Techno – economic design of hybrid electric vehicles using multi objective optimization techniques

Zlatina Dimitrova[a] , François Maréchal[b]

[a] *Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland, zlatina.dimitrova@epfl.ch*
[b] *Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland, francois.machechal@epfl.ch*

Highlights:

- Multi objective optimization is applied for optimal hybrid electric powertrain designs.
- A holistic approach for optimal design and control strategies is presented on vehicle usages.
- Hybrid electric vehicles can reach large range of efficiency – 26% to 45%.
- Hybrid electric vehicle can emit very low CO_2 emissions – 30 g/km for D class vehicles.

Abstract:

The improvement of the efficiency of vehicle energy systems promotes an active search to find innovative solutions during the design process. Engineers can use computer-aided processes to find automatically the best design solutions. This kind of approach named “multi-objective optimization” is based on genetic algorithms.
The idea is to obtain simultaneously a population of possible design solutions corresponding to the most efficient energy system definition for a vehicle. These solutions will be optimal from technical and economic point of view.
In this article this kind of “genetic intelligence” is tested for the holistic design of the optimal vehicle powertrain solutions and their optimal operating strategies.
The methodology is applied on D class hybrid electric vehicles, in order to define the powertrain configurations, to estimate the cost of the powertrain equipment and to show the environmental impact of the technical choices. The optimal designs and operating strategies are researched for different vehicle usages – normalized, urban and long way driving.

Key words: hybrid electric vehicles, multi objective optimization, economic models, driving cycles

Nomenclature:

f_1- function 1

f_2- function 2

MOO – Multi Objective Optimization

GLPK, Cplex – solvers

SoC – state of charge of the battery in [%]

γ- gear ratio [-]

m – vehicle mass in [kg]

F – force in [N]

w_s – rotation speed of the driving shaft [rpm]

w_w- rotation speed of the wheels in [rpm]

P_s – *power of the drive shaft in [kW]*

H_r – *hybridization ratio in [-]*

T_s – *torque on the drive shaft in [Nm]*

T_{ICE}- *torque of the internal combustion engine in [Nm]*

T_{EM}- *torque of the electric motor in [Nm]*

DoH – degree of hybridization

EM – electric motor

ICE – internal combustion engine

PA- power amplifier

BT- high voltage battery

$\dot{V}$ – *vehicle acceleration or deceleration in [m/s²]*

V – vehicle speed in [m/s]

P_{BT} – *power of the battery in [kW]*

P_{SC} – *power of the supercapacitors in [kW]*

$f_{scaling}$ – *scaling factor for the electric motor [-]*

k_1, k_2 – *structural parameters of the torque coupler [-]*

c_{11}, c_{22}, c_3, c_4 – *high voltage battery coefficients*

p_em – power of the electric motor in [kW]

p_th_engine – power of the thermal engine in [kW]

NEDC – New European Driving cycle

$\eta_{powertrain}$- powertrain efficiency in [-]

Introduction:

With the increasing trend of mobility of the human population, vehicles now face the problem of primary energy resources scarcity. Future regulations for the automotive industry will require a sharp decline in emissions within the next decade. For example in Europe, the regulation of the Tank-to-Wheel CO_2 emissions requires 130 g of CO_2 per kilometer, and by 2020 the CO_2 should be reduced to 95 g of CO_2 per kilometer, for the all car maker vehicle fleet. Therefore higher efficiency and better adaptation to alternative energy sources is required for new vehicles. At the moment the development of hybrid vehicles seems to be the solution chosen from the automotive industry to archive higher Tank-to-Wheel efficiency.

The state of the art today is to consider the “Tank-to-Wheel” energy balance of thermal powertrain. For example Caton in [1] and Reitz and Duraisamy in [2] present a review of the efficiency for internal combustion engines. They determine the energy balance of a thermal powertrain on an analytical way. The results show that 30% of the energy is used for the mobility as mechanical power. The other 70% are wastes – waste heat in coolant ˜ 30% and waste heat in exhaust gases ˜ 40%. The hybrid electric vehicles recover the kinetic energy in the vehicle deceleration phases.

The hybrid electric vehicle is seen as a good compromise between increased “Tank-to-Wheel” efficiency, enough long range of autonomy and acceptable cost for the customer [3]. Many researches are performed on the energy conversion balance on the vehicle board. They are based on analytical methods. Katrasnik proposes in [4] analytically based method to calculate corrected fuel consumption of parallel and series hybrid electric vehicles (HEVs) at balanced energy content of the electric storage devices. The energy conversion phenomena are explained in [5]. Energy flows and energy conversion efficiencies of commercial plug-in hybrid-electric vehicles (PHEV) are analyzed for parallel and series PHEV topologies. The analysis is performed by a combined analytical and simulation approach.

Various type models and algorithms derived from simulation and experiment are explained in details in [6]. Most of them are heuristic and based on iterations of designs and energy management strategies. The performances of the various combination of HEV system are summarized. The article provides comprehensive survey of hybrid electric vehicle on their source combination, models, energy management system (EMS) etc.

The design of the converters and the stockers is optimized for global best tank-to-wheel efficiency. Finesso et al. focuse in [7] on the design, optimization and analysis of a complex parallel hybrid electric vehicle, equipped with two electric machines on both the front and rear axles. Bayindir et al. present in [8] an overview of HEVs with a focus on hybrid configurations, energy management strategies and electronic control units. Poullikkas presents in [9] an overview regarding electric vehicle technologies and associated charging mechanisms is carried out. The review covers a broad range of topics related to electric vehicles, such as the basic types of these vehicles and their technical characteristics, fuel economy and CO_2 emissions, the electric vehicle charging mechanisms and the notions of grid to vehicle and vehicle to grid architectures. In particular three main types of electric vehicles, namely, the hybrid electric vehicles (HEVs), the plug-in electric vehicles (PHEVs) and the full electric vehicles (FEVs) are discussed in details.

Genetic algorithms are mostly used for the optimizations of the HEV components design. Eren et al. in [10] deal with optimal sizing of HEV and propose a methodology for the optimization of HEV components using the multi-objective approach considering the minimization of operating cost, weight and volume simultaneously. To optimize the sizing of HEV components, the mixed integer linear programming (MILP) model is tested and optimization processes are performed for different range of drive cycles. Song et al. used in [11] a multi-objective optimization of a semi-active battery/ supercapacitor energy storage system for electric vehicles. Dynamic mathematical programming is applied to the energy management optimization, including heuristic management strategies. In [12] Khayyam et al. propose a soft computing based intelligent management system developed using three fuzzy logic controllers. The fuzzy engine controller within the intelligent energy management system is made adaptive by using a hybrid multi-layer adaptive neuro-fuzzy inference system. Torres et al present in [13] the development of an energy management strategy of a plug-in hybrid electric vehicle (PHEV). In this case, a rule-based optimal controller selects the appropriate operation mode. Tribioli et al. study in [14] a real time energy management strategy for Plug-in hybrid electric vehicles based on optimal control theory and the optimal problem is solved with the Pontryagin's Minimum Principle. The robustness of the fuel economy as a function of the different customers behaviors are measured and analyzed. In [15] Santiangeli et al. do experimental analysis of the auxiliaries' consumption in the energy balance of a pre-series Plug-in hybrid-electric vehicle. Davies et al. study in [16] the implications for energy and emissions impacts of plug-in hybrid electric vehicles. Predictive control modes are researched for the fuel reduction robustness in [17] where Cost analysis of plug-in hybrid electric vehicles using GPS-based longitudinal travel data is presented.

Sakti et al., perform in [18] a techno-economic analysis and optimization of Li-ion batteries for light-duty passenger vehicle electrification. They conduct a techno-economic analysis of Li-ion prismatic pouch battery and pack designs for electric vehicle applications. They develop models of power capability and manufacturing operations to identify the minimum cost cell and pack designs for a variety of plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV) requirements.

Mock et al. propose in [19] techno-economic assessments of battery and fuel cells. A detailed assessment of past progress of key technological parameters and their technical limits enables judgment of the probability of reaching target values set for the future. Examination of production costs using a combination of a top-down learning curve approach and a bottom-up mass production costs approach identifies potentials for future cost reductions. The method of techno-economic assessment is applied to the technologies of fuel cells and batteries, illustrating past developments and resulting in an outlook on a likely future introduction of both technologies, with focus on the market for passenger car propulsion systems.

Wu et al. study in [20] a component sizing optimization of plug-in hybrid electric vehicles. This paper describes a methodology for the optimization of PHEVs component sizing using parallel chaos optimization algorithm. In this approach, the objective function is defined so as to minimize the drivetrain cost. In addition, the driving performance requirements are considered as constraints. Finally, the optimization process is performed over three different all electric range (AER) and two types of batteries.

Hung et al. in [21] present an integrated optimization approach for a hybrid energy system in electric vehicles. They develop a simple integrated optimization approach for deriving the best solutions of component sizing and control strategies of a hybrid energy system which consists of a lithium battery and a supercapacitor module.

Osornio-Correa et al. in [22] present a multi-objective genetic algorithm optimization methodology of powertrain and control strategy of a hybrid electric vehicle for maximum energy economy. A heuristic Control Map is created to analyze the restrictions and benefits of using either of the onboard power plants under different driving conditions. The control strategy follows the Control Map with a logic that responds to the Battery State of Charge.

S. Hamut et al. in [23] propose an analysis and optimization of hybrid electric vehicle thermal management systems. The thermal management system of a hybrid electric vehicle is optimized using single and multi-objective evolutionary algorithms in order to maximize the exergy efficiency and minimize the cost and environmental impact of the system. They perform an exergoeconomic and an exergoenvironmental optimization and compared trade – off of the solutions.

To optimize the energy “Tank-to- Wheel” balance of the system vehicle, one needs to perform a behavior study of the system, through system “vehicle simulation” model. The first step is to assume a real system to a model though model objectives and parameters. The components are sized and grouped in powertrain architecture. This architecture is researched for optimal energy management strategy and evaluated for minimal fuel consumption. The “heuristic” energy management strategies are the state of the art in most prototypes and mass-production hybrids. Strategies derived from optimal control theory (“optimal” strategies) are the subjects of research and are gradually being introduced in the industry [3]. The selected design is evaluated from cost point of view. Then a second optimized sizing of the components is researched and approach is applied in a second iteration. This heuristic optimization approach based on components design iterations is summarized in Figure 1.

