Large size optimization problem for power management in a fuel cell electric race car using combinatorial approach

Essolizam Plante, Eric Bideaux, Mylène Delhommais, Mathias Gerard

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Essolizam Planté
Univ. Grenoble Alpes
CEA, Liten, DEHT
38000 Grenoble, France
Email: essolizam.plante@cea.fr

Eric Bideaux
Univ Lyon, INSA Lyon
Université Claude Bernard Lyon 1
Ecole Centrale de Lyon
Ampère, UMR5005
69621 Villeurbanne, France
Email: eric.bideaux@insa-lyon.fr

Mylène Delhommais
and Mathias Gérard
Univ Grenoble Alpes
CEA, Liten, DEHT
38000 Grenoble, France
Email: surname.name@cea.fr

***Abstract*—Hybrid electrical systems are complex to size because there is a strong dependence between components design and power management control law. In order to pre-size a hybrid rally race car, which uses hydrogen and batteries as energy sources, an offline power management method, which is formulated in a combinatorial form, is developed to be readily incorporated in a bi-level optimization problem. The exponential growth of memory space as a function of the size of the problem, in particular for long power profiles, is a well-known problem of this type of approach. This paper proposes solving techniques, which consist in using battery state trajectory following and constraints relaxation. Obtained results show satisfying improvements compared to the state of art. Sensitivity analyses show the influence of resolution parameters on the optimization problem solution and its required computation resources.**

***Index Terms*—Optimization, Large-size problems, Power management, Sizing, Hybrid electric vehicles, Fuel cells, Batteries**

I. Introduction

Electrical sources in hybrid vehicles are an alternative for ecological transition in transportation sector. To validate the choice of the size of these system's components and to guarantee their optimal operation, optimization techniques are used. The most widespread are dynamic programming [1], convex optimization [2], heuristics methods [3], combinatorial approaches [4] and aim to reduce either fuel consumption or total cost of ownership based on predefined power profiles that must be globally satisfied under some constraints.

Common issues encountered when using such methods are computation time and memory limitations [5], which strongly depend on the size of the optimization problem. This can either be related to the number of control variables, the number of constraints or the length of the power profile. To cope with issues brought by the length of power profiles, short driving cycles such as WLTP are used in the literature [6] as they give an ideal low frequency model of regular cars usage phases, with a power rise dynamic of about 2.3 kW/s and a power profile length of 1800 seconds. However, they are no longer representative of more specific applications such as racing cars. Buerger et al [7] propose an alternative for such problems, but often, a simplification of the initial power profile is used, which leads to a loss of information, and a power management control not adapted to the problem.

We propose in this paper a linear programming method inspired by works achieved in [4] and [8] to optimize the power management for a racing car application whose architecture is illustrated in Fig. 1 and a long duration power profile of 6000 seconds that exhibits strong dynamics of more than 150 kW/s, which we might not neglect. The optimization problem is here improved in order to be adapted for long driving cycles, as one drawback of combinatorial approaches is the rapid growth of the problem dimension.

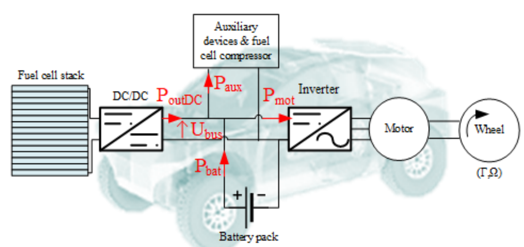


Fig. 1: Race car electrical architecture

The rest of the paper is organized as follows: after components and power profile modelling, the power management optimization problem is formulated in a combinatorial form. Solving techniques algorithms to tackle memory issues are then developed. Finally, obtained results including sensitivity analysis are discussed.

II. Components and power profile modelling

A. PEMFC model

The fuel cell system uses a model which is based on the electrical response of a single cell displayed in Fig.2.

