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Optimal Components Sizing and Power Management for a Fuel Cell Electric Race Car Using a Bi-level Strategy

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Abstract—To improve the performances of a hydrogen hybrid vehicle, it is necessary to optimally size its components and elaborate optimal power management control between the different embedded sources. As both operations are systematically linked, it is advisable to avoid solving these optimization problems separately. In this paper, we propose a coupled method for components sizing and offline power management in a fuel cell electric racing vehicle. The bi-level strategy developed uses Non-dominated Sorting Genetic Algorithms for electrical components optimal sizing and Mixed Integer Linear Programming for optimal power management control. The final results obtained show good performances and acceptable compromise between the models used, the simplifications made on the power profile, and the relevance of the preliminary design parameters.

Index Terms—Bi-level optimization, Components sizing, Offline power management control, Fuel cell electric vehicles, Batteries

I. INTRODUCTION

The recent European environmental laws and regulations on climate impose an ecological transition in the field of transport by a gradual elimination of thermal sources, and their replacement by cleaner energy sources such as hydrogen and batteries [1].

To build and operate these hybrid renewable energy systems, the steps of components sizing (CS) and system power management (PMS) are used during the preliminary design phase to provide a detailed set of specifications for the different energy sources of the system. These two steps are based on optimization methods, and are strongly linked [2]. They determine which resources are necessary for the design, the control and the maintenance of the system [3].

Literature review details three existing strategies for coupling CS and PMS by using optimization techniques [4], [5]. While the use of iterative strategies such as in [6] pose the problem of convergence, simultaneous strategies are complex to implement and solve [7]. Finally, in the bi-level strategy, PMS, called lower level optimization problem is formulated

as a sub-problem of the CS's, called upper level optimization problem [8].

For usual electric vehicle applications, an exhaustive search method and conventional optimization methods such as dynamic programming or convex programming are generally used for CS and PMS problems respectively [9], [10]. Such approaches used for preliminary design become limited for specific high-power demand and high-dynamic applications where computational time issues and memory limitation are usually encountered [11].

In this paper, we propose a coupled optimization method for CS and offline PMS in a fuel cell electric racing car whose architecture is illustrated in the Fig.1, and where electrical components technologies have been already chosen. The bi-level strategy used is inspired by the works [11] and [12]. It uses an heuristic method based on Non-dominated Sorting Genetic Algorithm (NSGA-II) for CS, and a combinatorial approach based on Mixed Integer Linear Programming (MILP) for PMS between the fuel cells and the energy storage system.

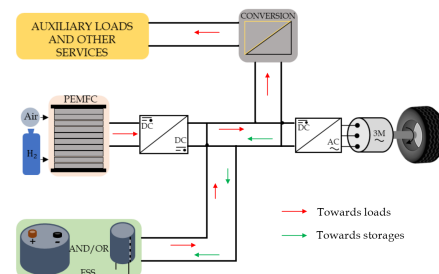


Fig. 1. Fuel cell racing car system architecture

The novelty of the work presented lies in the studied automotive application and the main contributions of this paper are:

- A detailed CS method of the on-board energy sources, which has discrete decision variables compared to the literature, which usually only returns the required power and energy of sources [13];

- An acceleration of the offline PMS problem in the inner loop in order to evaluate in the outer loop more combinations of CS design parameters;
- the consideration of DC-DC converter mass with respect to fuel cell system design parameters.

This paper is organized as follows. Section 2 presents the mathematical formulation of the CS and PMS problems. In section 3, the coupling strategy and the optimization methods used at each level are presented. The results of components sizing and optimal power management are presented in Section 4, and Section 5 concludes the paper.

