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Co-design Approach and Optimization for Plug-In Hybrid Buses

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Abstract

This paper proposes a new co-design optimization framework for the powertrain sizing and control parameters of Plug-In Hybrid Electric Buses (PHEB). The PHEB must have the lowest powertrain Total Cost of Ownership (pTCO) while respecting a set of dynamic performances and lowering the fuel consumption as much as possible. Previous works have addressed the problem of powertrain sizing or control strategies independently but have failed to combine them in a multilevel system for heavy duty vehicles. In this paper, the energy management strategy is nested within the plant design to create a co-design system-level in which the controller is optimized using the Equivalent Consumption Minimization Strategy (ECMS) and the sizing of powertrain. Components are optimized using a Genetic Algorithm (GA). The GA implemented in Matlab performed simulations on a parallel configuration of PHEB simulated in Simulink, in which the power sharing factor was chosen according to the ECMS implemented in Matlab. The proposed co-design optimization successfully achieved better results than the conventional brute force search and proves that, compared to conventional Internal Combustion Engine (ICE) buses, PHEB manage to reduce both the consumption and the pTCO while meeting the same driving requirements.

Keywords: co-design, equivalent consumption minimization strategy, genetic algorithm, powertrain total cost of ownership, plug-in hybrid buses

1 Introduction

The road transport has a negative impact on the environment. The emissions released by the combustion of fossil fuels (i.e. diesel and gasoline) in the conventional vehicle using an Internal Combustion Engine (ICE) have a significant impact on air pollution. Heavy-Duty Vehicles (HDV) are responsible for 30% of on-road CO2 emissions in Europe while representing only 4% of the road sector activities [1]. Improvement in fuel consumption of HDV will have a big impact on the pollution problem that the world is facing today.

Among all possible new energy vehicles, there is a trend for the electrification and more precisely for the Hybrid Electric Vehicles (HEV) in the short term. The HEV became one of the most promising solutions by combining the advantages of the ICE and the Electric Motor (EM). Combining both EM and ICE into HEV allows a long driving cycle, good power performances, a convenient refueling, low emissions and noise [2], a downsizing of the engine, a braking energy recovery, a shut off of the engine during standstill, and an increase of the efficiency [3]. Moreover, the Plug-in Hybrid Electric Vehicles (PHEV) contain a battery that can be charged by using the excess engine power, but also by plugging it into the grid. To be cost and fuel efficient and to respect the dynamic performances, the Plug-in Hybrid Electric

Buses (PHEB) need to be well designed and controlled. It is therefore important to optimize the powertrain parameters as well as the control parameters using a driving cycle corresponding to a Transport Assignment (TA).

The optimal design of a hybrid electric vehicle is a multiobjective optimization problem [4]. The topology, size and control are dependant parameters and cannot be optimized sequentially otherwise the solution would be sub-optimal [5]. These dependant parameters therefore form a multi-level problem that can be solved using system-level design. The review in [4] presents three different architectures for the system-level design of plant and control design as shown in Figure 1.

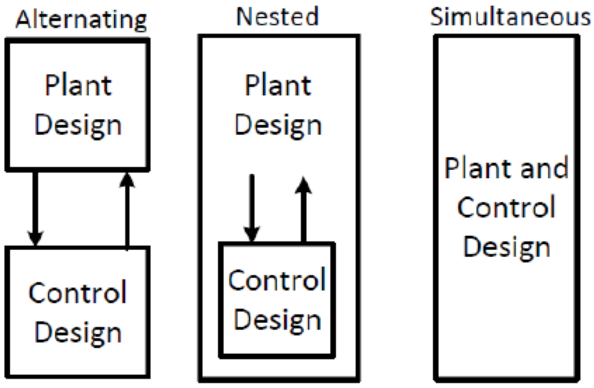

Figure 1: Architecture for System-Level Design in HEV [4]

The plant optimization consists of finding the best size for the battery, EM and ICE, to minimize an objective function while ensuring some performance requirements. In literature, the derivative free algorithms are widely used for plant optimization. These algorithms consists of Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA) [12] and Divided Rectangular (DIRECT) [13]. Comparisons between these algorithm can be found in [14]– [16]. GA is widely used in the field of hybrid vehicles.

