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Applying Modular Energy Management Strategy to HEV Powertrain Design & Control

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Executive Summary

This paper presents the development and validation of an automated tool for powertrain topology design and control (TOPDSIGN), which aims at providing initial advice on the powertrain design and control for hybrid-electric vehicles. The tool incorporates a library of real-life components modelled using quasi-static and convex representations. We propose a three-layer optimization framework that solves the joint design problem. The outer loop picks the most suitable topology, while the intermediate one selects the best components. The most inner layer of this framework derives the energy management strategy by applying decomposition to the Equivalent Consumption Minimization Strategy (ECMS), and by doing so a scalable and reusable solution is developed. All designs are simulated using an automatic closed-loop methodology implemented in the Simulink/MATLAB environment. Two validation use cases verify and validate that the tool produces viable results.

Keywords: HEV (hybrid electric vehicle), powertrain, power management, simulation, optimization.

1 Introduction

The automotive industry, like many other industries, is set the goal of drastically reducing its CO_2 impact, and ultimately eliminating it through net-zero emissions in the long run by 2050. To do so, intermediate steps are required and legislated, such as the CO_2 emissions benchmarks for passenger vehicles, heavy duty commercial vehicles, and others, set (and revised) regularly by the European Union [1]. In addition to the CO_2 targets, many European cities introduce zero emission zones from 2025 onwards, placing restrictions on the operations of engines within cities [2]. These various requirements are pressuring automotive OEMs to come up with smarter and greener solutions when designing vehicle powertrains. A highly noticeable trend by manufacturers is vehicle hybridization and electrification. While battery electric vehicles currently still suffer from economical (high initial cost) and technological (range, charging) limitations [3], electric hybrids show a greater potential for the near future.

Vehicle hybridization offers many advantages such as engine downsizing, elimination of idling and clutching losses, additional control freedom, and energy recuperation. Most manufacturers have been using heuristic (rule-based) control for this additional control freedom, mainly because of its simplicity and robustness. However, this type of control limits the potential of the hybrid-electric vehicle (HEV) as it does not provide the globally optimal solution. Conversely, algorithms such as dynamic programming guarantee global optimality but are computationally expensive. Such solutions are often tailored to a specific problem and are therefore, not reusable for other topologies. Realizing the trade-off between heuristic and optimal control strategies, TNO has developed a scaleable Modular Energy Management

Strategy (MEMS) [4]. MEMS is based on applying dual decomposition to the Equivalent Consumption Minimization Strategy (ECMS) optimal control problem, reformulated into a scheme which is scalable. In other words the optimal control problem is split into smaller problems related to each subsystem. This approach is considered to be able to substitute current rule-based control and exploit the advantages of hybridization to a higher degree.

Electric hybrids are still a new technology and extensive know-how for designing such a powertrain for specific usage profiles is not common. Choosing the right configuration of engine and electric machine/s is often tricky and heavily dependant on the type of vehicle and its use profile. Simultaneously, optimization studies which deliver optimal results often focus on a single topology for small fixed set [5],[6],[7],[8]. Therefore, a problem arises for the industry where manufacturers face a tough choice - either spend significantly large budget on optimizing several topologies and select the best one or select via engineering judgement and optimize only one. To solve this issue OEMs need a tool which can advise which would be the optimal topology for a given usage profile. Thus, the objective of this paper is to develop an automatic tool for hybrid-electric powertrain topology design and control, incorporating TNO's Modular Energy Management Strategy. This tool's objective is to recommend a topology, component sizing, and derive an energy management strategy based on a library of actual components.

In the remainder of this paper, the developed tool and its required inputs are introduced in Section 2. In this section the optimization framework (the core of the tool) is discussed in detail. Results from two optimizations are presented in Section 3, while Section 4 discusses two important aspects of the study. Finally, conclusions from this paper are drawn in Section 5.

2 Methods

Fig. 1 provides an overview of the developed automated tool for powertrain topology design and control (named TOPDSIGN). This section introduces the component library and how quadratic fits are performed on these components in Subsection 2.1. Subsections 2.2 and 2.3 discuss the topology library used and the required user inputs, respectively. The optimization framework and its layers are formulated in Subsection 2.4. Finally, the methodology for automatic closed-loop testing of the powertrain is presented in Subsection 2.5.