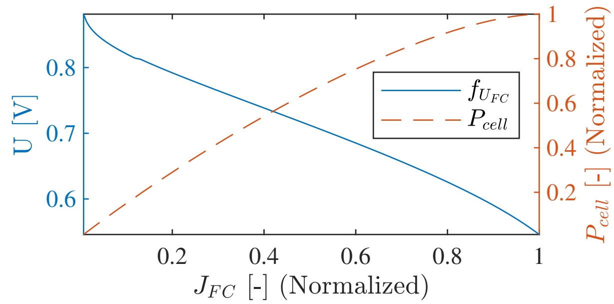


Fig. 2: Fuel cell electric response

$f_{U_{FC}}$ is a pseudo-empirical function which depends on the current density J_{FC} and fixed operating conditions which are the stoichiometries St_{H_2} and St_{O_2}, the anodic and cathodic partial pressures P_{H_2} and P_{O_2}, the temperature T and the relative humidity H_r. The usefull power of the fuel cell system P_{FC_s} is written below

$$P_{FC_s} = P_{stack} - P_{FC_{aux}}, \tag{1}$$

where $P_{stack} = N_{stack} \times U_{FC} \times I_{FC}$ is the gross power of the fuel cell system. N_{stack} is the number of cells in the stack, $I_{FC} = J_{FC} \times A_{FC}$ is the current, A_{FC} is MEA's surface and $P_{FC_{aux}}$ is the compressor power, which depends on cathodic pressure and is the most consuming component among auxiliaries. We derive the hydrogen mass equation

$$m_{H_2}(t) = \int_0^t q_{mH_2}(t)\, dt, \tag{2}$$

where $q_{mH_2}(t) = \mathcal{M}_{H_2} \times St_{H_2} \times N_{stack} \times \dfrac{I_{FC}}{2F}$ is the anodic mass flow, $\mathcal{M}_{H_2}$ is the hydrogen molar mass and F is Faraday's constant. Knowing the hydrogen lower heating value (LHV_{H_2}), it is possible to compute the fuel cell system efficiency using (3)

$$\eta_{FC}(t) = \frac{P_{FC_s}(t)}{P_{FC_{th}}(t)} = \frac{P_{stack}(t) - P_{FC_{aux}}(t)}{LHV_{H_2} \times q_{mH_2}(t)}. \tag{3}$$

Finally, the net power available at the output of the DC-DC boost converter is

$$P_{out_{DC}} = \eta_{conv} \times P_{stack} - P_{FC_{aux}}, \tag{4}$$

where η_{conv} is the converter efficiency with respect to its input power P_{stack}.

B. Li-ion battery model

A 1-R battery cell model composed of a voltage source V_{oc} and an internal resistance r_{cell} is used to compute the current and the voltage of the battery pack as follows

$$I_{bat} = \frac{N_p\Big(V_{oc} - \sqrt{V_{oc}^2 - \frac{4 \cdot r_{cell} \cdot P_{bat}}{N_s \times N_p}}\Big)}{2 \times r_{cell}}, \tag{5}$$

$$U_{bat} = N_s\big(V_{oc} - r_{cell} \times \frac{I_{bat}}{N_p}\big), \tag{6}$$

where P_{bat} is the power delivered or absorbed by the battery pack. V_{oc} and r_{cell} depend on the state of charge SoC and temperature T, N_s and N_p are respectively number of cells in series and parallel branches in the pack. Battery state of charge SoC and state of energy SoE are needed to compute DC bus voltage and the remaining energy in the pack during the mission. They are written in (7) and (8)

$$SoC(t) = SOC(t_0) - \int_{t_0}^{t} \frac{I_{bat}(t)}{Q_{bat}}\, dt, \tag{7}$$

$$SoE(t) = SoE(t_0) - \int_{t_0}^{t} \frac{P_{bat}(t)}{E_{bat}}\, dt, \tag{8}$$

where $E_{bat} = Q_{bat} \cdot \displaystyle\int_0^{SoC} V_{oc}(SoC)\, dSoC$ and Q_{bat} are respectively battery pack energy and capacity.