In the literature, the researches about control optimization nested within plant optimization are very limited. Many papers only consider one driving cycle without taking the whole transport assignment into account. Moreover, in plant design optimization, a simple RB EMS is usually used and the objective function only focuses on fuel consumption or emissions, without considering the investment cost or operational cost. This paper proposes a co-design framework combining plant and control optimization for PHEB. The goal is to minimize the powertrain Total Cost of Ownership (pTCO) while meeting a set of performance constraints. Here, the pTCO consists of the components costs and the operational costs. On top of that, the fuel consumption of the proposed PHEB should also be minimized.

This paper is organized as follows: Section 2 will develop the PHEB implementation and the proposed co-design optimization. Then, Section 3 will provide results and compare them to the brute force search results. Finally, Section 4 will provide conclusions based on the results obtained.

2 Proposed co-design optimization framework

2.1 Co-design optimization framework

The simulation and co-design will be implemented in Matlab and Simulink. The main idea of the proposed framework is presented in Figure 2.

The proposed co-design framework is a control design nested within plant design. Being more efficient than a sequential design, it is suitable for the plant and control optimization. Genetic algorithm is used to find the optimal size of the EM, ICE and battery by minimizing the pTCO (component cost + operational cost). For every new combination of EM, ICE and battery, the simulation is performed over a certain distance using the related transport assignment. During this simulation, the requested power is split between the EM and the ICE using a sharing factor $\lambda = \dfrac{P_{EM}}{P_{EM} + P_{ICE}}$. This λ is calculated using the ECMS that will minimize the total equivalent consumption at every time instance of the driving cycle.

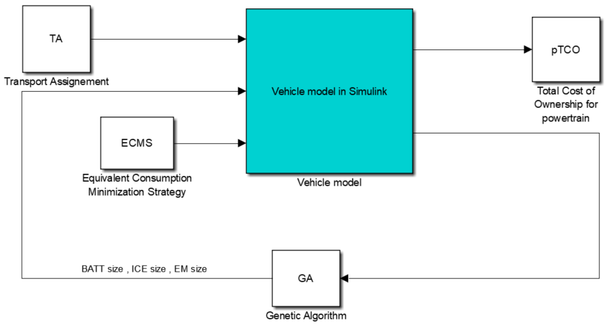

Figure 2: Proposed co-design optimization framework

2.2 Fitness function

The objective function to minimize in this process is the pTCO which is the combination of the components cost (Capital Expenditure (CAPEX)) and the operational cost (Operational Expenditure (OPEX)). These costs only concern the engine, the motor, the battery and the inverter without taking into account all the other costs related to the other components of the bus. It is a simplified representation of an economic function. A penalty function is applied to this powertrain cost if the performance requirements are not met. This is an efficient way to take the constraints into account. The fitness function (J[€]) is defined by

$$J = CAPEX + OPEX + penalty \tag{1}$$

In which $CAPEX$ and $OPEX$ can be calculated by

$$CAPEX = C_B \cdot Q_B + P_{ICE} \cdot Q_{ICE} + P_E \cdot (Q_E + Q_{INV}) \tag{2}$$

$$OPEX = BATT_{repl} + ELEC_{life} + FUEL_{life} \tag{3}$$

In (2), C_B [kWh] is the battery pack capacity. Q is the specified component cost expressed in [€/kW] for ICE (ICE), EM (E) and inverter (INV) and in [€/kWh] for the battery (B). P_{ICE} and P_E are respectively the nominal power of the ICE and the EM expressed in [kW]. In (3), $BATT_{repl}$ represents the battery replacement cost, $ELEC_{life}$ is the electric cost over the full vehicle lifetime and $FUEL_{life}$ is the fuel cost over the full vehicle lifetime.

