Comparison of Ultra capacitors and Batteries Technologies to Optimize Hybrid Electric Vehicle Efficiency

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***Abstract*— The acceptance of Electric and Hybrid Electric Vehicle is related to their eco-efficiency, i.e. their ability to both reduce environmental impact while also providing a sufficient user satisfaction. The objective of this study is to provide a rationale design tool based on a multidisciplinary optimization approach to support the design of hybrid electric powertrain to simultaneously maximize user satisfaction complex criteria and minimize the Eco-score. In order to carry out the optimization problem efficiently the approach makes use of metamodeling techniques in order to save computation time in the optimization process that is driven by a Genetic Algorithm. The approach is applied to highlight the effect of different energy storage systems (batteries v.s. ultra capacitors) upon the optimized HEV design taking care of both Eco-score and User satisfaction. In the selected application that is a heavy urban bus with a mild hydrid electric powertrain, the ultra capacitors are slightly superior to NiMH batteries when emphasizing the Ecoscore criterion.**

I. INTRODUCTION

Hybrid Electric Vehicle (HEV) is expected to be one of key technologies for future cleaner and fuel efficiency vehicles [1]. Typically, the hybrid architecture includes an internal combustion engine (ICE) associated with an electric motor and its energy storage system (Battery or Ultra Capacitors). A successful HEV design requires an optimal sizing of its key mechanical and electrical components combined to an optimal energy management (control strategy). Therefore, in the design process of a HEV, engineers are faced with a large variety of design variable choices including HEV configuration, key mechanical and electrical components sizes and control parameters while satisfying several conflicting design constraints and objectives aiming at increasing performances and comfort while minimizing environmental impact. Conversely to the importance of this practical issue, the number of works dealing with the application of the structural and multidisciplinary optimization to HEV design (se for instance Ref. [2-5]) is rather limited.

Most of the works focus on a 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. This approach is able to provide a rationale framework in order to handle efficiently the design problem that consists in minimizing the vehicle environmental impacts while simultaneously maximizing User satisfaction criteria (US). The multi objective approach is able to consider naturally the conflicting criteria of different natures and circumvents the difficulties of most Ecoefficiency approaches that have to define aggregate indices for US & Ecoscore, and that are sensitive to the weighting of the two criteria.

The multidisciplinary optimization framework provides a tool to carry out different coupled analysis problems. The environmental impact is assessed on the basis of the Ecoscore [6,7] whereas the User Satisfaction that requires evaluating several criteria related to vehicle characteristics i.e. performances, daily cost, reliability, safety, etc. Thus at first the EV or HEV model is simulated using ADVISOR (advanced vehicle simulator) [8,9]. Then emissions can be determined for several driving scenarios and the ECOSCORE indicator can be calculated. The User Satisfaction can be estimated 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.

Then the design problem is stated as the following optimization problem: select mechanical and electric components (like engine, motor and battery sizes) to minimize the ECOSCORE indicator and to maximize the user satisfaction criteria subject to discrete valued sizes of components chosen from catalogues.

Our work is based on multidisciplinary optimization approach using genetic algorithms (GA) and response surface methods. As response functions may be noisy and/or discontinuous, meta-heuristic algorithms like GA are preferred to gradient-based optimization algorithms to solve the problems. Multiobjective versions of Genetic Algorithms are available to handle the eco-efficiency design problem. On the other hand, a surrogate model or metamodel approach is necessary to carry out the optimization work with a moderate computational cost. The numerous direct evaluations of response functions required by optimization process are replaced by metamodel evaluations. For practical implementation, we have selected the software tool BOSS QUATTRO from SAMTECH [12]. BOSS QUATTRO handles the optimization problem definition and the results visualization, the design variable updates, the optimization and the task management tasks of the chain of simulation tools. Thus 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 BOSS QUATTRO.