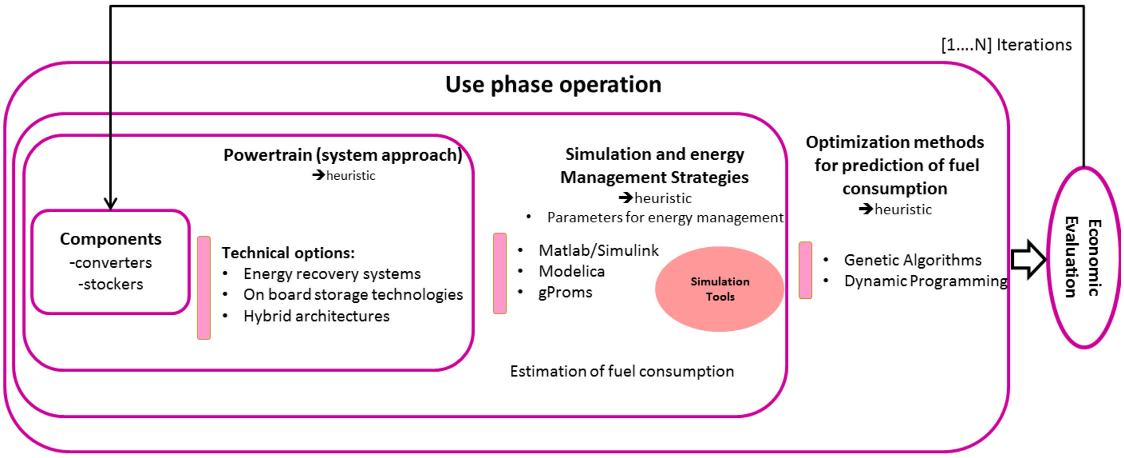


Figure 1 : Heuristic optimization approach for minimal fuel consumption

Multi criteria optimization is needed for the optimal vehicles design.

The number of components that are necessary to realize modern hybrid electric propulsion system is inexorably increasing. One needs an adapted design tool to design optimal powertrain configurations. The best possible results are not obtained by an isolated optimization of each single component. Optimizing the entire system however is not possible with heuristic methods as highlighted in [24]. According to Guzzella [3], the only viable approach to cope with this dilemma is to develop mathematical models of the components and to use model-based numerical methods to optimize the entire system structure and the necessary energy management algorithms for optimal mobility service.

The efficiency improvement need induces to search new structured methodologies allowing the integration of the efficiency/cost vision for different vehicle energy technologies, in the earlier design stage of the new vehicles and their propulsion systems. The assessment of environmental impacts is also needed. In this context the aim of this paper is to present the results of a global optimization methodology development for the design of the vehicle energy systems. This methodology can consider on a holistic way the “techno-economic” criteria for design. The methodology supports the decisions during the design process of the vehicle energy systems and their usages, according to the customers driving cycles. The optimization methodology developed in this paper is mainly used for the energy system design and sizing. In the same time, some simplified energy management strategies are optimized. The methodology allows sweeping the degree of hybridization of the different hybrid electric solutions and presents a global view of the techno-economic performances of the large types of HEVs, classified functionally to – full HEV, Plug-In HEV and range extenders (REX).

This paper illustrates the modelling of a hybrid electric vehicle conversion system and a multi-objective optimization methodology is applied for the design and the preliminary energy management strategies of the conversion system components. The optimal techno-economic hybrid electric configurations are defined for different vehicle usages – urban, peri-urban and long way drive. The benefit of this method is the simultaneously evaluation of the techno-economic trade-off of different hybrid electric configurations, which could be helpful for decisions for design of propulsion systems.

2 Optimization methodology:

To optimize the energy “Tank-to- Wheel” balance of the vehicle, one has a hybrid electric simulation model, described in part 2.1.

The optimization and simulation tool used for this publication have to fulfil the following requirements:

- Enough flexibility to simulate a wide range of conversion technologies with different level of detail
- Integrate a dynamic profile simulation , an estimation of the system performances and the resistance efforts, for different driving profiles
- Define the size of the equipment
- Include economic models to deduce the cost of the equipment
- Give operation strategies possibilities

In this study, multi-objective optimization is performed with the OSMOSE tool (Figure 2).

The general computational framework has already been described in [25], where techno-economic optimization is coupled with environmental indicators. The authors studied “environomic” optimal configurations of geothermal energy conversion systems. After that the superstructure is adapted for vehicle applications by the introduction of physical vehicle simulation models and vehicle economic and environmental models. After multi-objective optimizations the authors present in [26] “environomic” designs for hybrid electric vehicles. These designs are optimal from technical, economic and environmental point of view. “Environomic” designs of electric vehicles are studied in [27]. The superstructure contains a physical vehicle simulation model, with dynamic and thermal layouts. This model is described in the section 2.1. The cost equations are written in the economic model. The energy integration model uses the results from the dynamic and thermal flows calculations. The optimizer in OSMOSE is based on a genetic algorithm.

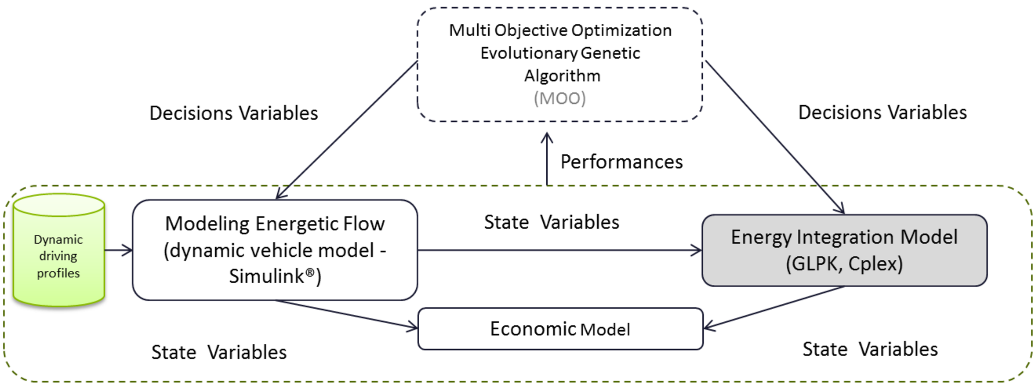


Figure 1 : Architecture of the multi-objective optimization tool, OSMOSE

2.1 Hybrid electric vehicle dynamic model:

The vehicle simulation tool is SIMULINK®. The vehicle model is based on mechanical and electrical flows. The thermal layout of the internal combustion engine is constructed from measurement maps and included in the vehicle model. The level of the model is quasi-static. The vehicle is able to follow dynamic profiles generated from a library of driving cycles. The model has a loop energy management structure, linked to the required mechanical power, to follow the dynamic cycle. This energy management loop is called "back and forward" and allows, for a given design of the vehicle powertrain to simulate the energy consumption of the vehicle, on the given driving profile. The energy flow is computed *backwards* from the wheels to the energy sources. Proceeding in this manner insures the flexible and fast nature of the simulations. This is an important advantage for an optimization study. However the quasi-static approach is limited in its non-causality.

The main characteristics of the hybrid electric simulation model are given in Table 1.

Table 1: D- Class vehicle characteristics

Sub-System	**Characteristic**	**Value**
Vehicle	Nominal mass [kg]	1660
Gear box	CVT efficiency [-][28]	0.84
	MGB efficiency [-]	0.95
	6 gears	
Engine	Displacement [l]	2.2
	Number of cylinder	4
	Rated power [kW]	120
	Max. speed [rpm]	4500
	Max. Torque [Nm]	380
	Idle speed [rpm]	800
	Idle fuel consumption [l/h]	0.33
	Deceleration Fuel cut- off	Yes
Fuel	Type	Diesel
	Density [kg/l]	0.84
	Lower heating value [MJ/kg]	42.5
Electric motor	Power [kW]	27
Battery	Ni MH	
	Capacity [kWh]	1.2

The model is based on a commercial D class diesel hybrid electric vehicle. Some adaptations due to the optimization predisposal and the non-normalized driving cycle's evaluations are done.

The results coming from the model in one run simulation are compared with commercial vehicles performances in Table 2:

Table 2: Model validation

CO_2 emissions	ICE 2.2 l Diesel	HEV with 2.2 l Diesel
Simulation	151	93
Commercial vehicles [30]	154	95

The difference is less than 10% and this could be acceptable for an optimization study.

Figure 3 illustrates the generic units that are modelled in the vehicle powertrain and the backwards approach to estimate the energy consumption.

