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Hybrid Powertrain Concept Evaluation Using Optimization

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Abstract—This paper describes automatic evaluation of series-parallel (combined) powertrain models using optimization. The novelty with the approach is the possibility to work with non-transparent industrial vehicle models, hidden for intellectual property reasons. The contribution extends the functionality of a recently developed tool for parallel hybrids, with the ability to operate on combined powertrains. Given the user inputs, which include dynamic vehicle model and driving cycle, the tool first produces a simplified powertrain model in the form of static maps, before dynamic programming is used to find an optimal torque split that minimizes fuel consumption. The main use of the tool is to evaluate the potential of a powertrain configuration. The paper contains an illustration of the tool operation on a non-transparent industrial vehicle model. The only requirement on the model is to provide access to some general variables and that it has a torque split that can be fully controlled *Copyright Form of EVS25***.**

Keywords—hybrid electric vehicle, powertrain evaluation, optimal control, non-transparent model, dynamic programming

1. Introduction

Hybrid Electric Vehicles (HEVs) have brought much attention recently. The increased interest for hybridization of the conventional powertrains is mainly due to the potential for reduced energy consumption in both, economic and environmental point of view, without compromising performance and drivability. HEVs, compared to conventional vehicles that possess a single, thermal energy source, are complemented with additional source of electric energy. The HEVs' powertrains include internal combustion engine (ICE), one or more electric machines (EMs) and an energy buffer, typically a battery or super capacitor, which depending on their configuration are commonly divided in three different topologies: series, parallel and series-parallel (combined). The powertrain topologies manly differ in the available degree of freedom in choosing the ICE operating point, but their capability to improve fuel economy can be commonly described by 1) the possibility to recover braking energy by using the EMs as generators and storing the energy in the buffer, 2) ability to shut down the ICE during idling and low load demands and 3) the possibility to run the ICE at more efficient load conditions while storing the excess energy in the buffer. For a detailed overview on hybrid vehicles, see, eg, [1].

The powertrain performance, example fuel consumption, is typically evaluated by driving cycle simulation, ie given a vehicle and powertrain model, simulations are done trying to follow a predefined velocity profile, [2]. A problem with this approach is the fact that this requires, at least for hybrid powertrains, a control strategy (an energy management strategy). The evaluation of the powertrain will become an evaluation of the complete system (powertrain and energy management strategy) and not the powertrain itself. In fact, a badly tuned or designed energy management strategy can deteriorate the potential of a promising powertrain concept.

This work describes strategies for automatic evaluation of HEV powertrain models using optimization. The strategies extend the functionalities of a recently developed tool [3], CAPSimO, for estimating the potential of parallel powertrain configurations, with the ability to operate on series-parallel powertrains. Given the user inputs, which include dynamic vehicle model and driving cycle, the tool first produces a simplified powertrain model in the form of static maps, before dynamic programming (DP), see eg [4], is used to find the optimal power split that minimizes fuel consumption. In DP each state transition is associated with a cost and this cost can be obtained using simulation of the powertrain model. A weakness of DP is that the computational time increases exponentially with the number of state variables [4]. For this reason, only few slow varying states are kept in the simplified powertrain model. This can be done since transients do not influence fuel consumption significantly, [1], [6]-[8].

The power split obtained by the tool is optimal only for the given driving cycle, since it is assumed that the demanded torque and vehicle speed trajectories are perfectly known. This control is not to be implemented in real time, but used for assessment of powertrain capabilities to meet the targets and constraints early in the powertrain design process. Hence, the main use of the tool is to evaluate the potential of a powertrain configuration. The novelty in this approach is the possibility to work on non-transparent industrial vehicle models, hidden for intellectual property reasons. It is not necessary to have details of the model; the only requirement on the model is to provide access to some general variables and that it has a torque split that can be fully controlled.

The paper is outlined as follows: tool overview and requirements on the dynamic model are discussed in Section 2; an example of the tool operation is demonstrated on a problem formulated in Section 3; the

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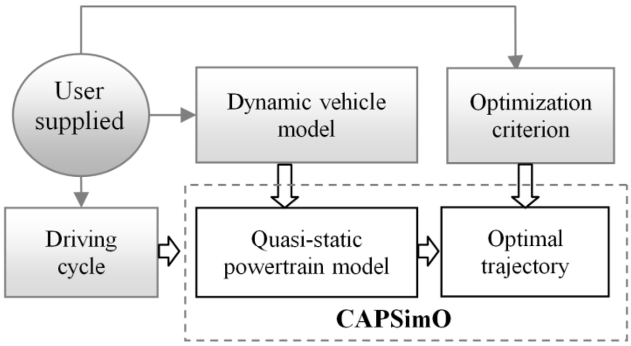

Figure 1: Block diagram of the tool. Vehicle model, driving cycle and optimization criterion are given by the user.

results are discussed in Section 4; the paper is ended with conclusion in Section 5.