II. BI-LEVEL OPTIMIZATION PROBLEM

Bi-level strategy consists in evaluating a coupled optimization problem at different levels in order to solve it in two interacting sub-problems. It is used in this paper to solve CS and PMS problems with the general form written in (1)

$$\begin{aligned}
& \min_{x_{\text{sizing}}} \Phi_0(x_{\text{sizing}}) \\
& \text{s.t. } G_i(x_{\text{sizing}}) \leq 0, i \in \{1, \dots, p\} \\
& x_{\text{sizing}} \in \mathcal{X}_{\text{sizing}} \\
& \min_{x_{\text{pms}}} f_0(x_{\text{sizing}}, x_{\text{pms}}) \\
& \text{s.t. } g_j(x_{\text{sizing}}, x_{\text{pms}}) \leq 0, j \in \{1, \dots, q\} \\
& x_{\text{pms}} \in \mathcal{X}_{\text{pms}}.
\end{aligned} \tag{1}$$

The upper level optimization problem regarding components sizing has as decision variables $x_{\text{sizing}} \in \mathcal{R}^n$ constrained in set $\mathcal{X}_{\text{sizing}}$, and aims to minimize the cost function $\Phi_0 : \mathcal{R}^n \rightarrow \mathcal{R}$ under the constraints $G_i : \mathcal{R}^n \rightarrow \mathcal{R}$. In the lower level, the optimization problem related to power management between power sources has $x_{\text{pms}} \in \mathcal{R}^m$ as decision variables constrained in set \mathcal{X}_{pms} , and aims to minimize $f_0 : \mathcal{R}^m \rightarrow \mathcal{R}$ such that constraints $g_j : \mathcal{R}^m \rightarrow \mathcal{R}$ are respected.

A. CS optimization model formulation

The CS optimization problem aims to find the optimal design parameters of the power sources in the car which minimizes the mass of the electrical components $M_{FCEV_{\text{elec}}}$ while maximizing its autonomy considered as the embedded energy in the vehicle $E_{FCEV_{\text{total}}}$. These components are the fuel cell (FC) system and its hydrogen storage tank (H_2TANK), the energy storage system (ESS), and the power electronics DC-DC converter ($CONV$), DC motor sizing being out of the scope of the current work. The upper level optimization problem is written in (2)

$$\begin{aligned}
& \min_{x_{\text{sizing}}} \Phi_1 = M_{FCEV_{\text{elec}}} \\
& \max_{x_{\text{sizing}}} \Phi_2 = E_{FCEV_{\text{total}}} \\
& \text{s.t. } M_{FCEV_{\text{elec}}} \leq M_{FCEV_{\text{max}}} \\
& E_{FC_{\text{max}}} + E_{ESS_{\text{max}}} \geq E(\varphi) \\
& P_{outDC_{\text{max}}} + P_{ESS_{\text{max}}} \geq P_{max}(\varphi) \\
& U_{CONV_{\text{min}}}^{LS} \leq U_{FC}(t) \leq U_{CONV_{\text{max}}}^{LS} \\
& U_{DC_{\text{min}}} \leq U_{ESS}(t) \leq U_{DC_{\text{max}}}
\end{aligned} \tag{2}$$

where $x_{\text{sizing}} = \{N_s, N_p, N_{fc}, A_{fc}, M_{H_2}\}$ is the sizing decision variables vector. N_s and N_p are respectively the ESS number of cells in series and modules in parallel, N_{fc} and A_{fc} are the fuel cell stack number of cells and active surface of membrane electrode assembly (MEA). Finally, M_{H_2} represents the hydrogen quantity needed to meet power profile demand φ whose total required energy and maximum power are parameters $E(\varphi)$ and $P_{max}(\varphi)$ expressed in (3) and (4).

$$E(\varphi) = \int_{t_0}^{t_f} P_{\varphi}(t) dt, \tag{3}$$

$$P_{max}(\varphi) = \max\{P_{\varphi}(t)\}, t \in [t_0; t_f]. \tag{4}$$

1) *Fuel cell system and its converter's constrains:* Fuel cell stack configuration and one polymer exchange membrane (PEM) voltage V_{FC} and power density response $P_{d_{FC}}$ with respect to its current density J_{FC} are shown in Fig.2