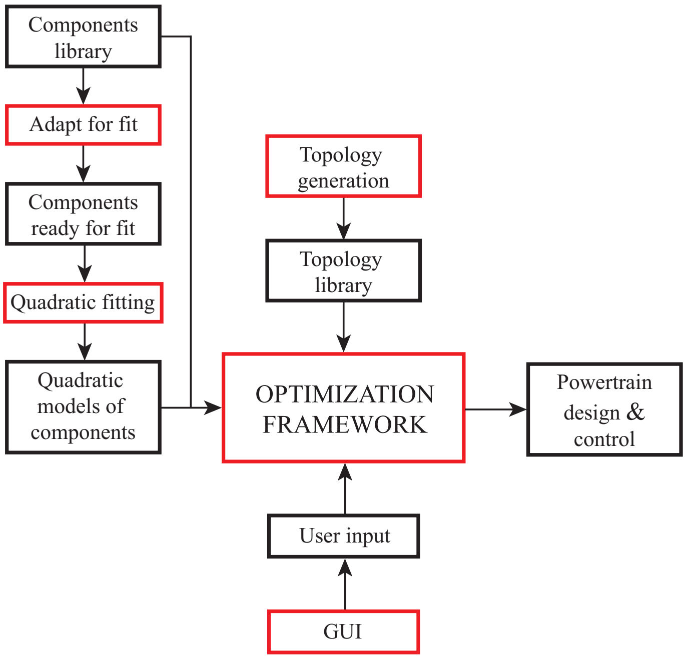

Figure 1: Overview of the TOPDSIGN tool (black indicating a data file and red - script, function, model or app).

2.1 Component library and quadratic fitting

An extensive list of real-life components is incorporated in the tool. These components are taken from the ADVISOR library [9] and can be scaled linearly with a maximum scaling factor defined by the user. All components are modelled following the quasi-static modelling approach in which the physical causality of the system is reversed. This subsection briefly discusses the modelling methodology for the main components of a HEV powertrain. Additionally, it explains how these quasistatic models are quadratically fitted to derive convex models.

2.1.1 Electrical machine

In quasi-static modelling the electrical machine rotational speed ω_{em} and torque T_{em} at the shaft are used as inputs to calculate the required or produced electrical power. Therefore, all electric machines (motors and generators) are modelled as efficiency maps. Motors can both produce and deliver power as their maps cover two quadrants, while generators can only produce electrical power. Scaling is performed in linear fashion (up to some limit) by multiplying the torques array of the efficiency map by the scaling factor.

2.1.2 Internal combustion engine

The internal combustion engine is modelled similarly to the electric machine but instead of efficiency, fuel-consumption maps are used. It is obvious that an engine can only deliver mechanical power. Torque T_{ice} is calculated using the normalized mean effective pressure p_{ice}

$$T_{\mathrm{ice}} = \frac{p_{\mathrm{ice}} \cdot V_{\mathrm{d}}}{N \cdot \pi}, \tag{1}$$

where V_{d} is the engine displacement volume and N is the stroke number. The engine torque is linearly scaled with its displacement volume (up to some limit). During simulations, it is assumed that any torque level can be achieved within the engine's limitations by adding the necessary amount of fuel. Warm-up effects and transient behavior of engine are not taken into account.

2.1.3 Electrical energy storage

The battery is initially modelled as an equivalent series resistance and a constant voltage source. It is assumed that the open-circuit voltage is neither state-of-charge, nor temperature dependent. However, such modelling requires precise parameter fitting, which can be challenging and time-consuming. Instead of that, the battery is represented as a box in which any amount of energy can be consumed or stored as long as it is in the power limitations. These power limitations are a function of the state of charge (SoC) of the battery (more on that to follow). Similar to the power limitations, the battery efficiency is dependent on the SoC. Temperature effects are completely neglected during simulations, as the operational temperature of the battery is considered to remain constant.

2.1.4 Transmission

A discrete-gear 5-speed gearbox is used for all possible topologies. Gear ratios are designed to reach the top speed and standstill slope requirements, specified by the user. The gearshift strategy is derived in the inner loop of the optimization framework which is discussed in Section 2.4. Each gearshift is assumed to be lossless, but the gearbox as a component has a constant efficiency.