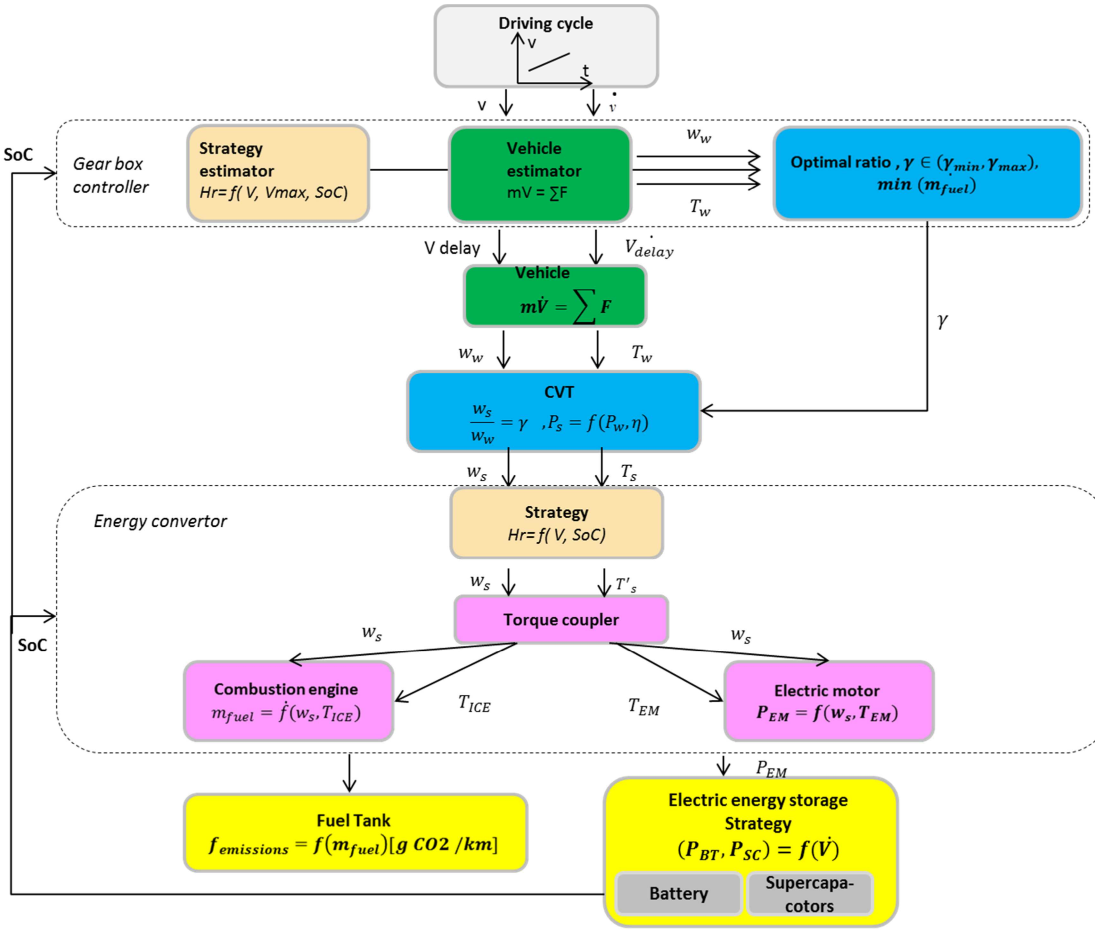


Figure 2 : Quasi- static model of the parallel thermal electric hybrid

The simulation model is based on parallel hybrid architecture. Hybrid- electric vehicles differ also according to the degree of hybridization of the powertrain (Figure 4), and the battery capacity. In the optimization part the battery capacity is one of the decision variables, so the solutions are classified according to the functional classification in Figure 3.

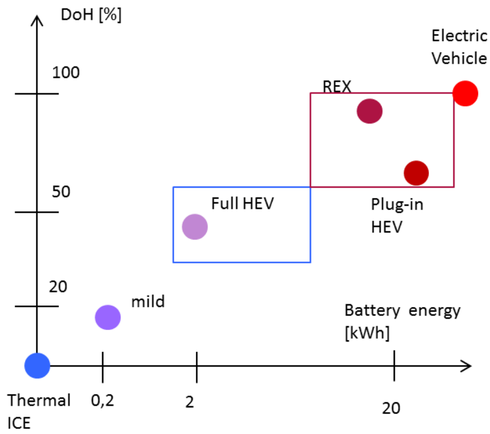


Figure 4: Functional classification of HEVs in term of degree of hybridization and battery capacity [3]

Driving cycle: the input of the model is a predefined discrete time and speed profile. The profiles used in this study are described in paragraph 2.3.

The vehicle model uses the traction force on the wheels, in order to find the power demand. It takes into account the rolling and aerodynamic resistance, the vehicle mass and the uphill force if driving on a slope.

A transmission model is used between the wheels and the energy convertor to adapt the speed and the torque levels. The model has a manual gear box used for the validations on harmonized driving cycles, with imposed gear ratios. For the usage driving cycles, when the gear ratio are unknown a CVT is used for the estimation of the optimal gear ratio for each point of the drive cycle.

The energy convertor transforms the energy (chemical or electrical) from the energy storage into the mechanical power. The dynamics of such convertors can be complex. Their modelling is simplified using efficiency maps, obtained from measurements from test benches.

The electric motor is considered in the model is a synchronous AC motor. The electromagnetic equations are not modelled, a black box approach based on motor efficiency being preferred. The inputs of the electric motor are its shaft's rotation speed w_{EM} and torque T_{EM} and the output is the power demand P_{EM} (Figure 5). Thus one can write for the positive and negative traction cases:

$$P_{EM}(t) = \frac{w_{EM}(t) * T_{EM}(t)}{\eta_{EM}(w_{EM}(t), T_{EM}(t))} \text{ for } T_{EM} \geq 0 \text{ (1)}$$

$$P_{EM}(t) = w_{EM}(t) * T_{EM}(t) * \eta_{EM}(w_{EM}(t), T_{EM}(t)) \text{ for } T_{EM} \leq 0 \text{ (2)}$$

The efficiency values $\eta_{EM}(w_{EM}(t), T_{EM}(t)$ for $T_{EM} \geq 0$ are obtained from the electric motor efficiency map of the QSS toolbox [29]. As the efficiency of the electric motors is usually not measured in generator mode, it is proposed in [3] to approximate it by mirroring the power losses:

$$\eta_{EM}(w_{EM} - |T_{EM}|) = 2 - \frac{1}{\eta_{EM}(w_{EM}, T_{EM})} \text{ (3).}$$

The efficiency map is illustrated in Figure 5:

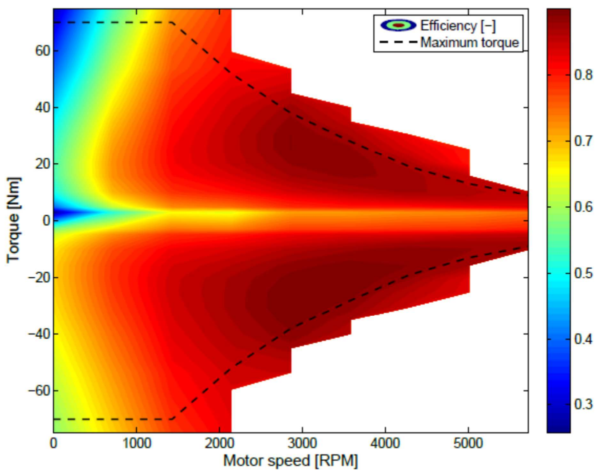


Figure 5: Two- quadrant electric motor efficiency map

The model of the combustion engine is based on the fuel consumption map. The inputs of the model are the engine shaft speed w_{ICE} and torque T_{ICE} and the output is the fuel consumption $\dot{m}_{fuel}$. An example of a fuel consumption map is given in Figure 6:

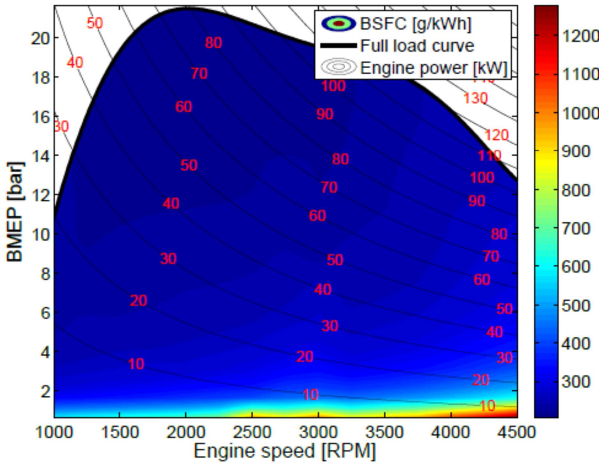


Figure 6: Fuel consumption map of a 2.2 liters Diesel engine

The engine fuel consumption map is not scaled numerically. A new map is imported for each displacement volume.

Hybrid electric vehicle contains an electric motor powered from the high voltage battery, which may be assisted by supercapacitors when short power boosts for accelerations are demanded. In order to increase the vehicle autonomy, a thermal internal combustion engine is added. In this study a parallel hybrid electric powertrain is modeled (Figure A.1). Its operating modes are the following:

- The internal combustion engine can drive the vehicle at high speed or when the battery charge is low.
- The electric motor can drive the vehicle when the battery is sufficiently charged to meet the power demand.
- The vehicle is driven by both simultaneously. The electrical motor and the ICE are connected to the drive shaft using a power split device.
- During deceleration phase the electric machine acts as generator and the electricity is stored in the high voltage battery. This mode is called regenerative braking.

The developed model is a parallel hybrid with diesel engine, electric motor and high voltage battery. The choice of diesel hybrid electric vehicles is done because of available measurement data on commercial hybrid electric vehicles. The model can choose engines map for different displacements. The electric motor map and the battery are adapted from QSS Tool Box [29]. Since in the quasi static model, the efficiency is interpolated in the electric machine map using w_{EM} and T_{EM}, the electric motor is scaled, by multiplying the rotation speed and torque vectors of the map with the appropriate scaling factor: $f_{scaling} = \frac{P_{EM}}{P_{ref}}$, where P_{ref} is the rated power of the electric motor for the original efficiency data. In parallel hybrid vehicles, the power split device connects the combustion engine and the electric machine to the drive shaft. These devices can be generally torque or speed couplers. The torque sent towards the transmission is expressed as a weighted sum of electric motor torque and the combustion engine torque.

$T_S = k_1 T_{EM} + k_2 T_{ICE}$ (4)

$$w_s = \frac{w_{EM}}{k_1} = \frac{w_{ICE}}{k_2} \qquad (5)$$

k_1 and k_2 are the structural parameters of the torque coupler.

Respectively for the speed coupler, the rotational speed of the shaft, connected to the transmission is as the weighted sum of the electric motor and the combustion engine shaft speeds.

$$w_s = k_1 w_{EM} + k_2 w_{ICE} \ (6)$$

$$T_S = \frac{T_{EM}}{k_1} = \frac{T_{ICE}}{k_2} \qquad (7)$$

The design of the coupler is not the focus of this study, therefor the simplest solution is chosen with $k_1 = k_2 = 1$ (8).

Battery:

Key variables and equations used in the battery quasi- static model are briefly introduced in the following paragraph. The battery model is adapted from the QSS toolbox [29]. The causality representation of the battery in the quasi-static simulations is sketched in the next Figure:

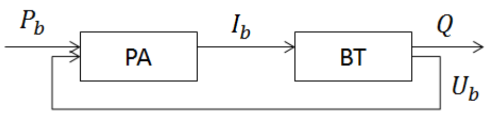


Figure 6: Causality representation of the battery

The charge variation can be calculated directly from the theoretical power of the battery$\mathrm{P_b}$. More generally the charge variation is related with the terminal current with $\mathrm{I_b} = \frac{\mathrm{P_b(t)}}{\mathrm{U_b(t)}}$ (9).