2. Tool Overview

This section gives overview of the tool and the requirements the dynamic model needs to comply in order to be used by the tool.

The tool, which is implemented in Matlab/Simulink, consists of two modules, one for generation of quasi-static (QS) powertrain model and another for power split optimization, see Figure 1. Input data to the tool is supplied by the user and these are dynamic vehicle model, driving cycle and optimization criterion. After user information is supplied, the tool generates a QS model where most of the dynamics is removed. This is done by simulating the dynamic model at gridded constant input values. The purpose of using a QS model in the second step, where the actual optimization takes place, is to obtain faster simulation, without losing much of the model accuracy.

2.1. Driving Cycle

The driving cycle is completely described by the longitudinal demanded velocity, $v_{dem}(t)$, and road slope, $\alpha(t)$

$$r(t) = [v_{dem}(t)\ \alpha(t)]^T. \tag{1}$$

The velocity profile used in this study is taken from the New European Driving Cycle; see the top row of Figure 3. The road is assumed flat.

2.2. Dynamic Vehicle Model

The dynamic vehicle model comprises a controller f_{ctrl}, consisting of a driver model and power split controller, continuous and discrete vehicle dynamics $f_{veh,c}$, $f_{veh,d}$ and available outputs g_{veh}. The vehicle dynamics include a model of a series-parallel powertrain, configured as a mild parallel hybrid powertrain propelling the front wheels, in addition to an electric machine propelling the rear wheels. The electric machine on the rear axle is supplied from the same energy buffer as the electric machine on the front axle, see Figure 2.

In general, the vehicle model is nonlinear and can be expressed as

$$\begin{aligned}
&u(t) = [u_{ICE}\ u_{EM1}\ u_{EM2}\ u_{brk},\ldots\\
&\quad F_{load}(t)\ \tau_{load}(t)\ u_r(t)]^T\\
&x_d(t) = [\gamma(t)\ x_{dr}(t)]^T = \text{constant for}\\
&\quad t \in (kh,(k+1)h]\\
&x_d\big((k+1)h\big) =\\
&\quad f_{veh,d}\big(x_c(kh), x_d(kh), u(kh), r(kh)\big)\\
&\dot{x}_c(t) = [\dot{soc}(t)\ \dot{T}(t)\ \dot{\omega}_s(t)\ \dot{x}_{cr}(t)]^T =\\
&\quad f_{veh,c}\big(x_c(t), x_d(t), u(t), r(t)\big)\\
&y(t) = [\dot{m}_f(t)\ v_{veh}(t)\ F_{veh}(t)\ \tau_s(t)]^T =\\
&\quad g_{veh}\big(x_c(t), x_d(t), u(t), r(t)\big)\\
&u_r(t) = f_{ctrl}\big(x_c(t), x_d(t), r(t)\big)
\end{aligned} \tag{2}$$

where $x_c(t)$ are continuous states consisting of battery state of charge $soc(t)$, ICE coolant temperature $T(t)$, shaft speed between the EM1 and the transmission $\omega_s(t)$, and states $x_{cr}(t)$ that will be removed from the QS model. The discrete states $x_d(t)$ consist of gear $\gamma(t)$, and states $x_{dr}(t)$ that will be removed from the QS model. The model outputs $y(t)$ consist of standard signals, such as fuel flow $\dot{m}_f(t)$, vehicle velocity $v_{veh}(t)$, traction force at the wheels $F_{veh}(t)$ and torque between the EM1 and the transmission $\tau_s(t)$. The control signals $u(t)$ consist of signals $u_r(t)$ that will be removed from the QS model, additional binary inputs u_{ICE}, u_{EM1}, u_{EM2} and u_{brk} that control the availability of the power sources and the friction brakes, and disturbances in the longitudinal vehicle dynamics $F_{load}(t)$ and $\tau_{load}(t)$. The input force $F_{load}(t)$ and torque $\tau_{load}(t)$ are zero normally, but are used by the tool to add an extra load in simulations. The integer variable k is the sample index and h is the sampling interval that may not be constant.

