Eco-efficiency optimization of Hybrid Electric Vehicle based on response surface method and genetic algorithm

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Abstract

The electric vehicles (EV) and sometimes the hybrid electric vehicle (HEV) technologies are environmentally very efficient but can not succeed on the market because of a smaller ability to satisfy customer's requirements. Comparison of clean technologies in automotive and transportation systems has been measured using different analysis tools such as LCA (life cycle analysis). However, these instruments never account for the user's satisfaction which partly explains the market acceptance problems. The Eco efficiency is a global index which accounts for both environment impacts and user satisfaction. The main objective of vehicle powertrain hybridization is to improve the fuel consumption and environment pollutants impact (Eco-score) without decreasing the vehicle performances and other user satisfaction criteria. The objective of this study is to minimize the Eco-score indicator of HEV with respect to the user satisfaction criteria. The approach is formulated as a multidisciplinary optimization problem. At first the EV or HEV are modeled and simulated using ADVISOR (advanced vehicle simulator) with respect to several driving situations. Then emissions can be determined and the Ecoscore indicator can be calculated. User Satisfaction can be evaluated based on performance criteria extracted from ADVISOR simulation and on simple evaluation tools relying on the state-of-the art of technological information for safety, reliability and daily cost. In this study the design problem is stated as follows: select mechanical and electric components (like engine, motor and battery sizes) to minimize the Ecoscore indicator and to maximize user satisfaction criteria subject to catalogue constraints on the choice of the components. The approach is illustrated on applications dealing with parallel hybrid electric vehicles.

Keywords: Ecoefficiency, MDO (multidisciplinary optimization), response surface model, multi objective optimization, multi objective genetic algorithm.

1 Introduction

Hybrid Electric Vehicle (HEV) is expected to be one of key technologies for future cleaner and fuel efficient vehicles. Typically, the architecture of these vehicles includes an internal combustion engine (ICE) associated with an electric motor and its energy storage system (Battery). A success HEV design requires optimal sizing of its key mechanical and electrical components. In addition, for more HEV efficiency, an optimal management of energy flow (control strategy) is required. Therefore, in the design process of a HEV, there is a large variety of design variable choices including HEV configuration, key mechanical and electrical components sizes and control parameters. Moreover engineers are faced with several conflicting design constraints and objectives aiming at increasing performances and comfort while minimizing environmental impact. Conversely to the importance of this practical issue, literature review provides a rather limited number of works dealing with the application of rationale tools such as structural and multidisciplinary optimization applied to HEV design (see for instance Ref. [1-7]).

In these works most of them focus on one single objective function and emissions are restricted to fuel emissions. In this study, HEV design problem is considered as a multi objective and multidisciplinary optimization problem. In addition one of the main goals is the simultaneous minimization of the vehicle environmental impacts (Ecoscore) while also maximizing User satisfaction criteria (US). Satisfaction of needs or user satisfaction (US) is formulated as an aggregation of several criteria which reflects several aspects of vehicle characteristics for users i.e daily cost, reliability, safety, performances, etc.

In order to assess more clearly the trade-off between these antagonistic criteria, the authors have developed in past works, the concept of an Ecoefficiency index to provide a global index which accounts for both environmental impacts and user satisfaction criteria. This Ecoefficiency index is based on one hand on the Ecoscore [8,9] for the environmental impact and on the other hand on a User Satisfaction composite index to assess the ability of the vehicle to meet customer’s expectations about his transport needs. Our work on eco efficiency showed clearly the difficulty to define aggregate indices for US & Ecoscore and the sensitivity of the results in the weighting of the two criteria on the result. Therefore this paper proposes a novel design approach of HEV and EV based on multidisciplinary optimization using genetic algorithms and response surface methods. The multiobjective approach that is developed naturally circumvents the problem of considering conflicting criteria of different natures. The approach is formulated as a multidisciplinary optimization problem based on different coupled analysis problems. At first the EV or HEV model is simulated using ADVISOR (advanced vehicle simulator) [10,11]. Then emissions can be determined for several driving scenarios and the Ecoscore indicator can be calculated. The User Satisfaction can be evaluated based on performances criteria evaluated from ADVISOR simulations and from simple safety, reliability and daily cost scores, which are computed from simple evaluation tools and data bases relying on state-of-the-art of technological information. In this study the design problem is stated as follows: select mechanical and electric components (like engine, motor and battery sizes) to minimize the Ecoscore indicator and maximize the user satisfaction criteria subject to discrete valued sizes of components chosen from catalogues. Because of the large number of HEV parameters, trial-and-error-based design approaches of a HEV is generally impossible and cumbersome to handle by human intuition. On the contrary, a rationale and efficient design procedure is based on digital simulation and optimization algorithms. As response functions may be noisy and/or discontinuous, derivative-free algorithms are preferred to gradient-based optimization algorithms, such as Sequential Quadratic Programming (SQP) to solve the problems. Moreover multiobjective versions of Genetic Algorithms are available to handle the eco-efficiency design problem. Finally since response functions are implicit functions of design variables and their evaluation requires every time a simulation run, the numerous direct calls to the simulation code are replaced by surrogate models or metamodels in order to carry out the optimization work with a moderate computational cost. In this study we have selected the software tool Boss Quattro from Samtech [12] to carry out the optimization and the task management tasks of the chain of coupled simulation tools.

