32nd Electric Vehicle Symposium (EVS32)
Lyon, France, May 19 - 22, 2019

Optimized Energy Management Strategy for a HEV Equipped with an Electrical Variable Transmission System

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Summary

One key research for developing an efficient drivetrain design is finding optimal Energy Management Strategies (EMS) where the control parameters are optimized for achieving a high performance, improving fuel economy, maintaining battery state of charge (SoC) and satisfying charging limitations at the meantime. The present work addresses an Electrical Variable Transmission (EVT) based HEV and combines a Rule-based (RB) strategy into an optimization-based (OB) low pass filter EMS technique for such a hybrid system. Investigation of the results indicates the proposed EMS enables efficient distribution of power between sources while minimizing fuel consumption and satisfying the EMS control objectives.

Keywords: HEV (hybrid electric vehicle); Modeling; Optimization; Energy consumption; Battery SoC (State of Charge)

1 Introduction

With the advent of novel electric machines, their industrial applications have provided promising potentials to powertrain configurations. The Electrical Variable Transmission (EVT), an electromechanical device, can be considered as an alternative solution to conventional transmission systems. This unique system could be used in both vehicles and machines powertrains. The EVT consists of two concentric inner and outer rotors nested in a stator frame to transfer and exchange mechanical and electrical energies [1, 2]. The EVT is suitable for use in any application where continuously variable and electric drive are combined in combination with electric power generation. This provides significant improvements in overall system efficiency and extended functionality. Example applications includes but not limited to transmission systems in Hybrid Electric Vehicles (HEV), constant speed power take-off with mechanical drive and electric capability, combined mechanical and electric drive for auxiliaries, electric clutches, and torque converters. Fig.1 illustrates a schematic of an EVT device.

Figure1: EVT electromechanical converter [3]

In HEV design, there are several variables which affect the performance of a vehicle, such as parameters of the powertrain components and control variables. Due to non-monotonic impacts of these variables on the objectives which should be satisfied simultaneously, the optimization of such systems is a challenging task. The previously performed studies indicate the significant role of energy management and control strategies in HEVs [4-6] and EVs [7-9] for improving fuel consumption and/or preserving battery charge balance, respectively. Throughout the literature, many studies have been carried out on modelling and optimization of HEVs to increase their performance with a focus on Energy Management Strategies (EMS) by using different optimization algorithms.

Evolutionary algorithms are a useful tool to address the complex optimization problems of EMS control for HEVs to address the non-linearities and multimodalities of non-convex objective functions. Genetic Algorithm (GA) has proven as a robust and feasible optimisation approach with a wide range of search space, useful for solving such problems [10]. Throughout the literature, different studies have considered GA as an optimization-based (OB) approach for power control and EMS design in HEVs. Huang et al. [11] performed an optimization of control strategy parameters for a series HEV topology to minimize the fuel consumption. The results indicated the validity of GA compared to DIRECT and Thermostatic methods. In another study, Gao et al. [12] used GA in PSAT environment for powertrain optimization of a parallel HEV topology to improve the overall fuel economy. Montazeri and Poursamad [13] examined a GA-based technique to optimize control strategy of HEVs via aggregating the constraints into the objective function. In that study, penalty functions were used to penalise the infeasible solutions by reducing their fitness values toward minimizing the fuel consumption and the emissions.

There have also been studies on rule-based (RB) approaches for EMS design focusing on various EMS control objectives. In [14], the authors proposed a rule-based control strategy for battery charge-sustaining, improving fuel efficiency, and examining power flow results through components. In another study in [15], Peng et al. focused on fuel consumption improvement via performing comparisons among different energy management strategies. The authors in [16] compared computational cost of using rule-based control strategy algorithms for a parallel HEV. Wu et al. [6] examined power split, SoC control and engine operating point strategies to evaluate the fuel consumption, power flow and battery SoC. Achievements on the evolution of SoC were also obtained in [4] via using a rule-based supervisory control approach. In [5], the authors considered a strategy working based on a driving cycle recognition approach to improve fuel efficiency.

Considering the previous studies, a promising control approach would be using techniques which can combine the merits of RB and OB power sharing methods to attain applicable control solutions, consider various control objectives, and minimize fuel consumption. For instance, If-Then-Else rules can be linked into OB power sharing methods such as a Low Pass Filter (LPF) technique. The optimal EMS design includes optimizing one or more objective functions via searching through the control design parameters meeting the constraints. In this paper, such an energy management strategy for powertrain of an EVT-based HEV is developed and the promising benefits are compared to non-optimized cases for NEDC driving cycle.