II. MODELING AND SIMULATION

A. HEV configurations

The basic two architectures of HEV powertrains are the series and parallel configurations [1]. However, complex types are also considered to combine the features of both series and parallel hybrids (i.e. Toyota Prius) as stressed by Ref. [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 is supplied by the electric motor. Sometimes, electric energy is also saved in the energy storage system (i.e. battery). In parallel HEV, both electric motor and IC engine can deliver power to wheels. 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.

B. Simulation

Simulation tools: 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 [8, 9] from 1994 to 2002. ADVISOR combines forward / backward facing approach for the vehicle performances simulation (see Ref. [8]). 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 parametrization in ADVISOR: To consider the effect of component sizes in the optimization of HEV design, ADVISOR approach is to consider a baseline configuration made of selected for the engine and electric motor. 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 electric buses that will be considered in the numerical applications is summarized in Table I.

Drive cycles: drive cycles that have been chosen to simulate and compare the different bus power train configurations are the three SORT (standardized on-road test) drive cycles developed by the UITP (International association of public transport) in collaboration with several bus manufacturers. These drive cycles has been developed in order to provide representative and repeatable tests for European transport public vehicle operators. The results are related to the SORT2 cycle (see Fig. 1).

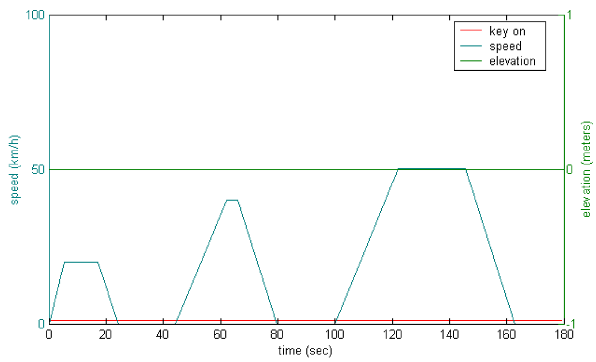

Fig.1. SORT 2 drive cycle for urban bus

TABLE I. BASE CONFIGURATION OF A HYBRID ELECTRIC VEHICLE

		CONV-BUS	Hybrid Bus_Battery	Hybrid Bus_Ultracapacitor
Component	Fuel Converter	Geo 7.2 litre CI 205 kW engine, peak efficiency: 0.44	Geo 7.2 litre CI 205 kW engine, peak efficiency: 0.44	Geo 7.2 litre CI 205 kW engine, peak efficiency: 0.44
	Motor	–	75 kW Westinghouse AC induction motor/inverter	75 kW Westinghouse AC induction motor/inverter
	Battery/ SC	–	NiMH6, cap=6.5 Ah and 7.2 V per module	Maxwell BMOD0018-390V
Aerodynamics	S	$7.24m^2$	$7.24m^2$	$7.24m^2$
	Cx	7.9	7.9	7.9
Tires	Rolling resistance	0.00938	0.00938	0.00938
	Rolling radius	0.5m	0.5m	0.5m

III. USER SATISFACTION CRITERIA

User satisfaction is based on several criteria i.e. security, daily cost, reliability, performances, etc. Some criteria like performances may be easily quantifiable but other ones like comfort are such qualitative 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. [11,12] for instance).

Maximum speed is evaluated by solving the equilibrium between the propulsion power and dissipated power by resistance forces (rolling resistance, aerodynamic drag…)

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

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.

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

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

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

Gradeability: 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

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

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 assure both the passengers and the safety of the other road users. Safety can be based on several criteria like security equipment available on the vehicle, crash test results (e.g. Euro NCAP [13]), static stability factor estimating rollover resistance [13], etc. However as the security systems of the vehicle are supposed to remain unchanged while modifying its propulsion system, 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:

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

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 Eq. (4) predicts a fatality ratio of 16:1 between the lighter car and the heavier one in a vehicle-to-vehicle collision. Thus in this study we decided to base the security index on Eq. (4) solely.

