Optimization-based energy management strategies for electric vehicles.

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***Abstract*—This article analyses three energy management strategies for an electric vehicle powertrain in order to maximize its global efficiency. The considered electric motor supply system is a multi-source system that consists of a fuel cell as a main energy source and an additional element that supplies peak power (at start-up and during fast transients) and charges by regenerative braking. Energy management is achieved by formulating an optimization problem, aiming to minimize the fuel cell hydrogen mass consumption while satisfying the system physical constraints (strictly positive fuel cell power, limited capacity of the storage element). First, the optimization is realized using dynamic programming, an off-line optimization method that requires the knowledge of the entire power load profile. Secondly, two on-line optimization approaches are used: the equivalent consumption management strategy and the model predictive control strategy, for which only the current power demand or its knowledge over a finite time horizon are demanded. The optimization strategies are tested in simulation using a power load profile that corresponds to an urban driving cycle.**

I. INTRODUCTION

The continuing increase of conventional energy consumption and the environmental concerns related to CO_2 emissions encourage the use of alternative energy, provided by electric power sources for example. In the automotive field, multi-source power supply systems have been considered for the propulsion system design of electric vehicles. An interesting choice for the primary power source is the fuel cell (FC) due to its high energy density [1]. However, the slow dynamics of the FC requires the use of a secondary storage element (battery, supercapacitor) capable to supply the power demand during the fast transients and to recover energy during the braking phase. In the literature, there are several possible architectures for multiple sources interconnection (series, cascade or parallel architecture) [2]. In this article, energy management strategies are investigated for a parallel architecture of an electric vehicle supply system.

Due to the presence of multiple energy sources (FC and secondary storage element), a supervision system for energy management is necessary to handle the energy flow and to optimize the system efficiency in terms of fuel consumption. Based on the power demand, the supervision system computes, at each sampling time, the power that each source has to supply. Generally, the energy management strategies (EMS) are divided in ruled-based (RB) and optimization-based strategies. The RB strategies - deterministic RB [3], fuzzy RB [4], [5] approaches - use if-then rules that require the definition of a large number of threshold values. The optimization-based strategies can be classified in off-line and on-line methods based on the knowledge of the power load profile. Usually, the EMS performances are evaluated using standard or real-world driving cycles.

Off-line methods consist in designing the optimization algorithm with the full knowledge of the driving cycle, and therefore, of the power demand. An optimization resolution using Pontyagin's minimum principle [6], which provides a local optimal solution, has been applied to reduce the fuel consumption and the CO_2 emissions for hybrid vehicles, using an internal combustion engine as primary source [7]. Also, dynamic programming (DP) has been used for energy management of hybrid [8], [9] and electric vehicles [10]. DP method [11] is based on the Bellman's principle of optimality and presents the advantage of providing necessary optimality conditions (global optimal solution) despite the substantial computational time. In addition to this, the real-time implementation is limited by the high memory capacity necessary to store the computed solution.

On-line strategies use the current power demand, without a prior knowledge of the driving cycle. Thus, these methods are suitable for real-time applications taking into account their low computational complexity. However, the optimization solution found at each sampling time represents a local optimal solution with respect to the power demand over the whole driving cycle. One of the methods employed in several studies is the equivalent consumption minimization strategy (ECMS) [12], [13] which has been applied on both electric [14] and hybrid [15], [16] vehicles. For electric vehicles, this strategy is based on the conversion of the electric power into equivalent hydrogen mass consumption of the FC. Another on-line method is represented by the model predictive control (MPC) that has been applied on electric vehicles for FC power optimization [17] and oxygen control [18]. The MPC strategy minimizes a cost function over a fine time horizon at each sampling instant, subject to model dynamics and constraints on the model inputs and states.