The state of charge SoC is the ratio of the electric charge Q that can be delivered by the battery to the nominal battery capacity Q_0. $\mathrm{SoC} = \frac{\mathrm{Q(t)}}{\mathrm{Q_0}}$ (10). The variation of the battery charge can be approximately related to the discharge current Ib, by the charge balance.

$$\dot{\mathrm{Q}}(\mathrm{t}) = -\mathrm{I_b}(\mathrm{t}) \ (11)$$

The battery is represented by an ideal open-circuit voltage in series with an internal resistance, expressed by the 2nd Kirchoff law.

$$\mathrm{U_b} = \mathrm{U_{oc}} - \mathrm{R_i}(\mathrm{t}) * \mathrm{I_b}(\mathrm{t}) \ (12)$$

The open circuit voltage Uoc is proportional of the voltage of the battery cells and represents the equilibrium potential of the battery. It is a function of the battery charge:

$$\mathrm{U_{oc}} = \mathrm{c_{22}} * \mathrm{SoC}(\mathrm{t}) + \mathrm{c_{11}} \ (13)$$

The coefficients $\mathrm{c_{11}}$ and $\mathrm{c_{22}}$ depend only on the battery design and number of cells, but not on operative variables, thus can be considered as constant in the time. When the current is applied a voltage drop occurs, after that the voltage varies linearly with the SoC. The internal resistance of the battery can be presented also as a function of the SoC.

$R_i = c_4 * SoC(t) + c_3$ (14)

When replacing (13) and (14) in (12), U_b can be expressed as a function of the battery coefficients, the SoC, and the battery power.

$$U_b(t) = \frac{c_{11}+c_{22}*SoC(t)}{2} \pm \sqrt{\frac{c_{11}+c_{22}*SoC(t)^2}{4} - P_b(t)*(c_4 * SoC(t) + c_3)} \quad (15)$$

Super capacitors:

Similarly to batteries, the state of charge is evaluated from the terminal current I_{sc} and the nominal capacity Q_0. The former can be calculated from the terminal power P_{sc}, using the relation:

$$I_{sc} = \frac{P_{sc}(t)}{U_{sc}(t)} \quad (16).$$

Also an equivalent circuit can be presented for the supercapacitor – double-layer capacitance and a resistor in series representing the ohmic losses in the electrodes and the electrolyte, described by the following equations:

$$R_{sc} * I_{sc}(t) - \frac{Q_{sc}(t)}{C_{sc}} + U_{sc}(t) = 0 (17),\ I_{sc}(t) = -\frac{d}{dt}Q_{sc}(t) \quad (18)$$

Substituting (13) in (14) and then solving the quadratic equation for $U_{sc}(t)$ yields:

$$U_{sc}(t) = \frac{Q_{sc(t)}}{2C_{sc}} + \sqrt{\frac{Q_{sc}^2(t)}{4*C_{sc}^2} - P_{sc}(t) * R_{sc}} \quad (19)$$

Thus the quasi-static model of the capacitor can be solved using the P_{sc} and Q_{sc} as input to find Usc. After that (16) is used to calculate I_{sc}.

Scaling the supercapacitor size:

The supercapacitors model is scalable by the number of the cells connected in the packs. The global capacitance is then written as: $Csc = N_{cells} * C_{SC,cell}$ (20).

The strategy dividing the electric power demand PEM between the P_b and P_{sc} is taken from [30]. It is a static strategy that enables the use of supercapacitors, only when the vehicle acceleration surpasses a predefined limit.

2.1.1Hybrid strategy:

A power distribution strategy is put into place at the coupling of the electric motor and the combustion engine torques. This strategy defines the hybrid ratio, which represents the power contribution of the electric side of the powertrain.

$$H_r = \frac{P_{EM}}{P_{TOT}} = \frac{P_{EM,max}}{P_{EM,max}+P_{ICE,max}} \quad (22)$$

The degree of hybridization is defined in equation (22), as the ratio between the electric power and the total power. The benefits i.e. the reduction of the energy consumption, but also the additional cost associated of the hybridization increase with the degree of hybridization. There are various possibilities to develop energy optimization strategies and most of them are heuristic based. Their guiding principles are that in the hybrid vehicle the engine should be used when its efficiency is relatively high and the battery charge and discharge should be regulated such that state of charge stays within predefined limits. The operating modes of the powertrain are so mapped, for example, the torque request is expressed as a function of the vehicle speed demand and the state of the charge of the battery.

In this study, instead to have a discontinuous map with modes switching, a continuous function, relating the hybridization ratio (the electric motor contribution), the state of charge of the battery and the speed demand is developed. Equation (23) gives the generic expression.

$H_r = f(V, SoC)$ (23)

Thus, the parameters relating the state variables of the electric motor usage can be optimized for minimal energy consumption and minimal size of the powertrain components. In the multi-objective optimization problem these are the variables for operating strategies. The optimization problem is solved with an evolutionary genetic algorithm and the optimal operating strategies solution is solved on a holistic way. This is one of the novelties of this article. According to Guzzella [3], the main stream approaches for evaluation of the optimal energy management are grouped into three subclasses optimization methods – static optimization, numerical dynamic optimization methods and closed-form dynamic optimization methods. All of them are largely explained in [3].

The batteries have low specific energy in comparison to the fossil fuels. The energy management strategy consists to use electric drive at low speeds and high state of charge (SoC) of the battery. The hybridization ratio decreases at high speeds and low SoC in order to save the battery from overload. A continuous S-curve function suits to archive these requirements.

$H_r(SoC) = 3 + \left(\frac{c_1 * SoC - (SoC_{min} + SoC_{\max})}{SoC_{min} + SoC_{max}}\right)^3$ (24)

The behavior of such shape is illustrated on Figure 7, where $SoC_{min} = 0.3$ and $SoC_{max} = 0.8$.

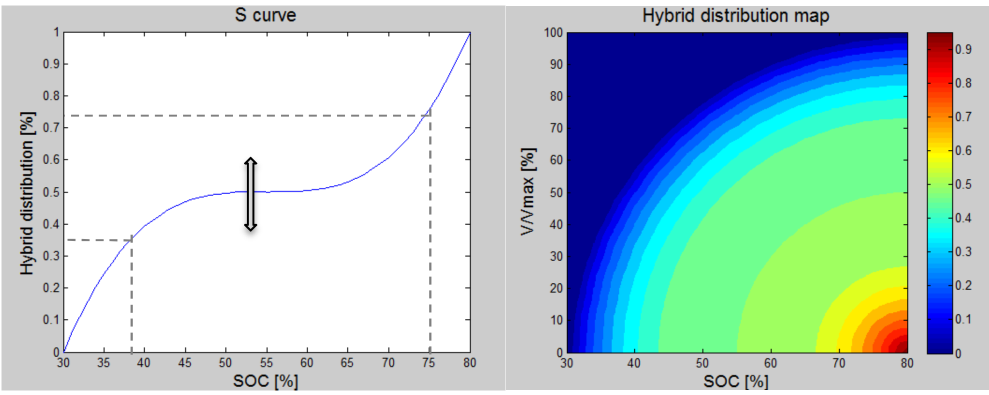
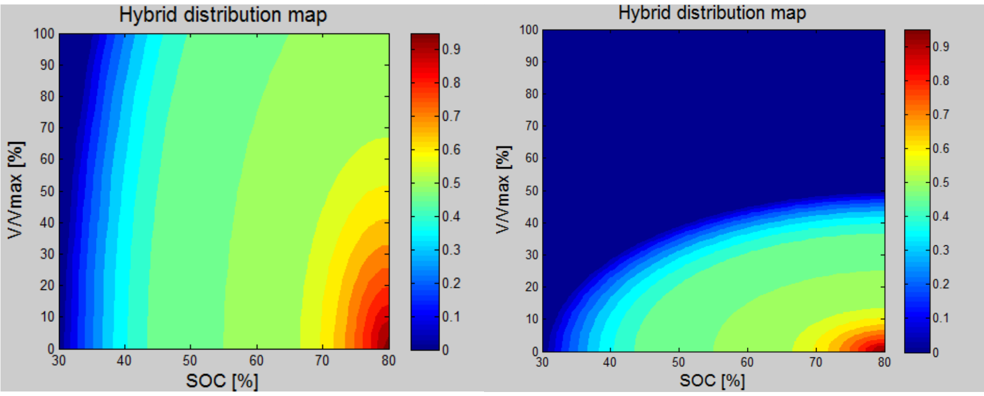


Figure 7: Hybridization ratio strategy

During simulation, if the SoC is high, the energy management computes a high hybridization ratio and drains the battery, so its SoC will tend to the central plateau of the S- curve. On other hand if the SoC is below the plateau, the strategy computes a low ratio of hybridization in order the battery to get recharged during the regenerative braking. The strategy has a stabilizing effect on the state of charge. The parameter $c_1$influences the high of the plateau. To extend the strategy to the vehicle speed, the S-curve is rotated in the space, around the upper vertical axe. The speed axe is normalized using the maximal speed V_{max} of the driving cycle. The parameter c_2 is related to the stretch of the rotation. Figure 8 illustrates the relation.



a) b)

Figure 8: influence of the $\mathbf{c_2}$ parameter on the hybridization ratio: a) After rotation with a large stretch factor $\mathbf{c_2}$, and b) After rotation with a small stretch factor

2.2 Economic Model

The cost of the vehicle is computed for each run, as a function of the energy convertors, energy storage devices size, the efficiency and the car shell mass.

The cost of the equipment comes from the literature [3] and is related to the size of the components:

- electric motor cost in euros: $30\frac{[€]}{kW} * P_{EM}\ [kW]$ (25)
- thermal engine in euros: $15\frac{[€]}{kW} * P_{ICE}[kW],$ (26)
- battery cost is given in Table 2

The nominal cost represents the vehicle body cost without the powertrain components. This linear correlation (Table 3) takes into account the prices of the parts and the manufacturing cost of the vehicle shell and includes the sales margin of the carmaker. The cost model is described in [27].

For each calculation, a new vehicle mass is calculated, updated with the mass of the defined powertrain.

A simplified vehicle objective cost function is constructed, taking into account the vehicle powertrain cost (production) and vehicle nominal cost.

Table 3: Equations for the economic model [27]

Components	Costs [€]
Storage system -Battery [3]	600*[€/kWh]* $q_{bat}^{0.2477*\log(bat_{specifmass}(bat\_type)+0.5126)}$, (27), qbat- battery capacity in kWh
Car shell	
Nominal cost	$17.3 * car_{shell_{mass[kg]}} - 3905.4$ in [€] (28)
Vehicle use in France 2013 French government, 2013	
Electricity household	0.14269 [€TTC/kWh]
Gasoline	1.645 [€/L]
Diesel	1.451 [€/L]

A simplified vehicle objective cost function is constructed (30), taking into account the vehicle powertrain cost (production) (29) and vehicle nominal cost (28).