C. Power profile modelling

The race car driving cycle relies on data recording campaign of a reference car, which provides vehicle speed v, acceleration a and helps to compute its required torque at wheel Γ_{wheel} and angular speed ω_{wheel} as follows

$$\begin{aligned}\Gamma_{wheel}(t) = m_{veh}\Big(&a(t) + g\cos\phi(t) C_r \\ &+ \frac{1}{2}\rho \frac{A_{veh}}{m_{veh}} C_d v^2(t) + g \sin\phi(t)\Big) \times R_{wheel}\end{aligned} \tag{9}$$

$$\omega_{wheel}(t) = \frac{v(t)}{R_{wheel}}, \tag{10}$$

where m_{veh} is the mass of vehicle, ϕ is the road's slope angle, g is the gravity acceleration, ρ denotes the air density, A_{veh} is the vehicle frontal area, C_d is the drag coefficient, C_r is the rolling friction resistance, and R_{wheel} denotes the wheel radius. As the car power profile might change with respect to its mass, let's assume the following assumption to adapt the torque of the designed car to the one of the reference vehicle:

Assumption 1: the ratio $\dfrac{A_{veh}}{m_{veh}}$ evolves according to a scaling law in the general form of

$$\frac{A_{veh}^{design}}{m_{veh}^{design}} = \left(\frac{A_{veh}^{ref}}{m_{veh}^{ref}}\right)^s, \tag{11}$$

where s is the scaling factor, and superscripts $design$ and ref are respectively related to the designed and reference car. □

Hence, by setting $s = 1$, we can express the torque at wheel of the the designed car as

$$\Gamma_{wheel}^{design}(t) = \frac{m_{veh}^{design}}{m_{veh}^{ref}} \Gamma_{wheel}^{ref}(t). \tag{12}$$

Finally, the mechanical power is

$$P_{mech}(t) = \frac{1}{\eta_t} \Gamma_{wheel}^{design}(t) \times \omega_{wheel}(t), \tag{13}$$

where η_t is the powertrain's efficiency.

III. PMS OPTIMIZATION PROBLEM

A. Mathematical formulation

The implemented power management system aims to find the optimal fuel cell current trajectory that reduces hydrogen consumption over the vehicle mission. Its associated optimization problem is formulated as follows

$$\begin{aligned}
\min_{I_{FC}} \quad & F_{obj} = \int_{t_0}^{t_f} m_{H_2}(t) \\
\text{s.t.} \quad & \frac{1}{\eta_m} P_{mech}(t) + P_{aux}(t) = P_{out_{DC}}(t) + P_{bat}(t), \\
& \frac{d}{dt} P_{stack}(t) \leq \mathsf{d}_{FC}, \\
& m_{H_2}|_{t_0}^{t_f} \leq M_{H_{2_{tank}}}, \\
& \lfloor P_{bat} \rfloor \leq P_{bat}(t) \leq \lceil P_{bat} \rceil, \\
& \lfloor SoE \rfloor \leq SoE(t) \leq \lceil SoE \rceil, \\
& SoE(t_f) = SoE^{\star}
\end{aligned}$$

where d_{FC} and $M_{H_{2_{tank}}}$ are respectively the maximum dynamic of power increase of the fuel cell and the total mass of hydrogen filled in the tank, η_m denotes the motorization group efficiency, P_{aux} is the power consumption of auxiliary components, and $SoE^{\star}$ is the state of energy targeted at the end of the mission. $\lfloor X \rfloor$ and $\lceil X \rceil$ are respectively the minimum and the maximum value of variable X.

B. Problem modelling

To cope with model non-linearity and a discrete time power profile, the optimization problem is written in a combinatorial form in order to be solved with a MILP method. This approach requires a discretization of the control variable I_{FC}.

1) Objective function: Let us introduce a new control variable ξ such that

$$\xi(t) = (\xi_1(t), \cdots, \xi_u(t), \cdots, \xi_{n_c}(t)), u \in [1, n_c] \tag{14}$$

$$\xi_u(t) \in [0, 1] \tag{15}$$

$$\sum_{u=1}^{n_c} \xi_u(t) = 1, \tag{16}$$

where $n_c = \dim(\xi)$ is the number of elements of vector ξ. Hence, fuel cell current can be expressed as a linear combination of coefficients ξ_u

$$I_{FC}(t) = \sum_{u=1}^{n_c} \Big(\xi_u(t) \times I_{FC}(u) \Big), \tag{17}$$

where $I_{FC}(u)$ is the value of fuel cell current associated with the control variable $\xi_u(t)$ and is expressed by a logarithmic function