The states $x_{cr}(t)$ and $x_{dr}(t)$, the inputs $u_r(t)$ and the functions $f_{veh,c}$, $f_{veh,d}$, g_{veh} and f_{ctrl} in (2) can be hidden from the user as long as the model provides:

- Access to the derivative of the states that are to be kept in the QS model, in this case $\dot{soc}(t)$, $\dot{T}(t)$ and $\gamma(t)$. Access to $\dot{\omega}_s(t)$ is not required.
- Access to the outputs $y(t)$.
- Possibility to fully control the torque split. This requires additional binary inputs in the torque split controller to enable/disable the ICE, $u_{ICE}(t)$, the EM1, $u_{EM1}(t)$, the EM2, $u_{EM2}(t)$ and the friction brakes, $u_{brk}(t)$. Alternatively, instead of the binary inputs, the tool may use other control signals, such as demanded torque from the power sources and the friction brakes, if the model provides access to them. The tool then decides whether or not to ground these signals, see [3] for details.
- Possibility to add external value to the states that will be kept in the QS model. For example, in the case of $\dot{soc}(t)$ this will mean external charging/discharging the battery and is used to keep $soc(t)$ constant although energy is taken out of the battery. This is explained in details in [3].
- Possibility to add an external vehicle load in simulations, in this case external force $F_{load}(t)$ acting at the wheels and torque $\tau_{load}(t)$ acting on the shaft between the transmission and EM1.

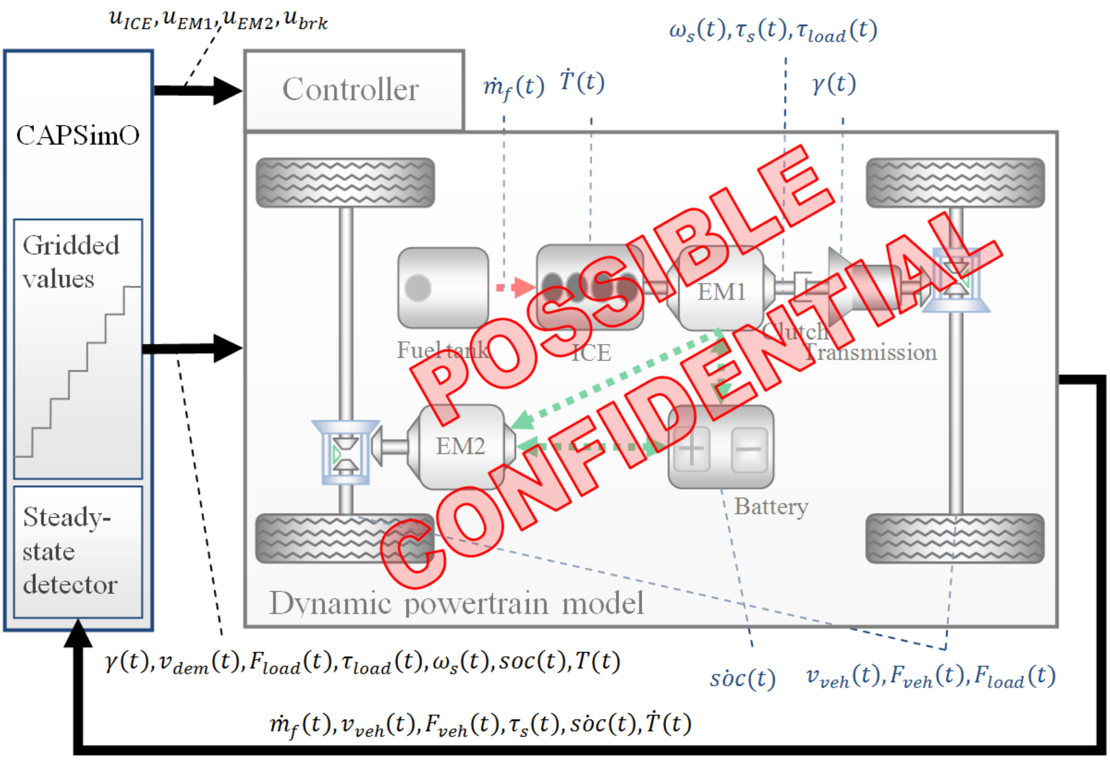

Figure 2: Dynamic powertrain model and the simplification process. The dynamic model, which may not be transparent, includes combined HEV powertrain. The tool decides the availability of the power sources and the friction brakes and simulates the dynamic model with constant gridded values for the inputs and the states that will be kept in the QS model.