$Cost_{powertrain=} Cost_{ICE} + Cost_{EM} + Cost_{battery} + Cost_{supercapacitors}$ in [€] (29)

$Cost_{vehicle} = Cost_{powertrain} + Cost_{car\_shell}$ in [€] (30)

All costs are calculated in Euros.

2.3 Vehicle driving cycles

Commercial vehicles are characterized on the current normalized driving cycle – New European Driving Cycle (NEDC). This cycle has an urban and extra urban part with repetitive patterns of low accelerations and constant speeds. NEDC is criticized for its lack of ability at representing the day-to-day driving conditions. In this study, two additional cycles are proposed to represent the daily city driving and the long distance trip, for example for holidays. These cycles are obtained by randomly choosing the low speed parts of the World Harmonized Light Vehicles Test Procedure (WLTP) and the high speed part of the highway US Highway Federal Test Procedure (FTP – Highway).

Table 4 summarizes the characteristics of the driving cycles used in this study.

Table 4: Drive cycles characteristics

Cycle	Distance (km)	Duration (s)	Average speed (km/h)
NEDC	11.023	1180	32.26
Urban	8.5	1644	18.8
Holiday	847	28800 (8h)	105

3 Results – Application on hybrid electric vehicles

3.1 Problem definition:

A hybrid vehicle with multiple propulsion systems can be operated independently or together. The model contents are the electric machine, battery, supercapacitors, thermal engine and fuel tank, with diesel fuel. The thermal electric hybrid powertrain model characteristics are given in Table 1. The vehicle model represents a commercial D- class [30] vehicle with a diesel electric powertrain.

In this study, instead of defining one vehicle with set of parameters and then studying its performances over various driving cycles, the reverse is done. It is the usage of the vehicle that is the starting point of the study. For each use the powertrain components and the energy management parameters are optimized. Thus each usage has its optimal vehicle design. The objective is to size the components of the hybrid powertrain – the convertors and the storage tanks, and to define optimal operating strategy, regarding the energy consumption and the cost objectives. A two objective optimization is considered, with minimization of the energy consumption and minimization of the powertrain cost.

The optimization problem is defined as:

$\min(-\eta_{powertrain}(x), Cost_{vehicle}(x))$, s.t. $x \in X_{decision\ variables}$ (31)

The decision variables for the powertrain design are defined in Table 5:

Table 5: Decision variables for energy operating strategy

Decision variable for design	Range
ICE displacement volume [l]	[0.8-1-1.4-1.6-2.2]
Electric motor rated power [kW]	[1-150]
Battery energy [kWh]	[5-50]
Number of super capacitors [-]	[1-10]

The decision variables for the powertrain energy management are defined in Table 6:

Table 6: Decision variables for energy management

Decision variable for energy management	Range
SoC strategy parameter c_1 [-]	[1.8-2.4]
SoC strategy parameter c_2 [-]	[0.1-10]

After each iteration of the model, the mean powertrain efficiency in traction is calculated as:

$\eta_{powertrain} = mean(\frac{P_{wheel}}{P_{fuel}+P_b+P_{SC}})$ (32), where P_b and P_{SC} are respectively the battery and the super capacitors powers.

The vehicle cost is recomputed for each iteration of the decisions variables. The vehicle cost is defined in equation (3) of the paragraph 2.2.

3.2 Multi objective optimization results for a hybrid electric vehicle with different usages:

3.2.1 New European Driving cycle

The solutions of a two objective optimization converged on a Pareto Frontier optimal curves (Figure 9), representing the trade-off between the energy consumption and the cost of the vehicles on normalized driving cycle.

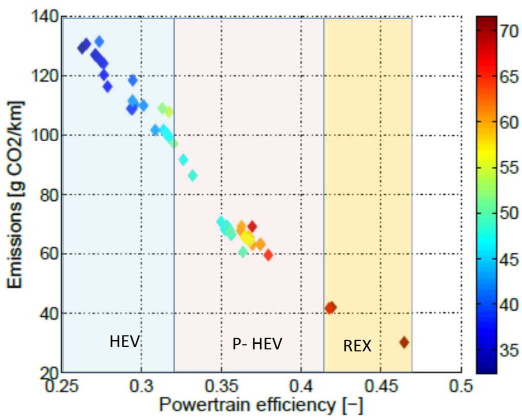
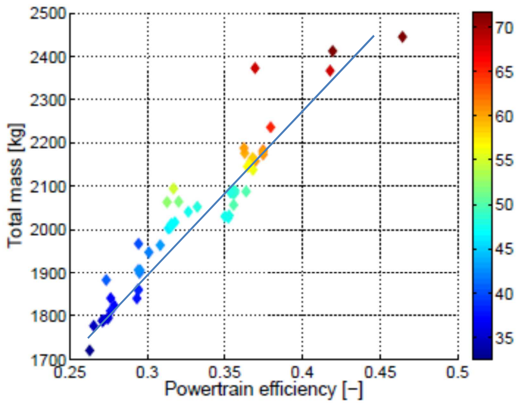
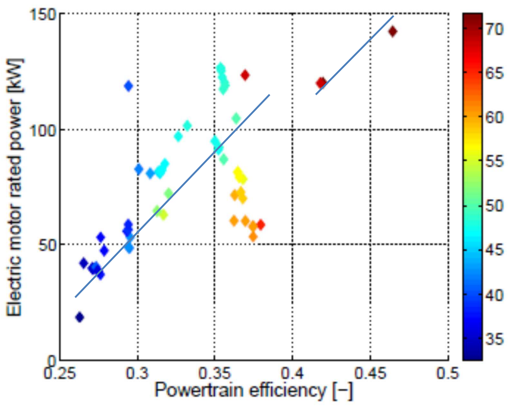


Figure 9: Pareto curves energy consumption to cost (color bar in thousands of Euros) – NEDC

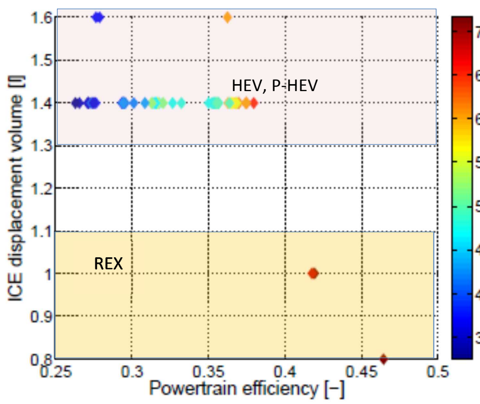
The vehicle body mass of around 1500 kg is characterizing the D –Class vehicles. These vehicles are usually used for family transportation or business trips on long distances. The D-Class vehicles are well equipped, and the technology is considered as additional value for the customer. The D- Class vehicles communicate prestige and the customer accepts to pay the cost of an efficient technology. The powertrain technology for low CO_2 emissions is an important requirement for the customers of these vehicles. The official technical characteristics are referenced on the NEDC by the car makers. The Pareto curve for the NEDC (Figure 9) defines a wide range of points for improved powertrain efficiencies (25-45.2%) and fuel emissions (30 to 130 g CO_2/km). In contrast, a thermal powertrain D class vehicle of 1660 kg of mass, with 2.2 diesel liters engine yields 12.9 % of powertrain efficiency and 151 g CO_2 / km [30]. To archive such high powertrain efficiency in the Pareto curves for all usages, the electric half of the powertrain is increased and more electric energy stored in the battery is needed. In dead the battery increases from 5 to 50 kWh. This considerably increases the vehicle mass. To follow the dynamic requirement on the cycle, the electric motor power also increases – from 20 to 145 kW. The emitted tank-to-wheel CO_2 emissions, which are proportional to the diesel consumption, are related to the hybridization ratio, expressed through the electric motor and the thermal motor size.



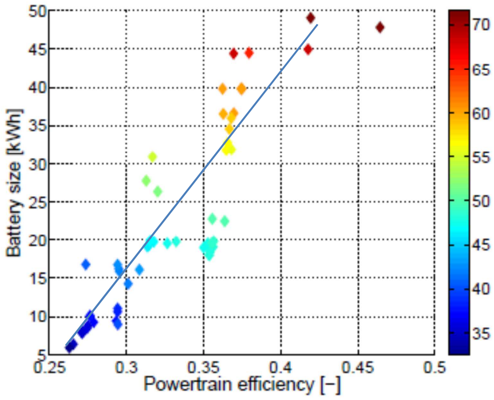
a)



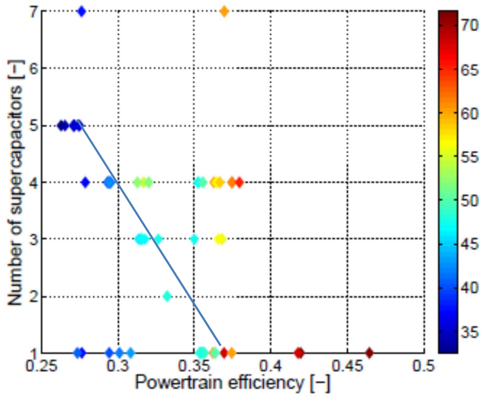
b)



c)



d)



e)

Figure 10: NEDC Pareto curves

One can notice (Figure 10b and 10c) that for the increasing size of the electric motor, the thermal engine is downsized. The downsized thermal engine can be loaded and so used in better efficiency zones. The algorithm converges to solutions between 35 000 and 70 000 euros. The powertrain cost is strongly influenced by the battery capacity, with a proportional coefficient of 600 €/kWh (Table 3). The solutions in Figure 9 can be functionally organized in three zones, according to the hybridization ratio: Hybrid Electric Vehicles (HEV), Plug-in Hybrid Electric Vehicles (PHEV) and Range Extender (REX).The algorithm converges on battery size solutions regarding from 5 kWh to 50 kWh. For a Li-Ion battery, with an energy density of 90 Wh/kg, the battery mass varies between 55 kg and 555 kg. Thus the battery mass is considerable for the P-HEV and HEV zones. The integral vehicle mass is between 1700 kg and 2450 kg.