2.1.5 Quadratic fitting

An important aspect within MEMS is obtaining accurate (as much as possible) convex models of the components. Generally, convex optimization is computationally effective and achieves the global optimum (valid also for ECMS which is in the core of MEMS). Subsystems are models as quadratic relations between their input (u_m) and output power (y_m). For the combustion engine, the motor and the generator the fitting parameters are speed (ω_m) dependent, i.e.,

$$q_m(\omega_m) \cdot u_m^2 + f_m(\omega_m) \cdot u_m + e_m(\omega_m) + y_m = 0 \tag{2}$$

and the output power of the mover (y_m) is constrained with

$$y_{m,min}(\omega_m) \leq y_m \leq y_{m,max}(\omega_m), \tag{3}$$

where $m \in \{\mathrm{ice}, \mathrm{em}_1, \mathrm{em}_2, \mathrm{em}_3, \mathrm{em}_4, \mathrm{eg}\}$, eg is abbreviation for electric generator and q_m, f_m and e_m are the fitting factors. For the high-voltage battery the fitting parameters are a function of the state of charge (SoC), i.e.,

$$q_m(SoC) \cdot u_m^2 + f_m(SoC) \cdot u_m + e_m(SoC) + y_m = 0, \tag{4}$$

where $m \in \{\mathrm{hvb}\}$ and hvb is abbreviation for high-voltage battery. Battery energy storage dynamics are used for the model and are given by

$$E_{\mathrm{hvb}} = -\dot{u}_{\mathrm{hvb}}, \tag{5}$$

where E_{hvb} is the energy storage of the battery.

ECMS requires a convex representation of the components to guarantee optimallity. As already mentioned, MEMS uses ECMS in its core and therefore, also requires convex models to obtain optimal results. To ensure the component models are convex the second-order condition for convexity [10] is applied

$$\nabla^2 f(x) \succeq 0, \tag{6}$$

where f is the function (in this case the quadratic model) and the Hessian is given by

$$\nabla f(x)_{ij} = \frac{\partial^2 f(x)}{\partial x_i \partial x_j} \tag{7}$$

Thus, to guarantee strict convexity, the square fitting q_m parameter is set to be always greater than zero. Equation (4) provides a relation between the input and output power for the battery component as a function of SoC. SoC is a state of the subsystem and, therefore, this relation cannot be convex. However, the impact of state variable on the model is not significant.

2.2 Topology library

In the current version of the tool twelve hybrid-electric combinations are implemented. These cover series, and post-transmission (P3) and pre-transmission (P2) parallel topologies. For each of these topologies the number of electric motors present can range from one to four. Using two or more electric machines in a parallel configuration essentially results in a series-parallel topology.

2.3 User input

The user is requested to specify a range of settings and requirements. These include basic vehicle parameters such as glider mass, resistance coefficients and etc. The driving profile is selected based on a driving cycle (15 of the most widely used cycles available) and number of repetitions of the chosen cycle. Additionally, performance requirements such as top speed and maximum gradient from standstill are available as settings. Most importantly, the user must specify the objective for the optimization. Currently a selection of the following objectives is available: fuel consumption per 100 km, energy consumption per 100 km and energy consumption per ton mass. All of these settings and requirements are loaded through a Graphical User Interface (GUI) depicted in Fig. 2.

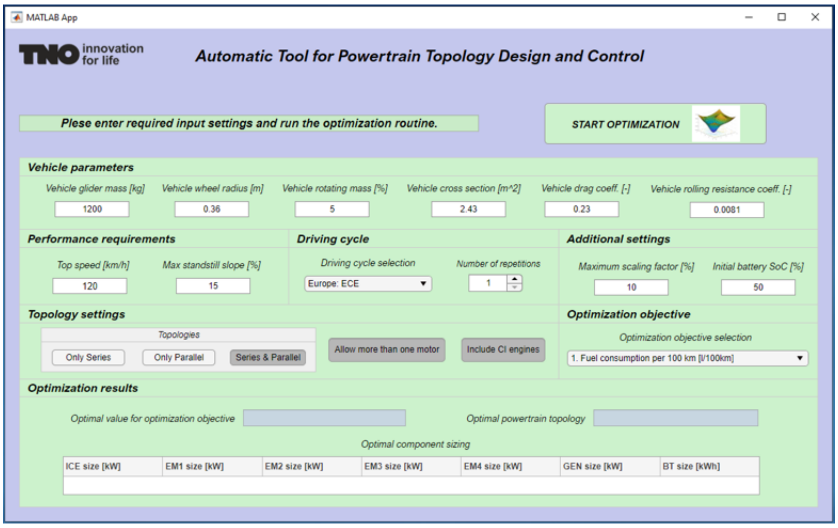

Figure 2: TOPDSIGN tool GUI.