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

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

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:

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

The term c_{bat} is the cost per unit module of battery and N_{bat} the modules number. The c_{fixe} accounts for the bodywork and all the accessory components, which is assumed to be fixed and 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: It is calculated as:

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

Where c_{fuel} is the cost per liter 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 time 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.

Aggregate performances 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 a global performance criterion aggregating the previously defined performance criteria (vehicle maximum velocity, gradability 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.

$$S\tilde{B} = \frac{\tilde{V}_{\max}}{100} + \frac{23}{\tilde{t}_{acc}} + \frac{\tilde{p}_{\max}}{6} + \frac{20000}{\tilde{m}} + \frac{500000}{\tilde{C}} \quad (8)$$

Where: $\tilde{V}_{\max}$ is the estimated maximum vehicle speed (to be maximized), $\tilde{t}_{acc}$ is the estimated acceleration time (from 0 to 60 kph) (to be minimized), $\tilde{p}_{\max}$ is the estimated gradability (to be maximized), $\tilde{m}$ is the vehicle mass (to minimized), and $\tilde{C}$ is the total cost estimate (to be minimized).

Making use of reference car target criteria also insures 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.

IV. Ecoscore model

Eco-score [7,8] 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:

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

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, and $E_{j,total}$ 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.

$$Q_i = \frac{D_i}{D_{i,ref}} \quad (11)$$

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

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

$$E = \sum W_i Q_i \quad (12)$$

where W_i is the weight of damage i.

V. Response Surface Method

Because of the larger number of function evaluations that can be necessary to carry out optimization process, especially when using meta heuristic algorithms like GA, a standard approach in structural and multidisciplinary optimization consists in resorting to global or local approximation models (see for instance [15,16,17]) Approximations will replace direct simulation runs during optimization iterations and will be updated during a limited number of steps ([18]). 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 that will be used here is to construct an approximate model using function values (from simulation runs or closed-form computations of analytical model) at some sampling points, which are typically determined using experimental design methods. Model fitness is subsequently checked using various statistical methods. In this section, we give a brief overview of the response surface methodology.

Design of Experiment (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. minimizing errors. The definition of the location of sampled points can influence the precision of the model because a correct plan of 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 a minimum (low bound: LB) and a maximum (upper bound: UB) value. For the problem of the hybrid powertrain that will be considered in the application one can see at Table II the different design variables and their bounds. The DoE table then defines the points that should be used to create the response surface.

Metamodeling approach: There are various response surface approximation methods available in the literature [15, 16, 17]. 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 providing 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 σ_a 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:

$$e_i = y_i - \hat{y}_i \qquad (13)$$

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

TABLE II: DESIGN VARIABLES AND ASSIGNED BOUNDS

Design Variable	Description	baseline	LB	UB
P_{ICE} (kW)	Fuel converter maximum power	150	150	200
P_{motor} (kW)	Motor maximum power	75	50	100
N_{bat}	Battery number of modules	568	150	800

Hence on gets:

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

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:

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

The prediction capability of the response surface is given by the coefficient of multiple determinations R_{adj}^2 defined as:

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

With

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

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 models surrogate models of performance criteria. Table III indicates the multiple determination coefficients for six response functions and their meta-models. As shown in the table III, the second order inverse polynomial model is the best efficient for all functions. The Fig. 4 shows two of those responses: the accelerate time (from 0 to 60 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. Once the surrogate models are available, any optimization method can be used to solve multi-objective optimization problems with a reduced computational effort.

