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Multiobjective optimization of a Parallel Plug-in Hybrid Electric Vehicle considering the fuel consumption, acceleration and elasticity on the vehicle performance

O. Torres [1], B. Bader[1], J. L. Romeral[1], G. Lux[2], J. A. Ortega[1]

[1]*EEL Departament d'Enginyeria Electrònica, MCIA Innovation Electronics, Technical University of Catalonia, Spain*

E-mail: oriol.torres@mcia.upc.edu

URL: http://www.mcia.upc.edu

[2]*SEAT Technical Center, Spain*

Short Abstract

The objective of this paper is to give recommendations for the component sizing of a Parallel Plug-in Hybrid Electric Vehicle (PHEV) studying the influence of the Electric Motor (EM) size, Final Drive ratio (FD), the Battery Capacity (BAT) and the Internal Combustion Engine (ICE). A multiple options for the size of the components are in the market and conflicting on the vehicle efficiency and functionality. Their selection is very important in order to achieve reduced fuel consumption and assure the vehicle performance with the minimum cost. This study explains a proposal methodology to solve this problem, firstly doing a problem model approach, then reducing his complexity doing a parameterization and finally analyzing the optimal variables for the multiple objectives. In this publication the component sizing is analysed using the Response Surface Methodology (RSM) of the Design of Experiments (DoE) technique. The parallel HEV has been parameterized and simulated to obtain the fuel consumption over NEDC driving cycle using Modelica/Dymola [2]. This tool is very useful for modeling and simulating complex integrated systems, for the automotive, aerospace, robotics and other applications. This paper contains an introduction, a brief explanation of the Parallel HEV modeled, a description of the all electric range operating strategy based on a rules, an explanation of the RSM method, the simulation results, and finally the conclusions of this study.

1 Introduction

In this paper a component sizing mathematical methodology for a Parallel PHEV is proposed. In a HEV there are a lot of components that affects directly to the fuel consumption and to the vehicle performance. There are some studies in the current literature about how to get the optimal components minimizing the fuel consumption using several techniques. This proposal is based on an intensive model parameterization applying Design of Experiments (DoE). Once the experiments are done a second order model fitting is used to calculate the coefficients of the equation terms and to obtain the parametric vehicle model in terms of fuel consumption and vehicle performance. As a first step, in order to evaluate the fuel consumption and the vehicle performance (acceleration and elasticity), two different sub models of a parallel PHEV has been modelled using Modelica/Dymola [5, 6]: energetic model and slip model. The energetic sub model with a rule-based operating strategy was done to obtain the fuel consumption under several driving conditions, meanwhile the slip sub model allows the evaluation of the acceleration and elasticity performance including a slip control in order to detect if wheels are slipping during acceleration. These sub models are used to evaluate the fuel consumption using different experiments changing the size of the components. In this case study, the influence of the electric motor size, final drive ratio, the size of the battery capacity, and the size of the engine has been studied. A rule-based operating strategy (All Electric Range strategy) was implemented and it selects the driving mode depending on the driver requests

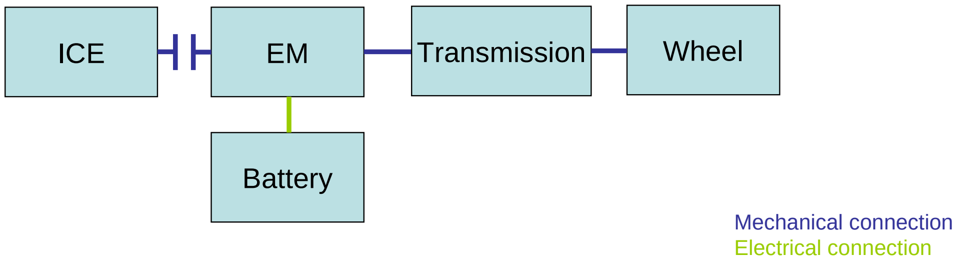

Figure 1. Powertrain of parallel HEV model

giving inputs to the electric motor (EM), internal combustion engine (ICE), gearbox and to the clutch. Simulating these vehicle models it is possible to obtain the fuel consumption and the vehicle performance under different driving conditions changing the size of the components with a total flexibility. As a second step of this study, a parameterization of the Modelica/Dymola PHEV models has been done applying Design of Experiments (DoE) using the Response Surface Methodology (RSM) in order to obtain a simplified mathematical model that gives a relation between the components (variables), and the fuel consumption, the acceleration, and elasticity performance (factors) as results. A screening process has been done in order to select the components than has a major influence on the results. The NEDC driving cycle is used in order to calculate the fuel consumption for each experiment changing the size of the EM, the ratio of the final drive, the capacity of the battery, and also the engine size. Once the experiments are done a second order model fitting is used to calculate the coefficients of the equation terms to know the curvature and the tendency of the fuel consumption for the components studied. After that the minimum of this model equation is computed in order to calculate the optimal size of the components that minimize the fuel consumption for this case study.