2 Drivetrain Architecture

In an EVT-equipped HEV, the ICE shaft is connected to the inner rotor while the outer rotor is linked to the wheels. The EVT system can provide possibility of decoupling the wheel and the engine speed [17] and help enhancing vehicle performance via having the engine operating in its optimized point [18]. In addition, it can reduce maintenance and prevents losses of gears' mechanical involvement as the power can be split in an electromagnetic way. The net power coming from the ICE can partially be transferred to the wheels and the remaining part is converted to electrical power to be stored in a battery pack or to supply the stator [19] for future propulsion use. The EVT system uses two back-to-back inverters connecting the battery to the inner rotor and the stator. Fig. 2 illustrates a schematic of a typical EVT-equipped HEV.

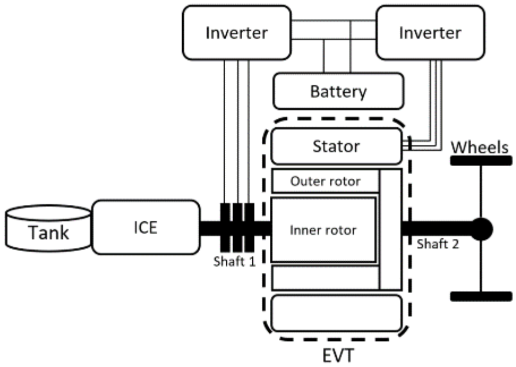

Figure2: EVT-equipped HEV topology

3 Modelling

To optimize the energy management strategy, it is required to incorporate the modelled vehicle into the optimization algorithm. In this study, the modelling and simulations are performed in the MATLAB/Simulink® environment. The backward-facing approach merges the advantages of simplicity and low computational cost [20] when it comes to model integration into optimization applications [21]. Hence, the backward calculation method [22] is used in this study to model the vehicle.

The vehicle longitudinal dynamic model uses speed and acceleration timeseries of a driving cycle to calculate the required tractive forces considering the drag resistance force, the rolling resistance force, the gradient resistance force, and the inertia force:

$$F_T = \frac{1}{2}\rho v^2 C_D A + C_r mg\cos a + mg\sin a + \mathrm{mC_J}\frac{dv}{dt} \qquad (1)$$

Knowing the wheels radius R_w, one can readily calculate the required torque and speed output of vehicle dynamic model on the wheels:

$$T_w = F_T R_w \qquad (2)$$

$$\omega_w = \frac{v}{R_w} \qquad (3)$$

Table 1 provides the descriptions and information of the parameters used for the passenger vehicle's dynamic calculations of the present study.

The core functionality of the ICE model used in this study is based on an input-output approach using torque-speeds pairs corresponding to the efficiency and the fuel rate map stored into look-up tables. Having the output fuel consumption rate data and the fuel density, the consumed fuel in litre can be modelled as follows where $\dot{m}$ represents the fuel consumption rate and ρ_f is the fuel density:

Table1: Constant parameters for vehicle dynamic calculations

Description	Parameter (unit)	Quantity
Mass	m (kg)	1350
Drag coefficient	C_D	0.24
Rolling resistance coefficient	C_r	0.009
Rotational inertia coefficient	C_J	1.075
Frontal area	A (m^2)	1.74
Wheel radius	R_w (m)	0.287
Air Density	ρ (kg/m^3)	1.2
Auxiliary load	P (W)	500

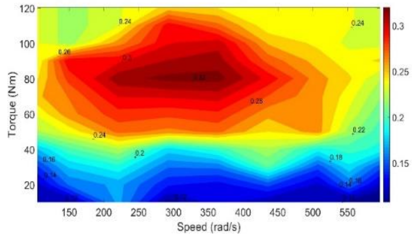

Figure3: The efficiency map of the ICE

$$Fuel = \int_0^t \frac{\dot{m}_f}{\rho_f} dt \tag{4}$$

Fig. 3 represents the efficiency map of the 60-kW engine considered for the present study.

