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Optimal Design Methodology for Sizing a Fuel Cell / Battery Hybrid Power Source

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***Abstract*— This paper presents an optimal design methodology enabling to exhibit the best parameters of a complex energy system combing several components and their related control parts. It is based on a Particle Swarm Optimization (PSO) technique for component sizing, combined with optimal control to consider energy management (EM) constraints. This approximate resolution is valuable since it permits to achieve a robust and effective resets using low computational resources: it enables to tackle large search spaces in engineering time constrains.**

The selected use case is a Fuel Cell/Battery hybrid power source based on a power-split parallel architecture. Its performance index is defined as the fuel consumption. Regarding this objective, the drivetrain components size and the control parameters values are strongly coupled and both physically constrained. In this context, the methodology makes tradeoff between component sizing and energy saving.

Simulation results show the relevance and robustness of this approach regarding different driving cycle and operating condition. It validates the replicability of this method to other optimization problems in the field of energy optimization. A comprehensive review of the simulation tests enables to highlight the present limits of this optimization and provide new perspectives for future works.

Keywords*— *Optimal design; Design Methodology; Particle Swarm Optimization; Optimal Control; Fuel-Cell; Battery;

I. INTRODUCTION

Today, international legislation and car industry policies promote to change the automotive model by developing electrification, mainly developing hybrid vehicles (HEVs).

Indeed, the HEVs purpose is to combine two technologies in order to comply with a demanding application specification, whereas each single technology could not meet them [3, 4]. Therefore HEVs are among the most promising solutions considering transportation constraints. Many alternative technologies like Fuel Cell (FC) as a power source and Batteries/Ultra-Capacitors (BAT/UC) as energy storage are used to design HEVs [1, 2] and contribute significantly towards the reduction of pollutant emissions.. It is a challenge for industries and academics to optimize the design of such systems and the associated energy management strategy.

Hybridization concept unfortunately increases the complexity of the drivetrain. The powertrain designer faces more design and control parameters, constraints, strong coupling between the different parts, new operating modes, etc. In addition, the design space exploration becomes increasingly large and complex because of the multiple possibilities of design combination and energy management strategy. In this context, establishing a systemic optimization procedure is clearly a valuable, if not vital, element for the design process.

A suitable engineering methodology to consider the fundamental design choices in HEVs received considerable attention and is currently developing. Various optimization methodologies already address this issue. Most of them use a systematic approach with individual optimization [5-9], first, a sizing optimization, then an optimal energy management strategy, and finally a validation. This strategy presents some limitations depending on the complexity of the system; they may be computationally demanding and have a premature convergence to a local minimum. Consequently, strong coupling and interactions between sizing and control parameters are not considered, omitting many potential designs in the large and complex search space.

Other suitable approaches are emerging [10-13], which introduce combined methodologies by allowing a full account of the parameters affecting the performance of the system. They present in most cases, a limitation related to the search space, thus significantly reducing the solution set, and consequently the design choice. For further solutions, including the case of multi-objective optimization, their performances are related to the tradeoff between complexity formulation (parameters / constraints / objectives), conflicting requirements, computational time, exploration abilities (poor convergence).

To tackle this problem, a new methodology for design space exploration is suggested. It takes simultaneously component sizing and energy management strategy

enabling to find the optimal powertrain parameters with respect to the hybrid architecture specifications. This method combines the performances of PSO technique [ref] able to search very large search spaces of design component parameters, with a rapid Pontryaguin optimal control algorithm [ref] considering energy management behavior. Doing so, it provides a fast convergence speed and a good robustness in finding the global optimal design

The remainder of this article is structured as follows. Section 2 describes the optimal methodology in a theoretical way. Section 3 presents the studied architecture (FC–Batt) and the associated models. The problem formulation and the implementation of the approach are described in section 4. Then, the results are presented and discussed in section 5 using different driving cycles for sensitivity analysis. Section 6 provides conclusion and perspectives.

II. Optimal Design Methodology

The aim of optimal design is to determine the main parameters affecting system design by considering one or many performance indexes. In simple cases, the best solution can be computed through a direct analytic approach [ref]. Otherwise, finding the best available values needs to use numerical techniques. Standard optimization approaches intend to maximize the criterion around a specific operating point, usually the rated one [ref].

To avoid wrong local minima and reach the global optimum, several effective Stochastic Iterative Methods can be used [8, 14, 15], such as Ant Colony Optimizations (ACO), Genetic Algorithms (GA), Particle Swarm Optimizations (PSO), and Sequential Quadratic Programming (SQP). The convergence time is highly dependent on the design search space size. Therefore, achieving a good tradeoff between computation time and accuracy requires in depth knowledge of the studied system: it enables to choose the most sensitive variables and to limit their range dynamic

A more precise optimization is to consider typical use cases, permitting to propose a downsized design. It is the overall trend in automotive applications. Using directly the previous paradigm, where all instantaneous control variables are tuning parameters, is a way to solve this complex issue. However, it leads to an oversized formulation. Conversely, dedicated algorithms enable to find optimal trajectories. Popular ones are Pontryagin's minimum principle (PMP) [ref], dynamic programming (DP) [ref] and Model Predictive Control (MPC) [ref]. The new proposed paradigm consists in finding the whole control policy dedicated to each sized system. The sources control values become the determined parameters of the system. This way, the metaheuristic algorithm solves efficiently a small-scale problem.

Naturally, sizing and control parameters are highly dependent which leads to propose a combined methodology. It uses two imbricated optimizations with internal and external loops of optimization as presented in Fig. 1.