2 Parallel PHEV model

The parallel hybrid configuration switches between the two power converters, the internal combustion engine and the electric motor. Depending on the situation, both power sources can also be used simultaneously to achieve maximum power output. Figure 1 shows the system configuration of a parallel PHEV. The advantage of this vehicle structure is that the system has the ability to offer high efficiency during highway driving conditions avoiding low efficient points of the ICE. On the other hand, the electric motor can be used during urban driving cycles to prevent the ICE from operating in its low-efficiency range, thus providing higher overall efficiency. In order to evaluate the fuel consumption, the acceleration and elasticity performance, two different models of a parallel PHEV (figure 2) has been modeled using Modelica/Dymola [1, 2]: energetic model and slip model. The energetic model has been done to obtain the fuel consumption under several driving conditions, meanwhile the slip model allows the evaluation of the acceleration and elasticity performance due to is more focused on the wheels and has a slip control in order to detect if wheels are slipping during acceleration. These models are based on a systematic approach using sub-models for the different vehicle subsystems. For the internal combustion engine (ICE) is used a look-up-table for the fuel consumption, and for the electric motor (EM) a loss map. Also models of the rest of the powertrain such as gearbox, clutch, inverter, battery, and of the operation as battery management system or hybrid control unit (HCU) are implemented. Furthermore in order to simulate the vehicle model a cycle, driver and driving resistances are modelled too [3, 4].

In figure 2 it is shown a blocks diagram of the model developed. The driver controls the accelerator and brake pedals to achieve the vehicle speed. HCU (Hybrid Control Unit) controls the operating strategy. The battery can be recharged during the trip by the combustion engine or by connecting it to the electric grid. Once the vehicle model was done, it had been validated in a motor test bench, in order to adjust the model to the reality using Hardware in the loop (HIL). The main components in this validation are the ICE and EM. In order to validate the ICE a conventional vehicle model had been tested, and to validate the EM an electric vehicle model was used.

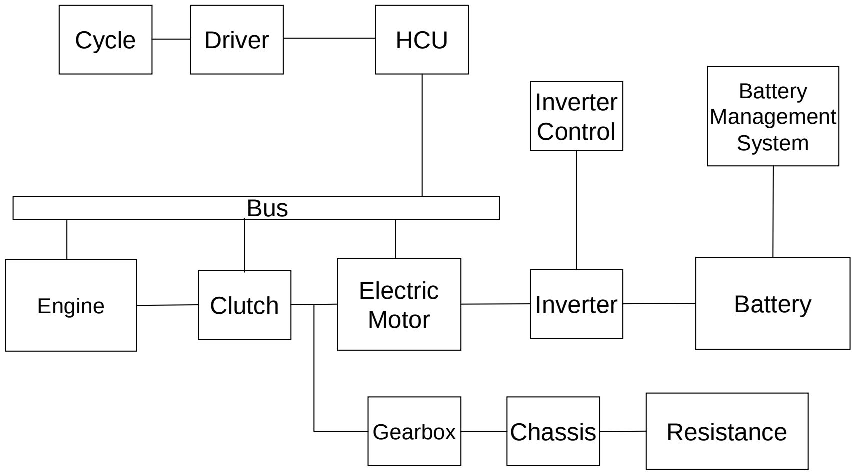

Figure 2: Blocks diagram of a parallel PHEV model

3 All Electric Range operating strategy

To simulate the fuel consumption using this vehicle model under the NEDC driving cycle, a basic operating strategy was implemented in the hybrid control unit model. The All Electric Range (AER) operating strategy based on rules has two different modes called charge depleting (CD) and charge sustaining (CS). For each mode (figure 3) five operating modes are implemented (figure 4). The CD mode uses the energy stored in the battery until to reach a minimum SOC (State Of Charge) of 20 % using electric and regeneration modes. Afterwards in CS part the strategy attempts to maintain this minimum level SOC mode using also recharge, boost and ICE driving mode. At the time that the battery SOC reaches his minimum, the strategy enters the CS mode, in which the combustion engine is also used.

Depending on the vehicle speed, in this case at 50 km/h, the vehicle enters the hybrid mode (Boost or Charge) or remains in electric mode. The strategy has to choose the mode of operation, the gear and torque set point of the engines. The ICE and the EM, in a parallel hybrid electric vehicle, work on the same mechanical axis to add their torque. The maximum torque is the sum of the curves of maximum torque of EM and ICE. When power demand is low, it may be sufficient to use only the EM ("Electric mode"). In regenerative braking the electric motor is used as a generator charging the battery when the SOC does not exceed its maximum value, which means that the battery can store this energy ("Regeneration mode"). In hybrid mode has been implemented "Recharge mode" and "Boost mode", where in both the traction motors are used. In "Recharge mode" mode, combustion engine generates more torque demanded by the driver to recharge the battery. If the driver, demands more power than the electric motor can generate, "Boost mode" is entered, in which the two machines accelerate the vehicle. Finally the "ICE mode" is used when the SOC is too low and the ICE power is directly transferred to the wheel. The changing process between the modes depends on the SOC of the battery. To avoid continuous changes between the modes, a hysteresis of 5 km/h has included, in case that the vehicle drives just at this edge. At speeds above 50 km/h the engine is turned on and the vehicle enters to the hybrid mode. Therefore if the vehicle speed exceeds the limit of the maximum speed in electric mode, the car changes into the hybrid mode. This means that the ICE is on and the two machines contribute to the acceleration of the vehicle. The strategy intends to use the ICE at every moment at the highest efficiency point of the current angular velocity. If the driver request more torque, the strategy sends the maximum possible torque, getting out of this efficient curve. The gear is chosen by the vehicle through the Hybrid Control Unit subsystem, the driver has no chance of selection, and is determined according to the speed. Moreover, the decision of the gear follows the same strategy in hybrid mode as in electric mode. The shift points are adapted while driving at low speed to the EM and at high speed to the ICE, as this engine has to always work in his optimum zone.