The following solution flowchart is used:

- Use a parametric study in BOSS QUATTRO to construct some response surface approximations (polynomial) of US and Ecoscore from ADVISOR simulation models.
- Formulate a multi objective optimisation problem to minimize the Ecoscore and maximize the US.
- Solve the eco efficiency design optimization problem using a multi objective genetic algorithm (MOGA) available in BOSSQUATTRO.

The approach is illustrated on eco-efficiency design problems of parallel HEV, series HEV and an HEV bus.

2 Modeling and Simulation

2.1 HEV Configurations

The basic two architectures of HEV powertrains are the series and parallel configurations. However, multimode and complex types are also considered to combine the features of both series and parallel hybrids (i.e. Toyota Prius) as stressed by Ref [1]. As shown in Figure 1, the series HEV configuration includes a fuel converter (ICE), a generator, a battery and an electric motor. In this case, the engine does not drive the vehicle shaft directly, but the mechanical power is converted into the electrical energy using a generator. Then, the torque required to drive the vehicle can be supplied by the electric motor. Sometimes, electric energy is also saved in the energy storage system (i.e. battery). However, in parallel HEV, both electric motor and IC engine can deliver power to wheels as shown in Figure 2. The electric motor can also be used as a generator to charge the battery by either the regenerative braking or by absorbing the excess power produced by the engine when its output is greater than that required to drive the wheels. In the combined series-parallel hybrid, the configuration involves an additional mechanical link compared with the parallel hybrid and also an additional generator compared with the series hybrid, which makes the series-parallel HEV a relatively more complicated and costly version.

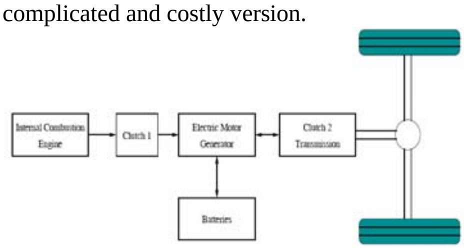

Figure 1: Series HEV Configuration

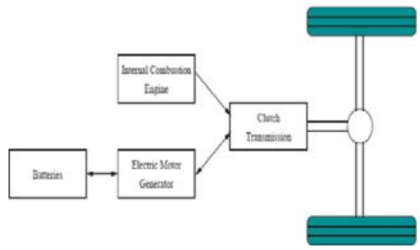

Figure 2: Parallel HEV configuration

2.2 Simulation

Simulation tool: ADVISOR (advanced vehicle simulator) is used for simulating the fuel consumption, the emissions and the performances of the vehicles. ADVISOR was initially developed by the National Renewable Energy Laboratory [10,11] from 1994 to 2002. ADVISOR combines forward /backward facing approach for the vehicle performances simulation (see Ref. [10]). In addition, it offers graphical user interface to select the component modules required to construct the vehicle system. Among several components of a HEV, the IC engine, electric motor and energy storage system are considered as the most critical components. Proper selection of these components mainly affects the vehicle characteristics and performance.

Design model parameterization in ADVISOR: To consider the effect of component sizes in the optimisation of HEV design, ADVISOR approach is to consider a baseline configuration components. The baseline configuration can then scaled up during the design process. For instance for the energy storage system, a battery pack is selected and then the number of battery modules is modified. The baseline scaling factor will later be naturally considered as our design variables during optimization process. For example the baseline configuration of the hybrid vehicle in the first numerical applications is summarised in Table 1.