$$I_{FC}(u) = \log_c(\beta \times (u - h)), \tag{18}$$

where $c = \left(\frac{n_c - h}{1 - h} \right)^{\frac{1}{I_{FC_{max}} - I_{FC_{min}}}}$ and $\beta = \left(\frac{1}{1-h} \right) \times c^{I_{FC_{min}}}$. $I_{FC_{min}}$ and $I_{FC_{max}}$ denote respectively the minimum and the maximum current delivered by fuel cell system. This non-uniform discretization is preferred to a linear one to have a coarse discretization in the vicinity of low current values which are generally not solution and an accurate one elsewhere by tuning coefficient $h, (h < 1)$. The objective function is then written as follows

$$F_{obj} = \zeta \cdot \sum_{t=t_0}^{t_f} \sum_{u=1}^{n_c} \Big(\xi_u(t) \times I_{FC}(u) \Big) \times \delta t, \tag{19}$$

where $\zeta = \dfrac{\mathcal{M}_{H_2} \times St_{H_2} \times N_{stack}}{2F}$ and $\delta t = 100$ ms is the sampling time.

2) Fuel cell system constraints: Fuel cell power dynamic constraint is expressed linearly at each time as follows

$$\begin{aligned}
& \sum_{u=1}^{n_c} \Big(\xi_u(t+1) \times I_{FC}(u) \times f_{U_{FC}}(I_{FC}(u)) \Big) \\
& - \sum_{u=1}^{n_c} \Big(\xi_u(t) \times I_{FC}(u) \times f_{U_{FC}}(I_{FC}(u)) \Big) \leq \mathsf{d}_{FC} \times \delta t.
\end{aligned} \tag{20}$$

Hydrogen consumption limitation is written in (21)

$$\zeta \cdot \sum_{t=t_0}^{t_f} \sum_{u=1}^{n_c} \Big(\xi_u(t) \times I_{FC}(u) \Big) \times \delta t \leq M_{H_{2_{tank}}}. \tag{21}$$

3) Battery pack constraints: Battery pack constraints are charge and discharge power limitations and control of its state variable SoE. The power balance between sources and loads helps to write battery power in a linear combination form

$$\begin{aligned}
P_{bat}(t) = & \frac{1}{\eta_m} P_{mech}(t) + P_{aux}(t) \\
& - \eta_{conv} \times \sum_{u=1}^{n_c} \Big(\xi_u(t) \times I_{FC}(u) \times f_{U_{FC}}(I_{FC}(u), t) \Big)
\end{aligned} \tag{22}$$

Using (8), battery pack SoE boundary constraint and final value constraint are respectively written in (23) and (24)

$$\lfloor SoE \rfloor \leq SoE(t_0) - \frac{1}{E_{bat}} \sum_{t_0}^{t} P_{bat}(t) \delta t \leq \lceil SoE \rceil \tag{23}$$

$$\frac{\left| SoE(t_0) - \frac{1}{E_{bat}} \sum_{t_0}^{t_f} P_{bat}(t) \delta t - SoE^{\star} \right|}{SoE^{\star}} \leq \epsilon_{SoE}, \tag{24}$$

where ϵ_{SoE} is the admitted relative error between the final state $SoE(t_f)$ and its target $SoE^{\star}$.

IV. SOLVING TECHNIQUES

We write the problem modelled in Section III-B in the general form of $A \cdot x \leq b$, were A is the problem matrix, x is the decision variable, and b is the constraint vector. The purpose of the techniques developed below is to reduce the number of elements Prb_{size} in matrix A, which is function of the number of evaluated combinations N_{comb}. For combinatorial approaches, this number grows exponentially and is expressed in (26)

$$Prb_{size} = rows(A) \times columns(A) \tag{25}$$

$$\mathsf{N}_{comb} = n_c^{\mathsf{H}_p}, \tag{26}$$

where the horizon H_p is the number of time steps of the considered power profile.