The external loop is an optimization of the sizing components. For this matter, the genetic algorithm is really appreciated for its flexibility and accuracy [17, 18]. These advantages are counterbalanced by the complexity of this methodology regarding the design space exploration. To lessen this issue, PSO techniques are suggested and investigated. This approach is particularly adapted to this requirement with the advantages of implementation simplicity and short computing time. In addition, many improvements have been made to this algorithm [19, 20] : they enhance its behavior in improving the speed and the precision of the solution convergence even in case of large space exploration.

To consider control parameters, a criterion based on the energy consumption is introduced. This is addressed in the internal loop (Fig. 1), which enables to optimize the overall cycle consumption of the designed architecture with respect to each specific sizing.

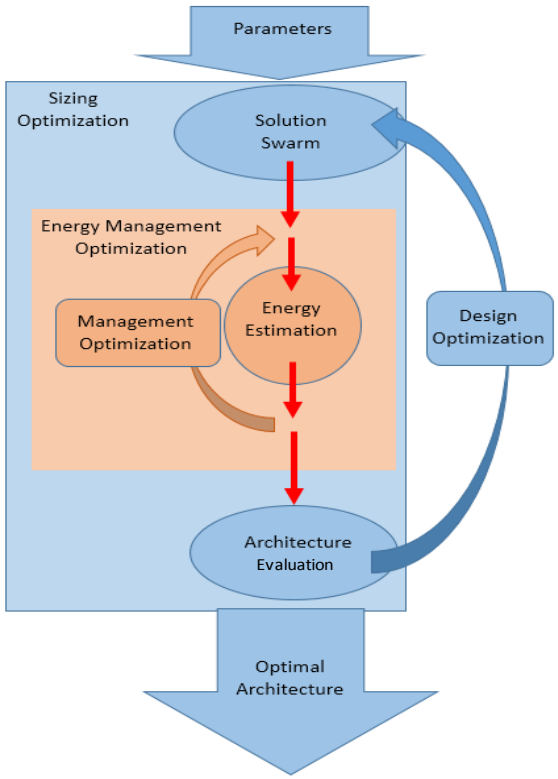

Fig 1. Theoretical Global Methodology Algorithm

The two major strategies (DP and PMP) applied for energy management problems use optimal control theory to address global optimization methods. The DP technique based on the Bellman's principle of optimality, guarantees the optimal solution by considering all possible solutions (exhaustive search). The PMP produce a single optimal trajectory by minimizing the Hamilton function. It has a significant computational advantage and faster response for large space design, which is so important for the proposed approach.

In order to manage efficiently the interaction between loops, each one exchanges relevant information. The energy management (EM) needs the architecture sizing and the constraints resulting from it while the sizing needs the EM results to assess the suitability of the proposed architecture. This approach increases the convergence speed and its accuracy.

In sum, the proposed methodology is based on two imbricated optimizations: the external one searches for the best architecture - according to a criterion defined by the expert user - while the internal loop optimizes the EM strategy to suit the external criterion. This internal loop assesses the cost function of the external optimization to evaluate the performance of each tested design. Fig. 1 shows the global flowchart of the suggested optimization methodology while Tab. 1 and 2 summarize the Input-Output of each optimization

Tab. 1 Input-Output of the sizing optimization

Sizing Optimization	
Input	**Output**
Customer Specifications: WLTC, vehicle model, Cost Function	Optimal Sizing: P_{FC}, C_{BAT}
Sizing Variable Limits: $P_{FCMaxMin}$ $C_{BATMax/Min}$	Associated EM: $P_{FC}(t)$, $P_{BAT}(t)$, SOC(t)
Optimization Parameters: Particles number, Iterations number	

Tab. 2 Input-Output of the EM Optimization

EM Optimization	
Input	**Output**
Load Cycle $P_{LOAD}(t)$	Optimal EM $P_{FC}(t)$
Hybrid Source models Eq (1, 2, 3), Fig 3-4	Sources Behaviors $P_{BAT}(t)$, SOC(t), $\eta_{FC}(t)$
Sources Sizing P_{FC}, C_{BAT}	
EM Optimization Parameters $SOC_{MAX/MIN}$	

III. SYSTEM DESCRIPTION

The global architecture model is an energetic hub between two sources and a load. The parallel structure choice is based on previous works dealing with the possible FC-BAT architectures [21]. This architecture uses a specific power converter connected to each source. It is hence well suited for optimal design and energy management related to its freedom degrees. Fig. 2 shows this architecture: the FC is the main source and the BAT is the auxiliary one with a storage capacity for recovering energy while braking.

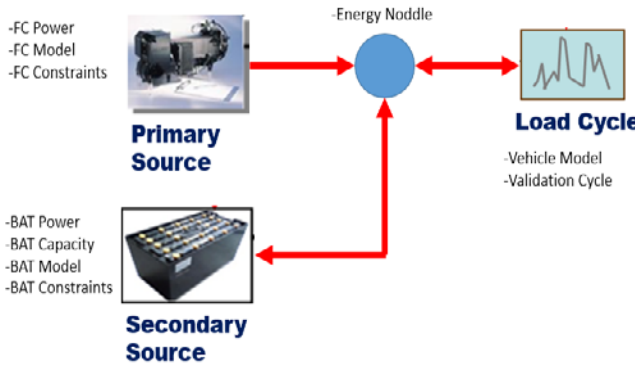

Fig. 2. FC-BAT power system

The approach system involves energetic modeling to take into account the different power flows and subsystems interactions. The primary source is a static FC model based on its power efficiency [22]. A classic electrical circuit models the lithium-ion battery based on a voltage source and a first order circuit. Regarding energetic behavior, its three main parameters are the terminal voltage (V_{BAT}), the battery state of charge (SOC), and a related constant power efficiency coefficient [23, 24].