The penalty function is used to take the driving performance requirements into account. The first requirement concerns the battery capacity. The vehicle needs to have an All Electric Range (AER) of 30 km on the SORT cycle (explained in Section III). To fulfill this requirement, the battery State of Charge (SoC) needs to be above its minimal value (20%) at the end of this AER period. The other requirements concern accelerations ability in hybrid, electric and ICE mode, and are detailed in Table 1.

Table 1: Driving performance requirements

Mode	Spedd [km/h]	Time [s]
Electric	0-20	7
	0-50	20
Engine	0-15	7
	0-40	20
Hybrid	0-20	10
	0-50	26

2.3 Powertrain description

This paper focuses on a parallel hybrid configuration presented in Figure 3. This configuration allows the use of the EM and the ICE either combined or separately. This configuration allows a size reduction of the ICE and the EM since for high power demands, the power can be split between the two power sources.

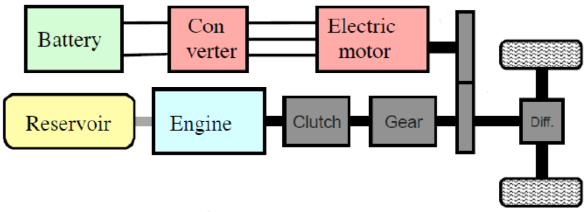

Figure 3: Parallel hybrid configuration [17]

The electric power consumed and generated are obtained using respectively (4) and (5) depending on the current direction.

$$P_{elec} = \frac{T_{EM} \cdot \omega_{EM}}{\eta_{EM}} \qquad \text{discharging mode} \tag{4}$$

$$P_{elec} = \eta \cdot T_{EM} \cdot \omega_{EM} \qquad \text{charging mode} \tag{5}$$

Where η_{EM} is the efficiency of the electric motor computed using the efficiency map, T_{EM} [Nm] is the achievable torque provided by the EM, and ω_{EM} [rad/s] is the rotation speed of the EM.

The power delivered by the fuel combustion is expressed as

$$P_{fuel} = \dot{m} \cdot LHV_{fuel} \tag{6}$$

in which $\dot{m}$ [kg/s] is the fuel mass flow obtained by a look-up table which depends on the required torque and the rotation speed of the engine (T_{ICE} and ω_{ICE}). LHV_{fuel} [J/kg] is the fuel lower heating value.

The vehicle environment is used to model all the external forces acting on the vehicle such as the wind, the slope of the road and the friction. It takes as an input the combined torque of EM and ICE, adds all the external forces and finally computes the total driving torque used for the vehicle acceleration. The velocity is computed by

$$v = \int \frac{1}{m}(F_{tract} - F_{aero} - F_{roll} - F_{slope})dt \tag{7}$$

in which m[kg] is the vehicle mass, F_{tract}[N] (8) is the combined tractive force of the ICE (F_{ICE}) and the EM (F_{EM}), F_{aero}[N] (9) is the resistive force due to the aerodynamic friction, F_{roll}[N] (10) is the rolling resistance due to the friction between the wheels and the road and F_{slope}[N] is the gravitational force acting on the vehicle.

$$F_{tract} = F_{ICE} + F_{EM} \tag{8}$$

$$F_{aero} = \frac{\rho \cdot v^2 \cdot C_D \cdot A}{2} \tag{9}$$

$$F_{roll} = C_{rr} \cdot m \cdot g \cdot \cos(\alpha) \tag{10}$$

$$F_{slope} = m \cdot g \cdot \sin(\alpha) \tag{11}$$

In these equations, ρ is the density of air, v is the vehicle speed, C_D is the drag coefficient, A is the frontal area, C_{rr} is the rolling resistance coefficient, m is the mass of the vehicle, g is the gravitational acceleration, and α is the slope angle of the road which is assumed to be zero in the simulation.

