is used for the rear electric drive .

$$\begin{cases} i_{ed_fr} = \frac{\Omega_{ed_fr} T_{ed_fr}}{U_{bat_fr} \eta_{ed_fr}} \\ T_{ed_fr_ref} = T_{ed_fr} \end{cases} \quad (2)$$

$$\text{with } \begin{cases} \gamma_{em_fr} = 1 \text{ if } T_{ed_fr} \geq 0 \\ \gamma_{ed_fr} = -1 \text{ if } T_{ed_fr} < 0 \end{cases}$$

3) Belt connexion between F-ED and ICE

The ICE and the F-ED are connected by a belt. The total torque going to the gearbox is the sum of the ICE and F-ED torque. The F-ED speed is proportional to the ICE speed, using the pulley-belt ratio K_{belt} .

$$\begin{cases} T_{tot_fr} = T_{ed_fr} + T_{ice} \\ \Omega_{ice} = \Omega_{cs} \\ \Omega_{ed_fr} = \Omega_{cs} \cdot K_{belt} \end{cases} \quad (3)$$

4) Chassis

The chassis couples the force produced by the front F_{wh_fr} and rear axle F_{wh_re} to give the final speed.

$$\begin{cases} F_{tr} = F_{wh_re} + F_{wh_fr} \\ v_{veh_tr} = v_{wh_fr} = v_{wh_re} \end{cases} \quad (4.1)$$

$$\begin{cases} M_{veh} \frac{dv_{veh}}{dt} = F_{tot} - F_{res} \end{cases} \quad (4.2)$$

All these equations give the global EMR of the vehicle (Fig. 2).

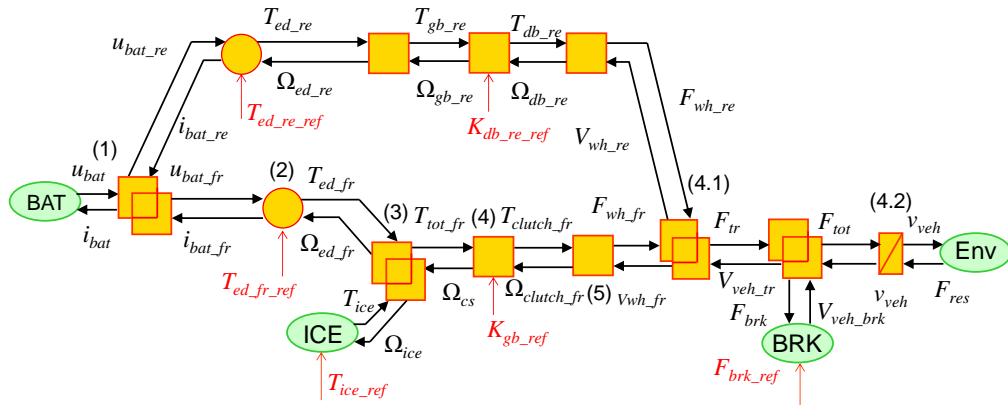


Fig. 2: EMR of the studied P-HEV vehicle

III. OPTIMAL ENERGY MANAGEMENT STRATEGY

To the different subsystems, an energy management strategy must be implemented.

A. Deduction of the backward model

Dynamic programming (DP) is an off-line optimization method using backward models. In this method, the principal dynamics are generally described following derivative causality. Mathematically, the minimization of the fuel consumption can be summarized in equation (16). With J^* the minimization of the cost function J [12], [13]

$$J^* = \min(J) = (\sum_{k=0}^{N-1} [L(x(k), u(k), k)]) \quad (16)$$

It represents the sum of each local transfer cost L (cost between two calculation steps) [14].

For this study, the aim is to minimize the fuel consumption of the engine on the WLTC class 3b cycle. EMR organizes the model in causality way and a backward model (Fig. 3) is deduced from the EMR-based model [14], [7]. The new backward model gives 5 control inputs which influence the distribution of power energy in the vehicle:

- $K_{ice_fed_dp}$: power split between F-ED and ICE
- K_{gb_dp} : gear shifting inputs
- $k_{rear_front_dp}$: power split between front and rear axle
- K_{break_dp} : brake power split
- K_{db_dp} : order opening for the dogbox

B. Global Implementation

The P-HEV model (Fig. 3) is directly implemented in the generic dynamic programming Matlab function [13]. In the model, we find two sets of variables: the control inputs and the state variable.

