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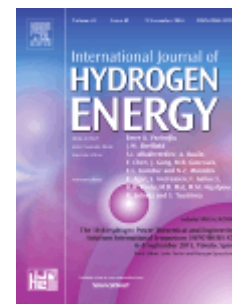
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1
2 **A COMPARISON OF REAL-TIME ENERGY MANAGEMENT STRATEGIES OF**
3 **FC/SC HYBRID POWER SOURCE:**
4 **STATISTICAL ANALYSIS USING RANDOM CYCLES**

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15
16 **Abstract.**

17 This paper presents a comparative study of two promising real-time energy management strategies for fuel cell electric vehicle
18 applications: adaptive equivalent consumption minimization strategy (A-ECMS), and stochastic dynamic programming (SDP). An
19 off-line algorithm –classic dynamic programming - provides reference results. On-line and off-line strategies are tested both in
20 simulation and using a dedicated test bench completely consistent with an electric scooter powertrain.

21 The hybrid power source combines a fuel cell, a supercapacitor pack and two related power converters. The system model is
22 carefully calibrated using experimental data. This allows meaningful identification of parameters of the various strategies. The
23 model data is determined using a motorcycle certification driving cycle.

24 The robustness of each strategy is then analyzed using a large number of random driving cycles. Experimental and simulation results
25 show that a specific SDP approach, based on Markov chain modeling, has the best overall performance in real-world driving
26 conditions. It achieves the minimum average hydrogen consumption while respecting the state-sustaining constraint. Conversely,

1 the A-ECMS results lack robustness and show poor performance indexes when facing unknown real world power demand profile.
2 In conclusion, the present results indicate SDP is an interesting approach for future hybrid source energy allocation.

4 **Keywords.**

5 Fuel Cell System, on-line Energy Management, Adaptive Equivalent Consumption Minimization strategy, Stochastic Dynamic
6 Programming, Markov chain, statistical analysis.

9 **1. Introduction**

10 With increasing climate change concern, public attention tends to focus on the environmental impacts of fossil fuel use,
11 especially after the DieselGate emissions scandal [1]. New legislative measures promote clean energy technologies and specifically
12 electric vehicles [2,3]. In comparison with grid charged battery electric vehicles, Fuel Cell Electric Vehicles (FCEVs) permit fast
13 refueling and extended driving range within strict integral mass constraints. This advantage means hydrogen energy seems to be
14 the new trend of both public and individual zero-emission transportation methods [4-6]. In this context, large car manufacturers,
15 like Toyota, Honda and Hyundai have been already manufacturing and selling FCEVs for several years [7].

16 A FCEV commonly contains two power sources, a Fuel Cell system (FC system) made up of an H₂ tank and a Fuel Cell (FC)
17 combined with an Energy Storage System (ESS) such as a supercapacitor (SC) pack or a rechargeable battery pack [8-12]. Currently,
18 SCs are often chosen because they have a higher specific power than batteries and a longer lifetime in terms of the number of
19 charge/discharge cycles [12,13].

20 The combination of the FC system and the ESS constitutes a hybrid source and the dual source power sharing gives a degree
21 of freedom which can be utilized to improve the system management. It permits the main energy source, the FC system, to operate
22 more efficiently and the vehicle kinetic energy to be recovered during braking into the ESS. However, the fuel saving and the related
23 vehicle autonomy increase strongly depend on the embedded Energy Management Strategy (EMS) that controls in real-time the
24 power sharing between the two sources (FC system and ESS) to fulfill the power requirement of the drivetrain [14-17].

25 While finding the optimal solution for this sharing, can be achieved off-line using Pontryagin's Minimum Principle (PMP) [18-
26 20] or Dynamic Programming (DP) [21-24], the design of an adequate on-line EMS for real-world applications remains a challenge
27 and an open question. Off-line optimization requires a complete knowledge of the vehicle driving conditions which cannot be
28 obtained in advance in the real world. This issue has had considerable research interest and the related literature is very rich. The

1 present article aims at assessing two prominent on-line EMS systems dedicated to supervising the on-board electrical power
2 distribution to the FCEV powertrain. The first approach is based on the equivalent consumption concept, derived from PMP [25,
3 26]. This approach is popular because of its simplicity and ease of implementation. The present paper focuses on the Adaptive
4 Equivalent Consumption Minimization Strategy (A-ECMS) proposed in [25-28]. The second method under study is Stochastic
5 Dynamic Programming (SDP) [31-35], which generalizes DP in the case where random processes are involved, as in real-life
6 driving. Despite its complexity, SDP is appealing because it has a clear theoretical background and can take into account statistical
7 information for future driving cycles.

8 This paper focuses exclusively on the EMS [36, 37] and not on the system itself [38, 39]. Thus, all EMS strategies are applied
9 to the same FC/SC hybrid system, in the same context, and are then tested both in a simulation environment and on the
10 corresponding experimental setup. The on-line EMS results are compared to DP, which provides reference results. Two indicators
11 are defined in order to quantify the consumption performance on one hand, and the state of energy (SOE) sustaining performances
12 on the other hand.

13 To obtain a relevant assessment of the EMS performance, this study uses a large number of driving cycles representative of real
14 world operational conditions, and not only certification type cycles as it is usually done. To limit operating expenses, the vehicle's
15 owner is basically interested in minimizing his fuel consumption not for a single standard route, but for a global use, including
16 multiple itineraries. For instance, commuting from home to work is a typical use which shows daily differences due to changing
17 traffic conditions. This naturally leads to base the EMS assessment on a large statistical study. To the best of our knowledge, this
18 statistical approach, closely taking account of real world use, is novel and differs from earlier studies focusing only on certification
19 driving cycles. Hence, this paper provides an improved understanding of the EMS performance and permits to offer suggestions for
20 possible improvements.

21 The main highlights of the present contribution are:

- 22 1. A statistical assessment of two pure on-line EMS regarding real-life use based on a very large number of trials (thousand).
23 To this end, a Markov chain model is used to generate random but realistic powertrain power profiles.
- 24 2. The development of a new methodology to carry out this comprehensive study. Pure DP provides an absolute reference,
25 against which each real-time EMS is compared. Two performance indexes are also derived from the analysis of the customer
26 expectations.
- 27 3. The results clearly show that real-life performances may strongly differ from the certification cycle one. From that
28 perspective, SDP proves to be a very attractive on-line EMS.

1 4. More generally, any on-line EMS approach should be evaluated using such statistical analysis in order to significantly
2 account for the future user experience.

3 The remainder of the paper is organized as follows. Section 2 presents the FC/SC hybrid system and its related model. In
4 Section 3, the energy management problem is stated. A short review of existing real time strategies is given and the tested ones are
5 presented. Section 4 describes the model experimental calibration and validates the DP benchmark result using a certification cycle.
6 Section 5 presents the performance criteria and discusses the performances of the tested EMS on a statistical basis. Section 6
7 concludes the paper and provides some perspectives for future work.

8 **2. FC/SC hybrid system description and modeling**

9 Our goal is to carry out a full-size test, representative of the real use of a FC/SC hybrid system. The rated power of the FC
10 system available in our lab is 800 W. Hence, we have chosen to conduct the present study with data corresponding to a low
11 power vehicle, namely a light urban scooter. Such vehicles are promising candidates for FC applications [9] in the city driving
12 context, in which pollution effects have a high impact in densely populated areas [40] [41]. This type of scooter operates at low
13 speed (< 50 km/h) and the urban part of the WLTC certification cycle dedicated to light vehicles provides a speed profile
14 representative of its use. We have verified that the corresponding power remains within the limits of our experimental system
15 (see section 2.D).