2.4 ECMS control

The equivalent consumption minimization strategy is used as an on-line control for the energy management system. The main idea is to solve an instantaneous optimization problem by minimizing a cost function. This cost function takes into account the fuel consumption and the electrical energy variation. The electrical energy variation is multiplied by an equivalence factor $s(t)$ that needs to be defined. The cost function is be written as:

$$J = \arg\min_{\lambda}(P_{fuel}(t) + s(t)P_{batt}(t)) \tag{12}$$

Where the control variable λ represents the sharing factor used to distribute the requested power between the ICE and the EM and is defined as follows:

$$\begin{cases} \lambda = \dfrac{T_{EM,wheel}}{T_{wheel}} & \in [0,1], \text{for } T_{wheel} > 0 \\ \lambda = 1, & \text{for } T_{wheel} < 0 \end{cases} \tag{13}$$

The equivalence factor $s(t)$ depends on the battery SoC deviation and its equation is given by:

$$s(t) = s_0 + s_0 \cdot K \cdot \tan\left(\frac{SoC_{ref} - SoC(t)}{6\pi}\right) \tag{14}$$

in which s_0 is an average of suitable constants found from earlier simulation on a given driving cycle and has a value of 2.4 for the SORT cycle. K is a gain used to adjust the weight given to the SoC deviation. The division of the deviation by 6π is done to give more flexibility to the system in case of exceptional environment such as big slopes, quick wind, high load, etc. The tangent function provides a good control of the SoC trajectory and results in good fuel economy [18].

According to [19] and [20], a gradual discharge of the battery lowers the average discharge current which leads to lower resistive losses. The reference SoC equation is written as follows:

$$SoC_{ref}(t) = \frac{(SoC_{final} - SoC_{init}}{D_{tot}} \cdot d(t) + SoC_{init} \tag{15}$$

The basic principle of the ECMS control implemented in this paper is that, except for s_0 which is calculated once, a few steps are done in every time instance and make the power split decision based on the power demand. An overview of these steps is listed:

1. A certain lambda is chosen: $\lambda \in$ [0, 1]
2. The requested power at the wheels is split between ICE and EM (P_{ICE} and P_{EM}) using lambda.
3. Using the efficiency map with ω and the requested torque, the power needed from the fuel and from the battery is computed (P_{fuel} and P_{batt}).
4. The cost function J is calculated using the equivalence factor $s(t)$.
5. Steps 1 to 4 are repeated for every lambda
6. The best lambda is found when the cost function J is minimized.

On top of that, the constraints were taken into account using a set of IF-THEN rules. When the bus is braking, lambda is set to 1 to use the regenerative braking and to charge the battery. If the SoC is smaller than 20%, lambda is set to 0 to have an ICE only configuration and to avoid that the SoC goes below its lower limit.

2.5 GA implementation

The idea of GA is to start with an initial population (P) composed of individuals (p_i). Each individual is characterized by genes (or chromosomes) which represents the design variables (battery capacity, ICE size, EM size). Once the initial population is created, the model is run for each individual of the population and the result is given by an objective function. The next generation has the same number of individuals as the first population and is divided into three categories. The first category called elite children is simply the best individuals from the previous generation that will stay in the next one. The second and the third category, respectively called mutation and crossover are children from parents. The parents are selected based on the optimization of the objective function. For crossover, children are created by combining the genes of two parents and for mutation, children are created by making random changes to a single parent. This new population replaces the previous one and the process is repeated until one of the stopping criteria is met. The general principle of GA is illustrated in Figure 4.

The GA parameters consist of two different categories. The first one concerns the optimization variables which are the component sizes and are bounded between their minimal and maximal values. The second category represents the parameters of the GA itself such as the population size, the number of generation, the number of elite children and the crossover fraction. The parameters used in this paper are defined in Table 2.