The solutions in the REX zone shows that the maximal powertrain efficiency on NEDC is limited on 45.2% and the minimal tank-to-wheel CO_2 emissions are 30 g CO_2 / km. The minimal possible diesel consumption with a vehicle shell of 1600 kg (D – class) is 1.13 l/100 km. The conversion is done with the relation for diesel fuel: 1 l/100 km diesel is equivalent to 26.5 g CO_2/ km. The minimal displacement volume of the thermal engine is 0.8 l. An industrial solution for that can be a downsized two cylinders engine. But taking into account the future emission standards and also the diesel after treatment efforts for the automotive industry, the induced cost for such diesel engine presents a disadvantage in comparison to a small gasoline engine. So the recommended industrial solution, with large production volume for P- HEV and REX, is hybrid electric powertrain with small, two cylinder gasoline engine of around 30 kW. The REX vehicle solution presents the advantage of having extremely low CO_2 emissions- only 30 gCO_2/km, especially in its use phase of familial vehicle. These powertrains are technological solutions for the European automotive industry to achieve the strict CO_2 emission regulations –by 2020. The total carmaker vehicle fleet on the European market should archive an average value of 95 gCO_2/km. A special effort is needed on the business model development on the REX vehicles. These efforts are related with the customers' acceptance of the higher investment cost, due to the dominant part of the electrical powertrain components.

On the NEDC, the major impact on the cost comes from the battery size, which is proportional to the battery energy. The coefficient of proportionality between the cost and the energy in the battery is 600 €/kWh (Table 3). In light of this, the supercapacitor is a possible solution for cost reduction. The supercapacitor cost to power coefficient is 20 €/kW. The power capacity of one supercapacitor is limited by an upper bound of 17,5 kW. The supercapacitors are affordable solution for cost reduction on the HEV and P- HEV phases. In the acceleration and the deceleration phases the power is taken or stored in the supercapacitors and then the size of the battery can be relatively small. For example for a vehicle with 5 kWh of battery, an optimal structure of 5 supercapacitors is defined by the optimizer. As the supercapacitor is a short term power storage device, it is an efficient technology options for the transient (accelerations and deceleration) phases. Its usage is dependent on the driving profile and the supercapacitors suits very well for the urban driving cycle, with frequent accelerations and deceleration phases.

Sensitivity analysis:

The objective is to study the possible minimization of the total investment cost the HEV Pareto Solutions. The cost of the Li-Ion battery is impacted from the variation of the cost coefficient. Today the coefficient is 600 €/kWh. From interest is to observe how the competitiveness of the heavy Plug- In and REX vehicles could increase if the cost of the battery cost coefficient is reduced by two to 300 €/kWh. Figure 11 illustrates the impact of the battery cost on the investment cost of the vehicles on the points from the NEDC Pareto (Figure 9). One can observe that the solutions with powertrain efficiency higher than 35% are strongly impacted from the battery cost variation. This is due to the high capacity of the battery in these solutions. One can observe that in this zone of heavy PHEV and REX the investment cost could be significantly reduced in the case of optimistic decrease of the price of the Li-Ion battery. The optimistic investment price for these vehicles then is situated around 50000 €, and could be improved with 25000 €. In these conditions the heavy Plug-In and REX vehicles become more competitive.

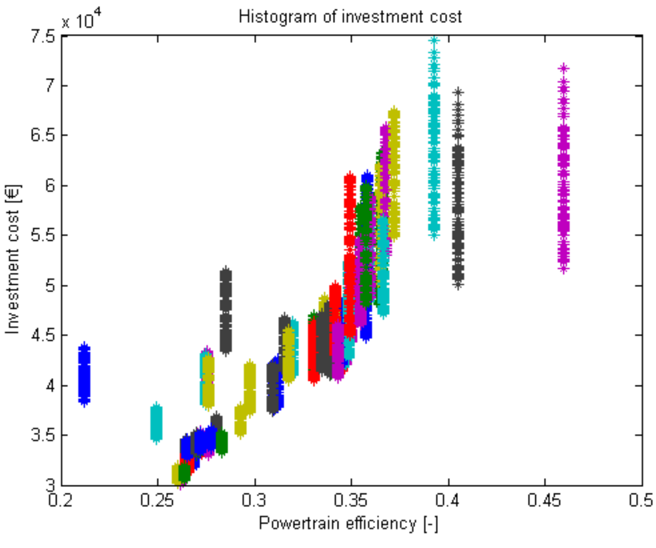


Figure 11: Impact of the battery cost on the investment cost evolution – NEDC Pareto

3.2.2 Urban driving cycle

Vehicle performances results are given in Figure 12. The Pareto curve defines a wide range of points for powertrain efficiency (25% to 43%) and fuel emissions (30 to 130 g CO_2 / km), corresponding to the different hybridization ratio concepts for hybrid electric vehicles. The optimal solutions converged to costs between 30 000 Euros and 55 000 Euros.

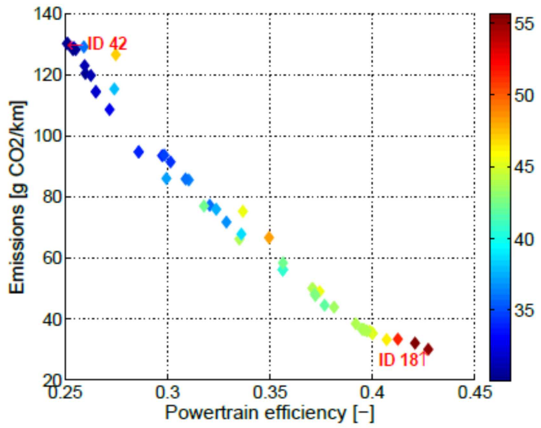


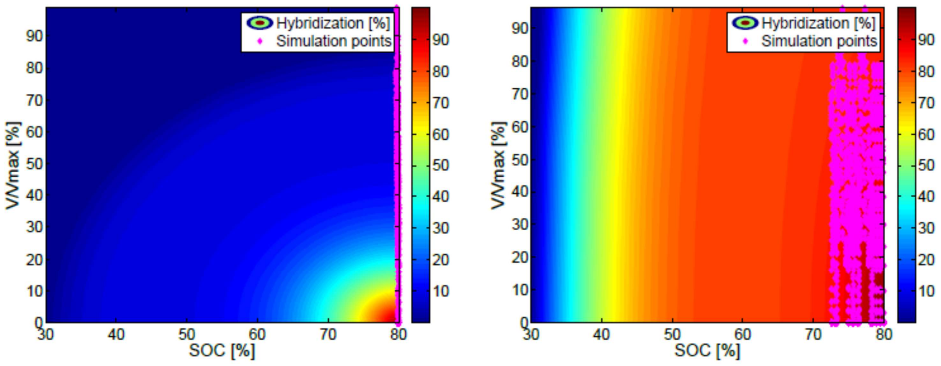
Figure 12: Pareto curve – urban cycle. Color bar in thousands of Euros.

The urban cycle is characterized with lower average speed in comparison with NEDC cycle. Even if the size of the engine is adapted to that drive profile, the thermal engine is used in low loaded and not optimal points (Figure 13). Thus the powertrain efficiency is slightly lower in comparison with the NEDC powertrain efficiency. To archive these efficiency levels the electric part of the powertrain is increased. The battery size increases from 5 to 30 kWh. The vehicle mass increases and to follow the dynamic profile the electric motor varies between 26 and 112 kW. The supercapacitors are adapted for the transient behavior of the urban driving and an optimal configuration of 2 supercapacitors is proposed for the REX vehicles, in order to diminish the cost of the electrical storage devices. The two extreme points of the Pareto, illustrates the range of solutions – ID 42 and ID 18. The performances and the decision variable values for these points are given in Table 7.

Table 7: Urban drive: definition of the design and energy management variables for the extreme points ID 42 and ID 18

Decision variables values	ID 42	ID 18
Design		
Emissions [g CO_2 / km]	130	30
Powertrain efficiency [%]	25	43
ICE displacement volume [l]	1	0.8
Electric motor rated power [kW]	21	112
Battery energy [kWh]	5	29
Number of supercapacitors [-]	1	2
Energy management		
SoC strategy parameter c_1 [-]	2.4	1.8
SoC strategy parameter c_2 [-]	0.58	0.11

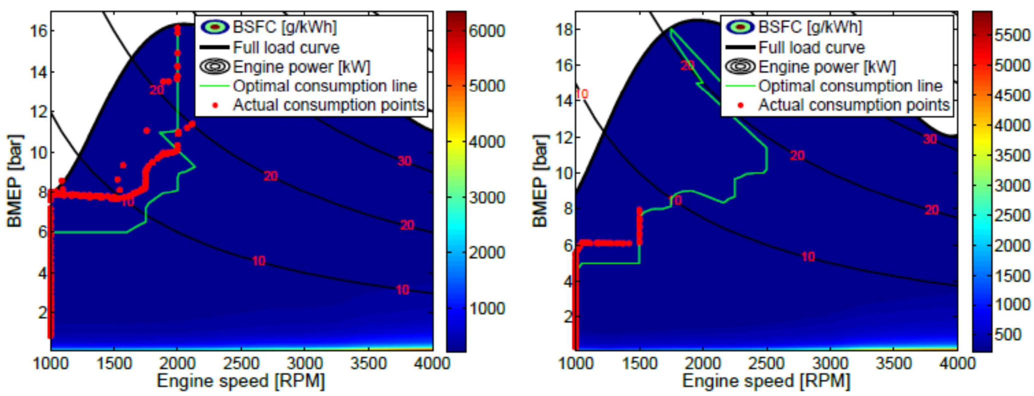
The increasing of the efficiency with the electrification induces a resizing of the powertrain components but also an adaptation of the hybridization strategy, as illustrated in the Figure 13.



a) b)

Figure 13: Urban drive hybridization points a) ID 42 and b) ID 18

The former of the point ID 42 (Figure 13 a) represents the HEV usage during the urban cycle. The strategy describes preserving of the battery charge and dominant use of the thermal engine. The peak hybridization ratio is situated below V/V_{max} = 10 %, this means for low speeds. This translates into a mild hybrid vehicle as shown by the shaft power dynamic profile at Figure 15, with 100% hybridization on the idle (stop and start). The electrical half of the powertrain is only used to provide traction power when the vehicle accelerates after idling. This allows to shut down the ICE and to reduce the idle fuel consumption. Thus, the ICE remains the primary means of driving the vehicle with operating points reaching the close to its best efficiency (Figure 14a).



a) b)

Figure 14: Urban drive fuel consumption points a) ID 42 and b) ID 18

During braking, the electric machine uses the incoming negative torque to recharge the battery.