2.4 Optimization framework

To find the optimal solution to the given problem the powertrain and the control strategies must be designed jointly [11]. Therefore, this becomes a co-design on a multi-level optimization problem. Fig. 3 depicts the developed optimization framework and its layers. These layers and the methodology used in them are discussed in this subsection.

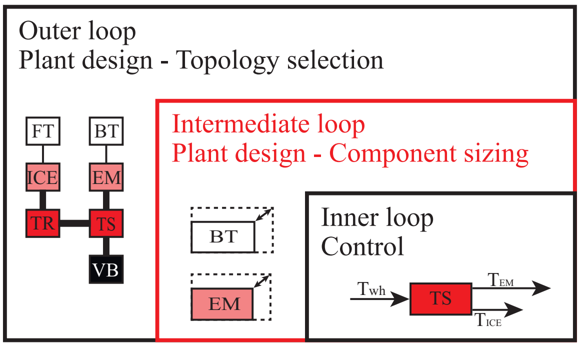

Figure 3: Optimization framework (**FT** - fuel tank, **ICE** - internal combustion engine, **TR** - transmission, **BT** - battery, **EM** - electric motor, **TS** - torque split, **VB** - vehicle body).

2.4.1 Outer loop - Topology selection

The task of the outer loop is to create the plant design in terms of a topology. As already mentioned there are twelve possibilities for a topology. Thus, the need for a sophisticated optimization algorithm is omitted on that level of the optimization framework. Instead, a loop with parallel execution is implemented to cover all possible topologies.

2.4.2 Intermediate loop - Component sizing

The intermediate loop is responsible for picking the optimal sizing of all powertrain components, which results in an enormous design space. To tackle that, the Surrogate Optimization (SO) algorithm is introduced. Essentially, a surrogate is a model that approximates a function. When searching for the minimum of that function, the surrogate can be evaluated over a huge amount of points and the best value can be taken as an approximation to the minimizer of the function. Therefore, SO is a particularly good solution for objective functions that take a long time to evaluate, like in this case (running a powertrain model over a driving cycle).

The MATLAB solver *surrogateopt* searches for the global minimum of a real-valued objective function in multiple dimensions, subject to certain bounds [12]. The whole process consists of two phases: construct the surrogate model of the vehicle over the driving cycle and search for the minimum. Thus, a trade-off is posed here between accuracy and speed. This framework is designed to provide initial design advice but at the same time the goal is to obtain results which are as close as possible to the global minimum.

2.4.3 Inner loop - Control design

The energy management strategy is based on the Modular Energy Management Strategy (MEMS) and controls the following aspects: torque split (for parallel hybrids or series with two or more motors), engine-generator setup control (for series hybrids) and gearshift strategy. MEMS applies dual decomposition to the ECMS optimal control problem, which means that the optimal control problem is split into several smaller problems, each corresponding to a subsystem, part of the topology (e.g., electric machine, combustion engine, etc.). The multi-modal powertrain is modelled using power flows in the system. By doing so, MEMS becomes scaleable as it can be applied to every powertrain configuration in which the power balances at the nodes are known.

An essential modification made to MEMS compared to ECMS, is that in MEMS the minimization objective is the the sum of the energy losses of each component [4]. The expression then becomes rather favorable for the decomposition because the objective is formulated as function of the input (u_m) and output (y_m) powers of each subsystem, rather than only as a function of the combustion engine output (y_{ice})

$$\textbf{min} \;\; \dot{m}_f(y_{ice}) - \lambda \dot{E}_s \Leftrightarrow \textbf{min} \sum_{m \in M} u_m - y_m - \lambda \dot{E}_s, \tag{8}$$

where $M \in \{ice, em_1, em_2, em_3, em_4, eg, hvb, bra\}$, $\dot{m}_f$ is the fuel mass flow, λ is the equivalent cost factor and $\dot{E}_s$ is the battery energy consumption. Using the redefined Equation (8) the Lagrange dual function is introduced

$$\mathbf{min} \sum_{m \in M} u_m - y_m - \lambda \dot{E}_s + \vec{\mu}\left(\vec{v}^T + \sum_{m \in M} A_m u_m + B_m y_m\right), \tag{9}$$

where $\vec{\mu}$ is the dual variables vector (one dual variable for each subsystem/component), $\vec{v}$ is a vector with the system's exogenous inputs and the matrices A_m and B_m are indicating how the components are connected within the powertrain. The MEMS algorithm is given in Algorithm 1. This loop essentially runs until equilibrium is reached, at which the expression in the brackets of Equation (9) goes to zero. Global optimum is guaranteed in all the cases in which the algorithm converges because the powertrain components are represented with convex models.