Table 1: Baseline configuration of a passenger car

Component	Baseline
Fuel Converter	Geo 1.0 litre SI 41 kW engine, peak efficiency: 0.34
Motor	75 kW Westinghouse AC induction motor/inverter
Battery	valve-regulated lead-acid (VRLA) battery, 25 modules of 25 Ah and 12 V each

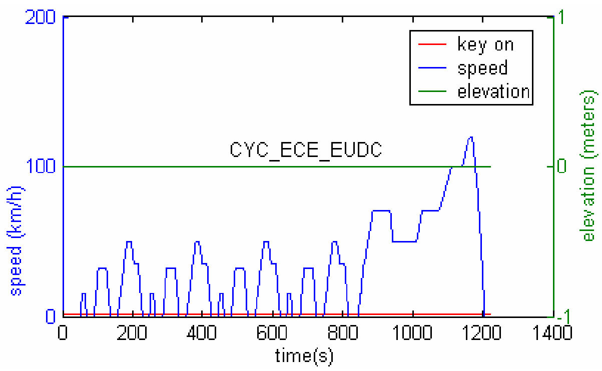

Figure 3: CYC_ECE_EUDC drive cycle

Drive cycles: In this study the New European Drive Cycle (NEDC) is selected for passengers vehicle simulation (see figure 3) because it is the legal reference in Europe. This drive cycle has two parts, the first one is representative of an urban cycle (ECE15 drive cycle) and lasts about 800s, the maximum speed being 50km/h, whereas the second part simulates an extra urban cycle (EUDC drive cycle) and lasts about 400s with a maximum speed of 120km/h.

3 User satisfaction criteria

The choice of a clean technology which respects both environment packaging, engineering constraints and user needs is a multi objective problem. Satisfaction of needs is based on several criteria i.e security, daily cost, reliability, performances, etc. Some criteria like performances are easily quantifiable but others like comfort are qualitative so that they can only be estimated by fuzzy description. In this study we will consider only quantitative criteria: cost, performances and security.

Performances: performances include maximal vehicle velocity, acceleration performances and gradeability. They can be evaluated by simulation in ADVISOR by following standard approaches described in classical vehicle theory (see ref [7,8] for instance).

<u>Maximum speed</u> is evaluated when solving equilibrium equation between propulsion power and dissipated power by resistance forces (rolling resistance, aerodynamic resistance…)

$$\eta P_{propulsion}(\omega) = P_{resistance}(v) = c_0 v + c_1 v^2 + c_2 v^3 \quad (1)$$

Where ω is engine speed while v is the vehicle ground speed, η is the transmission efficiency, c_0, c_1, c_2 coefficients of a general expression of the driving resistance forces.

<u>Acceleration time</u> (from V_1 to V_2 kph) can be evaluated by solving integration of equation of motion of the vehicle

$$\Delta t = m_{eff} \int_{V_1}^{V_2} \frac{dV}{F_{net}(V)} \quad (2)$$

Where m_{eff} is the equivalent or effective mass and F_{net}, the net force between propulsion force and driving resistance forces.

<u>Gradeability:</u> is estimated by solving the equation limiting the propulsion force that can be transmitted to the ground while taking care of mass transfer during climbing in steady sate motion

$$F_{propulsion} = F_{resistance} \leq \mu W_{f/r} \quad (3)$$

W_f and W_r are respectively the front and rear weight under front or rear wheels.

Security: It is the capability of the vehicle to ensure both the passengers and other road users safety. Safety can be based on several criteria like security equipment available on the vehicle, crash test results (e.g. Euro NCAP [15]), static stability factor estimating rollover resistance [13], etc. But the vehicle mass is the main factor for road security, especially for security of collision partners. Based upon the FARS (Fatal Analysis Reporting System) database, Joksch et al. [16] have estimated the relationship between the mass ratio of collision partners, and the fatality ratio of collision partners to be:

$$\frac{F_2}{F_1} = \left(\frac{m_1}{m_2}\right)^4 \quad (4)$$

where m_1 and m_2 are the mass of vehicle 1 and 2, F_1 and F_2 are the fatalities in vehicle 1 and 2. As an example, for a mass ratio of 2:1, the formula (4) predicts a fatality ratio of 16:1 between the lighter car and the heavier one. This mean that for vehicle-to-vehicle collisions in which one vehicle weighs twice more than its collision partner, for every fatality unit in the heavier car there would be sixteen in the lighter car. Because of this we decided to focus on the security criteria to evaluate security solely by formula (4) of the mass ratio between the considered vehicle and a reference one. In ADVISOR, the vehicle mass is a function of selected vehicle components.