In this configuration, the first generation is composed of an initial population of 30 individuals, each of them characterized by 3 genes (the scaling parameters). The next generation will also be composed of 30 individuals from different types:

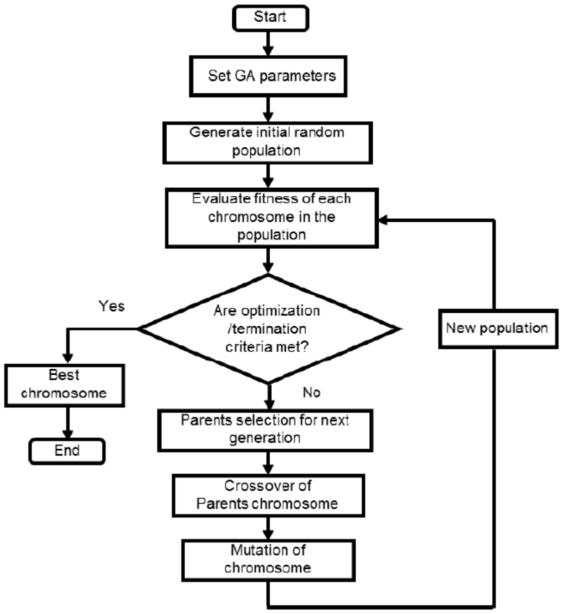

Figure 4: General principle of GA [21]

Table 2: Genetic algorithm parameters

Parameter	Value	
	min	max
ICE maximum power [kW]	[14	355]
EM maximum power [kW]	[99	355]
Battery capacity [kWh]	[50	150]
Population size	30	
Number of generation	30	
Number of elite children	1	
Crossover fraction	0.75	

- 1 Elite children
- 22 Crossover children
- 7 Mutation children

3 Technical assessment of co-design

3.1 The SORT cycle

The SORT cycle is the test consisting of defined acceleration and braking processes that simulates the typical driving conditions on the road for a bus. Three different cycles are defined:

1. SORT 1: defined for heavy urban cycle with an average speed of 12 km/h.
2. SORT 2: defined for easy urban mixed cycle with an average speed of 18 km/h.
3. SORT 3: defined for easy urban cycle with an average speed of 25 km/h.

In this paper, the used cycle is a combination of these three cycles and is presented in Figure 5 with the average speed of each cycle.

The transport assignment defined in this paper consists of 52 SORT cycles (= 150.38 km) during which the battery SoC is decreasing and finally reaches its minimal value. Then, the battery is fully recharged during the night at the charging station.

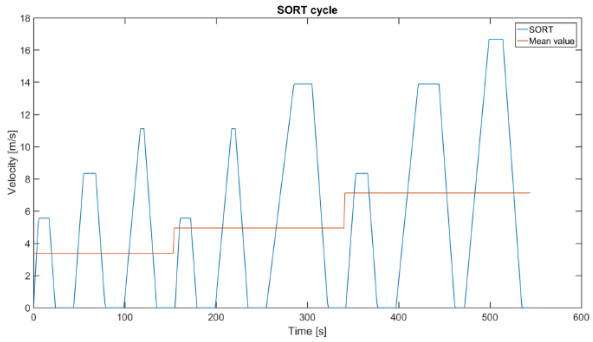

Figure 5: speed profile of SORT cycle combination used for simulations

3.2 Result of co-design

The best fitness value over the generations is presented in Figure 6 and one can see that the value is decreasing and converging to the optimal value after the 24^{th} generation.