2.3. Quasi-Static Powertrain Model

The QS model is a discrete time, backward simulation model that satisfies the following power balance equation

$$\begin{aligned} &\left(\tau_{ICE}(k) + \tau_{EM1}(k)\right)\omega_s(k) = \tau_s(k)\omega_s(k) \\ &\left(F_{EM2}(k) + F_{trn}(k) + F_{brk}(k)\right)v_{veh}(k) = \\ &\quad F_{veh}(k)v_{veh}(k) \end{aligned} \tag{3}$$

where $\tau_{ICE}(k)$ is the ICE torque, $\tau_{EM1}(k)$ is the EM1 torque, $F_{EM2}(k)$ is the force of EM2, $F_{trn}(k)$ is the transmission output force and $F_{brk}(k)$ is the force in the friction brakes. The power demanded from the QS model over a given driving cycle is the true output power of the dynamic model, $F_{veh}(k)v_{veh}(k)$, simulated over the same driving cycle, where we assume that the controller in the dynamic model closely follows the demanded velocity.

The QS model comprises four lookup tables from which f_{ICE}, f_{EM1} and f_{EM2} describe the three cases where the dynamic model is powered only by ICE, only by EM1 or only by EM2; and efficiency map of the transmission, f_{trn}, obtained when both ICE and EM1 power the vehicle. The QS model is expressed as

$$\begin{aligned} &\left[\dot{m}_f(k)\ \dot{T}(k)\ \dot{soc}_{aux}(k)\right]^T = \\ &\quad f_{ICE}\left(\omega_s(k), \tau_{ICE}(k), T(k)\right) \\ &\dot{soc}_{EM1}(k) = \\ &\quad f_{EM1}\left(\omega_s(k), \tau_{EM1}(k), soc(k)\right) \\ &\dot{soc}_{EM2}(k) = \\ &\quad f_{EM2}\left(v_{veh}(k), F_{EM2}(k), soc(k)\right) \\ &[\omega_s(k)\ \tau_s(k)]^T = \\ &\quad f_{trn}(\gamma(k), v_{veh}(k), F_{trn}(k)) \\ &\dot{soc}(k) = \\ &\quad \dot{soc}_{aux}(k) + \dot{soc}_{EM1}(k) + \dot{soc}_{EM2}(k) \end{aligned} \tag{4}$$

where $\dot{soc}_{aux}(k)$, $\dot{soc}_{EM1}(k)$ and $\dot{soc}_{EM2}(k)$ are derivative of the battery state of charge that correspond to the power used by the auxiliary devices, EM1 and EM2 respectively. Note that some variables in the QS model use the same nomenclature as the corresponding variables in the dynamic model.

The states and control variables in the QS model are

$$\begin{aligned} &x_q(k) = [T(k)\ soc(k)\ \gamma(k)\ on(k)]^T \\ &u_q(k) = [u_{on}(k)\ u_\gamma(k)\ \omega_s(k)\ \tau_{ICE}(k), \ldots \\ &\quad F_{EM2}(k)\ \tau_{EM1}(k)\ F_{brk}(k)]^T \end{aligned} \tag{5}$$

where $on(k)$ is the ICE on/off state, $u_{on}(k)$ is the control that switches the ICE on/off state and $u_\gamma(k)$ is the control that shifts gears. The shaft speed $\omega_s(k)$, which was used as a state in the dynamic model, is a control signal in the QS model.

Simulation of the QS model entails linear interpolation of the underlying three dimensional maps f_{ICE}, f_{EM1}, f_{EM2} and f_{trn}.

2.4. Automatic Model Simplification

The tool generates the map f_{ICE} in (4) automatically by simulating the dynamic model over a set of gridded values of $\tau_{load}(t)$, $\omega_s(t)$ and $T(t)$, having only ICE to power the vehicle, ie $\{u_{ICE}, u_{EM1}, u_{EM2}, u_{brk}\} = \{1,0,0,1\}$. For the rest of the control signals, $u_r(t)$, we choose to rely on the controller and let them keep the values set by f_{ctrl}. If this controller, which may not be known, is good, equilibrium will be reached fast. The map outputs are read under stationary conditions, where equilibrium is automatically detected by the tool. See [9] for detailed description of the steady-state detector. Values saved as map inputs are $\omega_s(t)$, $T(t)$ and $\tau_s(t)$.