Cost: A simple cost model is introduced to estimate the total vehicle cost witch is devised into two costs: an operating cost, $C_{operating}$ and an investment cost, C_{inv}

$$C_{inv} = c_{engine}P_{engine} + c_{elec}P_{elec} + c_{bat}N_{bat} + C_{fixed} \quad (5)$$

where c_{engine}, c_{elec} are respectively the cost per kW of the IC engine and the electrical components and P_{engine}, P_{elec} are the maximum rated power output in kW. In order to account for parallel hybrid designs that have no generator (since the electric machine works reversibly as a motor or a generator), the P_{elec} is defined as:

$$P_{elec} = P_{motor} + P_{generator} \quad (6)$$

c_{bat} is the module battery cost and N_{bat} the modules number. The c_{fixed} is taken to include the bodywork and all the accessory components, and is assumed to be fixed and is the same for a hybrid or a conventional vehicle. In reality it is clear that this is a greatly simplified costing, since as engine power varies so does the cost of many associated components such as braking systems, suspension systems and tires.
Operating cost is calculated as:

$$C_{op} = c_{fuel}M_{fuel} + c_{maintenance} \quad (7)$$

Where c_{fuel} is the cost per litre of fuel and M_{fuel} is the volume of fuel used over the assumed life of the vehicle. In this study we have assumed a life of 5 years with 100,000 km which is rather small. The maintenance costs have been neglected because we assume that the maintenance cost is more or less similar for the hybrid and conventional vehicles, which is again a rough approximation.

Aggregated performance criteria: When working with several metaheuristic algorithms such as Genetic Algorithms, one major issue is concerned with considering design constraints. Therefore one strategy to circumvent the problem consists in defining aggregate objective functions or constraints. In order to introduce the performance criteria into the multiobjective approach later, we define here global performance criteria embedding previously defined performance criteria (vehicle maximum velocity, gradeability and the acceleration performance). User satisfaction can therefore be estimated using a linear combination of different criteria weighted by appropriate targets values related to a reference vehicle.

$$S\tilde{B} = \frac{\tilde{V}_{max}}{140} + \frac{12}{\tilde{t}_{acc}} + \frac{\tilde{p}_{max}}{6} + \frac{1200}{\tilde{m}} + \frac{40000}{\tilde{C}} \quad (8)$$

Where:

- $\tilde{V}_{max}$ is the estimated maximum vehicle maximum speed (to be maximized)
- $\tilde{t}_{acc}$ is the estimated acceleration time (from 0 to 100 kph) (to be minimized)
- $\tilde{p}_{max}$ is the estimated gradeability (to be maximized)
- $\tilde{m}$ is the vehicle mass (to minimized)
- $\tilde{C}$ is the total cost estimate (to be minimized)

Making use of reference car target criteria also ensures the consistency of metric units in the aggregated function. For maximum accuracy, it is a standard procedure in multidisciplinary optimization to estimate each criteria using response surface approximations and then, in a second step, to calculate the user satisfaction from the linear combination of the values coming from the surrogate models.

4 Eco-score model

Eco-score [1,2] is a single environmental indicator which integrates different aspects of the environmental impacts of the road vehicles such as global warming, air quality, energy depletion and noise pollution. The emissions pollutants considered by Eco-score are related to the direct and indirect emissions. Direct emissions are linked to the use of the vehicle itself (tank-to-wheel) whereas indirect emissions are those related to the extraction and transportation of the raw materials for the fuel production, together with the emissions linked to refining and distributing the carburant (well-to-tank). In this study the direct emissions are obtained by the vehicle simulation in ADVISOR and the indirect emissions are based on the fuel consumption and the indirect emissions factors. The air pollutants cause various damages divided into different categories like global warming, human health impairing effects, harmful effects on ecosystems and building dirtiness. The partial damage of each pollutant is calculated as:

$$d_{ij} = \beta_{ij}E_{j,totales} \quad (9)$$

Where

- d_{ij} is the partial damage of pollutant j to category I,
- β_{ij} is the impact factor of pollutant j to the category i
- $E_{j,totales}$ is the total contributing emissions of pollutant j to the category i

The damages are explained in common units by category so the total damage of each damage category can be obtained summing up the partial damages for the different damage categories:

$$D_i = \sum_j d_{i,j} \quad (10)$$

In order to quantify the relative severity of the evaluated damages of each damage category, a normalisation step based on a specific reference value is performed. The damage associated to the emissions norms EURO IV (directive 98/69/EC) is taken as the reference point.

$$Q_i = \frac{D_i}{D_{i,ref}} \tag{11}$$

Where:

- Q_i is the normalised damage on category i
- D_i is the total damage of the assessed vehicle on category i;
- $D_{i,ref}$ is the total damage of the reference vehicle on category i

The different damages are weighted before being aggregated to obtain the global damage.

$$E = \sum W_i Q_i \tag{12}$$

Where: W_i is the weight of damage i.