These models are simple but accurate to represent energy flows. Accepting an additional complexity may enable to consider specific phenomena. The principle of the approach would be retained but the proceeding time would be increased which may not be relevant for a pre-design tool. Indeed, in modeling, it is crucial to choose the appropriate level to provide relevant results without needing excessive computing capacity. The current choices enables to obtain realistic system behaviors while having an acceptable computing time (minutes/hours instead of days/week).

A. *Fuel cell modeling*

A FC system is made up of several cells connected in series and/or parallel to provide the desired output power (voltage and current), while exhibiting a nonlinear operating behavior (I–V characteristic). In low dynamic

conditions, its characteristic can be considered as a voltage source in series with 3 electrical dipoles representing ohmic, kinetic and mass transfer phenomena. The relationship between the FC voltage V_{FC} and the output current i_{FC} is given by the following equations (eq. 1, 2) [ref]. Fig. 3 shows the behavior of FC efficiency.

$$V_{FC} = N\left(E_{Cel} \cdot R \cdot j_{Stack} - A \cdot ln(j_{Stack} + j_1) - m \cdot exp(n \cdot j_{Stack})\right) \quad (1)$$

$$\begin{cases} j_{Stack} = \frac{I_{Stack}}{A_{Cel}} \\ I_{Stack} = \alpha + (1+\beta) i_{FC} + \gamma (i_{FC})^2 \end{cases} \quad (2)$$

Where A_{Cel} is area of each cell, N is the stack cell number. E_{Cel} is the reversible cell voltage, R is the membrane area specific resistance, A is the Tafel coefficient. I_{Stack} stack current, m and n are the two coefficients of the mass transfer equation, and α, β and γ and are coefficient of 2nd order model approximating I_{Stack} as function of the output current i_{FC}.

A=0.03 V, m= 2.11 10^{-5} V, n= 8 10^{-3} cm2 mA^{-1}, α=0.029, β=0.971, γ=-8 10^{-4}.

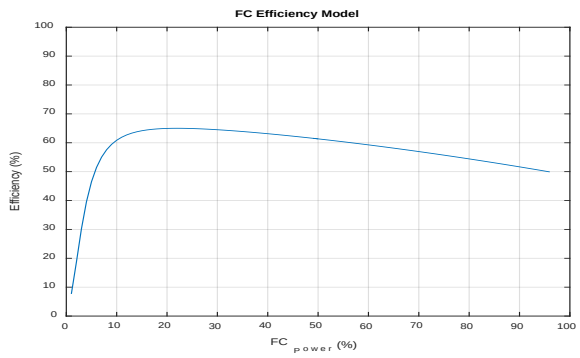

Fig 3. FC efficiency

B. Battery modelling

A propulsion Lithium- battery pack can be scaled simply according to its number of cells and its cells capacitances. It can be modeled over a large range of operating conditions by a model including an ideal voltage source U_{OC} to define the battery open-circuit voltage, internal resistances and equivalent capacitances (Fig. 4). The internal resistances include the ohmic resistance (R_O) and the polarization resistance (R_P). The equivalent capacitance (C_{Tr}) is used to describe the transient response during charging and discharging (eq. 3).

$$\begin{cases} U_{BAT} = U_{OC} - U - R_O i_{BAT} \\ \frac{dU}{dt} = -\frac{U}{R_P C_{Tr}} + \frac{i_{BAT}}{C_{Tr}} \\ SOC(t) = SOC_0 + \frac{\eta_{BAT}}{3600 \cdot C_{BAT}} \int i_{BAT} dt \\ SOE(t) = \frac{W(t)}{W_{Rated}} = \frac{SOC}{C_{BAT}} \end{cases} \quad (3)$$

Where, U_{BAT}, i_{BAT} and C_{BAT} are voltage, current and capacity Battery. SOE and SOC are State of energy and state of charge. W and W_{Rated} : are actual stored and rated energy.

The model parameters are estimated using a battery test bench presented in detail in [24]:

R_O = 0.072Ω, R_P = 0.021Ω, C_{Tr} = 1214 F.

Despite BAT capacity loss over time (calendar losses and cycling losses), the BAT energy efficiency remains almost constant and was fixed at the average value 90% [ref].

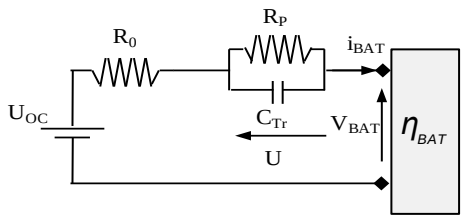

Fig. 4. Battery equivalent circuit model

IV. Implementation Methodology

A. Optimization Problem

The optimization process search the best system parameters set. To achieve this result, it aims at minimizing a cost function naturally depending on these parameters. In the present case, it is the architecture energy consumption which is obviously influenced by the driving cycle (eq. 4). To carry out its overall assessment, the algorithm tries several values of the following parameters :

- P_{FC} : FC power
- P_{BAT} : BAT power
- C_{BAT} : BAT capacity

Considering the model architecture, power balance (eq. 5) and sizing limits (eq. 6, 7, 8).

The cost function based on EM optimizes the consumption by finding the best FC power cycle of the tested architecture considering the physical constraints and the proposed sizing.