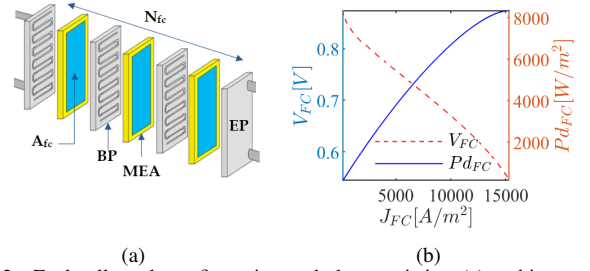


Fig. 2. Fuel cell stack configuration and characteristics. (a) architecture. (b) polarization curve.

Assuming that components are homogeneous, the mass of the fuel cell stack is written below

$$M_{FC_{\text{stack}}} = M_{MEA} + M_{BP} + M_{EP} \tag{5}$$

where $M_{MEA} = S_{P_{\text{total}}} \cdot \rho A_{MEA} \cdot N_{fc}$ is the mass of MEAs, $M_{BP} = S_{P_{\text{total}}} \cdot \rho A_{BP} \cdot (N_{fc} + 1)$ is the mass of bipolar plates, and M_{EP} is the mass of end plates assumed to be constant. Parameter $S_{P_{\text{total}}} = \frac{A_{fc}}{a_S}$, in $[m^2]$ is the total surface of fuel cell plates by considering a_S as the ratio between the active and total surfaces. Finally, ρA_{MEA} and ρA_{BP} , are respectively MEA and BP surface density.

By using a set of hydrogen tanks data-sheets, the mass of a full hydrogen tank $M_{H_2_{\text{tank}}}$ with respect to tank pressure P_{tank} and variable M_{H_2} can be approximated to a linear function with coefficients $\alpha(P_{\text{tank}})$ and $\beta(P_{\text{tank}})$

$$M_{H_2_{\text{tank}}} = \alpha(P_{\text{tank}}) \cdot M_{H_2} + \beta(P_{\text{tank}}). \tag{6}$$

To objectively take into account DC-DC converter mass M_{CONV} according to fuel system design, its power density $P_{d_{CONV}}$ with respect to its maximum input power $P_{FC_{\text{max}}}$ is approximated to a third-order polynomial function taken from [14] and shown in Fig.3.

The power density of the converter to be designed, in $[kW/kg]$, is then expressed as

$$P_{d_{CONV}}^{\text{design}} = \left(a_3 \cdot P_{pu}^3 + a_2 \cdot P_{pu}^2 + a_1 \cdot P_{pu} + a_0 \right) \times P_{d_{CONV}}^{\text{ref}}, \tag{7}$$

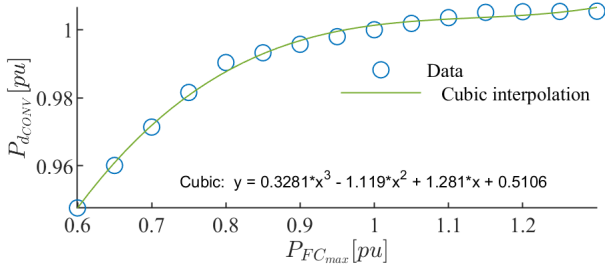


Fig. 3. Power density estimation of the DC-DC converter (pu:per unit)

where $a_i, i = \{0, 1, 2, 3\}$ are polynomial function coefficients, and the dimensionless parameter $P_{pu} = \frac{P_{FCmax}}{P_{CONVmax}^{ref}}$ denotes the ratio between the maximum fuel cell power and the reference converter input power. Superscripts “design” and “ref” are respectively related to the designed and reference converters. Knowing the DC converter’s efficiency η_{CONV} , the hydrogen lower heating value LHV_{H_2} and fuel cell system maximum efficiency η_{FCmax} , it is possible to evaluate the maximum converter output power $P_{outDCmax}$ and energy E_{FCmax} provided by the fuel cell system expressed as follows

$$P_{outDCmax} = P_{FCmax} \cdot \eta_{CONV} \quad (8)$$

$$E_{FCmax} = M_{H_2} \cdot LHV_{H_2} \cdot \eta_{FCmax} \cdot \eta_{CONV}. \quad (9)$$