16 **2.A. System presentation**

17 The present work deals with the FC/SC hybrid system shown in Fig. 1, suitable for powering a full-hybrid urban electric scooter.
18 The considered architecture combines a FC system rated for the powertrain power demand and a SC pack sized for braking energy
19 recovery. The scooter traction power is fed by a DC electric bus, connected to the FC through a unidirectional boost converter. The
20 SC pack is connected in parallel through a bidirectional converter, so that it serves as an energy buffer between the FC and the
21 scooter wheel power.

22 Since this study focuses exclusively on EMS comparative assessment, the experimental test bench includes neither the electric
23 motor drive nor the mechanical transmission. The power load connected to the DC bus directly emulates the powertrain demand
24 while neglecting the various losses in the inverter, the motor and the transmission. Hence, the DC bus load is directly the scooter
25 drive wheel power demand P_{wheel} , calculated using the motion equation of the scooter and the driving cycle, as explained in
26 section 2.D. A bi-directional power load emulates the scooter traction power: in acceleration and constant speed phases, the hybrid
27 source supplies power to the load, while this returns power back to the FC/SC source during braking.

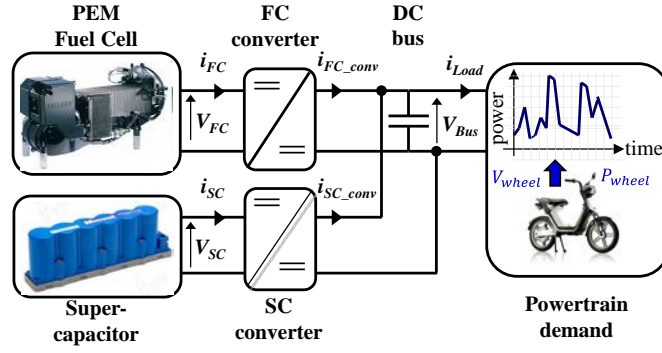


Fig. 1. Over-actuated system under study :
FC/SC EV scooter powertrain supply.

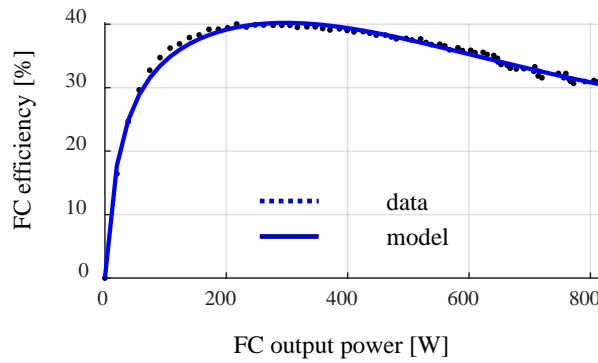
2.B. Component modeling

1) Fuel cell system

The main power source of the system is a 800 W proton exchange membrane FC. As it is operating at low frequency thanks to the energy storage system assistance, the FC is modeled using its static V-I characteristic [42]. The hydrogen chemical power P_{H_2} is expressed as a function of the FC system output electric power P_{FC} by fitting experimental data with a fourth-order polynomial. Then the hydrogen consumption rate is determined by (1), where HHV_{H_2} is the high heating value of hydrogen.

$$\dot{m}_{H_2} = \frac{P_{H_2}(P_{FC})}{HHV_{H_2}} \quad (1)$$

Fig. 2 shows the measured FC system efficiency and the modeled one. The FC system model gives a maximum efficiency for an output power around $P_{FC,opt} = 300 W$.



1 **Fig. 2.** FC system efficiency versus electric output power:

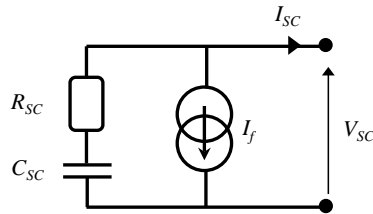
2 test data and model curve.

3
4 2) Supercapacitor stack

5 The SC pack is modeled as a RC circuit in parallel with an internal leakage current source which represents the losses due to the
6 active cell balancing technology used in SC pack [43], as shown in Fig. 3. For a given output current I_{SC} and output voltage V_{SC} ,
7 the internal capacitor is charged ($P_{SC_int} < 0$) or discharged ($P_{SC_int} > 0$) according to formula (2).

8
9
$$P_{SC_int} = R_{SC}(I_{SC} + I_{f_FC})^2 + V_{SC}(I_{SC} + I_{f_FC}) \quad (2)$$

10 The leakage current I_{f_FC} is expressed as a quadratic function of V_{SC} obtained by fitting experimental data measured in no load
11 condition.



24 **Fig. 3.** SC pack model.

25
26 3) Interface converters

27 The FC/SC hybrid system needs two DC/DC converters, both modeled as ideal converters connected in parallel with leakage
28 current sources that represent the converter internal losses. These losses are due to conduction and switching losses in the
29 semiconductor components, Joule losses in smoothing inductors and current ripples both in the filter inductance and DC bus filter
30 capacitor. The total losses are accurately measured using an opposition method described in [44].

31 The output current of the FC converter can be expressed by (3), where I_{f_conv} is the leakage current modeling power losses. It is
32 obtained by fitting the experimental data with a quadratic function of I_{FC} .

33
$$I_{FC_conv} = \frac{V_{FC} \cdot I_{FC}}{V_{Bus}} - I_{f_conv} \quad (3)$$

1

2.C. Power demand

3 The instantaneous power demand $P_{wheel} = F \cdot v$ depends on the vehicle speed and acceleration according to Newton's law (4):

4

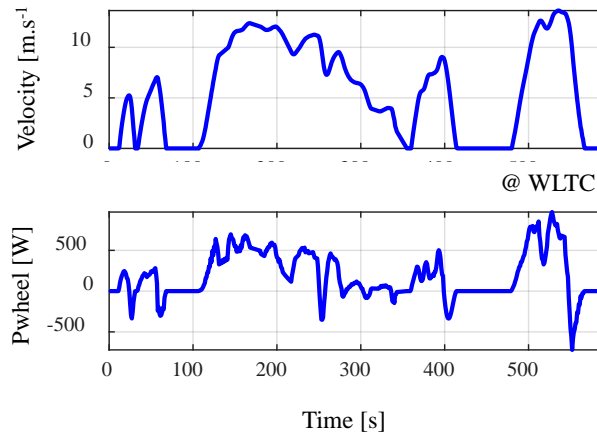
$$P_{wheel} = [0.5 \rho_{air} A C_d v^2 + \mu_r m g + m a] \cdot v \quad (4)$$

5

6 where ρ_{air} is air density; A is the vehicle reference area; C_d is the drag coefficient; μ_r is the rolling resistance coefficient; m is the
7 vehicle mass; g is the gravitational acceleration; v and a are the vehicle velocity and acceleration, respectively.

8 The present study is based on a standard driving cycle: the Worldwide Harmonized Light Vehicles Test Cycles (WLTC),
9 dedicated to low power motorcycles [45], and shown in Fig. 4. The current report uses it as a calibration driving profile. Its statistical
10 characteristics are used to generate various random profiles for sensitivity analyses.