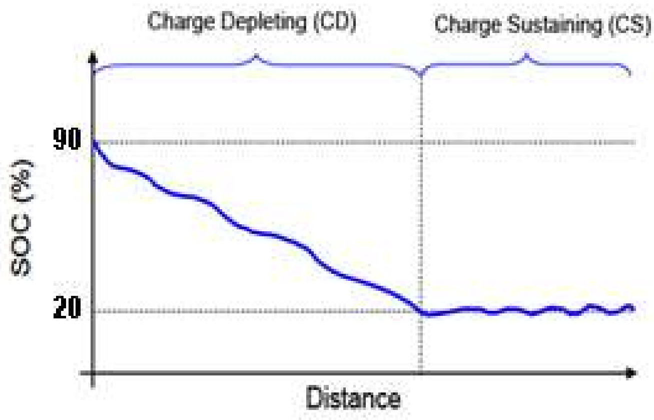

Figure 3. All Electric range operating strategy

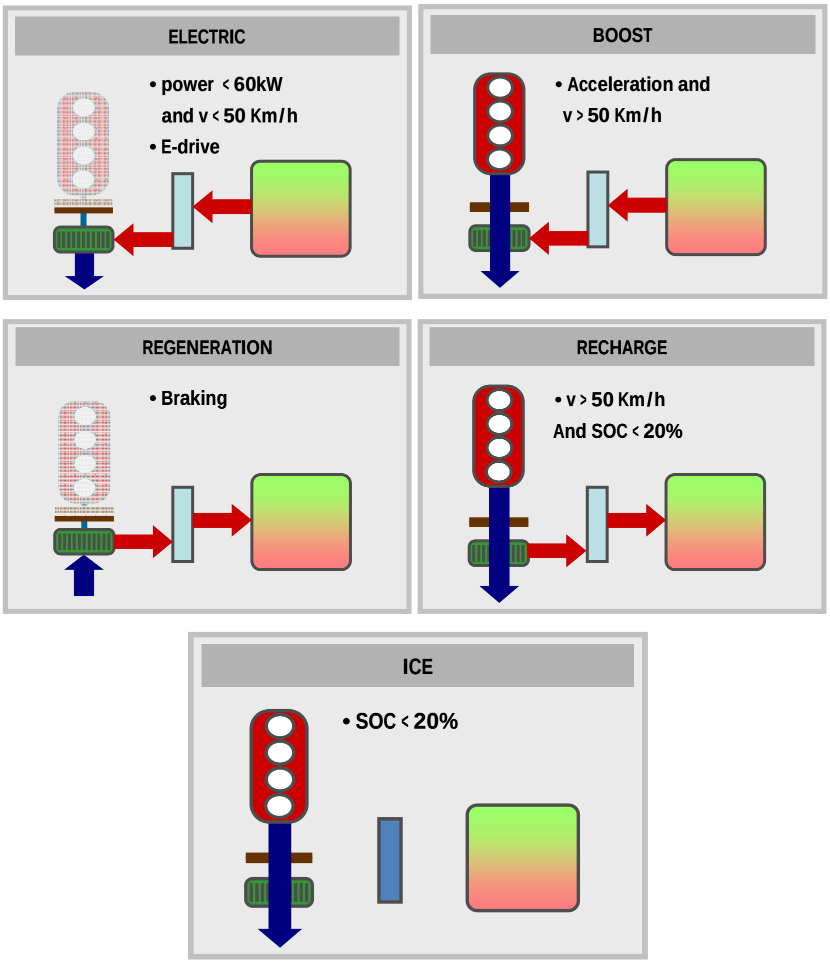

Figure 4. Operating modes of parallel HEV model

4 Definition of the parameters for this case study

The selected sizes of the components evaluated for each experiment are in a reasonable range, being any option as a real possible solution for a parallel HEV. The fixed size of the vehicle parameters are shown in table 1. To size the EM, the efficiency map is used for the nominal value, and an adaptation of this is done for the upper and lower size taking into account the losses in each electric motor tested (table

2). In table 3 it is shown the Battery mass depending on the battery capacity. And finally the driving cycle used in overall simulations is the standard NEDC (figure 6).