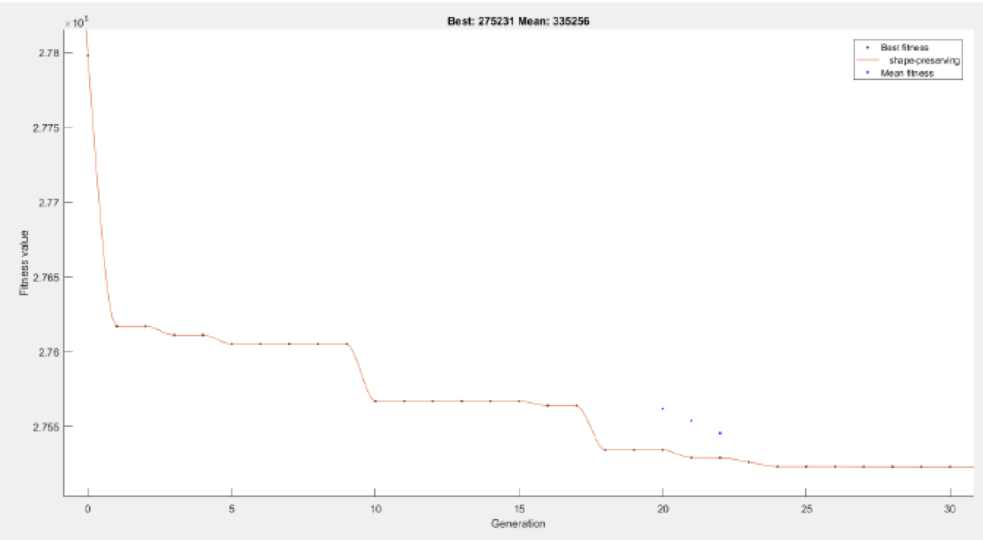

Figure 6: Best fitness value depending on the generation

The optimized size of the components is presented in Table 3 and the pTCO (CAPEX + OPEX) of this configuration is pTCO = 275,231 €

Table 3: Optimized components size

Battery capacity	ICE maximum power	EM maximum power
72.72 kWh	130.02 kW	147.98 kW

The repartition of the requested torque between the ICE and the EM is presented in Figure 7 along with the speed profile of the vehicle. The ECMS performed this torque repartition using the ECMS.

The linearly decreasing reference SoC and the real battery SoC is presented in Figure 8. The real battery SoC is varying depending on the acceleration needed and on the regenerative braking.

3.3 Results of brute force search

The brute force search is used to compare and validate the results of the proposed co-design optimization. The range of values for the brute force search are the same as presented in Table 2 for the ICE and EM