Constraints associated to converter input voltage boundaries are written in (10) and (11)

$$N_{fc} \cdot V_{FCmin} \geq U_{CONVmin}^{LS} \quad (10)$$

$$N_{fc} \cdot V_{FCmax} \leq U_{CONVmax}^{LS}, \quad (11)$$

where V_{FCmin} and V_{FCmax} are respectively the minimum and the maximum voltage response of a single cell and superscript “LS” relates to converter low side voltage.

2) *Energy storage system constrains*: The ESS is composed of Li-ion battery cells with a nominal voltage $V_{ESScell}$, a capacity $Q_{ESScell}$, and a constant internal resistance R_{int} . The ESS configuration and battery cells open circuit voltage curve are depicted in Fig.4.

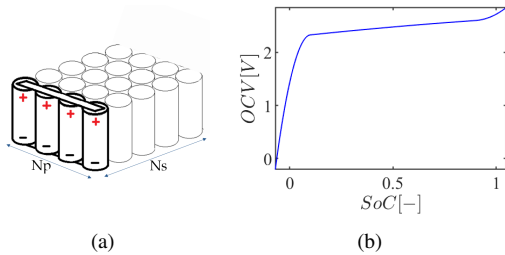


Fig. 4. Energy storage system configuration and characteristics. (a) battery pack architecture. (b) voltage response.

By assuming a global efficiency of battery pack η_{BAT} , the amount of battery energy storage available E_{ESSmax} , the maximum power delivered P_{ESSmax} , and its associated weight M_{ESS} are written as follows

$$E_{ESSmax} = N_s \cdot N_p \cdot V_{ESScell} \cdot Q_{ESScell} \cdot \eta_{ESS} \quad (12)$$

$$P_{ESSmax} = N_s \cdot N_p \cdot P_{ESScellmax} \cdot \eta_{ESS} \quad (13)$$

$$M_{ESS} = N_s \cdot N_p \cdot m_{ESScell} \cdot (1 + \lambda_{casing}). \quad (14)$$

where $m_{ESScell}$ is one battery cell mass and λ_{casing} is the weight ratio of the ESS casing with respect to the total weight of battery cells. Finally, ESS decision variable N_s is bounded by using DC bus voltage constraints (15)

$$U_{DCmin} \leq N_s \cdot V_{ESScell} \leq U_{DCmax}. \quad (15)$$

where U_{DCmin} and U_{DCmax} are respectively minimum and maximum voltage range of the electric motor.

B. PMS optimization model formulation

The purpose of the lower level PMS optimization problem is to guarantee the validity of the system CS design parameters, and to minimize hydrogen consumption over the whole racing car’s power profile φ . It is written as follows

$$\begin{aligned} \min_{x_{pms}} \quad & f_0 = m_{H_2}(t)|_{t_0}^{t_f} \\ \text{s.t.} \quad & P_{\varphi}(t) + P_{aux}(t) = P_{outDC}(t) + P_{ESS}(t), \\ & \frac{d}{dt} P_{FC}(t) \leq d_{FC}, \\ & m_{H_2}|_{t_0}^{t_f} \leq M_{H_2}, \\ & P_{ESSmin} \leq P_{ESS}(t) \leq P_{ESSmax}, \\ & SoE_{min} \leq SoE(t) \leq SoE_{max}, \\ & SoE(t_f) \geq SoE^* \end{aligned} \quad (16)$$

where $x_{pms} = P_{FC}(t), t \in [t_0; t_f]$ is the PMS optimization decision variable. Parameter d_{FC} is the maximum fuel cell power rise dynamic, and is linked to fuel cell compressor performances. Variable $SoE(t)$ is the ESS state of energy at time t , and SoE^* is the allowed final ESS state of energy.