Table 1: Fixed size of the vehicle parameters

Components	Size
ICE *(kW)*	51
Battery Voltage *(V)*	300
Weight *(kg)*	1450
Af *(m^2)*	2,2
Gears	7

Table 2: Size of the of the powertrain variables tested

Components	Lower	Nominal	Upper
EM *(kW)*	30	40	50
Battery Capacity *(kWh)*	4	8	12
Final drive ratio	3,5	4	4,5
ICE (kW)	43	51	60

Table 3: Battery mass depending on the battery capacity tested using a 50W/kg of density

Battery Capacity *(kWh)*	Size	Battery Mass *(kg)*
Lower	4	58
Nominal	8	115
Upper	12	180

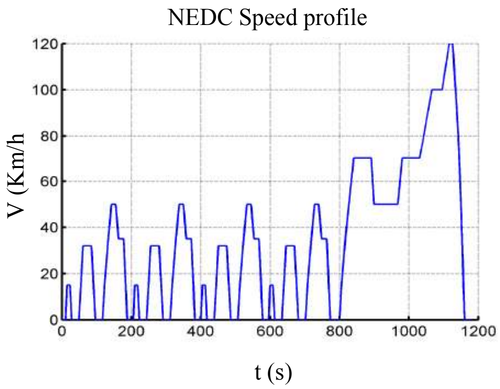

Figure 6: Speed profile of NEDC driving cycle

5 Design of Experiments parameterization

In order to evaluate the influence of the EM size, final drive ratio and battery capacity a DoE parameterization is applied using Matlab/Simulink. The concept of DoE uses a set of experiments which has to be performed by the experimenter. The aim of this so-called design is to parameterize a process or system by performing each experiment and to draw conclusions about the significant behaviour of the studied object from the results of the experiments [5]. As a second step of this study, a parameterization of the Modelica/Dymola PHEV models has been done using Design of Experiments (DoE) in order to obtain a simplified mathematical model that gives a relation between the components as variables, and the fuel consumption, the acceleration and elasticity performance as factors or results.

A screening process has been done in order to select the components than has a major influence on the results. As processes and products require more carefully controlled conditions to obtain lower costs and better quality, it will be necessary to conduct relatively complex experimental studies that examine four variables. The full-factorial designs are used in case that the studies of this nature were not very costly, and don't requires an inordinate amount of experimental time in order to test all the experiments of the region. Otherwise, such studies will be prohibitively expensive and can reduce the costs and time required using fractional-factorial designs. A full factorial design with four factors and three levels for each factor is created in this case study. This means that the DoE design matrix is formed by eighty-one experiments (4 factors ^ 3 levels = 81 experiments). In this case it is possible to use full factorial design because the simulation run time, and the number of experiments are reasonable to be calculated in less than 200h. These experiments are different options for the size and possible combinations of the EM size, final drive ratio, ICE size and battery capacity. Each row of such a design contains a combination of the values of those variables that are changed within their limits of variation. In the context under consideration here, each of these input-variable combinations is used for parameterization of a simulation run, in that the values from the respective input variable combination are used to parameterize the size of the EM and ICE, the final drive ratio and the battery capacity of the vehicle incorporated in the simulation model.

During a simulation run, the selected values are assigned to the variables of the experiment, and the fuel consumption and electrical autonomy under the standardized cycle (NEDC) are obtained. A second order model fitting has been obtained for each factor, calculating the mathematical influence of each component in the result. Applying Response Surface Methodology (RSM) is it possible to analyse graphically these influences.

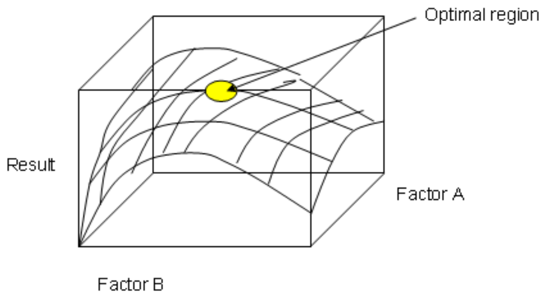

Figure 7: Example of Response Surface Methodology concept using two factors and obtaining the optimal region. In this paper case will be the minimization of the fuel consumption

6 Response Surface Methodology

The complexity of the hybrid drivetrains results in a large number of potential independent variables that affect the dependent variable under consideration to different extents. For this reason it is important to know how strong the effects of these factors are. A useful tool to know an optimal design for regression models, in this case the design that minimizes the fuel consumption is the RSM. The regression analysis is needed for modelling and to analyze several variables, to obtain the relationship between a dependent variable and independent variables. This means to calculate how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. RSM is applied to the results in order to evaluate the influence of each component on the final result, in this case the fuel consumption during charge sustaining mode. The RSM (figure 7) explores the relationships between several explanatory variables and one or more response variables. The main idea of RSM [6, 7] is to use a sequence of designed experiments to obtain an optimal response, the minimum of fuel consumption. Since the dependency of fuel consumption on the large number of variables does not exist as an explicit target function, they are approximated in the preceding process step of modeling, in the form of an adapted polynomial (equation 1). A second order model for the regression fitting is used to analyze the curvature and shape of the obtained model. Analyzing the surface obtained it is possible to estimate the influence of each component studied [8, 9].