To model the battery pack, the parameters for the open circuit voltage (V_{oc}), the internal resistance (R_{int}), the polarization capacitance (C_p), and the polarization resistance (R_p) are used based on the Thevenin model. The elements of Thevenin equivalent circuit as a function of the SoC are identified by using experimental data [23] which are considered in Simulink look-up tables. The terminal voltage of the pack V_{batt} and SoC to be modelled can be expressed as:

$$I_{batt} = \frac{I_{load}}{N_{Batt}} \tag{5}$$

$$\frac{dV_{cp}}{dt} = \frac{-V_{cp}}{C_p R_p} + \frac{I_{Batt}}{C_p} \tag{6}$$

$$V_{Batt} = N_{Batts}(V_{oc} - I_{Batt} R_{\text{int}} - V_{cp}) \tag{7}$$

$$SoC = SoC_0 + \frac{1}{3600}\int \frac{I_{Batt}}{C_b}dt \tag{8}$$

A LiFePO4 (LFP) battery type is simulated for the simulation in this study. Table 2 provides the specification of LPF battery used in the present study.

The output power of the power converters is modelled considering the power flow calculation direction and the components efficiency used in the corresponding look-up tables. The efficiency operators β=-1, and β=1 are used for the motoring mode (while P>0), and the braking mode (while P<0), respectively.

$$P_{out} = P_{in}\eta^{\beta} \tag{9}$$

Table2: $LiFePO_4$ battery specifications

Rated capacity	14 Ah
Nominal voltage	3.6 V
Max discharging current	100 A
N_{Batts}	120
SoC_0	80%
Min Voltage	2.5
Max Voltage	4.15
C_rate limit while charging	-3

The considered EVT component is a rotating field electrical machine with two concentric rotors of which the inner rotor contains a distributed three-phase winding and the outer rotor is equipped with permanent magnets. The inputs of the EVT model are the torque and speed operating points of inner and outer rotor shafts. Based on these operating conditions a set of 5 independent currents is chosen: stator current in d and q-axis, outer rotor current in d axis and inner rotor current in d and q-axis (see Fig. 4) which can minimize the iron and copper losses [24]. The corresponding fluxes (Ψ) are calculated based on look-up tables defined based on FE calculations and validated on a prototype [25]. Once the flux and current are known, the last step is to calculate the torque on each component:

$$T_1 = \frac{3}{2}N_p(\psi_{1q}I_{1d} - \psi_{1d}I_{1q}) \tag{10}$$

$$T_2 = -T_1 - T_3 \tag{11}$$

$$T_3 = \frac{3}{2}N_p(\psi_{3q}I_{3d} - \psi_{3d}I_{3q}) \tag{12}$$

where subscript 1, 2 and 3 represent stator, outer rotor and inner rotor, respectively. The number of pole pairs is denoted by N_p.

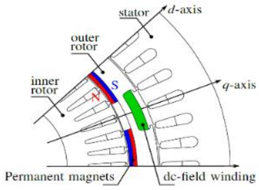

Figure4: Cross-sectional view of the PM EVT

In this study, the Simulink ® environment is used to integrate the individual subsystems and form the whole vehicle model as illustrated in Fig. 5.

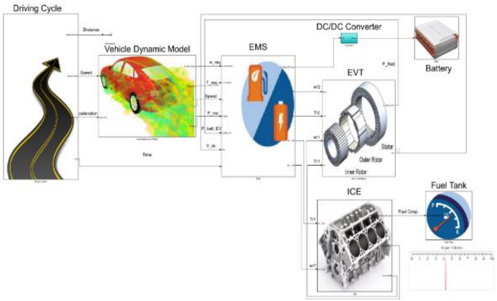

Figure5: Diagram of the backward calculations modelled in Simulink®

4 EMS

The main aim of the EMS is to define rules for power sharing control and achieving the desired EMS objectives. The core problem of the RB strategies is that they are subjected to predefined intuitions. This may satisfy a desired objective such as battery SoC sustaining, however may lead to non-optimal outcomes regarding the fuel consumption. Therefore, as illustrated in Fig. 6 the rules are predefined on the top of EMS and linked into an OB low pass filter control power sharing technique to provide a robust EMS block. This section goes through the rules and power sharing approaches used in the EMS block. Through selecting appropriate operating points and modes, the control objectives are: satisfy the required driving power, operate the ICE considering its efficiency map, use ICE and regenerative braking energy for charging the battery when possible provided not violating the charging limitations and allowable maximum and minimum SoC values, maintain the battery SoC in its allowable range while having the initial and final SoC values close enough to each other, and minimize the fuel consumption. The considered EMS objectives are summarized in Fig. 7.