11



12

13 **Fig. 4.** WLTC speed profile (a)

14 and related scooter traction power P_{wheel} (b).

15

16 2.D. Overview of the FC/SC hybrid system and its overall control system

17 Fig 5 shows the FC/SC hybrid system and its overall control system, subdivided into a power and an energy management control
18 parts. These two parts are organized in a hierarchical way. At the upper level, the EMS (purple box) monitors the SC pack state and
19 generates the FC system power set point (P_{FC}^*) according to the embedded algorithm, while matching the FC system and SC pack
20 constraints. The EMS algorithms are described in Section 3. Simultaneously the overall control system provides the load power
21 demand ($P_{load}^* = P_{wheel}^*$) according to the pre-recorded mission profile. At the intermediate level (red box), the DC bus voltage is

regulated at its 50 V constant set point by acting on the SC power (P_{SC}^*). Two low-level controllers (green boxes) enable controlling the FC system and SC pack powers by acting on the DC/DC converter duty cycles (d_{FC} and d_{SC}).

At all times a wide range of (P_{FC} , P_{SC}) couples can provide the powertrain demand, leading to a control allocation problem. The overall control system continually controls the power split between the FC system and the SC pack. To arbitrate between all possible solutions, it utilizes both the SC pack voltage, enabling to estimate the SC SOE, and the load power as inputs. This information is used by the EMS to compute its output, namely the instantaneous FC output power. Simultaneously, the low level controllers manage the voltage and current in the different parts of the system. Specifically, the SC power is controlled to achieve DC bus regulation, i.e. the combined sources permanently provide the powertrain required power [45].

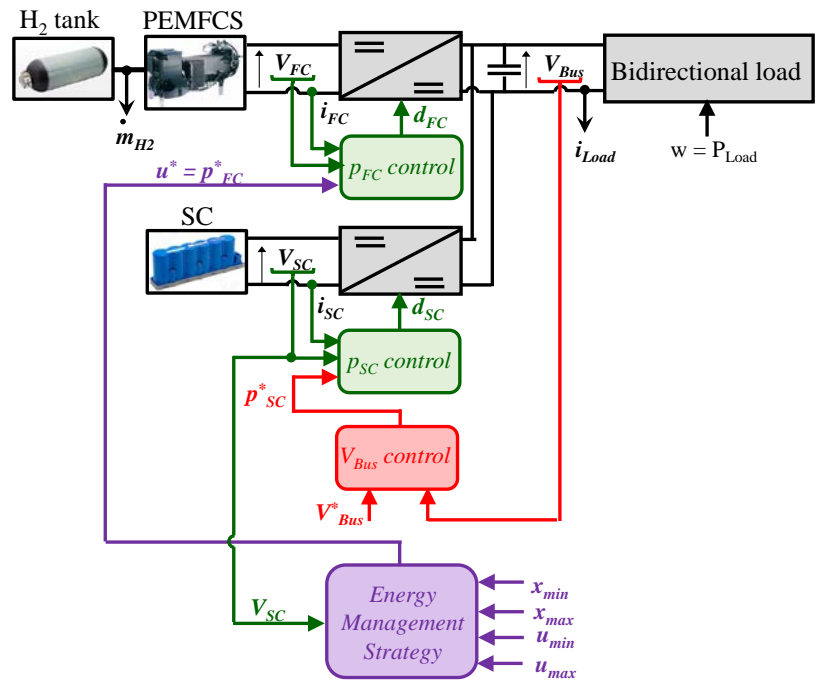


Fig. 5. Overview of the FC/SC hybrid system and its overall control system

3. Online energy management methods studied

3.A. Optimization problem statement

As depicted in Fig. 1, the powertrain demand is supplied by the DC bus, which is powered by two electrical sources, the FC system and the SC pack. This means that there are an infinite number of possibilities as to how to split the power between the sources and provide the instantaneous required power. This degree of freedom can be used to optimize a criterion. Clearly, a relevant criterion would be the fuel consumption during a defined route.

In this context, the EMS aims at minimizing the core cost criterion given by equation (5). In equation (5), t_0 and t_f are the initial

and final moments while the control variable $u(t)$ is the electric power $P_{FC}(t) = V_{FC}(t) \times I_{FC}(t)$ delivered by the FC system. The SC power is then defined to ensure the instantaneous DC balance. The whole system dynamics is modelled by the state equation (6). In this equation, the unique state variable is the energy stored in the SC pack, denoted by $x(t)$ and referred to as state of energy (SOE), whereas $w(t)$ stands for the powertrain demand P_{wheel} which acts on the DC bus as an external perturbation. This perturbation is known in advance in the case of off-line tests, using certification driving profile for example. In real-life cases, $w(t)$ is unknown but some of its characteristics can be estimated if route and traffic conditions forecast are available. This hypothesis is perfectly credible considering the rapid progresses of advanced driver-assistance systems in actual and future connected vehicles.

As well as optimizing such criteria, the EMS has to ensure the integrity of each of the system components: the different operating variables must remain within the specified limits of the devices. This results in the three inequality constraints listed in equations (7) to (9).

Finally, the difference between the final and the initial SC SOE has a great impact both on the global hydrogen consumption and on the capability to efficiently enable a new driving mission. To simplify consumption comparison between different EMS algorithms and to enable an easy sequence of driving cycles, the present study considers the standard charge sustaining strategy described by equation (10).

To sum up, the EMS optimization problem is formalized by the set of six equations (5) to (10).

$$\text{Minimize } J = \int_{t_0}^{t_f} \dot{m}_{H_2}(u(t)). dt \quad (5)$$

$$\dot{x}(t) = f(u(t), x(t), w(t)) \quad (6)$$

$$x_{min} \leq x(t) \leq x_{max} \quad (7)$$

$$\dot{x}_{min} \leq \dot{x}(t) \leq \dot{x}_{max} \quad (8)$$

$$u_{min} \leq u(t) \leq u_{max} \quad (9)$$

$$x(t_f) = x(t_0) = x_{ref} \quad (10)$$

3.B. Energy management strategies review

The optimization problem is different in nature, depending on whether the perturbation $w(t)$ is known ahead of time or not.

The first approach applies to situations where the driving cycle is known, typically for system design or system and EMS certification. This problem is addressed by two methods that have been developed and experimented in many dynamic systems for which various combinations of devices permit to ensure the requested output trajectory. The first one was created by the Russian

1 mathematician Pontryaguin [18, 19]. It uses Lagrange multipliers, referred to as co-state $p(t)$, to integrate the system dynamics in
2 the cost criterion minimization. Then the PMP is used, relying on the Hamiltonian minimization. The second method, DP combines
3 mathematics and computer science [21-24, 47]. This is a typical sampled approach both in time and in state. In this discrete
4 framework, the DP technique consists in both exploring a search tree and limiting the combinatorial explosion by subdividing the
5 initial problem in many smaller problems. This approach intrinsically enables to directly use the state and control constraints defined
6 in equations (7)-(10). Despite a higher computation cost than PMP, DP is used in this study in order to establish a benchmark for
7 each of the experiments (see section 5.A).