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i=1}^{k-1} \sum_{j=2}^{k} \beta_{ij} X_i X_j + \varepsilon \tag{1}$$

7 Parametric vehicle model validation

In order to validate the parametric vehicle model, has been done in tables 4, 5 and 6 a comparison with the Dymola model using for the acceleration time, the speed from 0 to 100 km/h meanwhile for the elasticity time from 80 to 120 km/h:

Table 4: Parametric model validation results of the experiment using the components with the lower values

Responses	**Dymola model**	**Parametric model**	**Difference (%)**
Fuel consumption for NEDC (l/100km)	2,48	2,56	3,12
Acceleration Time (s)	12,86	12,75	0,86
Elasticity (s)	6,99	7	0,14

Table 5: Parametric model validation results of the experiment using the components with the nominal values

Responses	Dymola model	Parametric model	Difference (%)
Fuel consumption for NEDC (l/100km)	2,4	2,31	3,89
Acceleration Time (s)	11,2	11,23	0,26
Elasticity (s)	6,28	6,29	0,15

Table 6: Parametric model validation results of the experiment using the components with the upper values

Responses	Dymola model	Parametric model	Difference (%)
Fuel consumption for NEDC (l/100km)	3,25	3,36	3,27
Acceleration Time (s)	10,86	10,79	0,64
Elasticity (s)	6,28	6,27	0,15

8 Parameterization Results

When planning an experimental program that will allow carrying out the study on the effect of factors on the response variable, the first step to take is the choice of factors that will be used in the experiment. In this case the factors selected are the EM power, the ratio of the final drive and the battery capacity. Once the factors are determined, the next step is to select the ranges of each factor to be analyzed in the experimental region selected. The experimental design matrix used is (equation 2):

X = [-1 -1 -1 -1
-1 -1 -1 0
…...................]; (2)

all possible combinations [factors X number of experiments]-->[4 x 81]

where each row corresponds to one experiment, first column to the final drive ratio, second column to the electric motor size, third column battery capacity and fourth column to the engine size. The values are coded meaning "-1" the lower value, "0" the nominal value, and "1" the upper value.

Once the fuel consumption and electrical autonomy are obtained, it is possible to calculate the fuel consumption according ECE-R 101, where the fuel consumption for a PHEV based on the NEDC (figure 7) is defined as (equation 3):

$$FC(l/100km) = \frac{De \cdot FC1 + 25km \cdot FC2}{De + 25km} \quad (3)$$

FC1→ Fuel consumption (l/100km) during charge depleting

FC2→ Fuel consumption (l/100km) during charge sustaining

De→ Electric autonomy (km)

Using the design of the experiments performed it is very useful to obtain the response surface model fitting the data set collected at points of design to a polynomial equation. Using the data of fuel consumption simulated in all experiments it is possible to obtain a second-order mathematical model with terms linear, quadratic and binary interactions of the three independent variables (x_1, x_2, x_3) analyzed (equation 4).

$$\begin{aligned}\mu_y &= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_{11} x_1{}^2 + \\ &\beta_{22} x_2{}^2 + \beta_{33} x_3{}^2 + \beta_{44} x_4{}^2 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \\ &\beta_{14} x_1 x_4 + \beta_{23} x_2 x_3 + \beta_{24} x_2 x_4 + + \beta_{34} x_3 x_4 + \zeta\end{aligned} \quad (4)$$

where,

μ_y = Average value of the response variable

β_0 = Average value of the response

β_1 = Lineal effect of factor 1 on the average response

β_2 = Lineal effect of factor 2 on the average response

β_3 = Lineal effect of factor 3 on the average response

β_4 = Lineal effect of factor 4 on the average response

β_{11} = Quadratic effect of factor 1 on the average response

β_{22} = Quadratic effect of factor 2 on the average response

β_{33} = Quadratic effect of factor 3 on the average response

β_{44} = Quadratic effect of factor 4 on the average response

β_{12} = Interaction effect between x_1, x_2 on the response

β_{13} = Interaction effect between x_1, x_3 on the response

β_{14} = Interaction effect between x_1, x_4 on the response

β_{23} = Interaction effect between x_2, x_3 on the response

β_{24} = Interaction effect between x_2, x_4 on the response

β_{34} = Interaction effect between x_3, x_4 on the response

ζ = error

The obtained coefficients of each term are shown in table 7. Using the equation (4) and the values of each term calculated in table 7 it is possible to formulate the three parameterized equations for fuel consumption, acceleration and elasticity time. Notice that the major components that contribute more to the fuel consumption result are the BAT and the ICE.