1) *Fuel cell system constraints*: The fuel cell system uses a model which is based on the instantaneous hydrogen consumption of a single cell and global efficiency η_{FC} with respect to its power density P_{dFC} displayed in Fig.5.

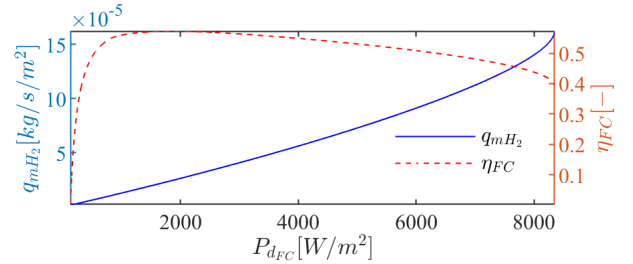


Fig. 5. Fuel cell system efficiency and hydrogen consumption

By calling q_{mH_2} , the non-linear hydrogen consumption function of a single cell, the total hydrogen consumed during the race car mission is written as follows

$$f_0 = m_{H_2}(t)|_{t_0}^{t_f} = N_{fc} \cdot A_{fc} \int_{t_0}^{t_f} q_{mH_2}(P_{dFC}(t)) dt. \quad (17)$$

The first PMS problem constraint related to system power balance is written by knowing fuel cell system auxiliaries power consumption P_{FCaux} such as

$$P_{\varphi}(t) + P_{FCaux}(P_{FC}(t)) = \eta_{CONV} \cdot P_{FC}(t) + \eta_{ESS} \cdot P_{ESS}(t). \quad (18)$$

2) *ESS constraints*: As only energy and power aspects are assessed by the PMS optimization problem, battery power and state of energy boundaries are the constraints associated to ESS. State of energy at any time t of the battery is derived by using (19)

$$SoE(t) = SoE_{init} - \int_{t_0}^t \frac{P_{ESS}(t)}{E_{ESS}} dt, \quad (19)$$

where E_{ESS} is the total energy of the battery, and $SoE_{init} = SoE(t_0)$ is the battery state of energy at the beginning of the race. We then impose a minimum value of the final state of energy constraint in (20) such that the racing car is able to perform additional maneuvers at the end of the race using only the energy remaining in the battery pack.

$$SoE_{init} - \int_{t_0}^{t_f} \frac{P_{ESS}(t)}{E_{ESS}} dt \geq SoE^* \quad (20)$$

III. OPTIMIZATION PROBLEM SOLVING

A. Coupled optimization framework

The coupled CS and offline PMS optimization problem resulting from (2) and (16) is written as follows

$$\begin{aligned} \min_{x_{sizing}} M_{FCV_{elec}} &= M_{FC_{stack}} + M_{ESS} + M_{H_2S_{tank}} + M_{CONV} \\ \max_{x_{sizing}} E_{FCV_{total}} &= E_{FC_{max}} + E_{ESS_{max}} \\ \text{s.t.} & \text{(3) to (15)} \\ \min_{x_{pms}} & \int_{t_0}^{t_f} q_{mH_2}(t) dt \\ \text{s.t.} & \text{(17) to (20)} \\ & x_{sizing} = \{N_s, N_p, N_{fc}, A_{fc}, M_{H_2}\} \\ & x_{pms} = P_{FC}(t) \\ & N_s, N_p, N_{fc} \in \mathcal{N} \\ & A_{fc}, M_{H_2}, P_{FC}(t) \in \mathcal{R} \end{aligned} \quad (21)$$

The upper level is a constrained bi-objective optimization problem with five mixed continuous and integer decisions variables. The lower level is a mono-objective constrained optimization problem with one continuous decision variables and two state variables which are battery state of energy and hydrogen tank level. The bi-level optimization problem framework is displayed in Fig.6. It uses Non-dominated Sorting Genetic Algorithm (NSGA-II) [15] at the outer loop to generate design variables. In the inner loop, those variables are evaluated and the same Mixed Integer Linear Programming (MILP) formulation as in [11] is used to solve the offline PMS optimization problem.