Algorithm 1 MEMS algorithm

```
while v⃗ + Σ_{m∈M} A_m u_m + B_m y_m ≠ 0 do
    for all subsystems do
        if subsystem is high-voltage battery then
            Solve min  u_m − y_m + μ⃗A_m u_m + μ⃗B_m y_m − λĖ_s
        else
            Solve min  u_m − y_m + μ⃗A_m u_m + μ⃗B_m y_m
        end if
        Update dual variable
    end for
end while
```

MEMS is used to control the power distribution to each mover through torque split. Therefore, the wheel speed is coupled to the speed of the movers. Additionally, MEMS is applied to two mixed-integer problems - generator-engine on/off and gearshift. The gearshift strategy is efficiency based, meaning that at each instance of the simulation it is calculated which gears are viable and the most efficient one is picked. This process is also executed during regenerative braking in order to recuperate as much energy as possible. Additionally, new gearshift is not allowed for three seconds after a gearshift has occurred, unless it is necessary to keep the operation point within the movers limits. The generator-engine control is realized by precomputing the combined maximum efficiency point of the setup and letting MEMS decide when to turn the setup on/off depending on the state of charge of the battery.

2.5 Closed-loop automatic testing

To test each of the possible plant and control designs an automated methodology for closed-loop testing has been developed. Essentially, MATLAB scripts and functions generate a Simulink model based on the topology and components settings. This Simulink model uses the publicly-available QSS modelling library [13] to construct a certain vehicle powertrain. The QSS library relies on the quasi-static representation of the system, meaning that the physical causality of the model is revered (more on quasi-static modeling in [14]). Fig. 4 illustrates such a representation of a pre-transmission parallel hybrid. However, to accommodate this approach, the QSS library underwent several changes.

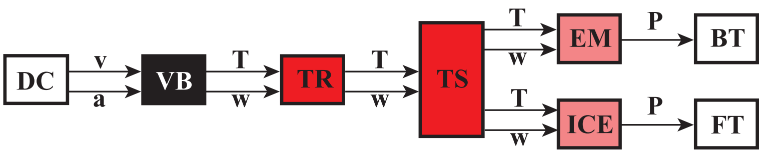

Figure 4: Parallel HEV causality representation in quasi-static modeling (**DC** - driving cycle, **v** - velocity, **a** - acceleration, **T** - torque, **w** - rotational speed, **P** - power).

3 Results

To validate the developed methodology two vehicle types are optimized and the results are presented in this section. The two vehicle types are compact and full-size passenger cars with glider (without powertrain) masses of 750 kg and 1250 kg, respectively. Additional basic parameters of the two vehicles are listed in Table 1. Both designs are optimized for energy consumption over 5 repetitions of the WLTP Class 3 cycle (depicted in Fig. 5), resulting in total driving time of 2.5 h or distance of 116 km. Additionally, a PI feedback controller ensuring charge-sustaining (CS) behaviour over the cycle is introduced in order to compare the fuel consumption of the hybrids against conventional ICE-driven vehicles.

Table 1: Compact and full-size vehicles parameters.

	Compact	Full-size
Air drag coefficient ($A_f \cdot c_d$)	0.6 m^2	0.7 m^2
Rolling resistance coefficient (c_r)	0.012	0.013
Total wheel radius (w_r)	0.3 m	0.36 m
Glider mass (m_{v0})	750 kg	1250 kg

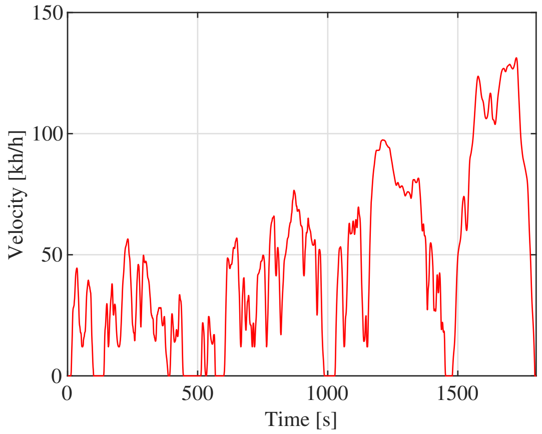

Figure 5: WLTP Class 3 driving cycle.