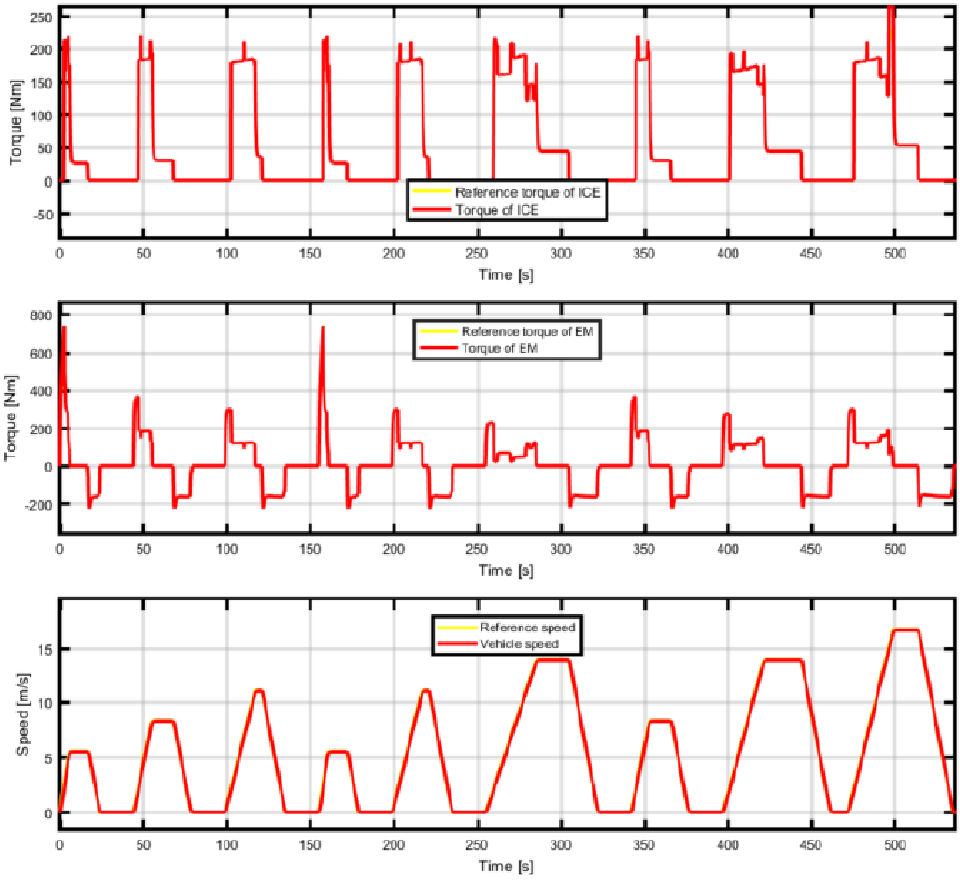

Figure 7: Torque repartition between ICE and EM and speed profile of the vehicle

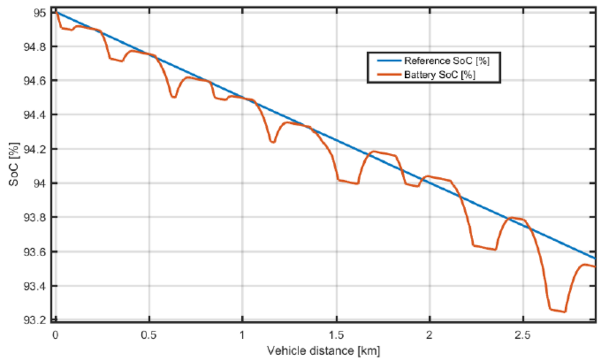

Figure 8: Reference and real battery SoC

size and for the battery capacity. For each parameters, the search space is divided in 8 as presented in Table 4 which gives 512 possible combinations.

Table 4: Search space of brute force search

Parameter	Possible values							
Battery capacity [kWh]	[50	64	79	93	107	121	136	150]
P_{max} of ICE [kW]	[14	63	112	160	209	258	306	355]
P_{max} of EM [kW]	[99	136	172	209	245	282	318	355]

The minimal pTCO found using the brute force search is pTCO = 294,430 € with the parameters combination presented in Table 5.

Table 5: Parameter combination that gives the minimal pTCO

Battery capacity	ICE maximum power	EM maximum power
64 kWh	160 kW	172 kW

3.4 Comparison between brute force search and co-design

The results of co-design optimization and brute force search is resumed in Table 6.

Table 6: Brute force search and co-design optimization results

		Brute force search	co-design optimization	gain of co-design
Batt capacity	[kWh]	64	72.72	+13.6%
P_{max} of ICE	[kW]	160	130.02	-18.7%
P_{max} of EM	[kW]	172	147.98	-14.0%
pTCO	€	294 430	275 231	-6.5%

if the battery size found using co-design optimization is bigger than the one found using brute force search, the pTCO is lower which proves the effectiveness of the proposed co-design optimization.

4 Conclusion

The co-design optimization framework for plug-in hybrid buses has been implemented and presented in this paper. An optimal control ECMS nested within plant optimization design GA was proposed for the co-design framework. The ECMS control was employed to reduce the equivalent consumption as much as possible by optimally computing the power split ratio λ. On top of that, the GA was used to design the optimal sizing of the battery, EM and ICE with the objective of minimizing the pTCO cost while respecting some driving requirements. These driving requirements were the main constraints concerning EM and ICE size while the battery size was optimized by the reference state of charge for a 150 km total driving distance. The proposed co-design optimization was able to find the global optimal solution given the transport assignment and managed to have a lower pTCO than the brute force search. Finally, the equivalent consumption was successfully lowered by using the ECMS.

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