5 Response Surface method

Because of the larger number of function evaluation that can be necessary to carry out optimization process, especially when using meta heuristic algorithms, a standard approach in structural and multidisciplinary optimization consists in resorting to global or local approximation models (see for instance [17,18,19]) Approximations will replace direct simulation runs during optimization iterations and will be updated during a limited number of step ([20]). They provide explicit relations that enable a fast and small cost evaluation of the considered response functions. This approach will avoid dramatic increase of simulation time related to iterative solution procedure.

The basic idea of global approximation used here is to construct an approximate model using function values (from simulation runs or mathematical model computations) at some sampling points, which are typically determined using experimental design methods such as factorial design, central composite design, or Taguchi orthogonal array. Model fitness is subsequently checked using various statistical methods. In this section, we give a brief overview of the response surface methodology.

Design of Experiments (DoE): Design of Experiments addresses the problem of distributing the experimental points in the design space. The difficulty lies in minimizing the number of points, and, at the same time, in obtaining an approximation with good quality, i.e. that minimizes errors. The definition of the location of sampled points can influence the precision of the model because a correct choice of evaluation points can reduce the uncertainty of the approximated model. The sampling points are typically determined using experimental design methods such as a factorial design, a central composite design, or a Taguchi orthogonal array. In a DoE each variable or factor, is assigned within a range, defined with minimum (low bound: LB) and maximum (upper bound: UB) values. For the problem of the hybrid powertrain that will be considered in the application one can see at Table 2 the different design variables and their bounds. The DoE table then defines the points that should be used to create the response surface.

Table 2: Design Variables and assigned bounds

Design Variable	Description	baseline	LB	UB
P_{ICE} (kW)	Fuel converter maximum power	41	20	65
P_{motor} (kW)	Motor maximum power	75	20	60
N_{bat}	Battery number of modules	25	20	80

Modelling approach: There are various response surface approximation methods available in the literature [19,20]. The polynomial-based approximations are the most popular. In this study, we typically use first or second-order models and their inverse in the form of linear or quadratic polynomial functions to develop an approximate model that provides an explicit relationship between design variables and the response of interest. The unknown coefficients in the model are determined with a least squares method. Statistical analysis techniques such as ANOVA (analyse of variance) are used to check the fitness of the response surface model. An appropriate order polynomial is fitted to a set of data points, such that the adjusted root mean square error is minimized. The adjusted root mean square error σ_a is defined as following: Lets *Np* be the number of data points and *Nc* be the number of coefficients and error e_i at any design point *i* being defined as:

$$e_i = y_i - \hat{y}_i \tag{13}$$

where y_i is the actual value of the function at the design points and $\hat{y}_i$ is the predicted value. Hence on gets:

$$\sigma_a = \sqrt{\sum_{i=1}^{N_p} e_i^2 \Big/ (N_p - N_c)} \tag{14}$$

If N_t is the number of additional test data that are used to test the quality of the approximation, the root mean square error σ_a is given as:

$$\sigma_a = \sqrt{\sum_{i=1}^{N_t} e_i^2 \Big/ N_t} \tag{15}$$

Prediction capability of the response surface is given by the coefficient of multiple determination R_{adj}^2 defined as:

$$R_{adj}^2 = 1 - \sigma_a^2 (N_p - 1) \Big/ \sum_{i=1}^{N_p} (y_i - \bar{y})^2 \tag{16}$$

With

$$\bar{y} = \sum_{i=1}^{N_p} (y_i / N_p) \tag{17}$$

For a good fit, R_{adj}^2 should be close to 1. In this study, the response surface method is employed to generate simulation-based surrogate models of performance criteria. Table 3 indicates the multiple determination coefficients for six response function and their meta models. As shown in the table 4, the quadratic polynomial model is efficient for three functions (Ecoscore, m and C) and second order inverse polynomial is efficient for also three functions (v_{max}, p_{max}, t_{acc})

Table 3: R^2_{adj} for different models

	1st order polynomial	Quadratic polynomial	1st order inverse	2nd order inverse
Eco-score	0.97131	0.98826	0.8758	0.98634
$v_{\max}$	0.63539	0.90885	0.6938	0.93896
t_{acc}	0.60948	0.92955	0.6411	0.96041
$p_{\max}$	0.73877	0.96565	0.7184	0.98176
m	1	1	0.8937	1
C	0.99292	0.99873	0.8989	0.99870

Figure 4 shows two of those responses: the acceleration time (from 0 to 100 kph) and the vehicle maximum velocity.