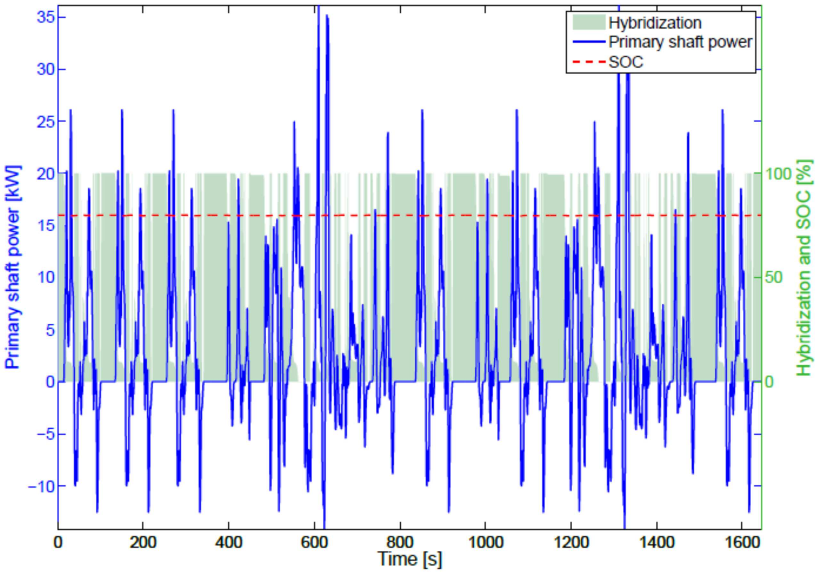


Figure 15: Dynamic hybridization profile on urban driving for ID 42

The point ID 18 represents a heavy electrified vehicle with dominant size of the electric components and strong hybridization ratio (Figure 13b). Figure 16 illustrates the hybridization dynamic profile. The vehicle is almost all the time on electric drive, the ICE covers only the high power demands. This is relevant for the ICE use. Even with very small engine of 0.8l, the operating points are located on the low loads (Figure 14b).

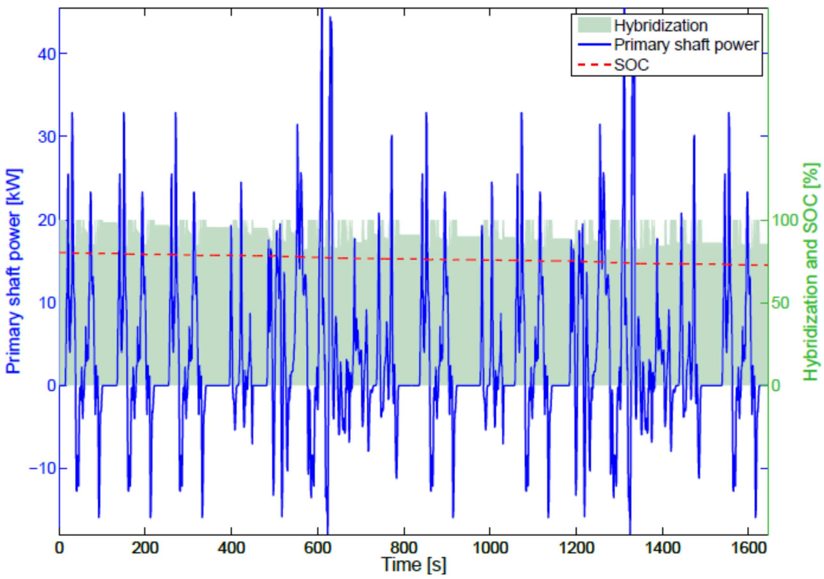


Figure 16: Dynamic hybridization profile on urban driving for ID 18

3.2.3 Holyday driving cycle

The Pareto curve for the holiday driving is represented on Figure 17. The holiday drive is characterized by a long distance – over 800 km and high average speed- 105 km/h. The optimal solutions converge in a very small efficiency range, between 30.3% and 30.9%.

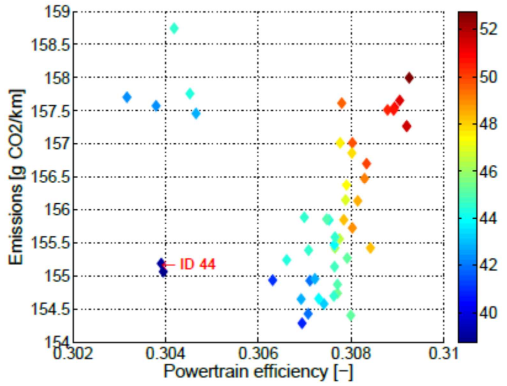


Figure 17: Pareto Curve – Holiday driving

Despite the increased size of the electric powertrain components the powertrain efficiency varies in a very small range. The optimizer reaches an efficiency barrier beyond it is no longer profitable to increase the electric part. From Figure 18 one can consider that the most of the operating points are in the thermal engine zone and the electric mode is progressively activated for around 60 % of SoC and when the vehicle speed is 15% from the maximal profile speed. This is traduced by the stop and start conditions in the beginning of the holiday driving profile. The electric powertrain is not used for traction on the highway (Figure 20). The optimal size of the ICE engine for the highway operation is 1.6 l (Figure 19). The ICE is so operated close to its optimal consumption line.

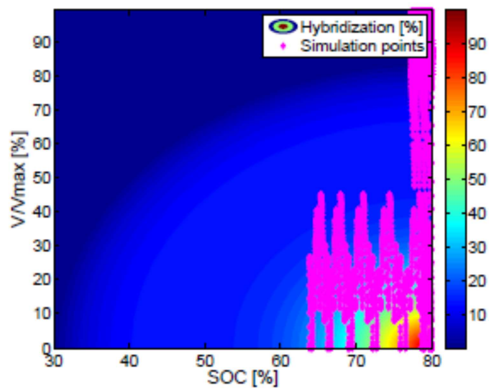


Figure 18: Holiday drive – hybridization for point ID 44

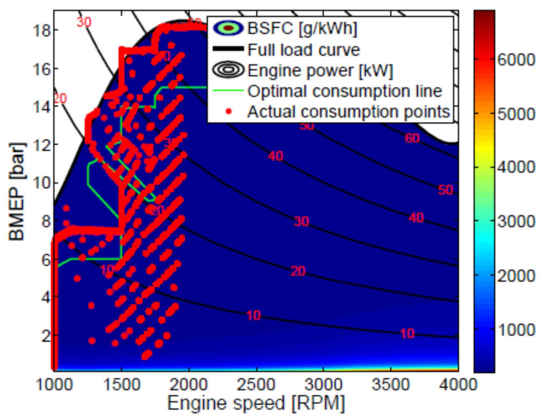


Figure 19: Holiday drive fuel consumption points for ID 44

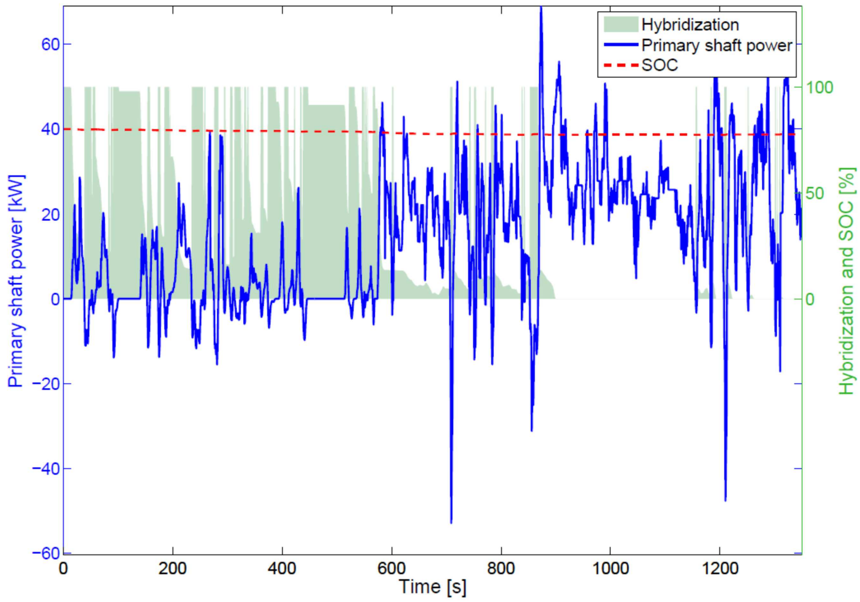


Figure 20: Dynamic hybridization profile on the beginning of the holiday driving cycle – ID 44

The efficiency barrier in the Pareto curves is a result of the long distance drive at high speeds (Figure 20). The optimizer converges towards hybridization strategy solutions which tend to not use the electric motor at high speeds in order to decrease its size and cost. The ICE is then completely used. The design point 44 is defined in Table 8.

Table 8: Holiday drive: definition of the design and energy management variables for the point ID 44

Decision variables values	ID 44
Design	
Emissions [g CO_2 / km]	155
Powertrain efficiency [%]	30
ICE displacement volume [l]	1.6
Electric motor rated power [kW]	60
Battery energy [kWh]	12
Number of supercapacitors [-]	2
Energy management	
SoC strategy parameter c_1 [-]	2.3
SoC strategy parameter c_2 [-]	0.59

The optimizations show that the hybrid electric powertrain has a wide range of Pareto optimal solutions in terms of improving the tank-to-wheel efficiency of a D-Class vehicle. The possible design solutions are researched for the normalized new European driving cycle and for customers' real driving situation – urban drive and holiday drive. The optimizations on the customers driving profiles show solutions that are corresponding to the different usage. A D-Class vehicle has to combine optimal solutions for antagonist usages for urban and long way drives. A compromise can be the design of a vehicle in the HEV zone vehicle with a reference powertrain efficiency of 30% on NEDC and cost of around 45 000 Euros (Table 9).

Table 9: Definition of the design and energy management variables for optimal D-Class vehicle powertrain design

Decision variables values	Optimal design point (NEDC)

Design	
Emissions [g CO_2 / km]	87
Powertrain efficiency [%]	33
ICE displacement volume [l]	1.6
Electric motor rated power [kW]	40
Battery energy [kWh]	12
Number of super capacitors [-]	2
Energy management	
SoC strategy parameter c_1 [-]	2.3
SoC strategy parameter c_2 [-]	0.59

4. Conclusions:

This article presents a powertrain design study on hybrid electric vehicles, considering different vehicle usages through adapted driving profiles – normalized cycle, urban and holiday drives. The optimal techno- economic configurations are researched by using multi objective optimization techniques. The optimization methodology is based on a genetic algorithm and is applied for defining the optimal set of decision variables for powertrain design and energy flows management. The studied configurations are for D- Class vehicle. Its quasi-static model was presented and run in optimization mode to determine the influence of the powertrain components size, the energy management parameters and the vehicle usages on the tank-to-wheel powertrain efficiency and the vehicle cost.