B. Offline PMS problem solving technique

Though PMS optimization problem has continuous decision variables $P_{FC}(t)$, MILP method is chosen to rapidly achieve design parameters evaluation at the lower level, especially for long duration power demand profiles. As the objective function and constraints are non-linear with respect to $P_{FC}(t)$, it is sampled in discrete variables $P_{FC}(k)$ in order to use simplex method. Finally, to cope with memory limitations and computational efforts, the power profile number of time steps is reduced by applying a low pass filter. The PMS problem

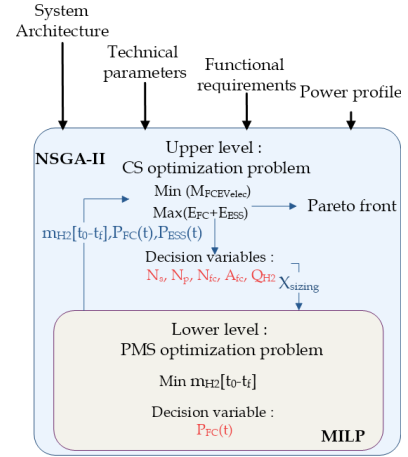


Fig. 6. Bi-level optimization problem framework

solving algorithm is finally detailed by pseudo-code shown in Table I.

TABLE I
OPTIMIZATION PROBLEM SOLVING APPROACH

1.	While:	convergence is not reached do
2.		Get $N_s, N_p, N_{fc}, A_{fc}, M_{H_2}$ variables
3.		Evaluate $M_{FCV_{elec}}$
4.		Compute corresponding power profile φ
5.		Apply Gaussian filter on φ and decrease its number of time steps
6.		Solve PMS problem
7.		If: PMS is feasible do
8.		Return control states and decision variables
9.		Store results for population selection and mutation
10.		else:
11.		Reject selected population
12.		End If
13.		If: Number of evaluation reached do
14.		Move to 18
15.		else:
16.		Move to 2
17.		End If
18.	End While	

IV. RESULTS AND DISCUSSION

After a description of the vehicle application and parameters employed for the study, this section shows CS and offline PMS optimization results.

A. Case study description

The coupled optimization problem described in Section 3 is used to achieve components sizing and optimal control of a fuel cell car dedicated to rally race competition. The power profile considered lasts 5000 s with typical portions displayed in Fig.7(a) and 7(b).

Figure 7(c) shows the cumulative energy consumption of the original power profile of 50000 time steps versus the one used for optimization reduced to only 1000 time steps. Even though the filtering and under-sampling processes result in a loss of high frequency power information, we notice that it does not globally affect the total energy required by the vehicle. Power profile characteristics, parameters used, and their numerical values are summarized in Table.II

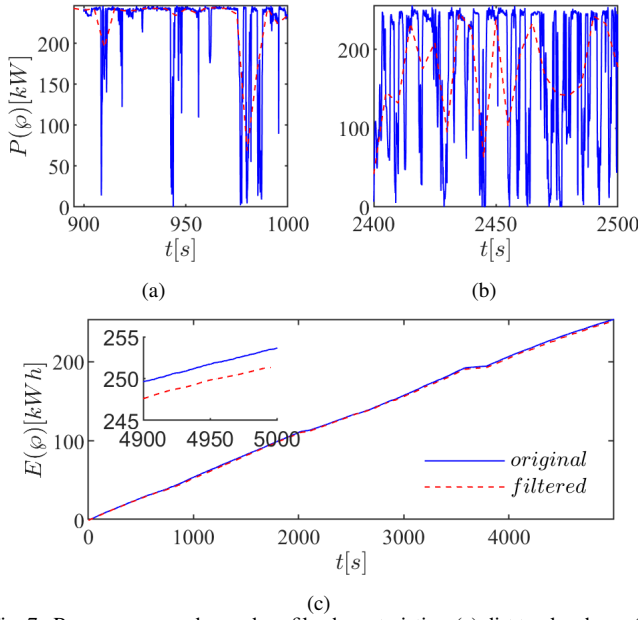


Fig. 7. Race car power demand profile characteristics. (a) dirt tracks phase. (b) Sand dunes phases. (c) Cumulative energy consumption comparison between the original (in blue) and filtered under-sampled (in red dash) power profiles.