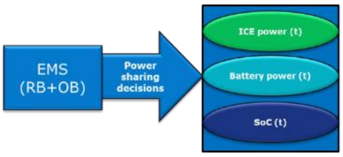

Figure6: Power sharing based on RB and OB LPF strategy

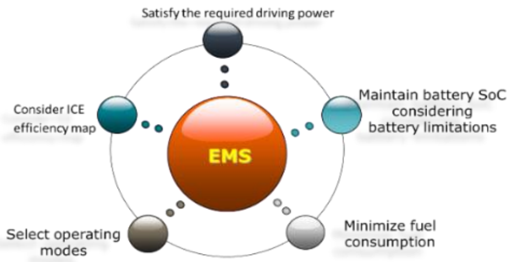

Figure7: The EMS objectives

1.1 Rule-based strategy and operating modes

The main objective of defining a rule-based strategy is to establish a set of "If-Else-Then" rules which consider driving pattern features for the power sharing. These control rules can be designed based on intuition in view of desired objectives. The rules are included as a subsystem of the EMS block to work cooperatively with the LPF power split technique. The EMS will allow the ICE to operate flexibly in efficient operating points to meet the demands and satisfy the charging requirements. The operating points can be defined using speed-torque pairs stored into a look-up table based on the ICE efficiency map. The rules are used to update the operating modes through the simulation considering the current requested load, speed, accessible power from energy sources, SoC and power split control variables. The modes of the study can be categorized and considered as follows. More detailed explanations of these modes and corresponding used rules can be found in [26-28].

- Pure electric mode
- Hybrid-traction mode
- Engine traction and battery charging mode
- Hybrid battery charging by both ICE and regenerative breaking
- Regenerative braking mode

1.2 Low pass filter power

The performance and the fuel economy are crucially depending not only on the SoC rules, but also on the used power splitting method. The utilization of a power splitting method in EMS subsystem lies in the concept of proper power sharing toward improving the efficiency and control robustness. In this regard, a low pass filter (LPF) strategy can be used to optimize the power sharing control variable τ and satisfy the objectives. The utilization of a LPF decides on sharing power between the supplying sources to satisfy the requested power. It uses a transfer function and filters out the high frequency elements of the input and passes the low frequency ones leading to a slowly varying output. To share the demand power between the ICE and the battery, the filtered component of the power passes to be supplied by the ICE while its difference with the total demand will be supplied by the battery subsystem considering the downstream losses. One should consider that the output ICE power needs to be varying slowly enough to avoid experiencing abrupt changes in an operating engine. Here the standard transfer function of the LPF used in the energy management subsystem is:

$$f_{LPF} = \frac{1}{\tau . s + 1} \tag{13}$$

where the LPF denominator τ plays a crucial role as the control variable which can be found based on an optimization routine to have the control objectives satisfied.

5 Optimization algorithm and incorporation to the model

Genetic Algorithms (GA) work based on the evolutionary process concept of natural selection of Darwin's theory. This theory proposes that only the fittest populations can produce offspring through the natural selection and survive while the unsuitable population will be eliminated. The same concept can be conducted into mathematical optimization where during the processes like crossover, mutation and natural selection, the good design points can be selected while neglecting the bad ones toward finding the objective function solution (survival of the fittest) [29]. The design constraint can be defined separately or be integrated into the objective functions as penalties [13]. The design parameter here is the control decision variable of LPF strategy and the vehicle modelled in Simulink® is incorporated into a MATLAB-based GA. The GA iteratively works with the simulation model for the optimization process. The GA considers the decision variable as the input chromosome besides the minimum and maximum values of the constraints to minimize the fuel consumption. The interrelations of the modelling and optimization process is illustrated in Fig. 8. The optimization algorithm searches to minimize the fuel consumption while satisfying the EMS constraints:

$$\min(Fuel) = \min J = \min \int_0^t \frac{\dot{m}_f}{\rho_f} dt \tag{14}$$

$$| SoC_f - SoC_i | < \varepsilon_0 \tag{15}$$

$$SoC_{\min} - \varepsilon < SoC(t) < SoC_{\max} + \varepsilon \tag{16}$$

$$C\_Rate(t) \geq \beta \tag{17}$$

Regarding the first SoC constraint, (15) indicates the charge sustaining requirement of the HEVs, and (16) shows the allowable limits of the SoC over the total driving cycle considered for the optimization. As can be observed, the constraint in the inequality (15) is reformulated from the typical charge sustaining equality constrain $SoC_f = SoC_i$ so that the difference between the final SoC and the initial SoC, namely ΔSoC, stays within a small feasible bound ε_0 in the optimization process. The ε_0 can be selected and altered by the user for hardening/softening the constraint. The $C\_Rate(t)$ battery limitation must be defined based on battery specifications to avoid sudden charges, to avoid fast aging of the battery pack, and to improve battery's lifetime and performance where the negative sign stands for discharging here. It is notable that constraints must be incorporated into the objective function as penalties to penalize the cost via adding a big enough penalty value when a constraint is violated. This technique is useful to consider the inequality constraints which cannot be directly involved in the optimization formulations to lead us to feasible solutions without violating the constraints.

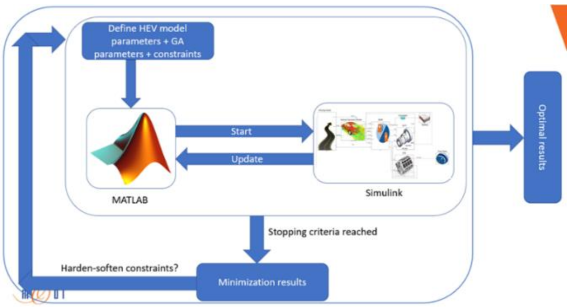

Figure8: Coordination of the optimization algorithm and the model

6 Discussion and results

Optimization and simulations are performed on NEDC driving cycle and the results are provided in this section. As discussed in the previous sections, the optimized EMS must satisfy the objectives while minimizing the fuel consumption. Regarding the battery limitation constraint, the $C\_Rate(t)$ must not violate its limitation value β. Hence, β value of -3 based on LiFePO4 battery chemistry specifications and a small enough value of $\varepsilon_0 = 0.3\%$ for achieving close values of the initial and final SoC are introduced to the algorithm. For the SoC range, values of 70% for the minimum and 80% for the maximum are considered in the optimization while having 80% as the initial SoC. After performing the optimization, the model is exposed to the optimized EMS to obtain the power distribution, SoC and $C\_Rate(t)$ results for the examined driving cycle. As illustrated in Fig. 9, the employed strategy considers the requested load to supply the demand via variable engine and battery power shares while maintaining the battery SoC for achieving close values of initial and final battery SoC. In addition, the allowable $C\_Rate(t) < -3$ limitation is satisfied while having the SoC fluctuating in the desired window range (70%-80%). This ensures avoiding overcharge/discharge the battery beyond the safe design range toward having an extensive life time.

For the optimized EMS case study, Fig. 10 plots the results obtained for the fuel consumption (in litre) versus the changes of the ICE power over one driving cycle. As can be observed, there would be no changes in the fuel consumption profile while the ICE turns off to save the fuel consumption. On the other hand, the fuel consumption increases over the cycle while the ICE operates in its operating points.

As already discussed, the denominator of LPF, τ, plays a key role as the decision variable in the considered EMS. Two trial and error non-optimized case studies are simulated using the same vehicle model to compare the results to the optimized EMS. The results indicate that the optimization algorithm has successfully weeded out the non-optimized cases via finding the appropriate denominator value sissifying the objectives. Fig. 11 illustrates the SoC profiles of the considered non-optimized versus the obtained optimized EMS case studies. It can be observed how selecting a wrong τ value (i.e. very high) affects the SoC profile whereas the optimized case maintains the SoC in the allowable maximum and minimum range. Table 3 provides a detailed comparison of the studied cases in terms of the EMS design goals where the optimized case outperforms compared to the non-optimized one by satisfying all the desired objectives of the design stage. In addition, table 4 compares the obtained average fuel consumptions (litre/100km) where the optimized EMS case outperforms by 15% while not violating the SoC constraints compared to the non-optimized EMS case.