8 The second approach deals with real-life operation where the mission profile is clearly unknown in advance. In this much more
9 challenging configuration, the EMS still has to define the best control law permitting to minimize the cost criterion defined by
10 equation (5). This is still an open problem, although many authors have proposed sub-optimal strategies. The major real-time EMS
11 can be divided into three categories: rule-based strategies, instantaneous optimization of an equivalent fuel consumption accounting
12 for the ESS power flux and global optimization based on dynamic programming.

13 Rule-based strategies are attractive due to their relative simplicity of implementation. Some authors propose heuristic rules that
14 define the FC system power according to the load power and the quantity of energy available in the ESS [48, 49, 50] including
15 those using fuzzy logic [51, 52]. However, evaluated on engineering common sense, it seems these strategies cannot guarantee an
16 optimal solution. Furthermore, they require long calibration periods which cannot easily be transferred from one system to another.
17 For those reasons, rule-based strategies are not considered in this comparative work.

18 The second approach is based on the equivalent consumption concept, derived from PMP [25, 26]. The equivalent consumption
19 minimization strategy (ECMS) minimizes an instantaneous equivalent fuel consumption. The key to this strategy is an equivalence
20 factor, representing the equivalent hydrogen consumption of the SC pack power. For an off-line optimization, its instantaneous
21 optimal value can be evaluated by PMP [18-20]. The latter is not applicable to real world systems since the driving cycle cannot be
22 known in advance. To overcome this difficulty and allow useful but sub-optimal behavior, several pragmatic methods have been
23 developed to adapt the equivalence factor. These are mainly based on ESS evolution [25-30]. The current work focuses on the
24 popular technique developed by Onori et al. [27], known as Adaptive Equivalent Consumption Minimization Strategy (A-ECMS).

25 DP is not only able to give the optimal strategy as a benchmark but also has the capability to deal with the on-line optimization
26 problem by integrating a statistical model of the real-world driving conditions. In this instance, the strategy is then called stochastic
27 dynamic programming (SDP) [31-35]. The perturbation $w(t)$ modeling the driving cycle is considered as a random variable with a
28 given probability law. The driving cycle prediction can be carried out either by a normal distribution of the vehicle speed as in
29 previous work [35], or closer to reality, by Markov chains [31, 53, 54]. SDP can be applied to on-line problem, provided that

1 statistical knowledge of the load power profile is available. This method adds complexity because at each time step and each state
 2 level many perturbation values may occur, weighted by their occurrence probability. On the other hand, it provides a framework to
 3 account for such statistical knowledge. SDP enables the creation of a control law which is optimal in an average sense, i.e. when
 4 many profiles are successively operated.

5 The present work aims at assessing both A-ECMS and SDP online EMS by evaluating their performances over a large number
 6 of random driving cycles with identical statistical characteristics. The idea is to establish if the complexity of SDP is worth it when
 7 facing real and hence random conditions.

9 3.C. A-ECMS strategy

10 A-ECMS is a continuous time technique derived from the Lagrange multipliers concept applied to equations (5) to (10). At all
 11 times t , the optimal control denoted $u^*(t)$ is obtained by minimizing the sum of the actual hydrogen consumption \dot{m}_{H_2} and a
 12 hydrogen cost $p(t)$ relative to the use of storage, as stated by equation (11).

$$\begin{aligned}
 \forall t, u^*(t) = \arg \min_u [& \dot{m}_{H_2}(u) \\
 & + p(t) \cdot \dot{x}(u, x(t), w(t))]
 \end{aligned}
 \tag{11}$$

14
 15 The parameter $p(t)$ represents the equivalent hydrogen cost of the power provided by the supercapacitor. It controls the power
 16 split between the FC system and the SC pack, and hence the SC SOE during the whole trip. A-ECMS relies on a feedback loop that
 17 controls the value of p so as to keep the SC SOE around a reference value x_{ref} defined by the user. In the present paper, the popular
 18 Onori's algorithm [55] is used: it combines a second-order low-pass filter and a proportional term representing a charge sustaining
 19 constraint. The value of the equivalent cost p is periodically adjusted according to equation (12). Clearly, real A-ECMS
 20 implementation in a microprocessor needs to use a discrete time technique. In this article the sampling time T_S is fixed at 1 s both
 21 for A-ECMS and SDP methods.

$$\begin{aligned}
 p_{k_{AECMS}} = \frac{p_{k_{AECMS-1}} + p_{k_{AECMS-2}}}{2} \\
 + K_p \cdot (x_{ref} - x_{k_{AECMS-1}})
 \end{aligned}
 \tag{12}$$

23
 24 A-ECMS has four parameters:

- the feedback sampling period of p , denoted $T_{AECMS} = N_{AECMS} \cdot T_S$, which is a multiple of the basic sampling period T_S and enables tuning the filter cut-off frequency. Note that $k_{k_{AECMS}}$ is the index of the sub-sampled variables,
- the proportional gain K_p ,
- the two initial conditions of the filter p_0 and p_1 .

Equation (11) alone cannot account for the operational state constraints (7). Hence, the two heuristic rules (13) and (14) supplement it.

$$\text{if } x(t) > x_{max}, u^*(t) = 0 \quad (13)$$

$$\text{if } x(t) < x_{min}, u^*(t) = u_{max} \quad (14)$$

3.D. SDP strategy

1) SDP Principle

In contrast to A-ECMS, SDP is a discrete-time process, with a sampling period denoted T_S hereafter. Within the formal framework of DP, SDP takes into account the random disturbance $w(t)$ as a random variable modeled using statistical information. Even if it is subject to uncertainty, the forthcoming itinerary can be analyzed using standard navigation aid systems. Extracting certain route macroscopic characteristics may help to take relevant decisions at all time. The optimization formal framework is the following:

$$\text{Minimize } J = \sum_{k=0}^{N-1} E_{w_k} [\dot{m}_{H_2}(u_k)] \cdot T_S \quad (15)$$

$$x_{k+1} = x_k + f(u_k, x_k, w_k) \cdot T_S \quad (16)$$

$$x_0 = x_N = x_{ref} \quad (17)$$

$$x_{min} \leq x_k \leq x_{max} \quad (18)$$

$$\Delta x_{min} \leq x_k - x_{k-1} \leq \Delta x_{max} \quad (19)$$

$$u_{min} \leq u_k \leq u_{max} \quad (20)$$

Where 0, k and N are the initial, current and final time steps indexes, respectively. w_k is a random power variable described by a probability law. SDP specifically addresses the cost J as a mathematical expectation, as set by (15), where $E_{w_k}[\cdot]$ represents the

1 mathematical expectation with respect to w_k probability law.

2 SDP consists in a recursive process (21)-(22) where $u_k^*(x)$ denotes the optimal control at time t_k as a function of the current
3 system state $x_k = x$ and the cost-to-go function $J_k(x)$ which is also defined at each time step t_k . $J_k(x)$ represents the minimum
4 average cost from a given state x at time t_k to the final state x_N . It is expressed by equation (21), showing that it is computed
5 backwards similarly to the optimal control value. The whole backward process from final state to initial one is computed off-line
6 and the command matrix $u_k^*(x)$ is stored for latter use. This part of the algorithm uses significant processing power since it considers
7 any power in any state at any time.