The map f_{EM1} is generated in a similar manner, with the difference that only EM1 is allowed to power the vehicle, ie $\{u_{ICE}, u_{EM1}, u_{EM2}, u_{brk}\} = \{0,1,0,1\}$. The dynamic model is simulated over gridded values of $\tau_{load}(t)$, $\omega_s(t)$ and $soc(t)$. Values saved as map inputs are $\omega_s(t)$, $soc(t)$ and $\tau_s(t)$.

For the generation of f_{trn}, both ICE and EM1 power the vehicle, ie $\{u_{ICE}, u_{EM1}, u_{EM2}, u_{brk}\} = \{1,1,0,1\}$. The tool simulates the vehicle with gridded values of $F_{load}(t)$, $v_{dem}(t)$ and $\gamma(t)$. The demanded speed $v_{dem}(t)$ is given to the model through the driving cycle $r(t)$, generated by the tool. The road altitude is constant throughout the whole simulation, since instead of the longitudinal slope, $F_{load}(t)$ is used to give extra load to the model. Values saved as map inputs are $F_{veh}(t)$, $v_{veh}(t)$ and $\gamma(t)$.

Gridded signals for the generation of f_{EM2} are $F_{load}(t)$, $v_{dem}(t)$ and $soc(t)$. The dynamic model is propelled only by EM2, ie $\{u_{ICE}, u_{EM1}, u_{EM2}, u_{brk}\} = \{0,0,1,0\}$, where the tool disables the friction brakes to find the maximum braking force of EM2. Values saved as map inputs are $F_{veh}(t)$, $v_{veh}(t)$ and $soc(t)$.

Special measures are taken for speeding up the map generation process. The tool automatically detects equilibrium, detects the operating region of the powertrain components and sorts the gridded values such that demanded power gradually increases. This is further explained in [9].

The process of the generation of a QS powertrain model is illustrated in Figure 2.

2.5. Optimization Criterion

The tool offers a number of optimization criteria to choose from. An optimization criterion is defined by an objective function that need to be optimized and a list of constraints. The optimization criterion in this study includes minimization of fuel consumption plus additional terms that shape the states trajectory. It is given as

minimize

$$\begin{aligned}
&J\big(x_q(0),0\big) = \\
&\quad \sum_{k=0}^{N-1} \psi\left(x_q(k), x_q(k+1), \dot{m}_f(k)\right) h \\
&\psi\left(x_q(k), x_q(k+1), \dot{m}_f(k)\right) = \\
&\quad c_1 \dot{m}_f(k) + \\
&\quad c_2 (\max\{soc(k) - 0.6, 0\} + \\
&\quad \max\{0.4 - soc(k), 0\})^2 + \\
&\quad c_3 |on(k+1) - on(k)| + \\
&\quad c_4 \min\{|\gamma(k+1) - \gamma(k)|, 1\}
\end{aligned} \tag{6}$$

subject to

constraints (3), (4) and,

$$soc(0) = 0.5$$

$$soc(0) = soc(N) \tag{7}$$

$$u_q(k) \in \left[u_{q,min}\big(u_q(k), x_q(k)\big), u_{q,max}\big(u_q(k), x_q(k)\big)\right] \tag{8}$$

$$x_q(k) \in \left[x_{q,min}, x_{q,max}\right] \tag{9}$$

where c_1-c_4 are user adjustable penalty coefficients and N is the total number of samples. The coefficient c_2 weights the cost for the battery wear by penalizing the battery state deviation outside the allowed 20% interval placed symmetrically around the 50% charge. The coefficients c_3 and c_4 penalize frequent ICE on/off switches and frequent gear shifts. The constraint (7) preserves charge sustain operation. The constraint (8) represents the physical limits of the powertrain components and contains the following limitations: the braking force cannot be positive; the allowed ICE on/off shift is $u_{on} = \{-1,0,1\}$; up shift of more than two gears is forbidden, $u_\gamma(k) = \{-6, \dots, 2\}$; the torque of the transmission, ICE, EM1 and the force of EM2 are limited with bounds, found automatically by the tool, which are function of the inputs in the corresponding lookup tables. The state limits (9) consist of bounds on the battery state, the ICE coolant temperature and allowed values for the ICE on/off state, $on(k) \in \{0,1\}$, and gear, $\gamma(k) \in \{0, \dots, 6\}$. The sampling interval h is constant in the QS model.