In the control inputs, $K_{ice_fed_dp}$, K_{gb_dp} , $k_{rear_front_dp}$ and K_{break_dp} are deduced directly by the dynamic programmed program (EMS n°1). Their values evolve between 0 and 1 except for the gearshift, K_{gb_dp} , which can take any integer value between 1 and 6 (discrete gearbox). The neutral state is managed directly by the mathematical model of the

vehicle. The last input K_{bd_dp} is deduced from an optimal rules-based strategy directly include in the DP to reduce the computation time [14]. The state variable corresponds here to the state of charge of the battery (SoC). P-HEVs usually have two distinct battery mode. The first mode consists of maximizing the electric drive, thus depleting the battery until it reaches at certain SoC. This mode is the so called "Charge depleting" mode (CD). The second mode keeps the battery to a constant SOC, alike any non-rechargeable HEV (Charge sustaining mode). In this study, the SoC must stay between 20% and 95% in charge depleting mode, and is regulated around 25% of SOC in charge sustaining. Both modes of operation will be simulated on the WLTC class 3b cycle [15].

C. Implementation of the electric drive models

In the first case, the front and rear electric drives are modelled with an efficiency map, function of the speed and torque of the machine (static model). The model of Fig. 4 is used for the dynamic programming.

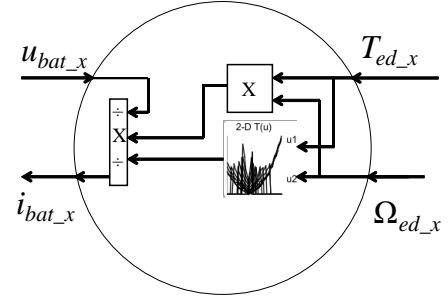


Fig. 4: Electric drive model - efficiency map

This method will be selected. A constant efficiency of 82% (common value [17]) is chosen for both electric drives (Fig. 5).