8

$$J_k(x) = \min_u \{E_{w_k} [P_{fuel}(u) + J_{k+1}(x + f(u, w_k) \cdot T_S)]\} \quad (21)$$

$$u_k^*(x) = \operatorname{argmin}_u \{E_{w_k} [P_{fuel}(u) + J_{k+1}(x + f(u, w_k) \cdot T_S)]\} \quad (22)$$

9

10 Conversely, the forward procedure simply consists of choosing at each time t_k the optimal control policy u_k^* corresponding to
11 the current state x_k and given by the command matrix $u_k^*(x)$ previously stored. This step can be easily implemented in real-time
12 and only needs to read the database previously established offline. The single limitation is the downloaded data volume of the
13 $u_k^*(x)$ look-up table.

14

15 2) Driving cycle modeling

16 SDP provides an interesting framework, but the quality of the results relies on the quality of the random process model. In the
17 present work, two methods are tested.

18 The first one models the driving cycle by a random wheel power. An empirical probability law is calculated using the
19 P_{wheel} histogram of the selected reference cycle. Fig. 6 shows the probability law obtained for the WLTC cycle, and to be used for
20 any driving cycle with identical statistical properties. This model is very easy to implement in the SDP algorithm, but its accuracy
21 is limited, since the power values at successive time steps are assumed to be independent.

22

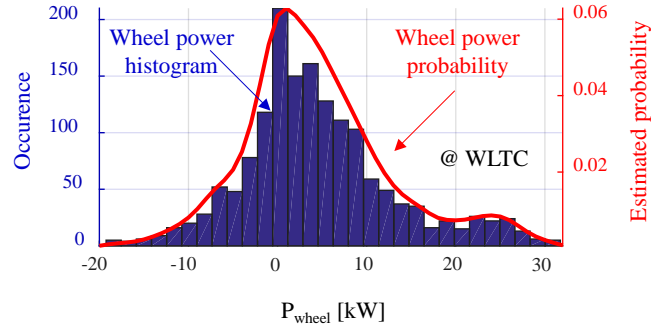


Fig. 6. P_{wheel} histogram and corresponding empirical probability law calculated for the WLTC scooter cycle.

The second model allows a richer statistical description of the driving cycle. It is based on two-dimensional Markov chains [55, 56]. As in [57], the power demand P_{wheel} at a given time step t_{k+1} is assumed to depend on both P_{wheel} and the scooter speed v^k at t_k . The probability that P_{wheel}^k is equal to a certain value P_l at time t_{k+1} , knowing that at time t_k the speed was v_i and the power was P_j is determined by the maximum-likelihood estimation (21):

$$\begin{aligned}
 P(P_{wheel}^{k+1} = P_l | v^k = v_i, P_{wheel}^k = P_j) &= p_{ij,l} \\
 &= \frac{m_{ij,l}}{m_{ij}}
 \end{aligned}
 \tag{21}$$

where $m_{ij,l}$ is the number of times the transition from P_j to P_l has occurred at v_i and m_{ij} is the total number of transitions that are initiated from P_j at v_i . A reference driving cycle is used to calculate transitions matrices at different speeds, and Fig. 7 shows the result obtained with the WLTC scooter cycle at the specific $6 \text{ m} \cdot \text{s}^{-1}$ speed.

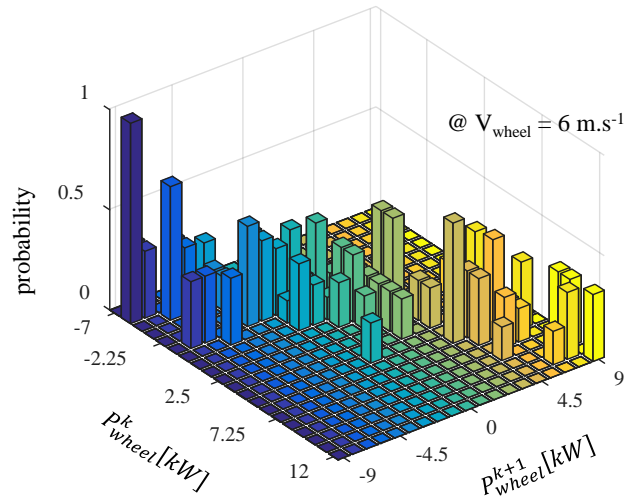


Fig. 7. Transition matrix for $v_{wheel} = 6 [m.s^{-1}]$.

4. Experimental setup and model calibration

As described above, the control laws related to either the off-line strategy (i.e. DP technique) or the various online approaches (i.e. A-ECMS and both SDP methods) require the best possible knowledge of the FC/SC hybrid system behavior. In order to realize a relevant study, a proper validation of the proposed model outlined in Section 2 is therefore required.

For this purpose, an experimental system has been implemented in the laboratory (Fig. 8). The hardware part is composed of a 800 W FC system, a 32 V/50 kJ SC pack and two identical 20 kHz buck-boost converters combined with voltage and current sensors. This electrical system is operated from a DS1103 DSPACE real-time control system. It ensures EMS as well as safety functions, fast loops to drive the power converters, and slow loops to achieve a constant DC bus voltage, as described in section 2-D. All programs are developed using Matlab/Simulink software and then compiled and loaded into the DSPACE system, which permits simple and fast prototyping.

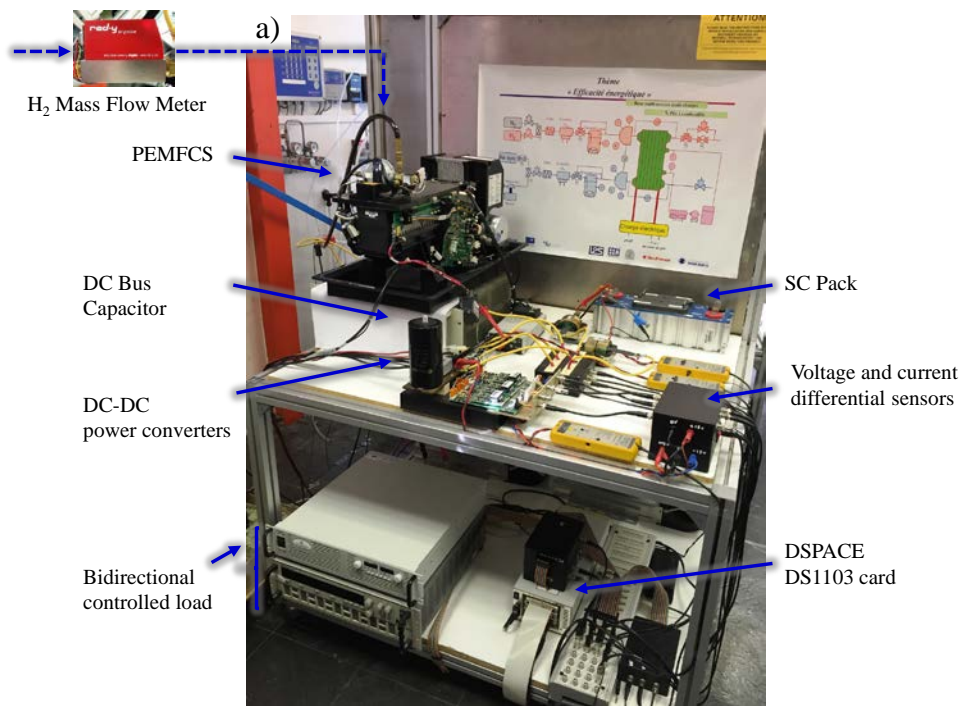


Fig. 8. Laboratory experimental setup of the FC/SC hybrid system

All components have been tested individually. For the sake of simplicity, Fig 9 shows the global response of only the main system variables; the setup is operated using the WLTC cycle and using the DP approach (EMS block in Fig. 5). Throughout the ten minute operation, the control board imposes the FC system power while the inner loops ensure at all times the accurate balance of the DC bus voltage (bus voltage control and source power control blocks in Fig. 5). As a consequence, the SC pack energy fluctuates while respecting its requirements (see equations (16) and (17)). The same experiment is replicated in pure simulation. Both trials exhibit close results as comparative Fig 9 shows. It synchronously depicts the instantaneous hydrogen consumption $\dot{m}_{H_2}(t)$ and the SC SOE $x(t)$. This leads to the conclusion both that the model is well calibrated and that the system management as well as the DP computation are correctly designed and implemented. This last point is particularly important since DP method is used as the benchmark of all following tests.