The mathematical description of such optimization problems can be presented as follows:

- Cost function which is the criterion to minimize : (energy consumption)

$$J = \sum_{Load\ Cycle} [P_{FC}(t) \cdot T_e] \quad (4)$$

- System model: (power balance)

$$P_{Load}(t) = \eta_{FC} \cdot P_{FC}(t) + \eta_{BAT} \cdot P_{BAT}(t) \quad (5)$$

- Constraints: (design)

$$P_{FCmin} < P_{FC}(t) < P_{FCmax} \quad (6)$$

$$P_{BATmin} < P_{BAT}(t) < P_{BATmax} \quad (7)$$

$$C_{BATmin} < C_{BAT}(t) < C_{BATmax} \quad (8)$$

- Constraints: (energy management)

$$SOC_{min} < SOC(t) < SOC_{max} \quad (9)$$

Where, J, $P_{FC,\,BAT}$, P_{Load}, SOC, $\eta_{FC,\,BAT}$, T_e and C_{BAT} are cost function, power sources, load power, state of charge, efficiency converters, sample time, BAT capacity. $P_{FCmin\,/\,max}$, $P_{BATmin\,/\,max}$, $C_{BATmin\,/\,max}$ and $SOC_{min\,/\,max}$ are maximum /minimum values.

B. *External optimisation - PSO sizing components*

The PSO algorithm is based on swarm intelligence (social behavior of birds), which makes a search mechanism based on the movement of a population (N particles). It uses randomness and information sharing between particles to identify the best position (optimal variable values) [18, 19, 25].

Each particle is a potential solution to the optimization problem and is depicted by information vector (M dimensions) including optimization variables (position) and stored parameters (Memory) as follow:

$$Vector_{Partical} = \begin{bmatrix} \left.\begin{matrix} P_{FC} \\ C_{BAT} \end{matrix}\right\} \ldots Position \\ \left.\begin{matrix} Fitness\ (cost) \\ Partical\ best \\ Global\ best \\ Speed \end{matrix}\right\} \ldots Memory \end{bmatrix} \quad (10)$$

The search space is defined by optimization variables considering the user's specifications. Fig. 5 represents the PSO design process of the sizing optimization using the following steps.

Initial Step: The algorithm generates a particle swarm; each particle is defined by its position and fitness (particle's cost). At the initialization step, the algorithm sets each particle in a random position with a random speed in the field. It allows the initialization of particle's vector.

Evaluation Step: Then each particle is iteratively evaluated considering the cost function (EM - internal optimization). Two scenarios can occur: if the actual cost is better than the ones achieved at the previous iterations, the information is stored (update the memory). Otherwise, the previous best cost and position are kept (hold the memory).

Evolution Step: After the cost evaluation, the algorithm moves each particle based on three sub-movement. The operation principle is illustrated in Fig. 6. The particle wants to continue its last movement (Inertia), the particle wants to turn back to its best position (selfishness) and the particle is attracted by the best position known at this time in the field (social behavior). Each sub-movement is weighted: the selfishness and the social behavior by a random coefficient and the inertia by a decreasing coefficient (Damp) to allow a wide exploration at the beginning and an appropriate final converging behavior.

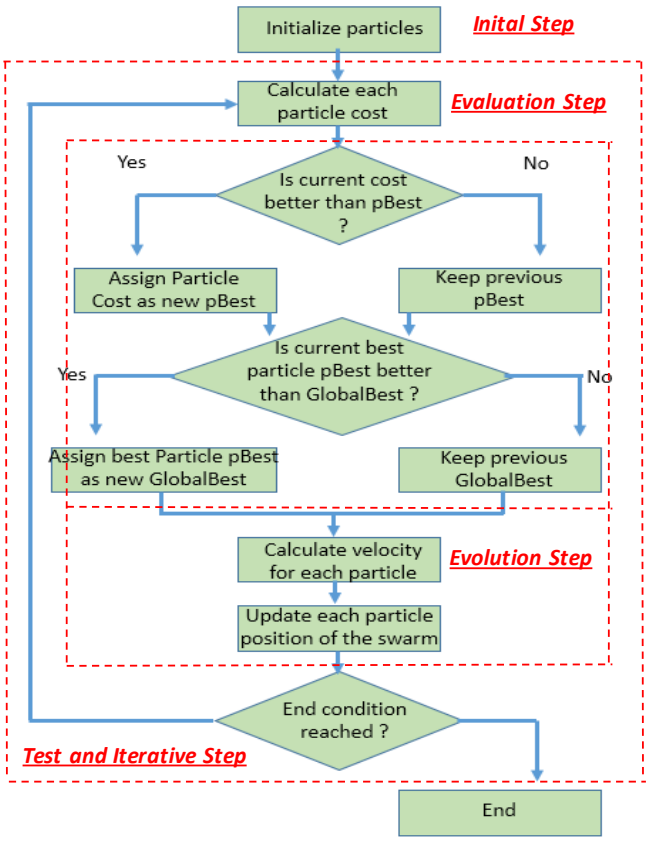

Fig. 5. Particle Swarm Optimization Algorithm

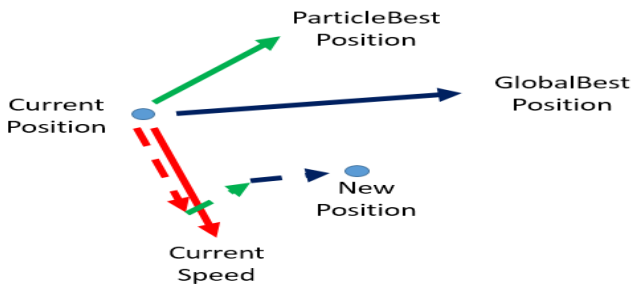

Fig. 6. Calculation of each Particle's Move Vector

Test and Iterative Step: The stop conditions are related to the iteration number and the average evolution generation. If they are reached the algorithm stops with the current best solution. Otherwise, the iterative process takes

place by looping *Evaluation and Evolution Steps* until the stop conditions are reached.
The PSO is relevant considering its low complexity (few design parameters) and its efficiency (fast convergence speed, short computation time and accuracy) compared to other optimization methods [26-27].