A. Low frequency and sequential optimization approach

Since we cannot solve at once the problem formulated due to memory limitations, we propose a first technique detailed in Algorithm 1. It consists at a first step in defining a global trajectory of battery's SoE by using a low-frequency filtered power profile, which is undersampled with a larger sampling time $\Delta t = \alpha \times \delta t$, and where $\alpha \geq 1$ is the sampling coefficient. The second step consists in splitting the original power profile P_o into n_{seq} sequences seq_i of acceptable length H_i such that

$$\mathsf{P}_o = \bigcup_{i=1}^{n_{seq}} seq_i, \tag{27}$$

$$\mathsf{H}_p = \sum_{i=1}^{n_{seq}} \mathsf{H}_i. \tag{28}$$

In order to solve those sequences iteratively by ensuring continuity of the battery's states, constraints based on (24) are added and expressed as follows

$$SoE^{seq_i}(t_f) = SoE_{lf}(t_f^\star) \tag{29}$$

$$SoE^{seq_{i+1}}(t_0) = SoE^{seq_i}(t_f), \tag{30}$$

where subscript *lf* stands for "low frequency" and $t_f^\star$ is the corresponding time step of t_f when using the filtered undersampled power profile.

Algorithm 1 Two steps optimization technique

Require: $Power\,profile\,and\,components\,data$
 $\Delta t \leftarrow \alpha \times \delta t$
 $\mathcal{A} \leftarrow \mathcal{A}_{lf}$
 $b \leftarrow b_{lf}$
Ensure: $\mathcal{A} \cdot x \leq b$
 return x
 $x_{lf} \leftarrow x$
 return SoE_{lf}
 $N \leftarrow n_{seq}$
 $H \leftarrow \mathsf{H}_i$
 for i=1:N **do**
  $\mathcal{A} \leftarrow \mathcal{A}_i$
  $b \leftarrow b_i$
  Ensure: $\mathcal{A} \cdot x \leq b$ **and** $SoE^{seq_i}(t_f) = SoE_{lf}(t_f^\star)$
  Return x
  $x_i \leftarrow x$
  $SoE^{seq_{i+1}}(t_0) \leftarrow SoE^{seq_i}(t_f)$
  $H \leftarrow \mathsf{H}_{i+1}$
 end for
 return $Solution$

B. SoE constraint relaxation

By imposing a trajectory of battery SoE in advance with the technique described in Section IV-A, we do not need to continuously add in the original problem SoE boundary constraint written in (23), which is memory intensive as it requires to store in matrix A all previous battery states. The technique detailed in Algotithm 2 consists in removing that constraint while solving for each sequence the optimization problem. This constraint is reevaluated if only if battery states are checked outside the loop and go beyond the defined SoE interval limits.

Algorithm 2 Conditional SoE boundary implementation technique

Require: $\lceil SoE \rceil$ **and** $\lfloor SoE \rfloor$
 $N \leftarrow n_{seq}$
 $H \leftarrow \mathsf{H}_i$
 for i=1:N **do**
  $\mathcal{A} \leftarrow \mathcal{A}_i^\star$ ▷ superscript $\star\, in\, X^\star$ stands for "matrix X without SoE constraint"
  $b \leftarrow b_i^\star$
  Ensure: $\mathcal{A} \cdot x \leq b$
  Return x
  Return SoE_{vect_i}
  if $\lfloor SoE \rfloor \leq SoE_k \leq \lceil SoE \rceil$ is **false**, $SoE_k \in SoE_{vect_i}$ **then**
   $\mathcal{A} \leftarrow \mathcal{A}_i$
   $b \leftarrow b_i$
   Ensure: $\mathcal{A} \cdot x \leq b$
   Return x
  end if
  $x_i \leftarrow x$
  $i \leftarrow i+1$
 end for
 return $Solution$