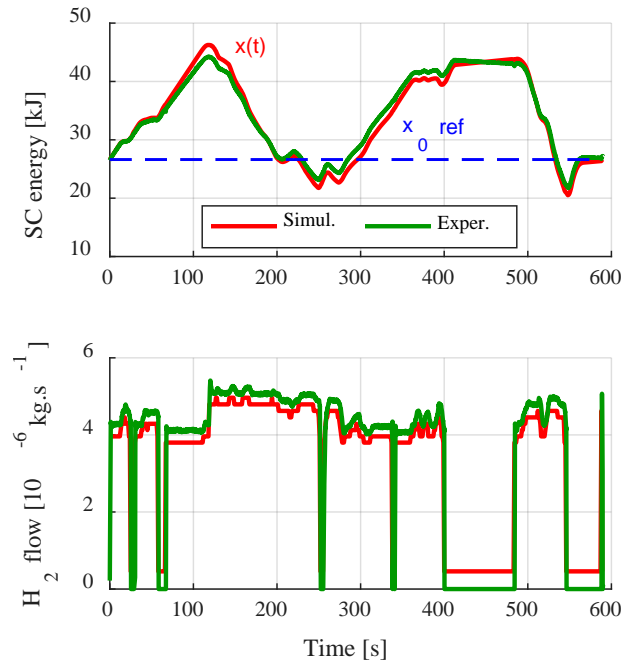


Fig. 9. Comparison between simulation and experimental results: SC stored energy and FC system H₂ mass-meter flow.

5. EMS assessment results

In the present section, the three studied real-time EMS are implemented and assessed: A-ECMS and two versions of SDP, referred to as “Classic-SDP” and “Markov-SDP” according to the $w(t)$ statistical model used. The former is based on modeling the driving cycle by a simple power demand probability density, whereas the latter relies on a finer statistical knowledge of the load profile modeled as a Markov process (see section 3.D.2). The assessment criteria are carefully defined and justified. Subsequently, the three EMS are calibrated using the WLTC certification driving cycle and their performances are compared in this context. Finally, the EMS are operated with a large set of random cycles generated by a Markov chain process, in order to evaluate the robustness of the various approaches facing real-life situations.

5.A. Performance criteria

This study focuses on the EMS strategies comparison for a given power architecture. To this end, two performance criteria are defined: the over-consumption with respect to an ideal EMS (namely DP) and the difference between the final and initial states. Indeed, as stated in equation (5), the primary goal of any strategy is to achieve the lowest fuel consumption on a specified trip, but

1 the control of the final SC SOE is also an important point in order to insure that the vehicle will be ready for the trip to follow.

2 The optimization problem has been stated with the charge-sustaining constraint expressed by equation (10). This constraint
3 insures that the FC system consumption exactly and solely corresponds to the energy needed for traction, with no energy stored or
4 coming from the SC pack. This condition is compulsory if one wants to compare the consumptions of different off-line strategies.
5 In the case of real-time strategy, the final SC SOE cannot be exactly controlled: each strategy ends up with its own final SOE,
6 making it impossible to directly compare their fuel consumption.

7 Hence, to allow the comparative investigation, the proposed novel approach defines an over-consumption criterion that compares
8 the actual fuel consumption of a given EMS with the optimal one, obtained using DP for the same initial and final SC SOE. This
9 ideal consumption is computed afterward, when the final SC SOE of the tested EMS is known. The over-consumption criteria
10 ΔJ (%) is defined by equation (22), where $J_{H_2}(RT)$ denotes the consumption obtained by the tested real-time strategy (RT = A-
11 ECMS or SDP) and $J_{H_2}(DP)$ denotes the optimal consumption, calculated afterward by DP for the same initial and final SC states
12 of charge. By definition, this factor is positive.

$$\Delta J (\%) = \frac{J_{H_2}(RT) - J_{H_2}(DP)}{J_{H_2}(DP)} \times 100\% \quad (22)$$

14
15 The over-consumption with respect to an ideal EMS is the first key criterion. On the other hand, it is also crucial that the on-line
16 EMS should be able to respect the charge-sustaining constraint as well as possible. For this reason, the second criteria, denoted Δx ,
17 intends to assess in relative terms the EMS capacity to achieve the final state objective. Δx (%) is defined as the SOE difference
18 factor, given by equation (23).

$$\Delta x (\%) = \frac{x(t_f) - x(t_i)}{x(t_i)} \times 100\% \quad (23)$$

19
20
21 The Δx criterion quantifies how well the charge-sustaining constraint is respected. A state-difference close to zero indicates that
22 the strategy is likely to perform well when applied to a longer mission (e.g. several cycles in a row).

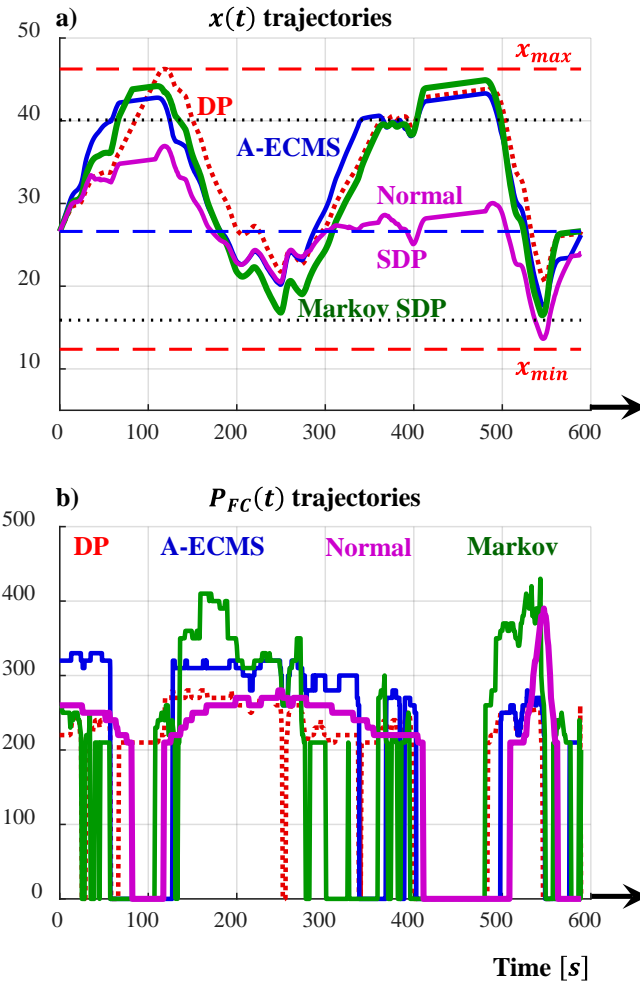
23 **5.B. Tuning the EMS using the WLTC driving cycle**

24
25 The first test to assess the online EMS performances is to tune them using a given cycle (WLTC in the present case) and compare
26 their performance criteria in these conditions. For the A-ECMS, the tuning phase consists in determining the four parameters that

1 allow the best performance for the considered cycle, using a genetic optimization algorithm [43, 58]. For SDP, the WLTC data are
 2 used to build empirical probability laws. This well-defined tuning procedure is an interesting feature of SDP. An intermediate initial
 3 SOE x_{ref} is chosen, which gives the EMS a great degree of freedom, to either charge or discharge the SC pack. The influence of
 4 this choice was discussed in a previous work [59].