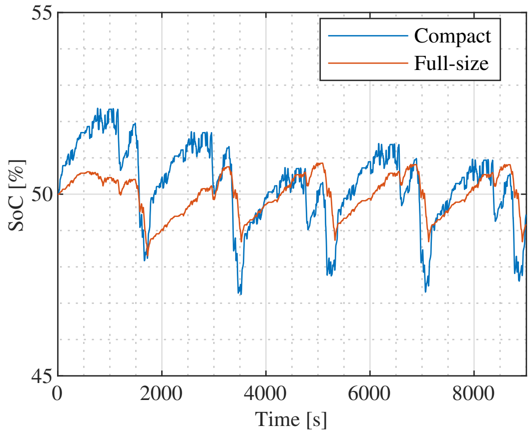

Figure 6: SoC of the two HEVs over the test cycle.

The parallel P2 (pre-transmission) topology results in the lowest energy consumption for the compact car, while for the full-size the parallel P3 (post-transmission) configuration delivers the best results. Optimized component sizes and fuel consumption of the two vehicle types are listed in Table 2 and battery SoC's over the cycle are depicted in Fig. 6. The compact P2 hybrid opts for engine and motor size with similar operation range as the two components are coupled via the transmission and operate at the same shaft speed. Thus, this is expected and the electrification level sits in the middle between an ICE-driven and electric vehicle. On the other side, the full-size P3 hybrid keeps the same motor size as the compact P2 but selects a rather larger engine. In post-transmission hybrids usually the engine is downsized by the transmission but the motor is larger as it needs a wider operational range. The reason for the opposite behaviour in this case is the CS strategy.

Table 2: Vehicles optimization results.

	Compact (P2)	Full-size (P3)
Combustion engine size [kW]	35	81.2
Electrical motor size [kW]	35	34.6
Battery size [kWh]	6.3	12.3
Fuel consumption [l/100km]	3.19	4.37
Vehicle mass [kg]	1024	1747

To understand better how the two hybrids operate Fig. 7 depicts the relative amount of time in percentages which each vehicle spends in the diffident operation modes. The compact P2 hybrid charges for a larger proportion of the time compared to the full-size P3 and the main reason for that is the larger engine of the full-size. This larger engine allows for charging at higher powers while operating in an efficient region, and thus, requires less time to provide the same amount of energy. Both hybrids spend less than 1 % of the cycle in electric only mode. Essentially, when a CS strategy is imposed the vehicle would try to charge the battery or/and operate in hybrid mode as much as possible. However, that is highly dependent on the design of the PI controller imposing the CS strategy.

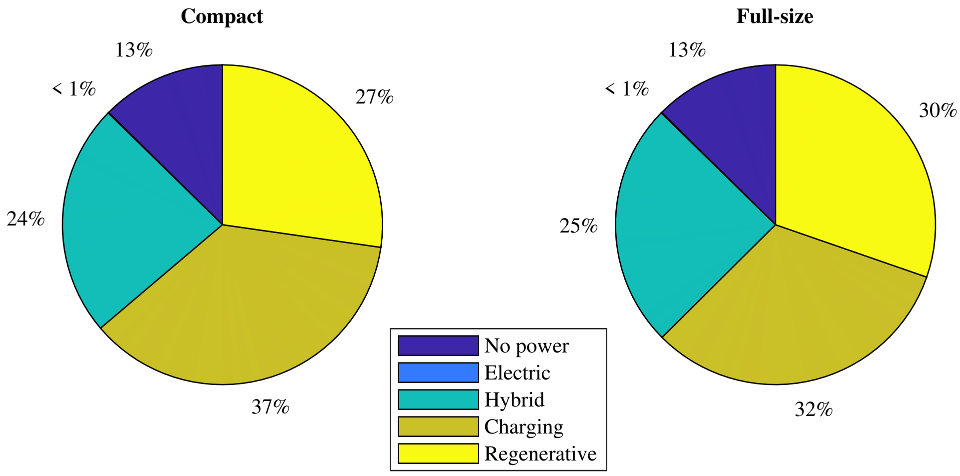

Figure 7: Mode distribution for the optimized compact and full-size HEVs.