Remind also the reader that meta models are built for single performance criteria and then the aggregate user satisfaction function is calculated, leading to a better precision.

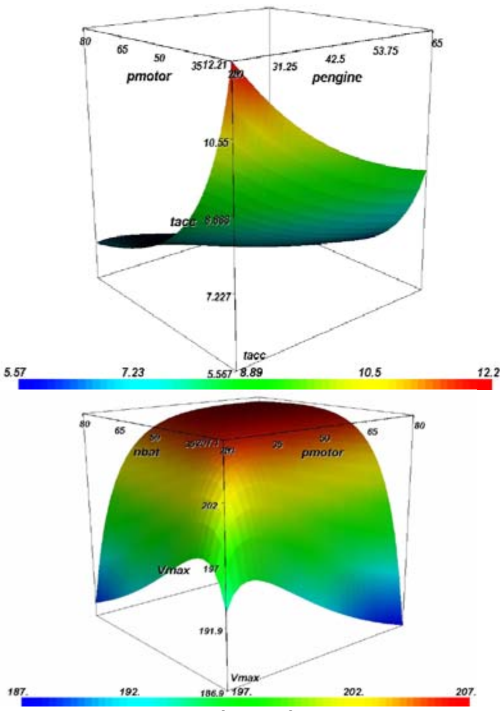

Figure 4: Response surfaces of Parallel HEV

Once the surrogate models are available, any optimization method can be used to solve multi-objective optimization problems with a reduced computational effort.

6 Optimization

6.1 Multi-objective optimization

Multi-objective optimization problem consists in finding a vector of design variables which simultaneously satisfies the constraints and minimizes / maximizes a vector of objective functions. These functions are usually antagonistic and conflicting with each other. Formally, multi-objective optimization problem is formulated as:

Minimize $F(X)$,

Where $F = \{f_i\} : \forall j = 1, M ; X = x_i : \forall i = 1, N$

Subject to:

$$C(X) \le 0 \text{, where } C = \{C_p\} : \forall p = 1, P \qquad (18)$$

$$H(X) = 0 \text{, where } H = \{h_k\} : \forall k = 1, K$$

All objective functions can not be simultaneously optimized. In others words, there is not a single solution which simultaneously provides the optimal value for all objectives. This introduces the Pareto optimality or the non-dominated solutions set concept.

6.2 Pareto-Optimality

When two design points are compared, they are non-dominated with respect to each other if no design dominates the other. In other words, a design X Є D (D is the set of all feasible designs) is non-dominated with respect to a set $A \subseteq D$, if $\nexists a \in A : a < X$. In addition, any design X is *Pareto optimal* if X is non-dominated with respect to D i.e there is no feasible design which would improve any objective function without worsening at least an other one. All non-dominated design points in set D sweep the *Pareto optimal set*. The objective functions representation of the Pareto optimal set is the *Pareto optimal front (POF)*. Figures 5 represents the Pareto optimal set for a two objectives problem.