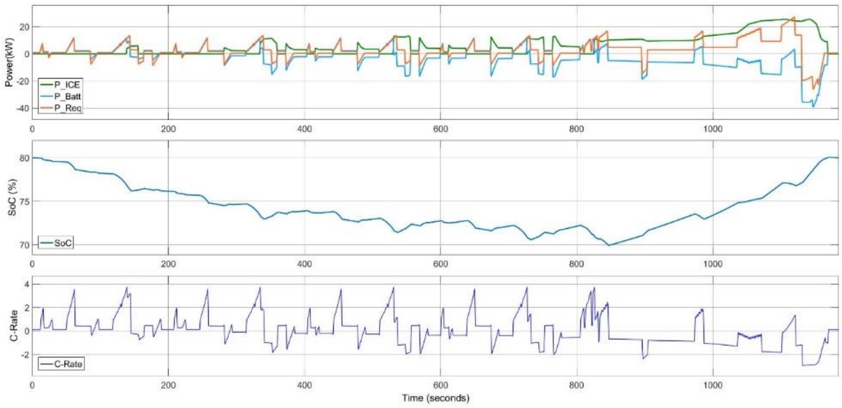

Figure9: Power distribution, SoC maintenance, and C-rate results for the optimized EMS case study for one cycle

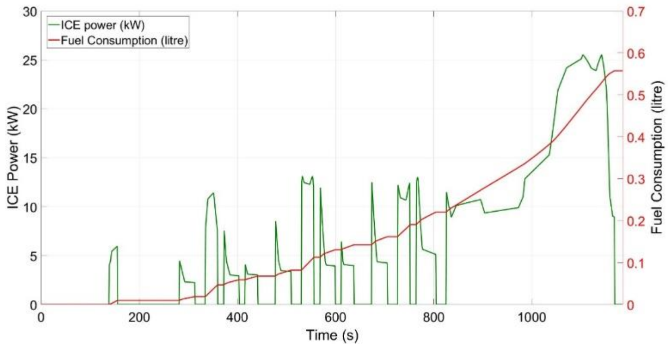

Figure8: Fuel consumption (litre) vs. ICE power for the optimized EMS case study

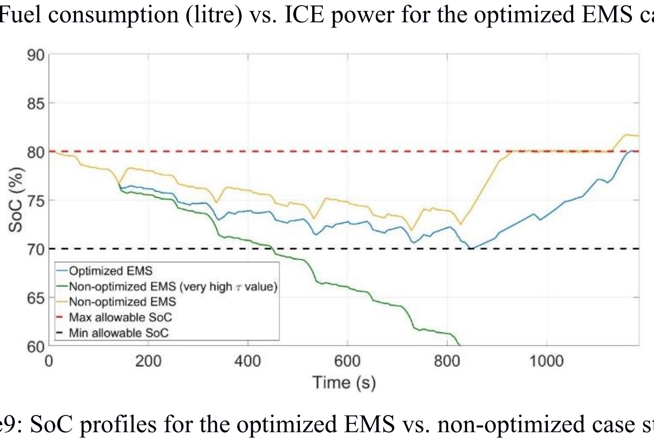

Figure9: SoC profiles for the optimized EMS vs. non-optimized case studies

Table3: Comparison of the EMS control objective satisfaction

Considered features	Non-optimized EMS	Optimized EMS
$\lvert \Delta SoC \rvert < 0.3\%$	✗	✓
70% <SoC< 80%	✗	✓
Driving power needs	✓	✓
$C\_Rate(t) < -3$	✗	✓
All EMS objectives satisfied?	✗	✓

Table4: Comparison of the average fuel consumption (litre/100 km)

Objectives	Before optimization	After Optimization
Fuel Consumption (litre/100 km)	6.10	5.15
Fuel consumption improvement (%)		**15**

7 Conclusions and future work directions

The present study proposed an EMS incorporating OB and RB approaches for a passenger HEV equipped with an EVT system. First the vehicle was modelled in components level and the proposed EMS was integrated into a GA-based algorithm for EMS optimization purpose. The power distribution and SoC results were obtained through the optimization and simulation procedures while considering battery limitations and EMS objectives. The results concluded that the proposed EMS could improve fuel consumption by 15% while maintaining the SoC in a desired range and not violating the battery charging limitations compared to the non-optimized case study. The integration of the EMS optimization into components optimal sizing merits investigations as a future work direction of the present research. It can investigate possible improvements in fuel consumption besides drivetrain cost reductions for the EVT-based HEV topology. In addition, the developed EMS paves the path for its real-time implementation in hardware-in-loop tests for validation purpose and consequently utilization in real-world applications.

Acknowledgments

The authors are grateful to VLAIO (ex. IWT) and Flanders Make, national funding schemes in Belgium, for the support to the current work, performed within EMTechno project (project ID: IWT150513).

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