TABLE III: R_{adj}^2 FOR DIFFERENT MODELS

	1st order polynomial	Quadratic polynomial	1st order inverse	2nd order inverse
Ecoscore	0.8154	0.9714	0.77641	0.9714
V_{max}	0.89686	0.9534	0.9033	0.9572
t_{acc}	0.9025	0.9840	0.9228	0.9867
p_{max}	0.9297	0.9818	0.9241	0.9824
M	1.0000	1.0000	0.9720	1.0000
C	0.9505	0.9918	0.96232	0.9959

VI. OPTIMIZATION

A. 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:

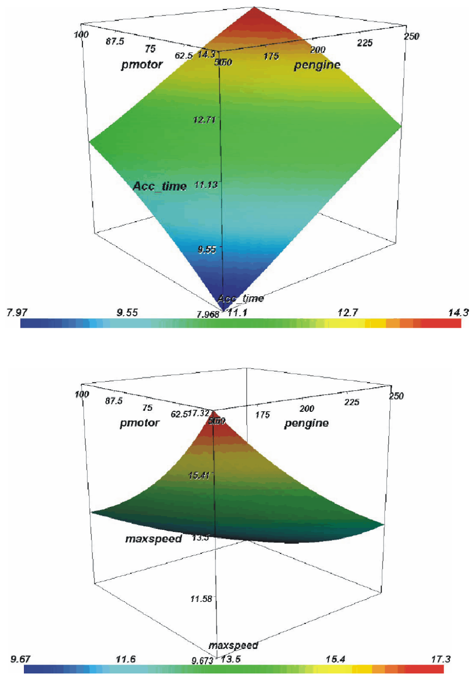

Fig. 4. Response Surfaces of Parallel HEV

Minimize $F(X)$,

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

Subject to:

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

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

B. *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 that is to say that there is no feasible design point which would improve any objective function without worsening at least another one.

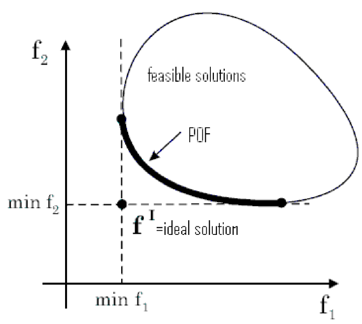

Fig. 5. Pareto-optimal front

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.

Generally it is not easy to find an analytical expression of the Pareto optimal front. Therefore, the multi-objective 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 explains 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 another solution (for Pareto front), the user has again to restart an optimization run with a 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 preferred 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 GA is an iterative procedure based on 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 optimization 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 [19]. The most popular are MOGA (Multi objective genetic algorithm), NSGA (Non-dominated Sorting Genetic Algorithm) and NPGA (Niched-Pareto Genetic Algorithm).

C. 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 a European normative driving cycle. The mathematical problem of the multi-objective 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

$$\begin{aligned} &\tilde{t}_{acc} \leq 20s \\ &\tilde{v}_{\max} \geq 100kph \\ &\tilde{p}_{\max} \geq 6\% \\ &\tilde{m} \leq 20000kg \\ &\tilde{C} \leq 500000€ \\ &150 \leq P_{engine} \leq 200 \\ &50 \leq P_{motor} \leq 100 \\ &400 \leq N_{MB} \leq 800 \end{aligned} \tag{19}$$

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 seen in Eq. (19), we have a two objective function optimization problem. Multi-objective genetic algorithms, MOGA and NSGA are available in BOSS-QUATTRO tools [19] and the MOGA one is selected in this study. This algorithm accounts for multi-objective aspects by a selection step.

VII. NUMERICAL APPLICATION

The method is illustrated with the example of parallel hybrid electric buses. The simulated buses are based on the VAN HOOL bus, which is a classically bus used by public transportation company in Belgium. Taking advantage of ADVISOR library, the buses are modelled using pre-existing components for buses or other heavy vehicles with only minor changes. The most important bus parameters are given in the table I.

We compare the conventional bus and the parallel hybrid electric bus using on one hand, NIMH batteries as energy storage system, and Maxwell BMOD0018-390V super capacity model, on the other hand.

The parallel architecture is the best configuration to take advantage mild hybrid electric vehicles [1] with energy accumulators having a low specific energy such as the ultra capacitors.