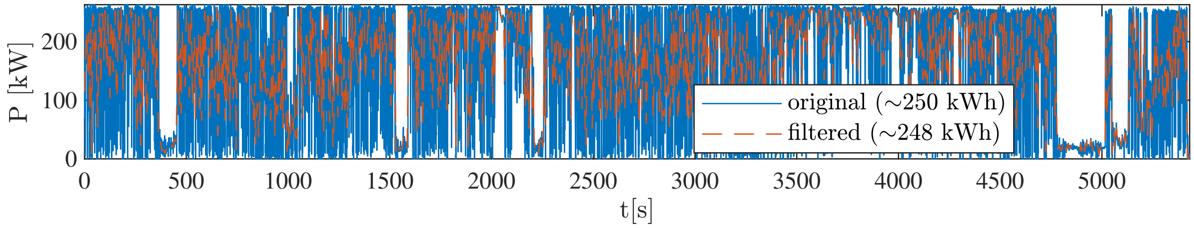
V. Results and discussion

A. General results

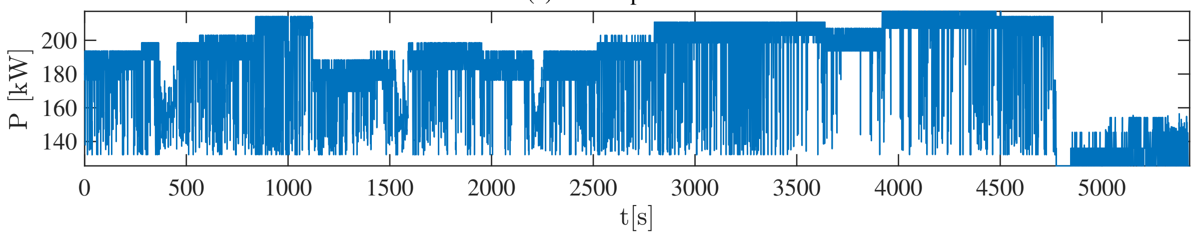
Table I summarizes optimization parameters selected to validate the developed method for fixed components sizing of battery pack and fuel cell elements. A Gaussian filter is used to get a low frequency signal of the original power profile, which is undersampled and displayed in Fig. 3a. The optimization problem solution returned by Gurobi solver for battery pack and fuel cell system is illustrated at Fig. 3b and Fig. 3c. Fuel cell system generally works near its maximum efficiency to reduce hydrogen consumption, and is assisted by batteries to store or compensate energy during low and high frequency power demand phases.

TABLE I: Simulation parameters

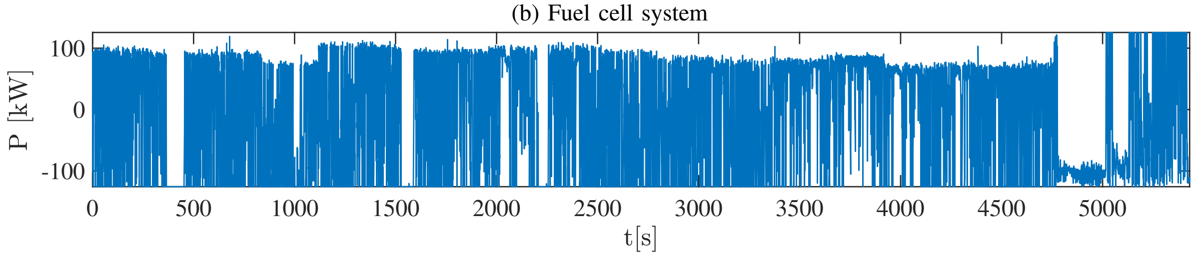
Optimization parameters					
n_c	30	α	50	H_i	2400
Battery pack fixed parameters					
N_s	305	N_p	6	SoE_{init}	0.7
Fuel cell fixed parameters					
A_{stack}[m^2]	0.08	N_{stack}	350	$M_{H_{2_{tank}}}$[kg]	21



(a) Power profile



(b) Fuel cell system



(c) Battery pack

Fig. 3: Power management results

Fig. 4 makes a comparison between power management strategies returned by optimization problems using the true power profile and the filtered one. As the filtered power profile requires less energy, it shows that fuel cell and batteries energy consumption of the associated problem are smaller than the one solved with the original profile.