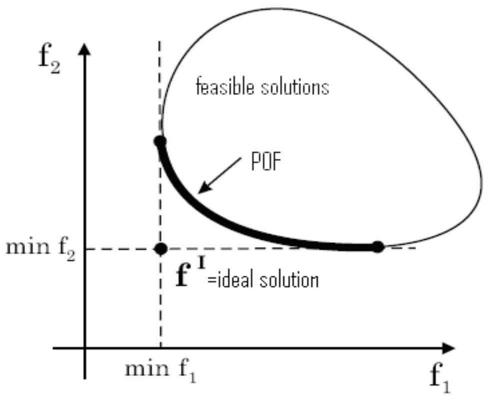

Figure 5: Pareto-optimal front

Generally it is not easy to find an analytical expression of the Pareto optimal front. Therefore, the multi-objective problem solutions consist in a discretization of the Pareto front and the algorithm aims at finding several non-dominated solutions by applying appropriate techniques. There are many methods to solve multi-objective optimization problems. They can be divided into two categories. In the first category, the user specifies his/her priorities before optimization (*a priori* methods). In this category, the initial multi-objective problem is transformed into a mono-objective problem by aggregating all objectives (weighted sum) or considering one objective as the main objective and other ones as constraints (i.e e-constraint method). The problem can then be optimized using a standard gradient based algorithm if derivatives are available or derivative-free algorithm. The common drawback of these methods is that a single solution is obtained after optimization. To find an other solution (for Pareto front), the user has again to restart an optimization run with an new problem formulation by modifying the weight coefficients or by expressing other priorities. In addition the Pareto front is in general not homogeneous, convex or even continuous and the non dominated solutions may be grouped in the same region so that the designer choice is limited. On the contrary, the *a posteriori* search techniques work without priorities information about the set of optimal solutions. Afterwards the designer can choose his/her most prefered solution from the pareto set after optimization. Genetic algorithm is one of these *a posteriori* techniques, because it yields a set of non-dominated solutions. In addition, the use of the sharing operator makes the Pareto front homogeneous. In its basic form, GA operates on a population of individuals (potential solutions), each of them being an encoded string (chromosome), containing the decision variables (genes). The structure of a GA is composed by an iterative procedure through the following five main steps:

1. Creating an initial population $P_{0;}$
2. Evaluation of the performance of each individual p_i of the population, by means of a fitness function;
3. Selection of individuals and reproduction of a new population;
4. Application of genetic operators: crossover and mutation;
5. Iteration of steps 2–4 until a termination criterion is fulfilled.

To apply GA to the optimisation of HEV, a fitness function is required to evaluate the performance of each solution. In this study, the fitness function is the objective function. To account for the multi-objective aspects, several GA have been drawn up [21] and the most popular are MOGA (Multi objective genetic algorithm), NSGA (Nondominated Sorting Genetic Algorithm) and NPGA (Niched-Pareto Genetic Algorithm).

6.3 Problem statement of HEV design

The objective is to optimize a Hybrid Electric Vehicle component to increase user satisfaction and decrease the Eco-score on the basis of European normative driving cycle. The mathematical problem of the multiobjective design problem of a HEV vehicle can be stated is as follows:

Minimize

$$F(X) = (f_1(x) = \tilde{E}; \quad f_2(x) = 1/S\tilde{B})$$

With respect to

$$X = (P_{engine}, P_{motor}, N_{bat})$$

Subject to

$$\begin{aligned} &\tilde{t}_{acc} \le 12s \\ &\tilde{v}_{\max} \ge 140kph \\ &\tilde{p}_{\max} \ge 6\% \\ &\tilde{m} \le 1200kg \\ &\tilde{C} \le 40000€ \\ &20 \le P_{engine} \le 65 \\ &20 \le P_{motor} \le 60 \\ &20 \le N_{MB} \le 80 \end{aligned} \tag{19}$$

The optimization is initially limited to three design variables, two of them defining the power ratings of the fuel converter and the motor controller. The third variable defines the number of battery modules. As it can be seen in formula (19), we have a two objective function optimization problem. Multi-objective genetic algorithms, MOGA and NSGA are available in BOSS-QUATTRO tools [20] and the MOGA one is selected in this study. This algorithm accounts for multi-objective aspects by a selection step based on filing:

- after each generation, population individuals are classified and each individual i have a value defined as:

$$r(i) = 1 + p(i) \tag{20}$$

Where p(i) is the number of j population individuals with an objective function f(j) that dominates f(i).

- For each individual, an intermediate fitness function value is calculated as a function of his filing:

$$f'_{ad}(i) = f'_{ad}(r(i)) \tag{21}$$

- A mean value is calculated on all of the population and an individual fitness function value is obtained:

$$f_{ad}(i) = N_{pop} \frac{f'_{ad}(i)}{\sum_{i=1}^{N_{pop}} f'_{ad}(i)} \tag{22}$$

- The sharing operator is then applied on the individuals which have the same filing;
- A roulette wheel with stochastic sample is applied for filing step.

7 Numerical application

The method has been illustrated with the example of a parallel hybrid electric vehicle. This application is continued along here, optimizing at first a parallel hybrid electric (PHEV) powertrain configuration and later a serial hybrid electric vehicle (SHEV).

We also develop here a second numerical application with the optimization of the serial hybrid electric bus with, in this case, a different baseline configuration (see Table 4). The selected battery packs are based on NiMH modules. The relevant drive cycle that is chosen is CYC_MANHATTAN for the bus, which is available in ADVISOR library.