4 Discussion

4.1 Fuel consumption comparison

To put the optimization results into context, the fuel consumption of the two vehicles is compared with vehicles from the same types. To do so, the best sold ICE vehicles in Europe for 2021 with the same total masses as the two optimized HEV designs are taken (data from [15]). For each of these the most efficient model configuration has been picked. Moreover, for the full-size case the average consumption in CS mode of three other HEVs is considered as well (data from [16]). Fig. 8 depicts the fuel consumption of all the vehicles over the WLTP Class 3 cycle. The two designs for this study score much better compared to the conventional vehicles and the full-size shows a 17 % decrease in consumption compared to other HEVs.

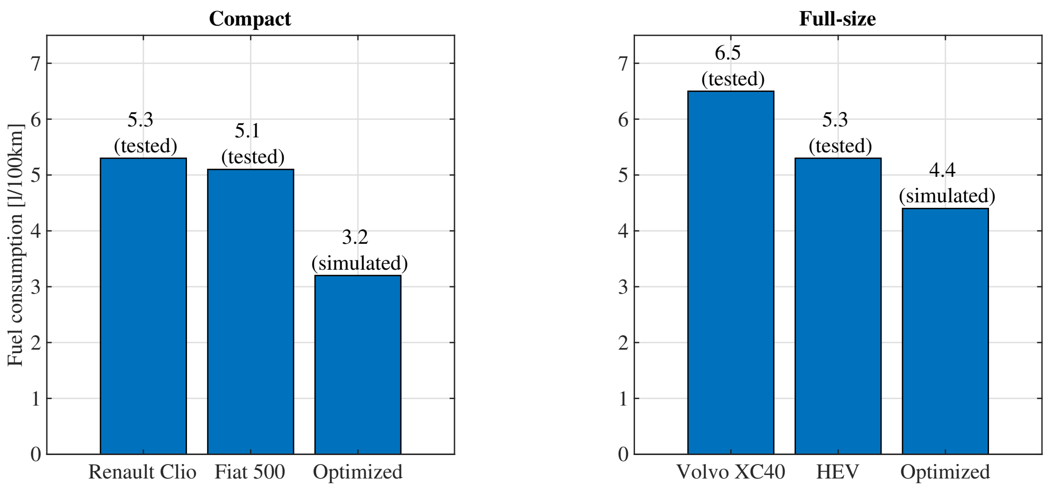

Figure 8: Fuel consumption (petrol) of different vehicles over the WLTP Class 3 cycle.

It is apparent that HEVs have a higher initial cost than conventional vehicles and this study did not optimize for total cost of ownership. However, doing a quick calculation on running costs using petrol price of 2.1 €/l (average for Netherlands as per 19.04.2022) at 13000 km/year, reveals yearly savings of 600 € if you use the optimized compact HEV rather than the Renault Clio.

4.2 Quasi-static vs convex models

As this is a study purely based on simulations, it is essential how the components are modelled. QSS represents the components in quasi-static (backwards) fashion, meaning their physical causality is reversed. This allows for significant reduction in computational time (compared to dynamic models) which comes in handy when solving sizeable optimization problems, like in this study. In general, backwards modelling is well suited for supervisory control systems that optimize power flows [14]. However, this paper aims at delivering the globally optimal solution when it comes to the power management of the system. As already discussed, MEMS requires convex models of the components to guarantee global optimality, and thus, the quasi-static models are converted towards such suitable for optimal control using quadratic fitting (more on that in Sub-subsection 2.1.5). This conversion, in some cases, requires approximations which distance the model from reality, and thus, could alter the performance of the powertrain. The components library has been checked for such big approximations and such have been excluded, but still some inaccuracies between model and fit exist. In other cases (like the battery) the quadratic fitting includes dependency on state variables in the model, and thus, the resulting model could not be convex.