C. Internal Optimization – EM constraint

1) Pontryagin OC main approach

The PMP is a very powerful technique in optimal control (OC) theory. It allows identifying a unique optimal trajectory for energy saving by minimizing the Hamilton function. This solution is defined using necessary conditions of optimality to make system globally optimal.

The optimization process can be summarized in a mathematical problem. It consists in minimizing FC hydrogen consumption during driving cycle. The total FC energy consumption reflects hydrogen consumption. Hence, the objective function is given in eq. 4.

The PMP requires the definition of Hamiltonian function (*H*) given by:

$$H = P_{FC}(t) \cdot T_e - \lambda \cdot [SOE(t+1) - SOE(t)] \qquad (11)$$

The BAT state of energy (SOE) is selected as the system state variable and can be described as :

$$SOE(t+1) = SOE(t) - P_{BAT}(t) \cdot T_e \qquad (12)$$

Minimizing the total FC energy involves the power split between FC and BAT. The Hamiltonian function has to be minimized at each time (t) to provide the optimal control trajectory $u^*(t)$ given by FC power P_{FC}. This allows introducing necessary conditions of optimality as follows:

$$u^*(t) = argmin\, H\, [SOE(t), P_{FC}(t), \lambda(t)\,] \qquad (13)$$

Where $\lambda(t)$ is the co-state optimization variables (equivalent Lagrange multipliers), and can be calculated using the following equations :

$$\begin{cases} \dfrac{\partial H}{\partial \lambda\,(i)} = SOE(i+1) \\ \dfrac{\partial H}{\partial SOE\,(i)} = -\lambda\,(i+1) \end{cases} \qquad (14)$$

In addition to the instantaneous constraints imposed on power components due to the physical limits (eq. 6 – 9), the constrained boundary values should be respected.

$$SOE_{min} < SOE(t) < SOE_{max} \qquad (15)$$

$$|SOC(End) - SOC(Init)| < \varepsilon \qquad (16)$$

Where, H, $P_{FC,BAT}$, T_e , ε and SOE are Hamiltonian function, power sources, sample time, admissible energy variation and state of energy. $SOE_{min/max}$ and *SOE (End) /(Init)* are maximum /minimum values and initial/ final values.

Furthermore, a dynamic limitation of FC power (1kW/s) is considered to address its slow dynamic mainly limited by the time response of the air compressor.

For a given driving cycle, optimal control trajectory leads with knowledge of the co-state (λ_0) initial value. This identification is most critical step to identify the optimal trajectory solution. Its design must minimize the Hamiltonian (eq. 11) at each time and satisfy the terminal condition (eq. 16). For this, a dichotomy method is used to find this parameter (λ_0) according to the tuning parameter (ε)

As presented in Tab. 2 the OC received some input with useful information to define an EM strategy. According to the tested architecture (a particle with a sizing), the OC algorithm tries at each time steps, all the allowed commands (from 0% to 100% of FC power) and evaluate their fitness considering the consumption criterion. Fig. 7 presents this algorithm.

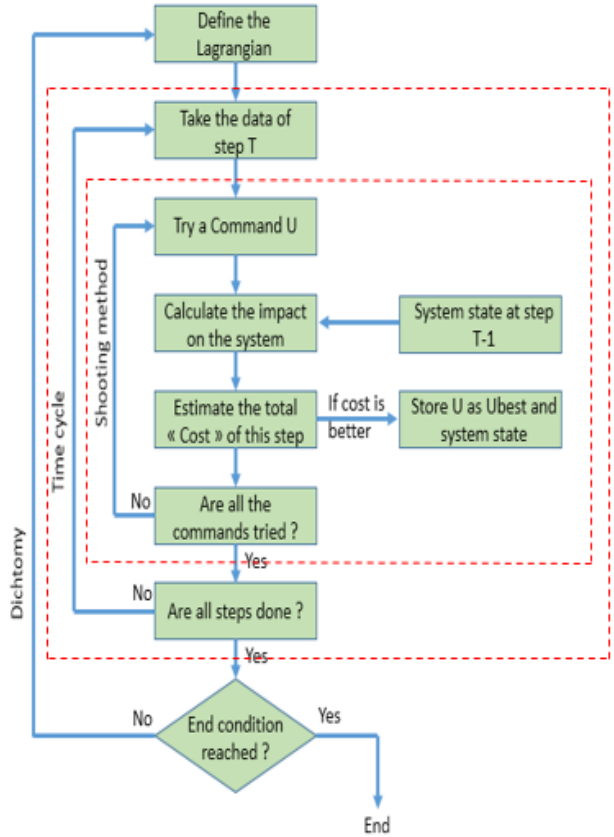

Fig. 7. Optimal Control Algorithm

<u>*Dichotomy:*</u> The co-state (λ_0) initial value is defined beforehand using a dichotomy method for a given driving cycle. The global SOE variation should to be small ($\varepsilon \approx 0$)

allowing the same scale to estimate the FC consumption for different driving cycle and energy management strategies. The parameter choice (λ_0) is related to the terminal condition and directly affects the power split between FC and BAT.

Time Cycle: In this loop, the driving cycle is evaluated step by step to identify each optimal command. This involves setting up the optimal trajectory for energy saving.

Shooting Method: This method uses an iterative process to evaluate all assigned commands.