Table 7: Coefficient results for second order model

Equation	Case study	Fuel Consumption Results	Acceleration Results	Elasticity Results
β_0	Constant	2,29144	11,2042	6,28715
β_1	FD	0,048085	0,035148	-0,04906
β_2	EM	0,032978	-1,00494	-0,44639
β_3	BAT	-0,81286	0,090204	0,129278
β_4	ICE	1,08715	-0,09763	2,16E-17
β_{11}	FD*FD	0,15832	0,034963	0,049056
β_{22}	EM*EM	-0,01143	0,512685	0,446389
β_{33}	BAT*BAT	0,312469	0,065685	-0,12928
β_{44}	ICE*ICE	0,445753	0,034963	1,53E-17
β_{12}	FD*EM	0,00817	-0,03808	-0,00292
β_{13}	FD*BAT	-0,01641	0,065194	0,001333
β_{14}	FD*ICE	0,014989	0,001639	-1,68E-17
β_{23}	EM*BAT	-0,02236	-0,06761	-0,01092
β_{24}	EM*ICE	-4,07E-04	-0,03081	-2,47E-18
β_{34}	BAT*ICE	-0,31307	-0,03883	-7,05E-18
ζ	error	0,0517	0,0309	0,0001

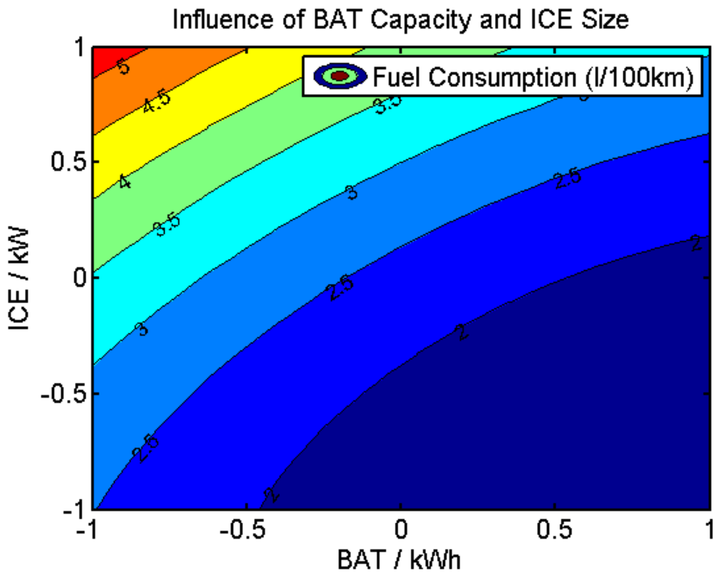

Figure 8: Response surface of fuel consumption among BAT capacity and ICE size fixing to the nominal value the FD and EM. On the ICE power it is possible to see an optimal on their lower value, when the power is far from the lower the fuel consumption increases over a NEDC

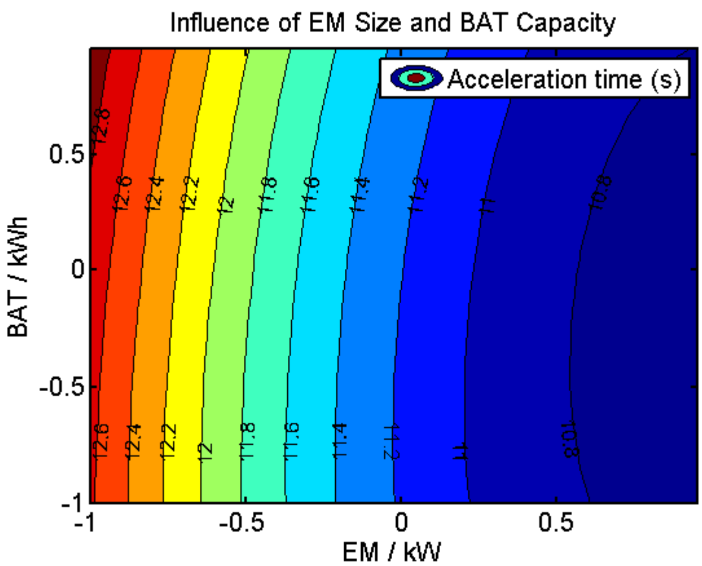

Figure 9: Response surface of acceleration time among EM size and BAT capacity fixing to the nominal value the FD and ICE. The BAT capacity is directly related to its weight and as greater is the EM size the acceleration time is reduced

In figure 8 it is shown the response surface for both components. As the BAT is greater the fuel consumption is reduced due to the Autonomy. It has been seen a strong influence of the BAT capacity below proportional, doubling the electrical autonomy, the fuel consumption is reduced by less than half. The current high cost of the battery makes this component very important on the process selection for the optimal set of components. The FD ratio has a direct influence on the fuel consumption in CS mode, and indirectly through electric consumption due to the electrical autonomy increases. The fuel consumption is reduced as the ICE power is low, due to a consumption map of an ICE with a less power than other one, the fuel consumption is also minus. The most efficient region obtained is when the battery size is big due to its influence on the autonomy, and also it happens when the power of the ICE is low.