2.6. Optimal Trajectory

The next step in the tool, after the model simplification, is the optimization of the energy management. The tool produces optimal control and state trajectory that minimize the cost (6). This kind of problem is conveniently solved using dynamic programming since it handles nonlinearities and constraints in a straightforward way [5]. Dynamic programming uses the Bellman's principle of optimality, [4], and solves the problem via backwards recursion

$$\begin{aligned}
&J^*\big(x_q(N), N\big) = c_5 (soc(N) - soc(0))^2 \\
&J^*\big(x_q(k), k\big) = \\
&\quad \min\left\{\psi\left(x_q(k), x_q(k+1), \dot{m}_f(k)\right) h + \right. \\
&\quad \left. J^*\big(x_q(k+1), k\big)\right\}
\end{aligned} \tag{10}$$

where $J^*\big(x_q(k), k\big)$ is a four dimensional cost-to-go function from sample k to the final sample N and c_5 is a penalty coefficient, usually a large number. The cost function is calculated over a grid of the states. The grid resolution determines the accuracy of the solution. For state values that do not lie on the grid nodes, the cost is obtained by linear interpolation in J^*. Grid in the control signals is also needed for finding the next possible state values, given the current state and time instant. There are four states and five control signals that ought to be discretized, see (5), where the rest two control signals, $\tau_{EM1}(k)$ and $F_{brk}(k)$, are found directly from (3).

3. Concept Evaluation

This section formulates a problem that demonstrates the tool operation on two non-transparent dynamic models of a passenger vehicle. Both models are modeled in Matlab, Simulink, and use variable step-size solver. The first model includes a combined powertrain and is described as in (2). The only difference in the second model is that it does not include the EM2; hence it operates as a mild parallel HEV. The problem of this study is to investigate how big improvement in fuel consumption a full hybridization can give, without considering the economic cost of the additional components. Both models fulfill the requirements listed in Section 2.2.

4. Results

This section discusses the results of the powertrain evaluation of the two non-transparent models supplied by the user. The optimization criterion, chosen by the user, is as presented in Section 2.5.

4.1. Optimal State Trajectories

The tool automatically simplified the dynamic models and optimized the criterion over the New European Driving Cycle. The resulting optimal state trajectories are given in Figure 3. The left column in Figure 3 gives the optimal state trajectories of the combined powertrain. The right column represents the results of the mild parallel powertrain. These results are further grouped in three rows, where the first row shows the optimal state trajectories for a cold ICE start, $T(0) = 30℃$, and penalties on frequent gear shifts and ICE on/off turns. The second row presents the optimal state trajectories with hot ICE start, $T(0) = 100℃$, and also penalties for frequent switching. In the third row, a cold ICE start is considered but frequent switching is not penalized, ie $c_3 = 0$ and $c_4 = 0$ in (6).

It can be noticed that there are similarities in the results of the different powertrains. Frequent gear shifts and ICE on/off switching are prevented when penalized in the cost function. This causes oscillatory behavior in the battery state, within the allowed 20% interval, since the optimal control tries to keep ICE off, or on, for longer time periods. While the ICE is off, the vehicle is driven by the EMs and the battery is discharging, until the ICE is turned back on to recharge the battery. This is especially evident for the combined powertrain. Without the switching penalties the battery state is steadier. The combined powertrain keeps $soc(k)$ close to the 50% charge for most of the driving cycle, while the mild powertrain slowly depletes the battery until the lower bound is reached, only to quickly recharge it before the end of the driving cycle.

The optimal control prefers shifting two gears up when frequent gear shifts are not desired. This happens because the penalty for fast gear shifting in the cost function can be understood as the energy wasted in the gear shifting transient. Hence, two gears up-shift (ecology friendly driving), which is equivalent to only one shifting transient, will increase the overall system efficiency.

The mild parallel powertrain reaches high ICE coolant temperature faster. Although the ICE has better efficiency on higher temperatures, the disability to recuperate braking energy makes this powertrain less efficient than the combined powertrain, see Table 1. There is no evident difference in the optimal control for the two cases of cold and hot ICE start, except that in the latter case the vehicle consumes slightly less fuel, see Table 1.

The combined powertrain never uses EM1 alone to power the vehicle. This is due to the clutch placement, see Figure 2, since when EM1 drives the vehicle, it will also need to rotate the ICE. This will waste additional energy and it will therefore lower the system efficiency. The better solution is to use the EM2 instead.