5 Fig. 10-a) shows the SC state evolution $x(t)$ obtained with the tested real-time control strategies and the reference one (i.e.
 6 optimal off-line DP) while Fig. 10-b) plots the four FC system powers in accordance with the SC state evolution. Table 1 reports
 7 the proposed performance indexes of the three EMS.

8



9

10

Fig. 10. Online EMS and DP simulation results:

11

a) SC pack energy profile.

12

b) FC system power profile.

13

TABLE 1. Performance criteria for the WLTC

Strategy	A-ECMS	Classic-SDP	Markov-SDP
ΔJ (%)	1	1	2
Δx (%)	2	0	-9

The three methods perform rather well; among them Markov-SDP seems to reach lower performances than the two others.

Indeed, A-ECMS and Classic-SDP results are close to the DP benchmark ones. Both have a 1% over-consumption and a final SOE very close to the initial one, 2% and 0% respectively. This in fact indicates that the parameters of the A-ECMS method, namely the gain K_p and the initial co-state values p_0 and p_1 , have been carefully adjusted to address the specific standard certification driving profile. This setting can be seen to be relevant for this calibration. However, its robustness with regard to real-life load cycle uncertainties has to be assessed.

Conversely, as a global optimization method, SDP methods use a statistical approach to predict the upcoming driver demand and calculate an average optimal control law based on this information and the actual SC SOE. Hence, these strategies minimize the hydrogen consumption in an average sense, rather than on some particular cycle. In the case of SDP, the certification cycle, which represents a typical motorcycle use is used to derive statistical characteristics. The so-called ‘‘classic’’ statistical modeling, based simply on a probability density whatever the actual speed v^k or power demand P_{wheel}^k , seems to have the best performance among the three methods. On the other hand, Markov-SDP establishes in a more realistic way how the future power demand P_{wheel}^{k+1} may evolve using the current information, which should make sense. For instance, an instantaneous high power demand P_{wheel}^k at low speed v^k indicates a strong acceleration of the driver, making a future negative power P_{wheel}^{k+1} quite unlikely. Based only on the WLTC calibration profile, the Markov-SDP over-consumption factor (+2%) is an acceptable outcome, while its SOE difference factor is, as an absolute value, higher (9%) than the two other competitors, and especially the other statistical based method, Classic-SDP (0%).

In summary, these preliminary results are best interpreted as both indicating a correct implementation of the three methods and a precise setting of their parameters. On the basis of this first analysis, it appears that an additional sensitivity analysis is the only way to assess the comparative performances regarding real scooter utilization. The latter is subject to large uncertainties. Typically, the end user requires both to make a good return on investment, which is a long-term goal, and to minimize surprises and problems regarding the vehicle range, which is a crucial mid-term aim.

This is why this second analysis requires a large number of tests. To speed up the process, it is performed using the validated simulation tools.

5.C. Robustness assessment by statistical analysis

The main disturbance affecting the real-time EMS results is the power demand uncertainty. It is necessary that the embedded EMS deals with those variations in the real-world driving conditions and that the fuel consumption remains low in any conditions. In the present section, statistical tests are conducted in order to assess the EMS robustness.

The stationary Markov model described in section 3.D.2 is exploited to generate random cycles with statistical characteristics identical to the WLTC [38]. One thousand random cycles are generated and the three EMS are applied to each of them, the setting parameters calculated in the previous section being unchanged [39]. DP is applied to all generated profiles enabling to compare the optimal FC system power profile with those defined in real-time. The resulting performance criteria are calculated and the corresponding histograms are shown in Fig. 11 and Fig. 12. Their mean value (Mean) and standard deviation (Std dev) are reported in Table 2; the former is representative of return on investment concern, while the latter is a good indicator of the risks of a temporary deterioration in the vehicle's range. It should be noted that this number of cycles was chosen after checking that it is sufficient to obtain significant results and draw conclusion on the sensitivity analysis, as it will be shown thereafter.

The over-consumption criterion shows significant disparities among the three tested EMS. Although the A-ECMS results in an average over-consumption (4%) a little higher (1.5) than the Markov-SDP one (2.6 %), its standard deviation is significantly higher. In a meaningful way, using the Markov-SDP improves this performance index by a 3.2 factor; this point is specifically relevant concerning the user experience. Indeed, even if rare, a fuel breakdown has a highly negative impact on the way the motorcycle is perceived. This good over-consumption performance represents the first benefit of the Markov-SDP approach.

The second main weakness of the A-ECMS is the drift of the final state. The parameters calculated using the WLTC cycle do not enable a good final state control for other driving cycles, although they are of similar nature. The A-ECMS Δx histogram (Fig. 12) presents a large number of occurrences around $\Delta x = 55\%$. This indicates that the SOE often drifts to the upper limit of the SC pack capacity. From the perspective of the control of final SC SOE, SDP approaches prove to be much better than A-ECMS strategy. As for the previous criterion, Markov-SDP exhibits the best Δx characteristics with a 5.2 times better mean value and a 7.5 times better standard deviation value than those of A-ECMS.

SDP performance relies on the adequacy of the vehicle power demand probability distribution to predict the future driving conditions. That makes Markov-SDP the most robust real-time strategy in the present context.

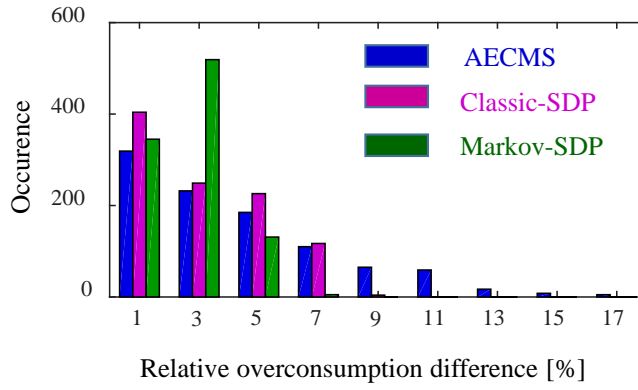


Fig. 11. Over-consumption ΔJ histogram for 1000 random cycles.