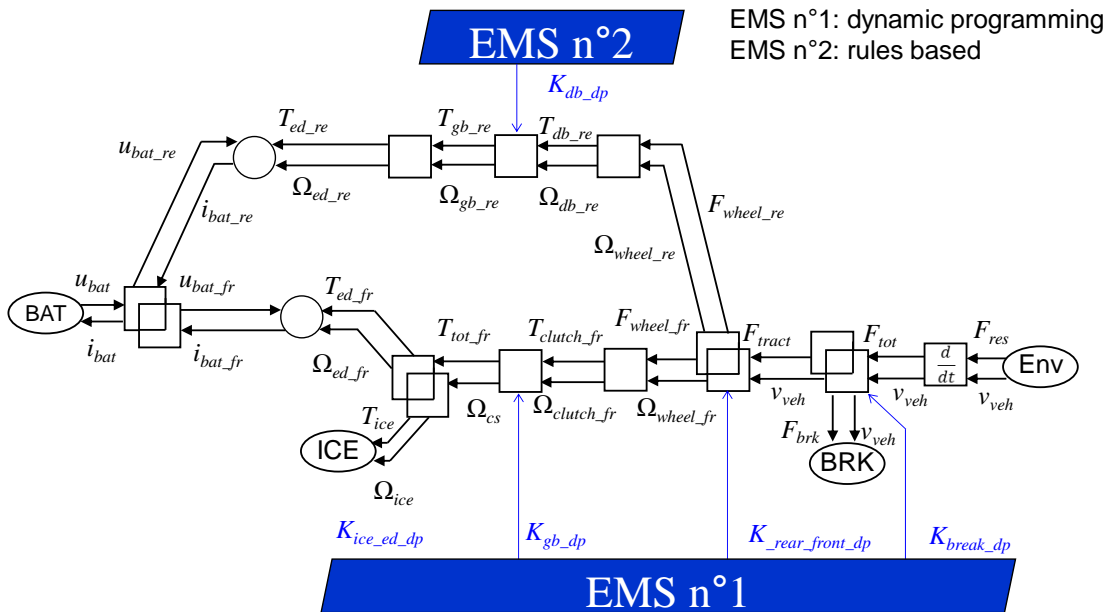


Fig. 3: Backward model of the P-HEV

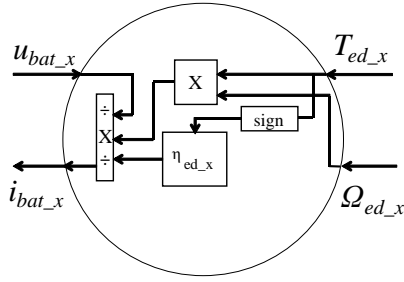


Fig. 5: Electric drive model - average efficiency

Generally, a different efficiency is used for motor and generator mode because losses generated in traction and generator modes are not symmetrical [8]. As a first step, we decided to use the same efficiency to keep the models as simple as possible.

III. SIMULATION RESULTS

In a first step, the charge sustaining mode is presented (Fig. 6) and secondly the charge depleting (Fig. 7).

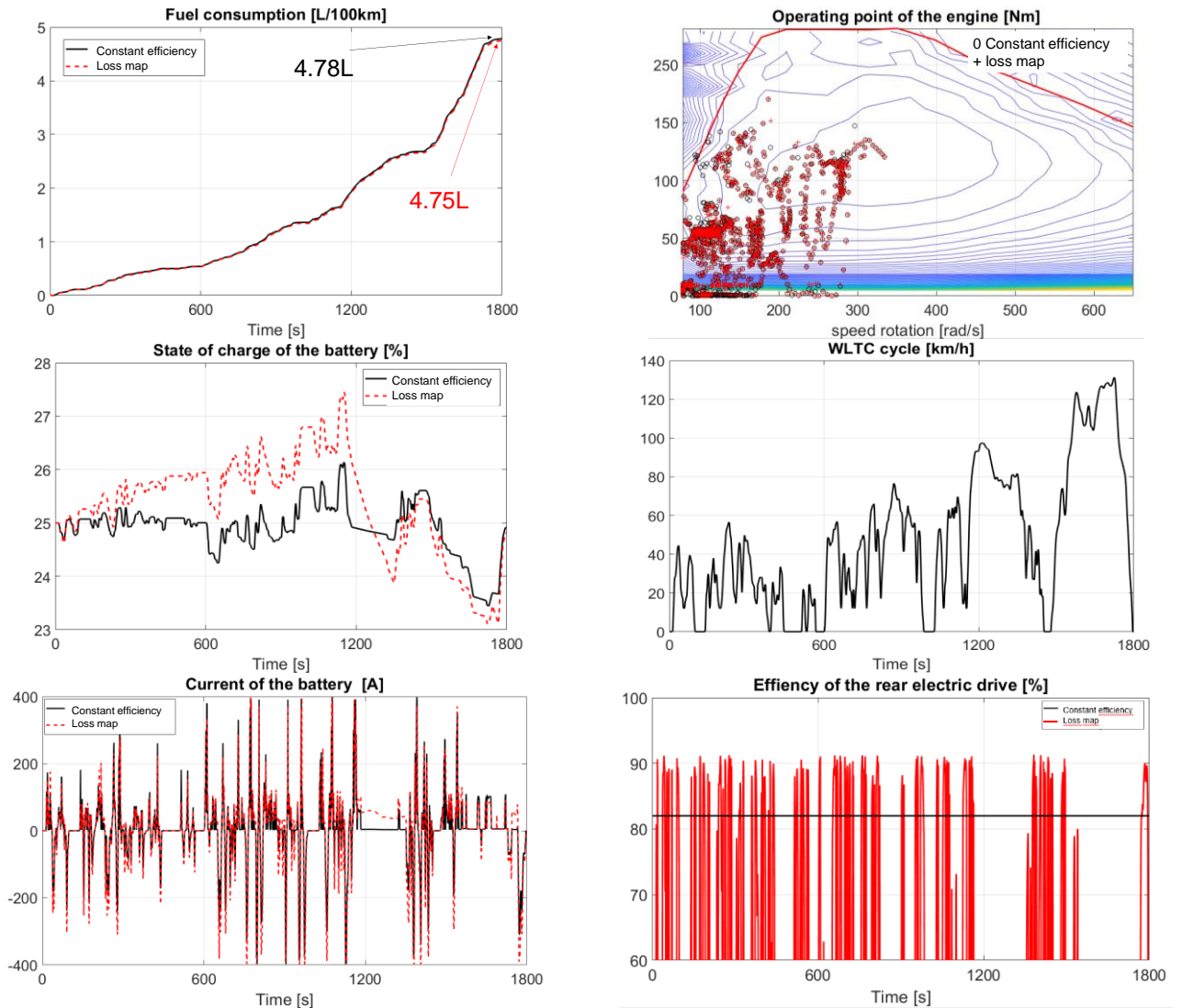


Fig. 6: Sustaining charge

Fuel consumption; Operating point of the engine; State of charge of the battery; WLTC cycle; Current of the battery; Evolution of the rear electric drive efficiency