B. Optimization results

Optimization problem code were implemented in Python by using Pymoo module for solving CS and Gurobi optimizer for PMS. The parameters of NSGA-II used for CS optimization problem have been set as follows. The population has been set to 80, the number of generation to 15, and the crossover rate has been set to 0.7.

As expected, Fig.8 shows that the heavier the car is, and the more energy its carries. The Pareto front between the two objective functions shows two main parts. The first one exhibits few solutions where energy increases rapidly with mass due to the increase of fuel cell design parameters. The second part of the Pareto front has more feasible solutions, but increases too much the vehicle mass without affecting the embedded energy.

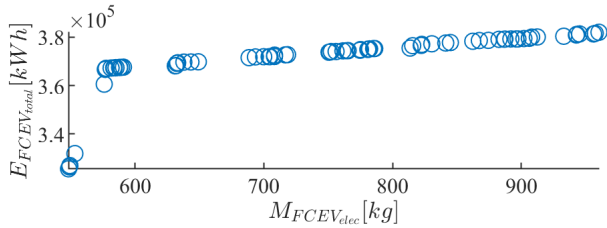


Fig. 8. CS optimization mass and energy Pareto front

Another aspect to take into account is that the vehicle will consume more energy to perform the same mission if it weighs more. Thus, a good trade-off has to be found to increase the car's autonomy while not increasing that much its weight. That compromise has been identified as the crossing point of the two parts of the Pareto front. Its corresponding design variables $\{N_s = 280, N_p = 2, N_{fc} = 351, A_{fc} = 856cm^2, M_{H_2} = 19kg\}$ have been chosen among

TABLE II
PARAMETER DEFINITION AND NUMERICAL VALUES USED

Power demand profile data		
$E(\varphi)$	Total energy of the power profile [kWh]	253
$P_{max}(\varphi)$	Maximum power of the power profile [kW]	262
	Power profile duration time [s]	5000
PEM parameters		
ρ_{AMEA}	MEA mass surface density [kg/m ²]	0.21
ρ_{ABP}	BP mass surface density [kg/m ²]	1.04
a_S	MEA active surface ratio [-]	0.45
M_{EP}	Mass of end plates [kg]	2
Hydrogen tank parameters		
P_{tank}	Hydrogen tank pressure [bar]	700
α, β	Linear interpolation coefficients [-]	[15.3, 20.8]
DC-DC converter parameters		
$U_{CONV_{min}}^{LS}$	Low side minimum voltage [V]	50
$U_{CONV_{max}}^{LS}$	Low side maximum voltage [V]	600
η_{CONV}	Converter efficiency [-]	98.9
P_{ref}^{dCONV}	Reference power density [W/kg]	6400
$P_{CONV_{max}}^{ref}$	Maximum power [kW]	180
a_0, \dots, a_3	Power density interpolation coefficients [-]	see Fig.3
Li-ion battery parameters		
$V_{ESS_{cell}}$	Battery cell nominal voltage [V]	2.4
$Q_{ESS_{cell}}$	Battery cell rated capacity [Ah]	2.9
η_{ESS}	Efficiency of the battery [-]	0.98
$m_{ESS_{cell}}$	Battery cell mass [kg]	0.15
λ_{casing}	Battery pack casing mass ratio [-]	0.4
$U_{DC_{min}}$	DC bus minimum voltage [V]	550
$U_{DC_{max}}$	DC bus maximum voltage [V]	750
SoE_{min}	Minimum battery state of energy [-]	0.3
SoE_{max}	Maximum battery state of energy [-]	0.95
SoE_{init}	Initial battery state of energy [-]	0.9
SoE^*	Accepted final battery state of energy [-]	0.4

CS optimization results in order to evaluate mass and energy distribution between components.