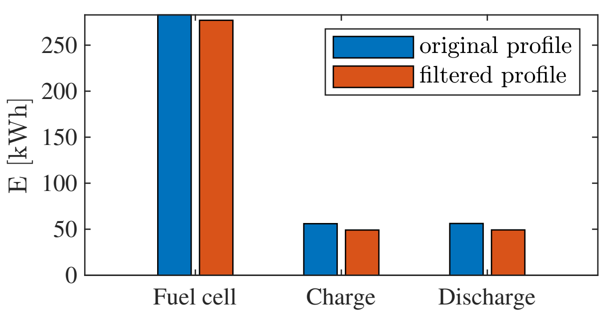


Fig. 4: Comparisons of initial and reduced optimization problem results

B. Sensitivity analysis

To objectively set optimization parameters, a sensitivity analysis is performed to show their impact on the objective function and the size of the problem. Fig. 5 shows the evolution of hydrogen consumption and the size of the problem with respect to the number of discrete control variables n_c, which corresponds to fuel cell current discretization. For a fixed horizon $H_i = 1000$ time steps, we observe a negligible drop of hydrogen mass needed for mission while the size of the problem increases.

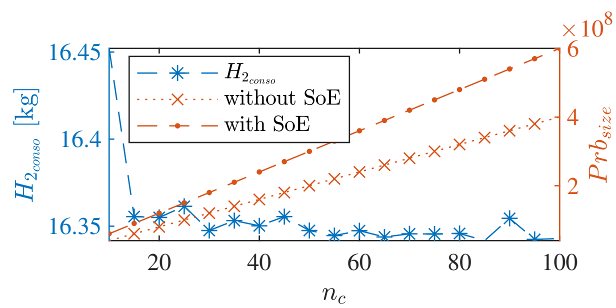
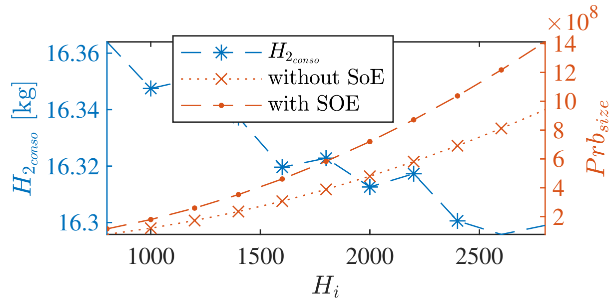
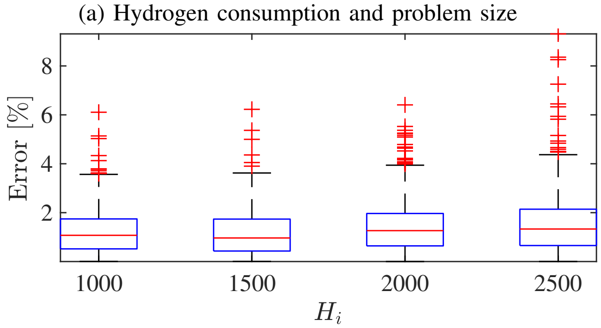


Fig. 5: PMS sensitivity to n_c

For a fixed value of $n_c = 30$, the effect of the sequence horizon on the optimization problem size and its solution is displayed in Fig.6a. By increasing the length of the sub-problems sequences, we improve slightly the fuel consumption. In counterpart, the size of the problem increases exponentially until we run out of memory. Fig.6b shows that the SoE trajectories exhibits low relative errors compared to the one obtained with the filtered power profile. The more H_i increases and the higher aberrant values are, as SoE final value constraints are applied only at the end of each sequence.



(a) Hydrogen consumption and problem size



(b) SoE trajectory errors

Fig. 6: PMS sensitivity to H_i

Table II summarizes major gains obtained by decreasing either n_c or H_i parameter values. It shows that decreasing these two parameters leads to non-negligible computation time savings, which is correlated to the problem size.

TABLE II: Influence of n_c and H_i parameters

Parameter	**Value**	$H_{2_{conso}}$ **[kg]**	Prb_{size}	**CPU time [s]**
n_c **for**	100	16.3429	4e8	449.1
$H_i = 1000$	30	16.3475	1.2e8	121.4
Gain [%]	**-70**	**+0.0281**	**-87.2371**	**-72.968**
H_i **for**	2800	16.2990	9.4e8	1525.7
$n_c = 30$	1000	16.3775	1.2e8	121.4
Gain [%]	**-64.2857**	**+0.2976**	**-69.9958**	**-92.0430**

Additionally, a parameter which affects the power management strategy is the trajectory following maximum error ϵ_{SoE}. Contrary to expectations, hydrogen consumption and battery pack solicitations decrease with the increase of the error. Hence, ϵ_{SoE} is the parameter that defines the degree of freedom of the battery power management strategy with respect to the predefined trajectory. Nevertheless, the model becomes infeasible if ϵ_{SoE} increases more. These errors accumulate while solving iteratively each sequence and battery states diverge from the low frequency SoE trajectory.