2) Pontryagin OC Improvement

Unlike the DP, the PMP saves a lot of computation time (mere seconds instead of days) for a limited accuracy loss [29]. The gap represents less than 1% of the results obtained with DP. The driving cycle is evaluated chronologically to perform optimal trajectory to be close to the real time processing. This requires an estimation of the future commands and associated costs. In addition, some improvements have been made to make PMP approach more relevant regarding component limits. In fact, this approach does not include physical constraints related to the limits of the operating system. To guarantee the system components integrity mainly, a penalisation function has been introduced and proceeds when physical constraints are not respected in order to focus upon the most interesting areas.

A fictive consumption ($SOE_{Penaltity}$) is introduced to monitor BAT limits. It uses a quadrtic function to ensure smooth behavior.

$$SOE_{Penalty} =< [SOE(t+1) - SOE_{max}]^2 + \left[SOE(t+1) - SOE_{min}{}^2\right] \quad (17)$$

At the same time, the driving cycle can be bypassed to fulfill power balance in the DC bus (eq. 5) using two differents strategies: discharging overproduced power ($P_{Load} > P_{Sources}$) or accepting deficits in power production ($P_{Load} < P_{Sources}$). These behaviors should be monitored to introduce more flexibility (freedom degrees) on energy management. They also need to be restricted by a penalty to avoid abuses (using this flexibility, which may lead to dangerous situations and at least inconfortable conditions).

$$OVERPRODUCE_{Penalty} = P_{Over}(t) \cdot T_e \quad (18)$$

$$DEFICIT_{Penalty} = P_{Defi}(t) \cdot T_e \quad (19)$$

Where, P_{Load} and $P_{Sources}$ are power load and power sources. $OVERPRODUCE_{Penalty}$ and P_{Over} are energy penality and power for overproduced situation. $DEFICIT_{Penalty}$ and P_{Defi} are energy penality and power for deficit situation.

These penalties are tuned by weighting coefficients for normalization and global balancing of system behavior. Equation (20) presents the new global cost function considering these penalties ($J_{Corrected}$).

$$j_{Corrected} = j + \left[k_1 \cdot SOE_{Penalty} + k_2 \cdot OVERPRODUCE_{Penalty} + k_3 \cdot DEFICIT_{Penalty}\right] \quad (20)$$

The weightings (k_1, k_2, k_3) tuning is done by a sensitivity procedure to make sure that appropriate penalties are applied only in constraining architectures. These situations require totality freedom degrees.

V. VALIDATION

A. Setting up

The proposed methodology is evaluated by extensive simulations of the hybrid system as shown in Fig. 2, using MATLAB environment. The optimization is run on Intel Core i7-7700HQ processor at 2.80 GHz, with a 2017 Matlab version. Table.3 gives the simulated system's data.

Tab 3. Methodology Parameters

Parameters	Value
Particles number and Iteration	30, 100
Values to design	P_{FC}, P_{BAT}, C_{BAT}
Search field	1-100 kW and 0.5-10 kWh
FC, BAT models	PEMFC static, Li-Ion
SOC_{Min}, SOC_{Max}, ε	15%, 90%, 1%
Computing Times	900 s

Different studies were conducted: the validation of the global methodology and the relevance of this approach, the study of the balance tuning in the OC, and a map of the different solutions showing the robustness considering the stochastic of real load cycle (WLTC, NEDC, ARTEMIS…)

The study of OC penalties is carried with full range variation from 0% to 100% for each weight. In addition, the map is realized with different load cycle (based on official cycles) using OC optimization, to analyze the approach sensitivity toward specification disturbance.

B. Results

1) Balance Penalties Study

Note that in our case, the penalties are only used in sizing limits to endow the algorithm capacity to

counterbalance the constraining sizing. Fig. 8 shows the sensibility study about these penalties.

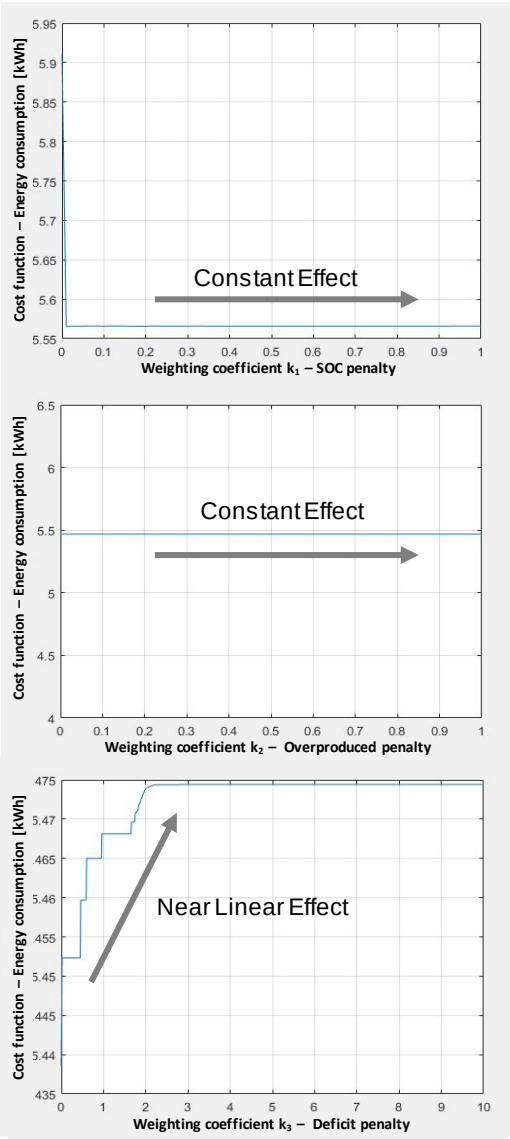

Fig. 8. Balance of weighting coefficient

SOC penalty: The behavior of this penalty is based on On/Off mode with a few effects on the final consumption (Fig. 8). The scale of the weighting coefficient has to be around one. This precision is enough for a good behavior of the penalty with a limited utilization rate. The scale and unit of the calculated penalties are similar to the energy consumed during the time step, so the normalization is not necessary. In addition, the equation for this penalty (eq.17) has a quadrature behavior.