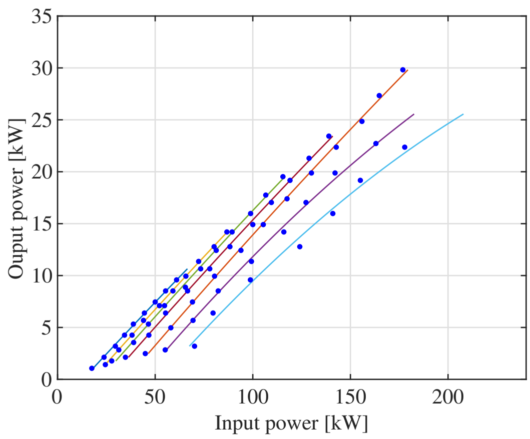

Figure 9: Model and quadratic fit of an engine.

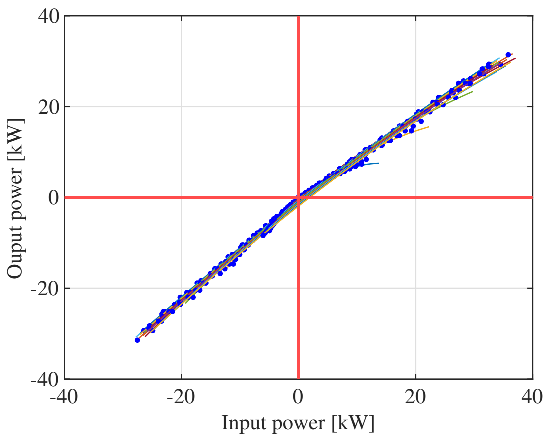

Figure 10: Model and quadratic fit of a motor.

Fig. 9 & 10 depict the the relations between input (chemical or electrical) and output (mechanical) power for an engine and motor, where the lines are the speed-dependent fits. Note that the quadratic fits could be improved, but to obtain convex models the quadratic fitting parameters must always be non-negative. These residuals in the fits influence the simulations and the optimization framework: at certain instances the energy management strategy (using the fits/convex models) could pick an operation point for the engine, motor or generator which is outside the operation region according to the quasi-static model and would interrupt the simulation. Therefore, it is essential for this framework that the convex models of the components are as accurate as possible.

5 Conclusion

This paper aimed at designing an automated tool which can provide initial advise on how to design and control a powertrain topology for certain use profile. The developed tool, named TOPDSIGN, provides a solution for the joint design problem by incorporating MEMS in its core. All plant and control designs are tested using an automated closed-loop testing methodology, which creates Simulink models based on the modified QSS modelling library.

Two vehicle types have been optimized over the main test cycle for Europe while imposing CS strategy. The pre-transmission parallel topology results in the lowest energy consumption for the compact HEV, while the post-transmission parallel configuration delivers the best results for the full-size car. Component sizing (especially for the full-size case) and mode distribution indicate that the design is heavily dependant on the battery management strategy (and how it is imposed). The fuel consumption of the two optimized HEVs is considerably lower when compared to the most popular ICE-driven vehicles from the same class on the European market. Additionally, the full-size car achieves 17 % savings in fuel consumption against other HEVs.

Convexifying component models is pivotal for the optimal control energy management strategy and this paper has demonstrated a method for converting quasi-static models into convex. However, as the powertrain test framework uses quasi-static models during simulations while the energy management strategy relies on the convex representations, it is very important that the mismatch between the two is minimal.

Acknowledgments

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Presenter Biography

Avedis Dadikozyan obtained his BSc. in Automotive Engineering at the Eindhoven University of Technology (TU/e). He is currently pursuing a MSc. degree in Automotive Technology at the Department of Mechanical Engineering at TU/e. Avedis is specializing in powertrains design and control at the Control Systems Technology (CST) group. He has undergone an internship at the Dutch Organization of Applied Research (TNO) and is currently working on the New Energy and mobility Outlook for the Netherlands (NEON) project as part of his graduation thesis.

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Dr. Steven Wilkins is a Senior Research Scientist at TNO, where he works in electrified powertrain research. He is also an Assistant Professor in the EPE group of the Department of Electrical Engineering at TU/e. He has a background in (H)EV systems and powertrain modelling and simulation, with a focus on battery management systems. He is an active member of EARPA, EGVIA/2ZERO, BEPA ERTRAC and others, and involved in the TRANSFORMERS, ASSURED, ORCA, AEROFLEX, URBAN1ZED and NEXTETRUCK European projects, and others.