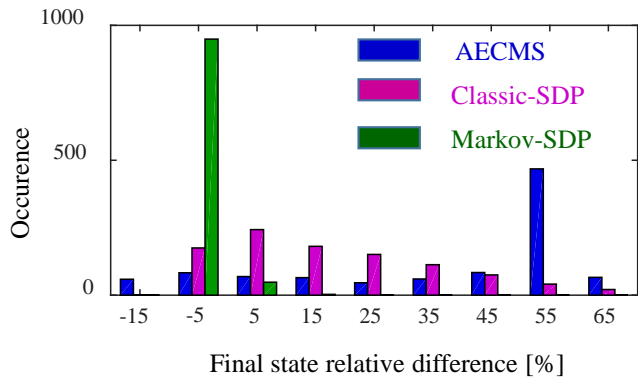


Fig. 12. Δx histogram for 1000 random cycles.

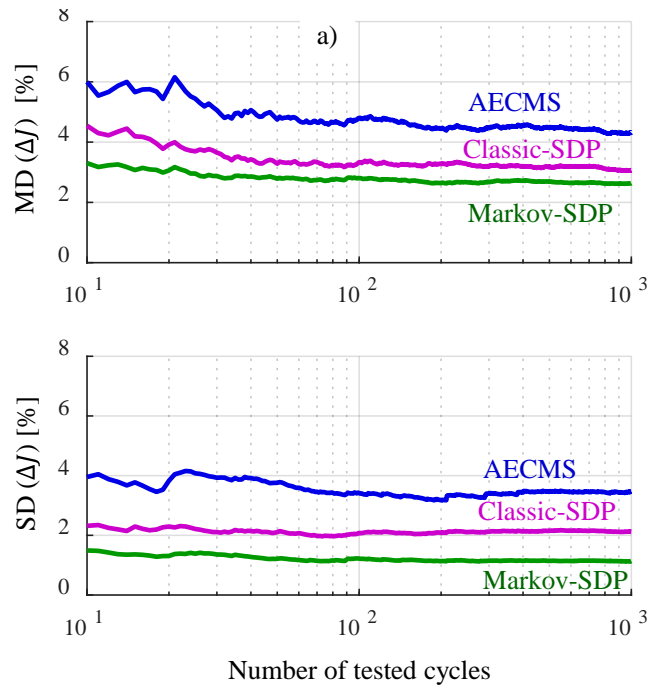
TABLE 2. Statistical analysis of the performance criteria

		A-ECMS	Classic-SDP	Markov-SDP
ΔJ (%)	Mean	4.3	3.1	2.6
	Std dev.	3.5	2.1	1.1
Δx (%)	Mean	36.7	18.1	-7.1
	Std dev.	24.9	17.7	3.3

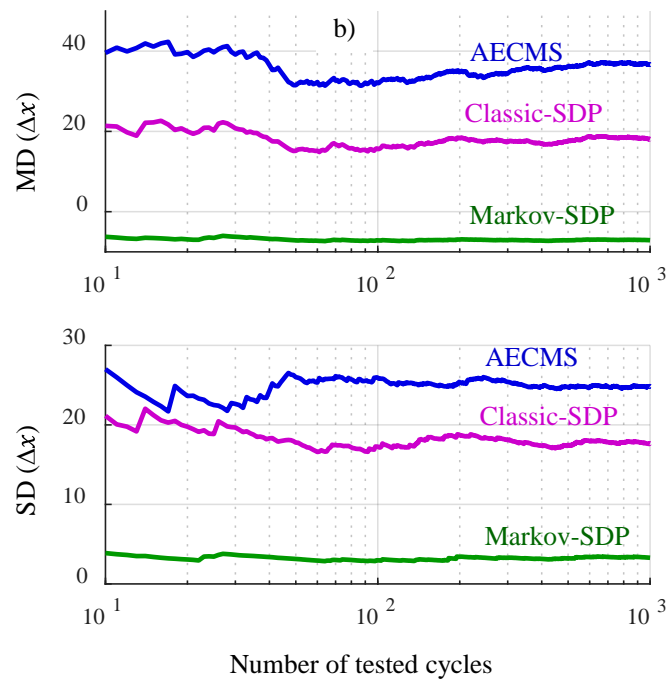
It is important to underline that the statistical study is based on a number of random cycles large enough to be statistically significant. This point is proven by Fig. 13(a) and (b), which represent the mean and standard deviation values calculated for an increasing number of random cycles. These statistical parameter tend to be stable after four hundred cycles, for both the over-

1 consumption and the state-difference. It confirms that a thousand cycles are sufficient to draw relevant conclusions on the sensitivity
2 analysis.

3



4



5

1 **Fig. 13.** EMS performance criteria mean and standard deviation (MD and SD) versus number of tested cycles

2 a) over-consumption factor ΔJ

3 b) SOE difference factor Δx

5 **6. Conclusion and perspectives**

6 This study focuses on methods that achieve a control allocation regarding a complete use cycle in hybrid power systems. Firstly,
7 this requires a dynamic system with redundant equipment, hence allowing to adjust in real-time their operating points in order to
8 increase the performance of the overall system. Secondly, this optimization only makes sense when considering a long time period.

9 The use case under consideration is a FC/SC electric scooter. In this case, the powertrain power can be delivered, at any time,
10 either by the FC system or the SC pack. The objective is to minimize the hydrogen fuel consumption on a chosen route. In contrast
11 to many previous works, the present paper considers pure on-line EMS strategies (namely A-ECMS, Classic-SDP and Markov-
12 SDP) and assesses their behavior regarding real-world use. This requires the development of a new methodology, which can then
13 be extended to other use-cases. The main contributions of this work are the following.

14 First, for a fair comparison, each EMS is carefully adjusted using the dedicated certification driving cycle. This requires a
15 preliminary modeling work of the global system under study. The EMS under test are implemented on the experimental setup and
16 shown to be working properly.

17 Secondly, after each test, an optimal consumption is calculated using a DP optimization applied to exactly the same conditions:
18 identical load profile, but also equal initial and final SC states of charge. This provides an absolute reference, against which each
19 real-time EMS is compared.

20 Thirdly, two performance indexes have been derived from the analysis of the user's expectations. The first index deals with the
21 return on investment closely linked to the global consumption reduction. The second index addresses the EMS capacity to efficiently
22 undertake the subsequent driving cycles.

23 Fourth, the assessment of each EMS is carried out by simulation based on verified modeling. It enables dealing with a large
24 number of tests, which is mandatory for real life operation is concerned. The results are analyzed in terms of mean and standard
25 deviation of the over-consumption and final SOE criteria. This gives an accurate and comprehensive view of the statistical analysis.
26 The average value provides an overall outline, while the standard deviation indicates the probability of extreme undesired events,
27 such as a breakdown due to a lack of fuel.

28 Finally, the statistical analysis, as conducted on one thousand random cycles with identical statistical characteristics shows that

SDP methods give better results for both criteria used. Specifically Markov-SDP achieves the best performances: well centered results with the lowest standard deviations. Conversely, the A-ECMS proves very sensitive to its tuning parameters. Facing multiple varied cycles, it induces higher fuel consumption and very poor final SOE control.

In sum, the performance of the SDP behaviors make their relative complexity worth the effort. Among these methods, Markov-SDP is by far the most promising approach. On the contrary, the A-ECMS ease of implementation seems to be the single argument in favor of this technique. Future works should tackle both the issue of Markov-SDP off-line complexity and its need for need for on-line data storage resources.

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