4.2. ICE Operating Points

The ICE operating points for the case of cold ICE start and no frequent switching are given in Figure 4. It can be noticed that the combined powertrain operates either in series mode (open clutch and EM1 used as generator), or recharging mode (the ICE provides more power than needed and the surplus is used to recharge the battery). Series mode is a reasonable choice when the battery has low energy level. Typical example would be charging the battery at stand-still or cruising. As can be seen in Figure 4 this mode occurs only at specific operating point. This is the point of optimal efficiency of the combined, ICE-EM1, unit.

The vehicle operates in recharging mode for most of its trip. This is not surprising, since running the ICE with higher load at some instance and keeping it off at other, increases the system efficiency and therefore decreases fuel consumption. It is clearly visible in Figure 4 that the combined powertrain never runs the ICE with zero torque and non-zero speed. This confirms what was previously concluded from Figure 3 that there is no incentive in driving with EM1 alone, when EM2 is also present in the vehicle. As a comparison, the mild parallel powertrain has no other choice to empty the accumulated battery power, but to rotate the ICE as well.

The combined powertrain is never operated in boosting mode (the EM1 and EM2 assist the ICE in delivering the power demand). This is because the ICE is obviously designed to handle much higher power requests and could drive the cycle even without the battery. This raises curiosity of evaluating alternative powertrain in which ICE is downsized by at least one quarter of its maximum power.

There are also no operating points where ICE alone operates the vehicle. This is because the ICE efficiency, in general, increases with the torque, see Figure 4. Hence, it is beneficial to either always lift the operating points (this is what the optimal control does in recharging mode), or to completely turn off the ICE.

The improvement in fuel economy of the combined powertrain, compared to the mild parallel powertrain, is as high as 10%, see Table 1.

5. Conclusion

This paper described a method for automatic powertrain evaluation of non-transparent, series-parallel powertrain models. The model details can be hidden from the user as long as the model satisfies the set of requirements stated in Section 2.2. The methodology of model simplification and powertrain evaluation is presented through an example of power management optimization of two powertrain models. The first model has a combined powertrain and the other has a mild parallel powertrain, constructed by removing EM2 from the combined powertrain.

This study showed two results. First, the combined powertrain can improve fuel economy by 10%, compared to the mild parallel powertrain. Second, the process of powertrain evaluation is automized as much as possible, so that user insight in vehicle modeling, simulation and optimization is not necessary.