A. Charge Sustaining mode

Fig. 6 shows the cumulated fuel consumption, the engine operating points, the battery state of charge, the vehicle velocity, the battery current and the rear electric drive efficiency for the rear electric drive. The loss map model is the reference to compare. The average efficiency model a fuel consumption of 4.78L/100km against 4.75L/100km for the efficiency map.

It represents an error of less than 1%. This is due to a similar torque request from the engine, resulting in a small impact on fuel consumption.

The state of charge curve evolve differently but the final SOC is still the same in both. The battery will keep the same behaviour (charge/discharging) but with different powers involved. Despite the differences in battery SOC variation, this difference in energy results in an allowable error in consumption in the case of a first step. Moreover, the current curve shows that the current peaks are more important with the losses mapping than with the average efficiency. The constant efficiency then tends to underestimate the currents mainly at the time of strong call of current. The bottom right graph shows the rear electric

drive efficiency evolution (main propulsion) give by the ratio between the mechanical and electrical power. The value is comprised between 60% and 100% in contrast at a constant efficiency which not evolve.

B. Charge Depleting

Fig. 7 shows the different results obtained during the charge-depleting test. The constant efficiency model gives a fuel consumption of 2.95L/100km against 2.87L/100km for the loss map. It represents an error of around 3%. For the loss map electric drive model, the final SoC is 50% against 47.6% for the constant efficiency model. It represents an error of 5% on the final SoC. This SOC variation is due to the efficiency difference between both models. In charge depleting, the strategy maximizes the electrical power use. Consequently, the electric machines are used at higher power than in CS, often close to their limits. Furthermore, if we continue to simulate until in DC the SoC reach the minimal SoC, the difference in available electrical energy will be more important and therefore will participate to increase error on the consumption (switch on the engine).

A second important aspect, if the mesh grid of the torque is increasing the accuracy near the boundary could tend to reduce this gap between the two SoC. On the other hand, the calculation time will increase. Especially if the system has a lot of input controls and state variables to handle. In this study, a compromise is made between the mesh size and the time calculation. In the case of DC, the used of a constant efficiency seems to be less adapted because more important errors are obtained. In general, an error of 5% is acceptable in the literature, moreover at a pre-design stage the error is acceptable on fuel economy.

IV. CONCLUSION

In order to select a hybridization solution for retrofitting vehicles, an evaluation of the fuel saving is required. A complete vehicle simulation is needed using a vehicle and its sub-component models and its energy management strategy. However, at the pre-design stage, accurate losses models of the electric drive are usually not available. In this paper, the case of a real vehicle retrofit is studied. Two electric drive models are used, using either a loss map obtained on test bench or a constant efficiency. The accuracy of the constant efficiency model, will be