VI. Conclusion

We proposed in this paper a combinatorial method to optimize power management strategy between fuel cells and batteries in a hybrid electric racing car. Obtained results show good performances as only few minutes are needed to solve the optimization problem over 60000 time steps of power profile.

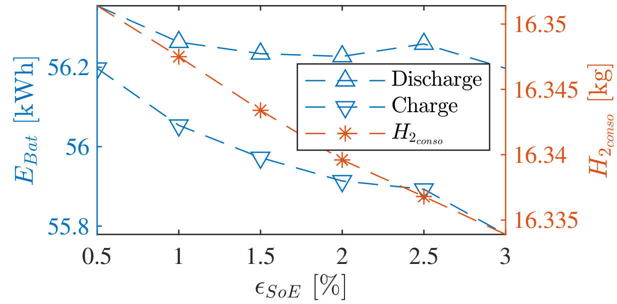


Fig. 7: PMS sensitivity to ϵ_{SoE}

It appears that the optimality of the result depends not only on the discretization of the control variable, but also on the length of sequences and battery pack state of energy trajectory. A sensitivity analysis shows the impact of theses parameters on the optimization problem size and helps to find a good compromise between the computation time and the accuracy of the solution. Future perspectives to accelerate computation will be to run optimization of the sequences in parallel by tuning the SoE trajectory following error. The final purpose of the proposed method is to easily couple components sizing optimization with an optimal control law.

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References

[1] Zhou W, et al. "Dynamic programming for new energy vehicles based on their work modes Part II: fuel cell electric vehicles," Journal of Power Sources; Vol 407, pp. 92-104, 2018.

[2] S. East and M. Cannon, "Optimal Power Allocation in Battery/Supercapacitor Electric Vehicles Using Convex Optimization," IEEE Transactions on Vehicular Technology, vol. 69, no. 11, pp. 12751-12762, Nov. 2020.

[3] N. Denis, M. R. Dubois, J. P. F. Trovão and A. Desrochers, "Power Split Strategy Optimization of a Plug-in Parallel Hybrid Electric Vehicle," in IEEE Transactions on Vehicular Technology, vol. 67, no. 1, pp. 315-326, Jan. 2018.

[4] A. Chauvin, A. Hijazi, E. Bideaux and A. Sari, "Combinatorial approach for sizing and optimal energy management of HEV including durability constraints," 2015 IEEE 24th International Symposium on Industrial Electronics (ISIE), 2015, pp. 1236-1241.

[5] S. G. Wirasingha and A. Emadi, "Classification and Review of Control Strategies for Plug-In Hybrid Electric Vehicles," in IEEE Transactions on Vehicular Technology, vol. 60, no. 1, pp. 111-122, Jan. 2011.

[6] H. Marzougui, A. Kadri, M. Amari and F. Bacha, "Energy Management of Fuel Cell Vehicle with Hybrid Storage System: A Frequency Based Distribution," 2019 6th International Conference on Control, Decision and Information Technologies (CoDIT), 2019, pp. 1853-1858.

[7] J. Buerger, S. East and M. Cannon, "Fast Dual-Loop Nonlinear Receding Horizon Control for Energy Management in Hybrid Electric Vehicles," in IEEE Transactions on Control Systems Technology, vol. 27, no. 3, pp. 1060-1070, May 2019.

[8] X. Huin, M. Di Loreto, E. Bideaux and H. Benzaoui, "Optimization Based Methodology for Hybrid Electric Vehicle Dedicated Internal Combustion Engine Design," 2020 7th International Conference on Control, Decision and Information Technologies (CoDIT), 2020, pp. 195-200.