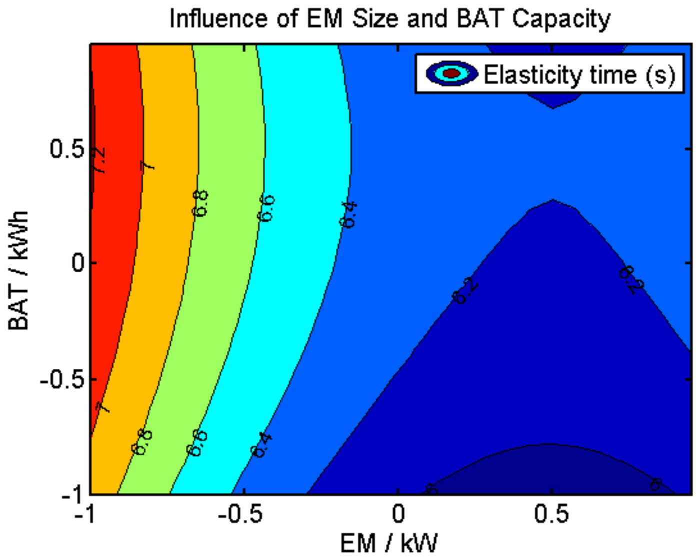

Figure 10: Response surface of elasticity among EM size and BAT capacity fixing to the nominal value the FD and ICE. The EM size and the BAT capacity are the components with the strong influence on the elasticity time due to this contribution in the elasticity margin

The figure 9 shows that the EM power and BAT capacity has an important contribution to the acceleration time, meanwhile the FD ratio and ICE size has a minor effect compared to the other ones. The EM size has a strong effect because is the main power source during the acceleration time, and also the weight of BAT contributes negatively to the acceleration time response. It is possible to say that as the power of the EM is bigger, the acceleration time of the vehicle will be reduced at least 0,2s each 1kW till the nominal value. Then when the EM power is increasing beyond the nominal value, the reduction of the acceleration time is lower as 0,2s each 5kW.

In figure 10 it has been analysed the elasticity time. In this case also the BAT capacity and the EM size are the components with the most influence on the response. Notice that there is an optimal region between the nominal and upper value of the BAT capacity when the EM size is around the nominal and upper value too. A vehicle with a bigger EM power has a quick elasticity time response, without depending directly of the BAT capacity.

9 Multiobjective Optimization

As a third step, multiobjective optimization has been done in order to obtain the pareto front solutions [10, 11] that reduces the fuel consumption maintaining the vehicle performance, in this case the acceleration performance (figure 11). In table 8 it is shown the internal parameters of the multiobjective optimization obtained as the total number of generations used, the total number of function evaluations to obtain the pareto front, the average distance of the solutions on the pareto front, and the spread. A smaller average distance measure indicates that the solutions on the Pareto front are evenly distributed.

After that the experiments that not accomplish with the acceleration time required, are not considered and are discarded to be the best options to use in a parallel PHEV. Therefore it is possible to guarantee a set of possible solutions with a required acceleration and elasticity performance meanwhile the fuel consumption is reduced (figure 12).

The combination that minimizes the fuel consumption is using the highest BAT capacity and the nominal value of ICE size in order to accomplish with the acceleration time and elasticity requirements. The minimum is 2,01 l/100km of fuel consumption using the nominal FD, high size of the EM, high BAT capacity and nominal size of the ICE.

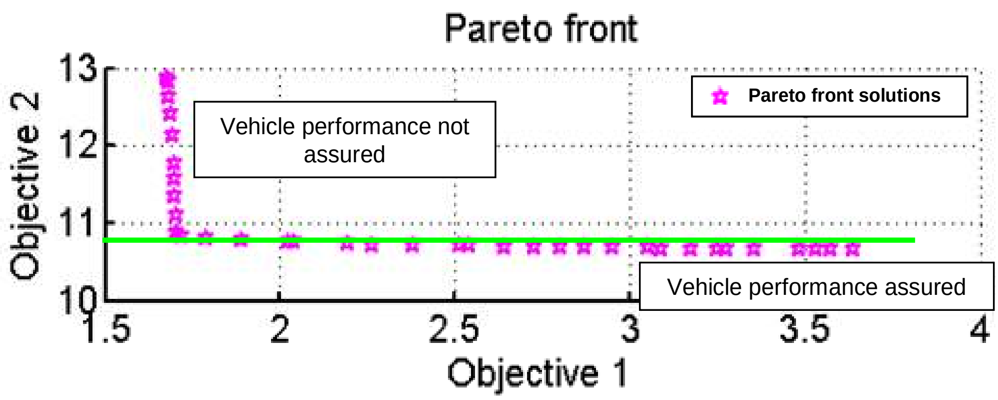

Figure 11 Pareto front results for an optimization of fuel consumption (objective 1) and the acceleration performance (objective 2)