TABLE IV: OPTIMIZED COMPONENT SIZING

Component	P_{ICE} (kW)	Pm (kW)	N_{bat}
CONV_BUS	205	-	-
HEV_BUS_NiMH	150	95	660
HEV_BUS_SCaps	164	60	319

TABLE V: OPTIMIZED HEV PERFORMANCE COMPARISON

	CONV_Bus	HE_Bus NiMH	HE_Bus_S Caps
Fuel consumption (l/100km)	62	45	47
Tacc (from 0 to 60kph)	20	13	14
Vmax (km/h)	106	105	98
Pmax @ 60km/h (%)	6.5	11	6
NOX (g/km)	132	49	50
CO2 (g/km)	1 618	1 174.5	1 226.7
M (kg)	16 242	16 805	16 507
C (€)	370 000	390 969	377 294
Eco score	1.2684	1.0542	1.03304
US	6.0	7.9	7.0

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 Fig. 6.

According to the set of points representing the possible pareto optimal solutions for the two technologies, it is noted that user satisfaction and ECOSCORE are close to each other in both cases. But when emphasizing the ECOSCORE, the super capacities (pink points) are slightly better than the batteries (purple points). When focussing on the satisfaction of the user on the other hand, the batteries offer better possibilities.

The optimum configurations that yield to a minimum ECOSCORE, respectively for the conventional bus, the HEV bus respectively with NiMH batteries and with ultra capacitors are given in Table V. At Table V, one provides the comparison the related performances of the optimized hybrid buses and the conventional one. For both HEV, the engine size is reduced compared to the conventional bus. The fuel consumption and NOX emissions are also reduced in both cases and one can notice subsequently an ECOSCORE improvement. More surprisingly, the performances of HEV are also improved compared to the conventional bus. Ultimately, in this case, the hybrid electric buses using the batteries have slightly better performances than those one using super capacitors.

In the present application considering a mild hybrid electric bus, the better choice would go towards super capacitors because they have other appreciable properties compared to the batteries: the very high lifetime, the higher efficiency of charge and discharge and the lower polluting recyclability.

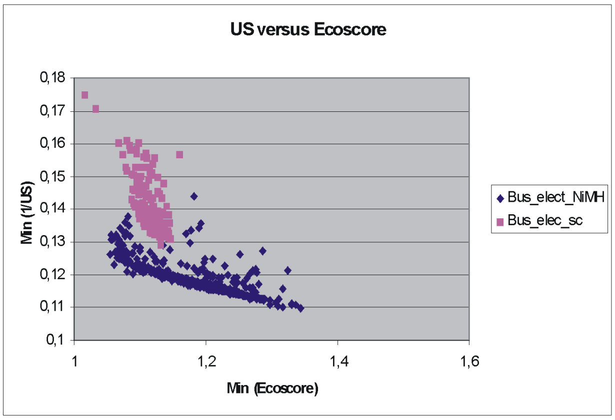

Fig. 6. Pareto optimality front for Eco-score et 1/SB functions

VIII. Conclusion

We have carried out a comparison between a conventional bus and a parallel hybrid electric bus using on the one hand, NIMH batteries as energy storage system, and, on the other hand, Maxwell BMOD0018-390V super capacitor model. The eco efficiency comparison is based on a multidisciplinary multiobjective optimization approach of HEV powertrains accounting for both ECOSCORE for environmental impacts and for an aggregate User satisfaction. The design problem formulation has to optimize the design scaling factors based on the conflicting objective functions of minimizing the environmental impact (ECOSCORE) and 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.

Optimization results show that the hybrid electric bus using super capacity has almost the same performances as the HEV using NiMH batteries. In the present case of figure, preferred choice would go towards super capacitors because they have other appreciable properties compared to the batteries such as higher lifetime, higher efficiency of charge and discharge and no polluting recyclability.

In on-going 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 that optimums are difficult to determine. For instance it will be interesting to couple genetic algorithms with local search algorithms.

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