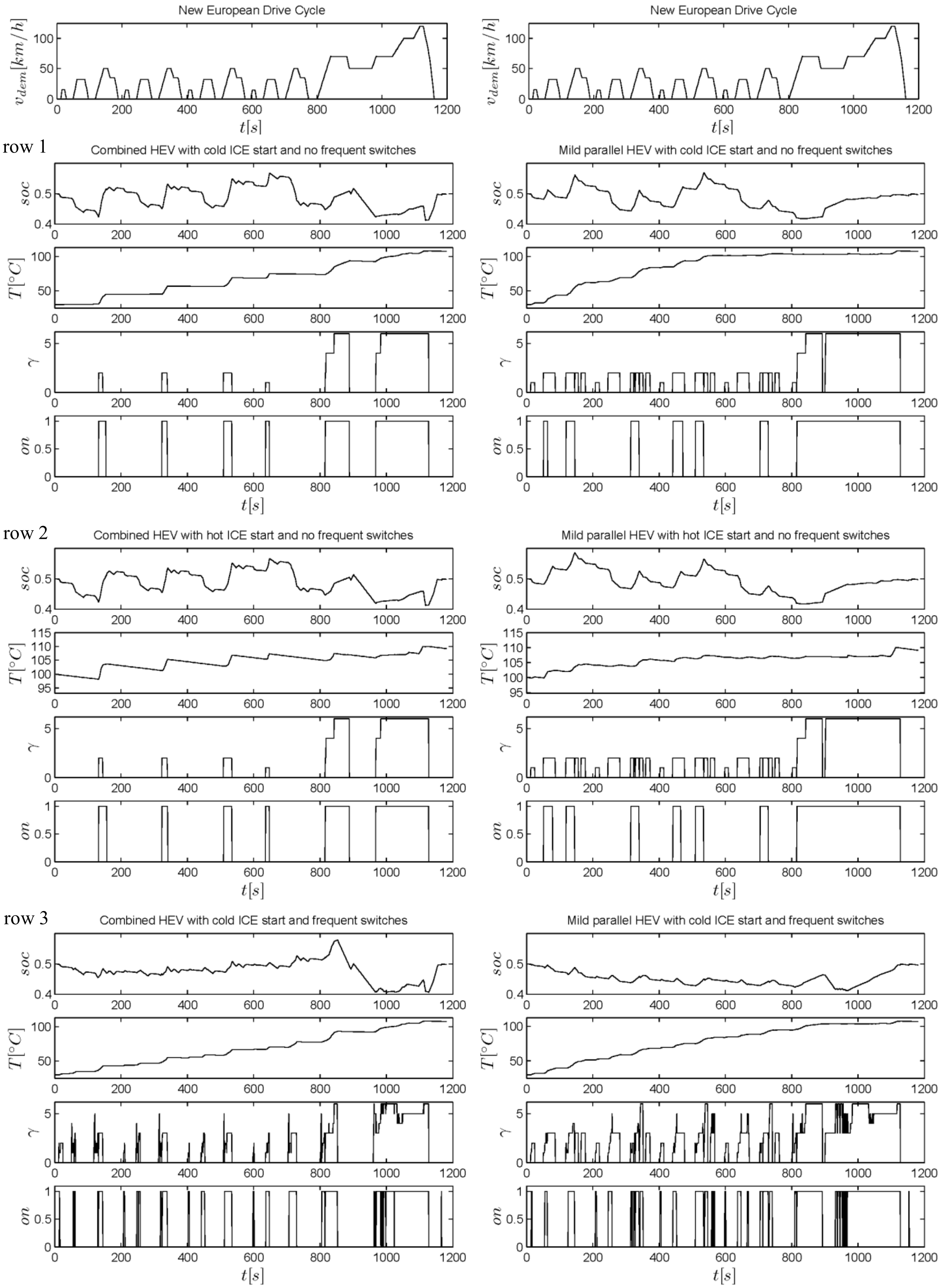

Figure 3: Optimal state trajectories. The left column shows states trajectories of the combined powertrain and the right column shows trajectories of the mild parallel powertrain. In the first row the powertrain is evaluated with cold ICE start and penalty for frequent gear and ICE on/off switching, in the second row hot ICE start is considered and in the third row results are given of cold ICE start with no penalty for frequent switching.

Table 1: Fuel consumption of the combined and the mild parallel powertrain.

Normalized Fuel Consumption	***Cold start***	***Hot start***	***Cold start and frequent switches***
Mild parallel HEV	1	0.99	0.92
Combined HEV	0.91	0.89	0.86
Improvement [%]	9.24	10.12	6.31

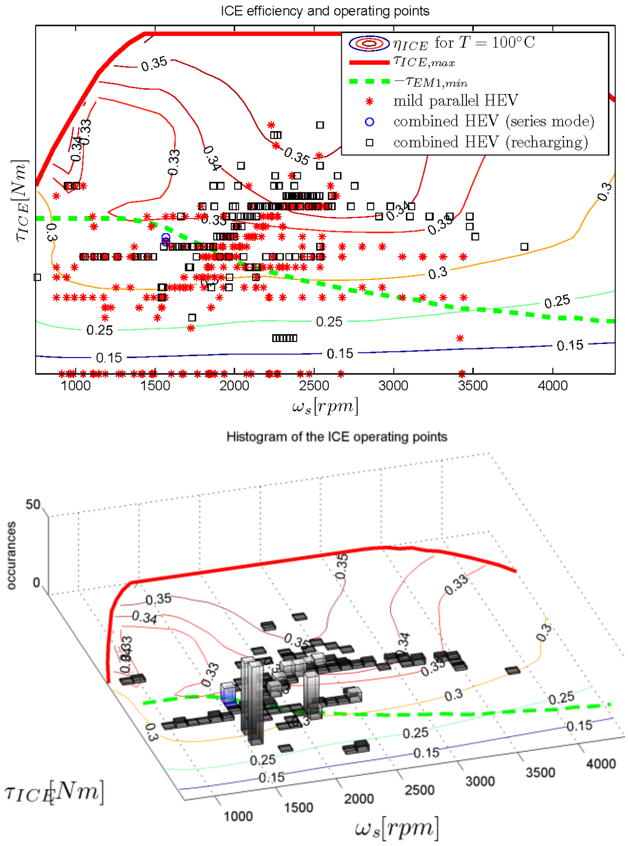

Figure 4: Operating points of the ICE for the case of cold ICE start and no frequent switching. The contour plot shows the ICE efficiency, η_{ICE}, for coolant temperature of 100°C. The bottom plot shows the number of occurrences of the operating points of the combined powertrain.

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