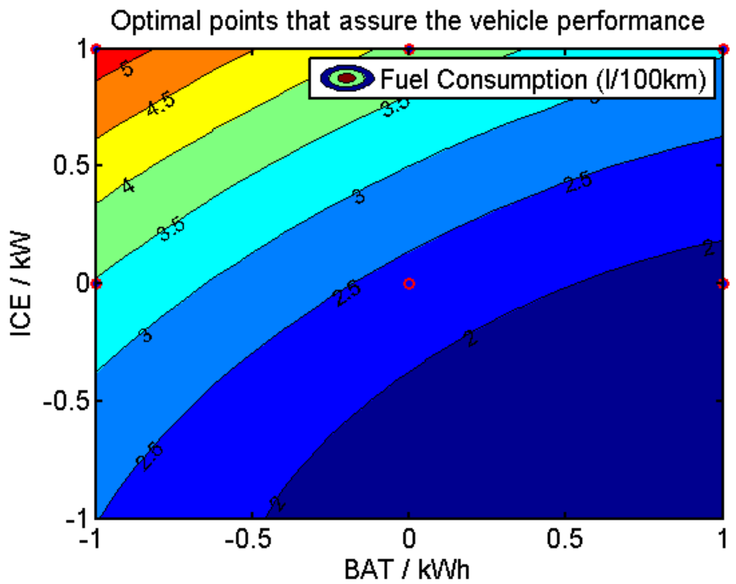

Figure 12: Optimal points that assure the vehicle performance. As a restrictions on the optimization process has been considered only the options that accomplish with an acceleration time less than 10,8 seconds and an elasticity less than 6,5 seconds

Table 8: Parameters of the multiobjective optimization

Total number of generations	148
Total number of function evaluations	15646
Average distance	0,0062
Spread	0,1240

10 Conclusions

This study gives a methodological way to solve the component sizing optimization of a Parallel PHEV describing the system in an analytic way. In this case has been studied the acceleration time, elasticity, and the fuel consumption defined as restrictions and objective respectively. Design of Experiments has been used to analyze the influence of the components and how it affects on the fuel consumption. Therefore has been calculated a parameterized equation that describes the system on an analytic way regarding the fuel consumption using ECE-R101. It has been observed a strong influence of the BAT capacity below proportional, in example, doubling the electrical autonomy, the fuel consumption is reduced by less than half. For this reason the BAT selection is very important on a optimal PHEV in terms of cost. The FD ratio has a direct influence on the fuel consumption in CS mode, and indirectly through electric consumption due to the electrical autonomy increases. In this case study, the EM size has a little influence due to the electrical machine is always working on an optimal efficiency region, but directly affects with a big influence to minimizes the acceleration and elasticity times. For the acceleration time it has been proved that the EM size and BAT capacity are the components with the strongest influence due to the EM is the main power source of the vehicle that is working on that speeds region, and also the BAT weight affects directly and negatively to have a quick acceleration time response. On the elasticity time analysis it can be seen that also the EM size and BAT capacity are the main components affecting on the results. To conclude it is possible to say that the selection of the components is a trade-off between reducing the fuel consumption and keeping the vehicle performance (acceleration and elasticity time) in order to produce more efficient PHEV vehicles maintaining the drivability performance.

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Authors

Oriol Torres received the Telecommunication Engineering degree from the Technical University of Catalonia (UPC), Spain in 2010. Since 2010 is doing his Ph.D. degree in Electronics at the MCIA research group of the Technical University of Catalonia (UPC) collaborating in a public research project on hybrid vehicles with SEAT (VERDE). His investigations are focused on hybrid powertrain, optimizations, modelling, simulation, and HIL tests.

Benjamin Bader received his degree in electrical engineering from the Technical University of Aachen (RWTH), Germany in 2009. Since 2010 he is Ph.D. student at the MCIA research group of the Technical University of Catalonia (UPC) working in a public research project on hybrid vehicles with SEAT (VERDE). He is working on modelling and energy management of HEV and HIL simulation.

Luis Romeral (M'98) received the Electrical Engineering degree and the Ph.D degree from the Technical University of Catalonia (UPC) in 1985 and 1995 respectively. His research interests include electric machines, power electronics converters and modulation strategies, variable-speed drive systems, fault detection and motor diagnosis, and microprocessor based real-time control algorithms. Dr. Romeral belongs to the Motion and Industrial Control Group (MCIA) at the UPC.

Gerhard Lux received his Electrical Engineering degree in 2002 and his Ph.D. in Mechanical Engineering in 2008, both from the Vienna University of Technology, Austria. Since 2009 he is working at the SEAT Technical Centre, Spain, where he currently leads the hybrid and electric powertrain development.

Juan Antonio Ortega (M'94) received the M.S. Telecommunication Engineer and Ph.D. degrees in Electronics from the Technical University of Catalonia (UPC) in 1994 and 1997, respectively. Since 2001 he belongs to the Motion Control and Industrial Applications research group working in the area of Motor Current Signature Analysis. His current R&D areas include: Motor diagnosis, Signal acquisition, Smart sensors, Embedded systems and Remote Labs.