The optimal solutions for NEDC can be organized in three zones, according to the functional hybridization ratio: Hybrid Electric Vehicles (HEV), Plug-in Hybrid Electric Vehicles (PHEV) and Range Extender (REX). The solutions in the REX zone shows that the maximal powertrain efficiency on NEDC is limited on 45.2% and the minimal tank-to-wheel CO_2 emissions are 30 g CO_2 / km. They have the maximal cost - 70 000 Euros. The increasing of the efficiency with the electrification induces a resizing of the powertrain components but also an adaptation of the hybridization strategy and a continuously S-curve function is presented for the management of the energy sources.

The main optimization results are presented in Table 10.

Table 10: Main optimization results for D Class hybrid electric vehicles on different usages

Vehicle Usage cycles	Distance (km)	Duration (s)	Average speed (km/h)	Emissions (g CO_2 / km)	Vehicle Cost (Euros)
NEDC	11.023	1180	32.26	30-130	35000- 70000
Urban	8.5	1644	18.8	30-130	30000- 55000
Holiday	847	28800 (8h)	105	155	40000- 52000

Finally, a D-Class vehicle has to combine optimal solutions for antagonist usages – urban and long way drives. A compromise for that can be a hybrid electric vehicle with powertrain efficiency of around 30% and cost of 45 000 Euros.

Acknowledgments

The authors thank EPFL for the support.

Appendix A:

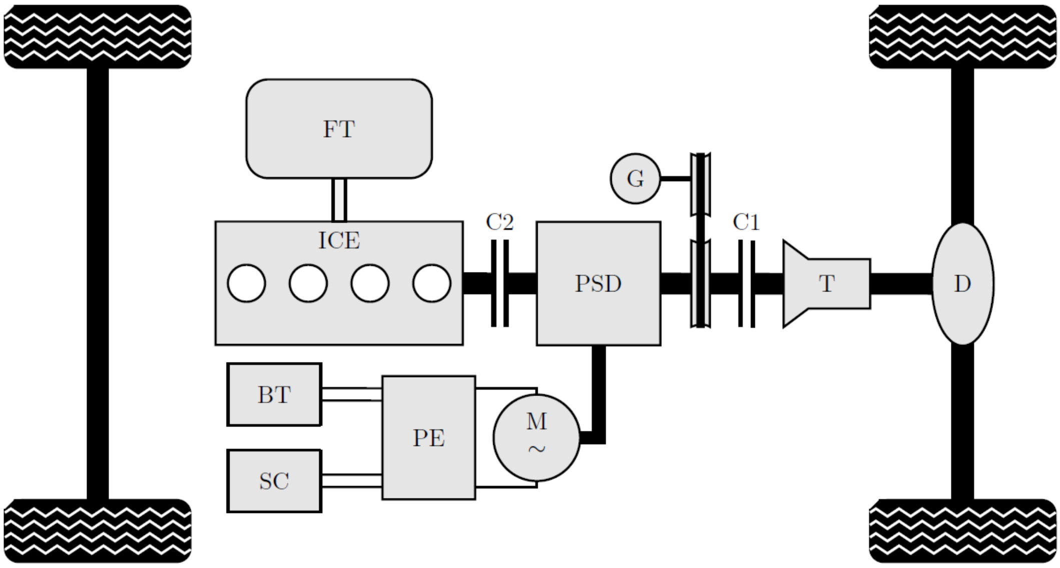


Figure A.1: Parallel hybrid electric architecture: FT – fuel tank, ICE – internal combustion engine, BT – high voltage battery, SC – super capacitor, PE – power electronics, M- electric motor, PSD – power split device, G – electric generator, C1- clutch 1, C2- clutch 2, T- Transmission, D- Differential

References:

[1] J. Caton, The thermodynamic characteristics of high efficiency internal combustion engines, Energy Conversion and Management, Volume 58, June 2012, Pages 84-93

[2] R. D. Reitz, G. Duraisamy, Review of high efficiency and clean reactivity controlled compression ignition (RCCI) combustion in internal combustion engines, Progress in Energy and Combustion Science, Volume 46, 2015, Pages 12-71

[3] L. Guzzella, A. Sciarretta. Vehicle propulsion systems: introduction to modelling and optimization, third edition, Springer, 2013

[4] T. Katrašnik, Analytical method to evaluate fuel consumption of hybrid electric vehicles at balanced energy content of the electric storage devices, Applied Energy, 87, (2010), 3330-3339

[5] T. Katrašnik, Energy conversion phenomena in plug-in hybrid-electric vehicles, Energy Conversion and Management, 52 (2011), 2637-2650

[6] M.A. Hannan, F.A. Azidin, A. Mohamed, Hybrid electric vehicles and their challenges: A review, Renewable and Sustainable Energy Reviews, 29, (2014), 135-150

[7] R. Finesso, E. Spessa, M. Venditti, Layout design and energetic analysis of a complex diesel parallel hybrid electric vehicle, Applied Energy, 134, (2014), 573-588

[8] K. Çağatay Bayindir, M. Ali Gözüküçük, A. Teke, A comprehensive overview of hybrid electric vehicle: Powertrain configurations, powertrain control techniques and electronic control units, Energy Conversion and Management, 52, (2011), 1305-1313

[9] A. Poullikkas, Sustainable options for electric vehicle technologies, Renewable and Sustainable Energy Reviews, Volume 41, January 2015, 1277-1287

[10] Y. Eren, H. Gorgun, An applied methodology for multi-objective optimum sizing of hybrid electric vehicle components, International Journal of Hydrogen Energy, Available online 30 December 2014, http://dx.doi.org/10.1016/j.ijhydene.2014.12.024.
[11] Ziyou Song, Jianqiu Li, Xuebing Han, Liangfei Xu, Languang Lu, Minggao Ouyang, Heath Hofmann, Multi-objective optimization of a semi-active battery/supercapacitor energy storage system for electric vehicles, Applied Energy, 135, (2014), 212-224
[12] H. Khayyam, A. Bab-Hadiashar, Adaptive intelligent energy management system of plug-in hybrid electric vehicle, Energy, 69, (2014), 319-335
[13] J.L. Torres, R. Gonzalez, A. Gimenez, J. Lopez, Energy management strategy for plug-in hybrid electric vehicles. A comparative study, Applied Energy, 113, (2014), 816-824
[14] L. Tribioli, M. Barbieri, R. Capata, E. Sciubba, E. Jannelli, G. Bella, A Real Time Energy Management Strategy for Plug-in Hybrid Electric Vehicles based on Optimal Control Theory, Energy Procedia, 45, (2014), 949-958
[15] A. Santiangeli, C. Fiori, F. Zuccari, A. Dell'Era, F. Orecchini, A. D'Orazio, Experimental Analysis of the Auxiliaries Consumption in the Energy Balance of a Pre-series Plug-in Hybrid-electric Vehicle, Energy Procedia, 45, 2014, 779-788
[16]J. Davies, K. S. Kurani, Moving from assumption to observation: Implications for energy and emissions impacts of plug-in hybrid electric vehicles, Energy Policy, 62, (2013), 550-560
[17] X. Wu, J. Dong, Z. Lin, Cost analysis of plug-in hybrid electric vehicles using GPS-based longitudinal travel data, Energy Policy, 68, 2014, 206-217
[18] A. Sakti, Jeremy J. Michalek, Erica R.H. Fuchs, Jay F. Whitacre, A techno-economic analysis and optimization of Li-ion batteries for light-duty passenger vehicle electrification, Journal of Power Sources, Volume 273, 1 January 2015, Pages 966-980
[19] P. Mock and S.A. Schmid, BATTERIES AND FUEL CELLS | Techno-Economic Assessments, In Encyclopedia of Electrochemical Power Sources, edited by Jürgen Garche, Elsevier, Amsterdam, 2009, Pages 566-585
[20] X. Wu, B. Cao, X. Li, J. Xu, X. Ren, Component sizing optimization of plug-in hybrid electric vehicles, Applied Energy, Volume 88, Issue 3, March 2011, Pages 799-804
[21] Y.-H. Hung, C.-H. Wu, An integrated optimization approach for a hybrid energy system in electric vehicles, Applied Energy, Volume 98, October 2012, Pages 479-490
[22] C. Osornio-Correa, R.C. Villarreal-Calva, J. Estavillo-Galsworthy, A. Molina-Cristóbal, S.D. Santillán-Gutiérrez, Optimization of Power Train and Control Strategy of a Hybrid Electric Vehicle for Maximum Energy Economy, Ingeniería, Investigación y Tecnología, Volume 14, Issue 1, January–March 2013, Pages 65-80
[23] H.S. Hamut, I. Dincer, G.F. Naterer, Analysis and optimization of hybrid electric vehicle thermal management systems, Journal of Power Sources, Volume 247, 1 February 2014, Pages 643-654
[24] A. Piccolo et al., 2001, Optimization of energy flow management in hybrid electric vehicles via genetic algorithms, Proceedings of IEEE/ASME Intern. Conference on Advanced Intelligent Mechatronics, 1, 434-439.
[25] L. Gerber, M. Gassner, F. Maréchal, 2011, Systematic integration of LCA in process systems design: Application to combined fuel and electricity production from lignocellulosic biomass, Computers & Chemical Engineering, 35, 1265-1280.
[26] Z. Dimitrova, F. Maréchal, Environomic design of vehicle energy systems for optimal mobility service, Energy (2014), http://dx.doi.org/10.1016/j.energy.2014.09.019
[27] Z. Dimitrova, F. Maréchal, Environomic design of vehicle integrated energy systems-application on a hybrid electric vehicle energy system, CET, volume 39, 2014, p. 475-480, DOI:10.3303/CET1439080

[28] CVT Nissan technology
http://www.nissanglobal.com/EN/TECHNOLOGY/OVERVIEW/cvt.html, accessed on 20.10.14
[29] L. Guzzella QSS Tool Box, http://www.idsc.ethz.ch/Downloads/DownloadFiles/qss
[30] La centrale, fiche technique de la Peugeot 508 SW, http://www.lacentrale.fr/fiche-technique-voiture-peugeot-508-sw+2.2+hdi+204+fap+gt+bva6-2014.html, accessed on 17.09.14