Table 5: HEV Performances comparison

	PHEV		SHEV		PHEV-BUS	
	before	After	before	after	before	after
Fuel consumption (l/100km)	7.5	6	6.8	5.9	56.2	52.7
Tacc (from 0 to 100 kmph)	9	10.4	8	10	8.9 (from 0 to 60 kph)	8.8
Vmax (km/h)	191	173	157	158	84	83.9
Pmax at 80km/h (%)	21	16.4	16	10	13.4 (at 48 kph)	13.6
NOX (g/km)	0.324	0.311	0.641	0.426	80	59
CO (g/km)	2	1.755	2.314	1.349	5	4.5
HC (g/km)	0.416	0.253	0.482	0.259	200	103
M (kg)	1350	1197	1648	1323	16016	15993
C (€)	28475	17282	35400	25952	256490	274210
Eco score	1.5799	1.2684	2.1326	1.6586	2.8585	2.1593
SB	8.7730	8.6	6.9	6.4	6.2328	6.2390

The multiobjective optimization is carried out using the MOGA approach. The initial population of the GA is set to 20 individuals. After 50 generations the objective functions of the population spans the Pareto front as illustrated in Figure 6.

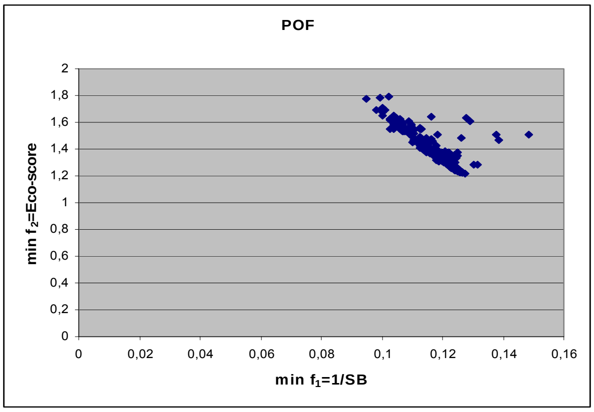

Figure 6: Eco-score and 1/SB functions results

In Table 4, we selected some optimized configuration to be compared with those before optimization (baseline configuration) in table 5:

Table 4: Components sizes comparison

	component	P_{ICE} (kW)	Pm (kW)	N_{bat}	Pgen (kW)
PHEV	Before optimization	41	75	25	
	After optimization	30	20	20	
SHEV	Before optimization	41	75	50	75
	After optimization	20	43	33	42
PHEV-BUS	Before optimization	206	122	571	
	After optimization	150	128	763	

As shown in Table 4, all component sizes have been decreased except in the bus case for which the motor power and the batteries modules numbers were increased.

In some cases the engine and motor power have been significantly decreased. The performances of the hybrid Electric Vehicle before and after the optimization are given in Table 5 for comparison. The fuel consumption of a parallel hybrid electric vehicle has dropped from 7.5l/100km to 6l/100km However the emissions have been reduced (about 20% for PHEV) in the three cases and one can notice subsequently a significantly Ecoscore improvement (about 20% for PHEV). In other hand, performances are slightly deteriorated because of the decrease in the fuel converter and motor sizes. However the user satisfaction is not significantly affected: the deterioration is about 2% while the Eco-score improvement is about 18% for PHEV.

8 Conclusion

We have developed a general optimization procedure to optimize the design of Hybrid Electric Vehicle powertrains based on the conflicting objective functions of minimizing the environmental impact (ecoscore) while maximizing the performance of the vehicle. In this study meta heuristic algorithms such as Genetic Algorithms have been selected in order to cope with noisy and non-smooth response functions. Performance criteria and emissions of vehicles are simulated using the ADVISOR software tool, while the optimization iterative process is carried out in Boss Quattro. In order to reduce the computational cost, one major contribution consists in developing approximations of performance and environmental criteria based on response surface methods. The approach has been illustrated on two numerical applications dealing with the optimization of a hybrid electric passenger car and of a serial hybrid electric bus.

In future developments, our approach should be extended to account for more parameters such as the HEV control strategy for further improvement. In addition, precision of response surfaces strategy will be further improved to be more robust in cases where optimums are difficult to determine. For instance it will be interesting to couple genetic algorithms with local search algorithms.

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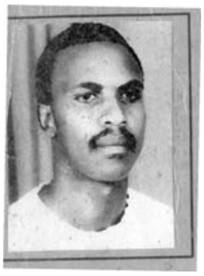

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