Overproduced penalty: It uses also On/Off mode with an insignificant effect on the consumption when activated (Fig. 8). The unit and scale of this penalty are also similar to the calculated consumption, explaining why there is no need for normalization. This coefficient has also to be around one.

Deficit penalty: This penalty has a more linear and significant effect on the final consumption. It avoids the artificial reduction of the Load Cycle, using the freedom degree. The tuning of this weighting coefficient must be around 10 to be relevant in counterbalancing the constraining architectures (Fig. 8).

With this tuning, the BAT SOC is kept within safe limits (10 % < SOC < 90 %) and the breach of power conservation at the sources node is sparingly used with no effect on optimization process. Fig. 9 shows the sensitivity study about these penalties under WLTC driving cycle. It clearly demonstrates a limited use, less than one percent of the cycle (1%), which remains an acceptable level

1) *Cycle Sensitivity*

This study quantifies the sensitivity of the methodology related to the use case. The WLTC is considered as the standard driving cycle while the NEDC, FTP US city, and FTP US Highway are also tested to analyze the algorithm response to operating condition fluctuations. First, the algorithm gives a consistent set of solutions whatever the load profile (Fig. 10). As expected, the load average power and the load power dynamics influence the system design. In each case, a bowl shape surface represents the Pareto frontier (Fig. 10) of the computed sizing solutions by considering the FC power and the battery capacity in x, y-axis and the consumption in the z-axis. The rated FC power of the minimal sizing increases with the load average demand while its battery capacity is related to the vehicle dynamic behavior.

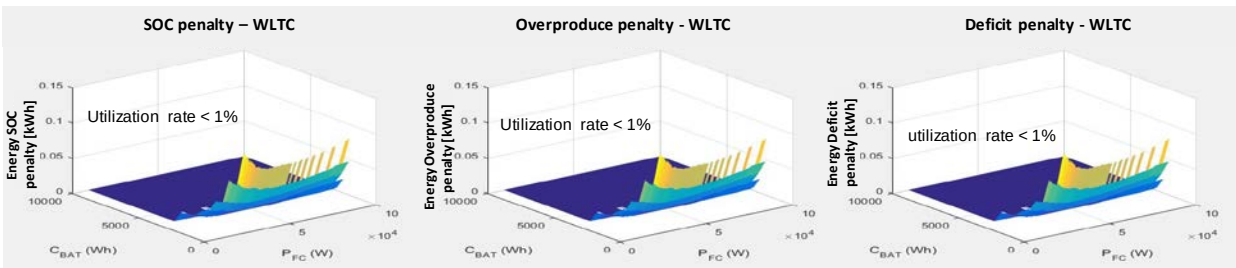

Fig. 9. Utilisation rate of penalties under WLTC en cours

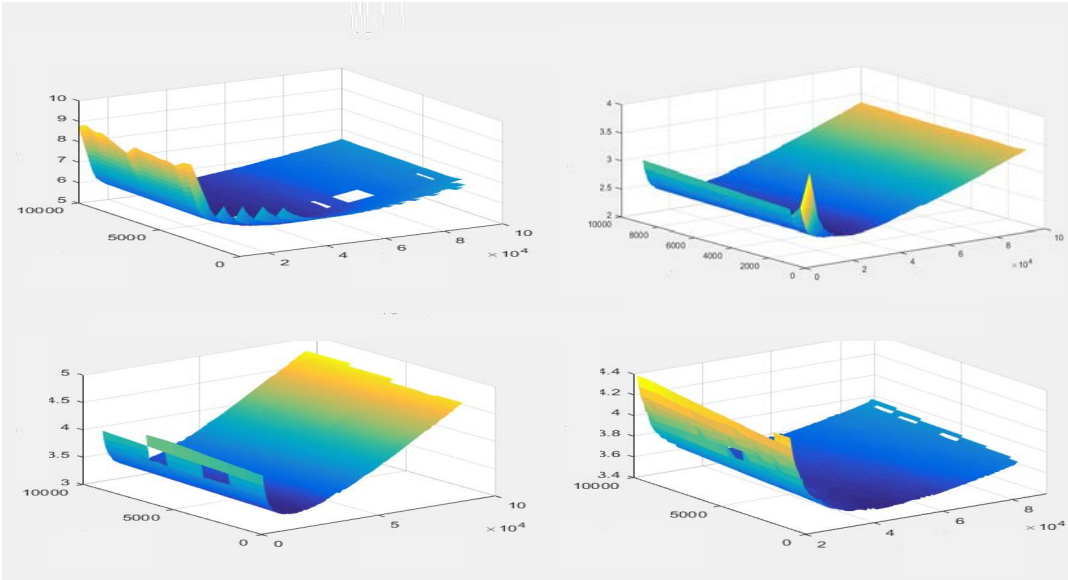

Fig. 10. Mapping results

Tab 4. Optimisation results towards driving cycles

Cycle	WLTC	NEDC	US city	US highway
Distance	23 km	11 km	18 km	16 km
Average and maximum speed	46.5 – 130 km/h	33.6 – 120 km/h	34.1 – 92 km/h	77 – 96 km/h
$P_{Load\text{-}Max}$ (Maximum power load)	41.41 kW	35.5 kW	29.9 kW	25.02 kW
$P_{Load\text{-}Mean}$ (Average power load)	10.6 kW	6.9 kW	7.18 kW	12.53 kW
P_{FC} (FC power)	17.5 kW	12 kW	11.5 kW	20 kW
ΔE_{Max} (Energy deviation Maximum) $\left[\sum \frac{P_{Load}-P_{Load-Mean}}{\Delta t}\right]$ (Max – Min)	1.22 kWh	0.66 kWh	0.44 kWh	0.32 kWh
C_{BAT} (Battery Capacity)	3 kWh	1.5 kWh	1 kWh	0.8 kWh
Hydrogen Consumption	0.69 kg/100km	0.64 kg/100km	0.67 kg/100km	0.72 kg/100km