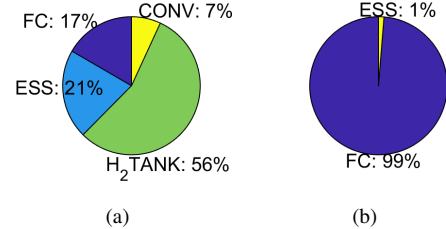


Fig. 9. Mass distribution between designed components and energy allocation between sources. (a) Mass distribution. (b) Energy distribution.

Figure 9 shows that more than 56% of the optimized mass is related to hydrogen storage tank (H_2TANK). Only 117 kg of batteries corresponding to 4.51 kWh of energy are needed. A logic explanation of this ESS design is that selected batteries are power rated types. Hence, batteries are designed not for their energy, but to deliver high power. ESS is then intended to come as support to the fuel cell during strong dynamics.

PMS optimization results of the selected CS design variables, and applied on the filtered power profile are displayed in Fig.10.

The offline PMS results show that fuel cell system seems to work at an average power of 200 kW. It shares high frequency power demands with batteries, which are used to compensate power demand during acceleration phases, and store exceeding power during deceleration phases. ESS state of energy and hydrogen tank level are respectively displayed in Fig.11(a) and 11(b)

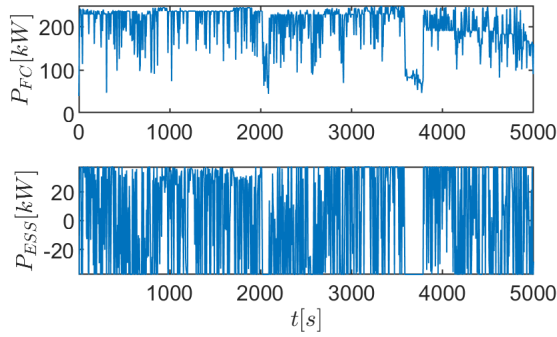


Fig. 10. PMS optimization results of fuel cell (top) and batteries (down).

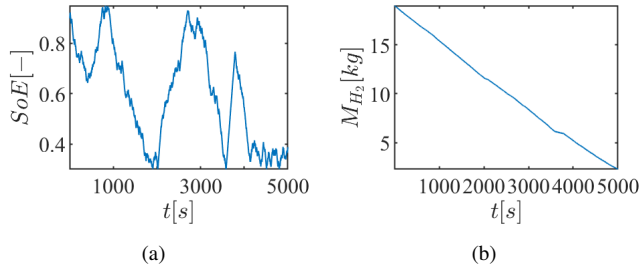


Fig. 11. ESS and hydrogen state variables over load duration. (a) Battery state of energy. (b) Hydrogen tank level.

The results shown above indicates that the PMS optimization problem succeeded in minimizing hydrogen consumption while respecting the constraints related to ESS on filtered power profile. Battery is used within its state of energy limits and the car finishes the race with enough power and energy as desired in the performance requirements.

V. CONCLUSION

A bi-level strategy for coupling optimal sizing and control for an electric vehicle composed of a fuel cell and a battery storage system has been proposed in this paper. The application studied is a rally racing car, but the methodology developed can be extended to high power applications such as heavy trucks. Satisfying results were obtained, and the assumptions made such as the simplification of the power profile for the offline power management have improved the time evaluation of the proposed method.

Final version of this paper will include convergence study of the heuristic method and validity of the components sizing selected and its associated power management on the original power profile.

Improvements to this work can be separated into two aspects: the first one is the implementation of the coupling method by achieving parallel calculations in the inner loop, and the evaluation of the optimal control on a more representing power profile. Thus, this will validate the obtained results on the true power profile which exhibits more dynamics. The second aspect will focus on the comparison of the current results with those to be obtained in the future with energy-rated battery technologies.

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