The objective of this article is to highlight the performances of two sub-optimal approaches (ECMS and MPC) in comparison to a reference optimal approach (DP), which provides a global optimal solution that cannot be exploited on an embedded system due to its high complexity. Thus, this article is organized as follows: Section II describes the model of the electric vehicle power supply system. In Section III, the optimization problem is formulated for different EMS: DP, ECMS and MPC. Section IV presents simulations results and an EMS comparison in terms of hydrogen mass consumption. Finally, conclusions and perspectives of this work are given in Section V.

II. Power Supply System Modeling

A parallel architecture of the multi-source system has been considered, which ensures a more effective power distribution control [2]. It consists on the connection of a fuel cell (FC) and a secondary storage element (SSE) to the DC link, using two DC-DC power electronic devices: a step-up converter and a bi-directional converter, as illustrated in Fig. 1. The presence of these auxiliary devices allows the DC voltage regulation that increases the system performance. Besides, from power optimization perspective, their conversion efficiency interferes in the power balance equation.

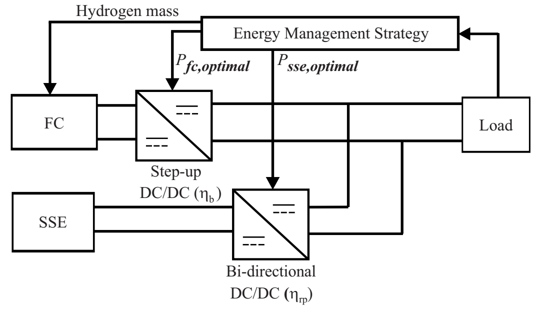

Fig. 1. Fuel cell/secondary storage element architecture

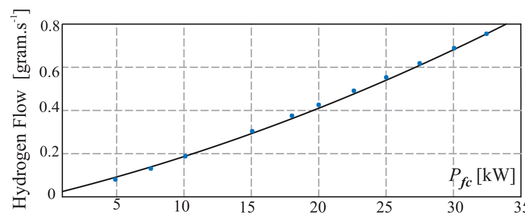

Fig. 2. Hydrogen flow ϕ_{H_2}: simulated values obtained using Pukrushpan's model (*), polynomial approximation (solid line).

A. Fuel cell model

The fuel cell is an electrochemical device that converts chemical energy into electrical energy through an oxidation reduction reaction between a fuel (hydrogen) and oxygen from air [19]. In this study, a polymer electrolyte membrane fuel cell (PEMFC) is considered, which is often used for automotive applications due to its properties: small volume and weight, high power density, low temperature allowing fast start-up. In fact, a FC system is used, composed principally of: stack, air compressor, hydrogen tank and humidifier [20]. An accurate but complex non-linear dynamic model of the FC system is the Pukrushpan's model. Based on this reference model and on the following hydrogen flow expression:

$$\phi_{H_2} = \frac{N_{cell} M_{H_2}}{n_{e^{-1}} F} I_{fc}(P_{fc}) \tag{1}$$

with: P_{fc} - the power produced by the FC $[\mathrm{kW}]$, N_{cell} - the number of cells, M_{H_2} - the hydrogen molar mass $[\mathrm{gram} \cdot \mathrm{mol}^{-1}]$, F - the Faraday constant $[\mathrm{C} \cdot \mathrm{mol}^{-1}]$, I_{fc} - the FC current $[\mathrm{A}]$, the instantaneous hydrogen flow values have been obtained for $P_{fc} \in [0, 35]$ kW. Subsequently, a static model of the fuel cell is determined by interpolation methods, in order to formulate and evaluate the proposed energy management strategies. Thus, the interpolation of the instantaneous ϕ_{H_2} values is approximated by the second order polynomial:

$$\phi_{H_2} = a_2 P_{fc}^2 + a_1 P_{fc} + a_0 \tag{2}$$

where: $a_2 = 0.0235$, $a_1 = 0.1535$, $a_0 = 0.0095$.

The interpolation yields the approximation of the static $\phi_{H_2} - P_{fc}$ characteristics illustrated in Fig. 2. The polynomial approximation from equation (2) is used in Section III to formulate the cost function for different optimization methods. As it concerns the FC dynamics, it is taken into consideration as constrains of the optimization problem.