The result values extracted from mapping results are shown in Table 4. It confirm the behaviors observed on mapping. The evolution of sizing depend on driving cycle. There is a close relation between FC and Load average power to ensure system autonomy. Whereas BAT capacity attend dynamic behavior given by the energy deviation. However, driving cycles having equivalent properties exhibit almost the same results: NEDC / US city for FC sizing and US city / US highway for BAT sizing.

Second, the performance index, i.e. hydrogen consumption is slightly influenced by the vehicle dynamic behavior. To prove this, each optimal design is tested using the three other cycles. Tab. 5 shows the relative consumption with respect to the best one. Indeed, this value is low as far as the average load power remains similar which is in agreement with the mapping of designed solutions (Fig. 9). This study confirms the solutions flatness and robustness conjecture.

1) *Approach validation*

The methodology is applied to a city car (RENAULT ZOE) in standard WLTC drive cycle. Identifying its best design parameters enables to verify the representativeness of the proposed results. The consumed energy on the WLTC (23km) is around 0.69 kg/100km related to the optimized architecture illustrated in Table. 6. This optimization results are close to standard electric vehicles, which proves the relevance of suggested methodology.

Tab 5. Relative consumption towards driving cycles

		Optimal Architecture			
	Relative consumption	**WLTC**	**NEDC**	**US City**	**US Highway**
Driving cycle	**WLTC**	0%	13%	13%	10%
	NEDC	3%	0%	1%	1%
	US City	5%	1%	0%	10%
	US Highway	2%	10%	12%	0%

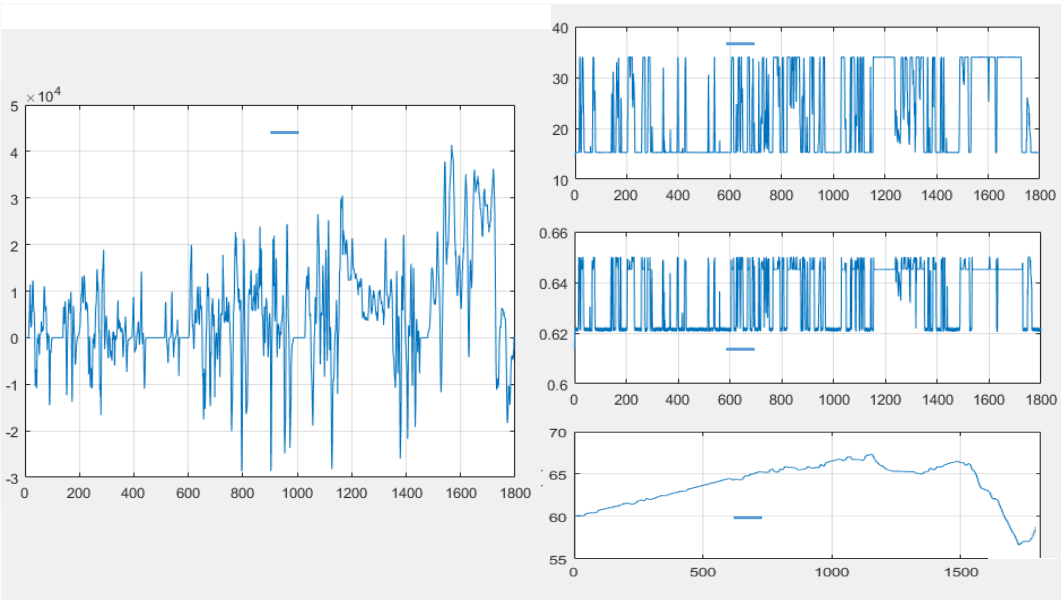

Fig. 11. Energy Management Results

Tab 6. Optimization results – WLTC

Variable	Value
FC Power	17.5 kW
BAT Power	29.2 kW
BAT Capacity	3 kWh
Hydrogen Consumption	0.69 kg/100km
Computation Times	900 s

Fig. 11 presents main variable waveforms of the optimal FC/BAT system response: Load power, Relative FC power, SOC and FC efficiency. Obviously the algorithm tries to use the FC in its best range, namely between 15 % and 40 % of its rated power, which are indeed to the most efficient FC operating points. The SOC trajectory tends to follow vehicle dynamic behavior and reaches the final condition. It demonstrates the effectiveness of dichotomy technique for co-state tuning value.

VI. Conclusion

The current study addresses the sizing of hybrid power architecture. This optimization process is complex because highly dependent on the load profile. It is therefore important to propose an approach respecting the strong coupling between sizing and control parameters.

The suggested method combines efficiently PSO metaheuristic and Pontryagin OC principle. The optimization process is built in a cascaded loop. Hence, the approach gets the most from each technique. Indeed, it enables to achieve a robust result in small computation time. This makes it possible to consider a large search space and to give competitive response with reduced time to market.

The approach is validated using city HEV car. For this use case, only energy consumption criterion is considered. The set of solution reveals robust regarding the driving cycle.

Based on very encouraging initial results, the future work will consider additional performance indexes leading to a multi-objective optimization process. It will increase the optimal design relevance and be more suited to industrial challenges. For automotive application, these new criteria would be cost, life duration volume and weight.

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