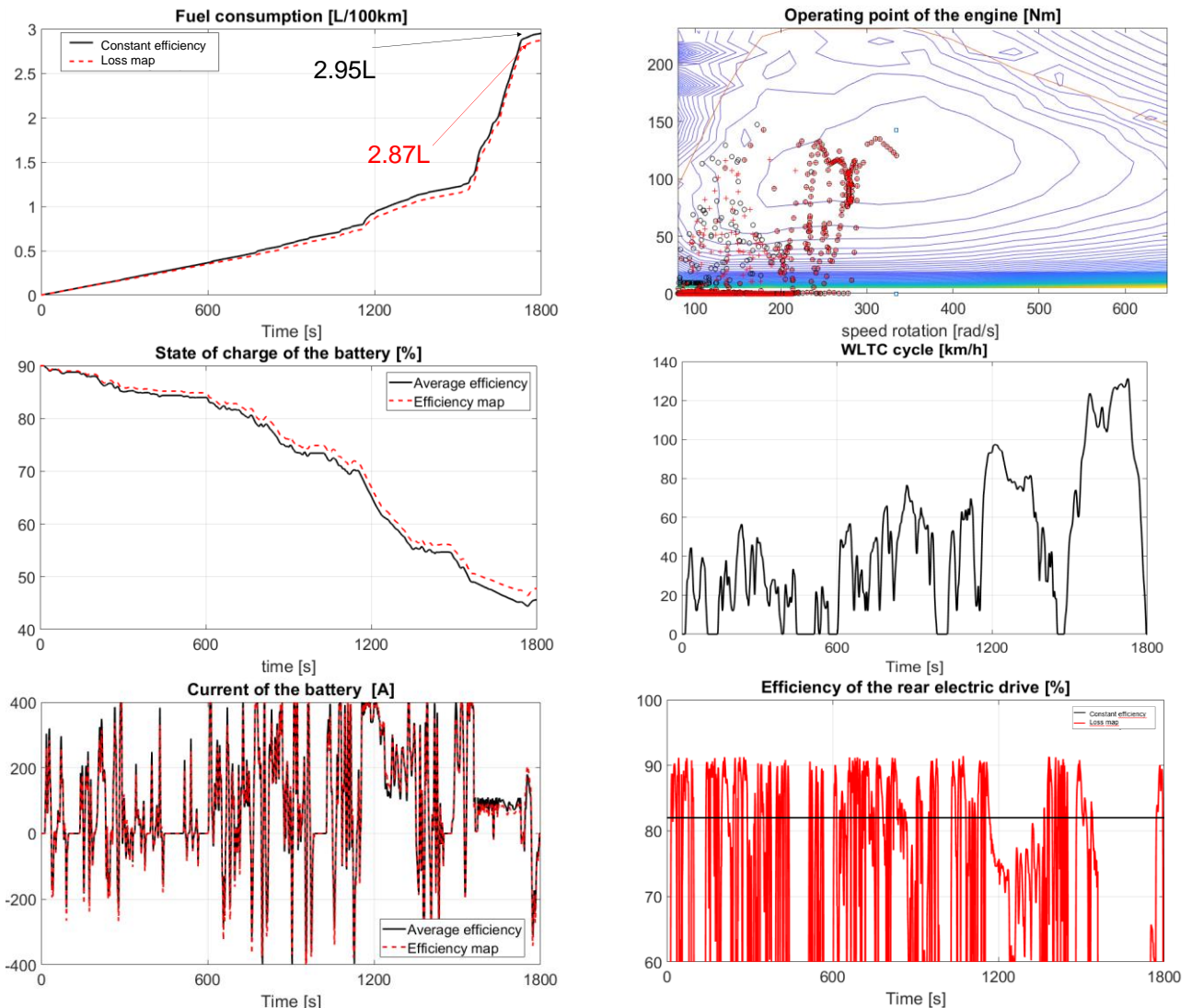


Fig. 7: Depleting charge
 Fuel consumption; Operating point of the engine; State of charge of the battery; WLTC cycle; Current of the battery; Evolution of the rear electric drive efficiency

compared to the map-based model. The objective is to demonstrate the use of constant efficiency model for future retrofits.

For sustaining charge, the efficiency will not strongly influence the fuel consumption of the vehicle but the battery behaviour will be different (power). For the SC, a constant efficiency is sufficient at a pre-design stage to evaluate the fuel gain, the energy to be loaded in the battery and to deduce an energy strategy. On the other hand, it is not enough precise to deduce the maximum current involved.

For the depleting charge, the result is a bit different. The constant efficiency is enough to obtain a correct approximation of the fuel gain and to define a strategy. On the other hand, the error at the SoC estimation level is getting bigger and start to be less realistic but 5% at the step of pre-design stay correct on the energy. Moreover, in CD, the dynamic programming gives us a good idea of the mechanical power needed for the electric drives.

To conclude, a constant efficiency is coherent for SC to evaluate performances in pre-design. However, it not looks adapted for DC. One possibility is to use a different constant efficacy between SC and DC to reduce the error. More works and investigation need to be achieved to conclude correctly the impact of an average efficiency in DP charge.

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Appendix: EMR Pictograms