B. Secondary storage element model

The scaled SSE state of energy is defined as: $SoE(t) = \frac{E_{sse}(t)}{E_{sse,max}}$, where $E_{sse}(t)$ represents the instantaneous energy stored in the SSE and $E_{sse,max}$ is the maximum energy capacity of SSE. The scaling is necessary to avoid numerical problems that might appear in the resolution of the optimization problems.

The dynamics of SSE is expressed in function of the power demand and the FC power, using the power balance equation, as follows:

$$\frac{dSoE}{dt}(t) = -\frac{P_{sse}(t)}{E_{sse,max}} = -\frac{P_{load}(t) - \eta_b P_{fc}(t)}{\eta_{rp} E_{sse,max}} \tag{3}$$

with: η_b, η_{rp} - the efficiencies of DC-DC step-up and bi-directional power converters used to interconnect the FC and the SSE to the DC link, P_{load} - the power demand, P_{sse} - the power supplied by the SSE.

Given the fact that the EMS in Section III are formulated in discrete time, the discretized dynamics of SSE is approximated by:

$$SoE(k+1) = SoE(k) - \frac{P_{load}(k) - \eta_b P_{fc}(k)}{\eta_{rp} E_{sse,max}} \triangle t \tag{4}$$

where $\triangle t$ is the sampling time.

Hence, concerning the energy management problem, the SSE choice (battery or supercapacitor) is not necessary at this stage of the study.

C. Vehicle model

The profile of the power demand is determined using the vehicle dynamics [21], which takes into consideration the speed variation, the losses due to rolling and to aerodynamic drag, and the gravity:

$$P_{load} = V[0.5\rho_{air}V^2SC_x x + M(g\sin(\alpha) + \frac{dV}{dt} + gC_r\cos(\alpha))] \tag{5}$$

with: M - the vehicle mass, V - the vehicle velocity, S - the frontal surface, C_x - the drag coefficient, α - the road slope, ρ_{air} - the air density, g - the gravity acceleration, C_r - the rolling resisting coefficient.

Generally, the velocity information comes from standard driving cycles or real-world driving cycles [6]. In this study, simulations of the proposed energy management strategies are performed using Artemis urban driving cycle [22], presented in section IV. This driving cycle provides an accurate representation of real driving conditions in urban environment.

III. Energy management strategies

The main objective of the energy management system is to optimize the power split between the fuel cell and the SSE while ensuring that the SSE state of energy at the end of the driving cycle, noted $SoE(T_{cycle})$, reaches the initial energy level $SoE(t_0)$. At the beginning of the driving cycle, the SSE is considered to be charged at a reference value SoE_{ref} and the optimization is performed by guaranteeing that the same energy level is achieved at the end of the cycle. The optimization implies minimizing the fuel consumption, represented by the hydrogen mass consumption of the fuel cell. Finally, the optimization solution yields the optimal power references $P_{fc,optimal}$ and $P_{sse,optimal}$ of the FC and SSE respectively.

A. Optimization problem formulation

In order to find the optimal FC power P_{fc}, the following discrete-time cost function is considered:

$$J = \sum_{k=t_0}^{T_{cycle}} \phi_{H_2}(k) \tag{6}$$

with ϕ_{H_2} defined in (1).

The minimization of the cost function J is done subject to constraints issued from the physical limits of the system. First, the FC power and the SSE power are bounded by min/max values noted: $P_{fc,min}$ (≥ 0), $P_{fc,max}$, $P_{sse,min}$, $P_{sse,max}$. Moreover, the FC power variation between consecutive sampling instants $\triangle P_{fc}$ is restrained in the range $[\triangle P_{fc,min}, \triangle P_{fc,max}]$. Secondly, the state of energy SoE is limited in the interval $[SoE_{min}, SoE_{max}]$. Consequently, the optimization problem to be solved is the following:

$$\min_{P_{fc}(k)} J \tag{7}$$

subject to: dynamics (4)

$$P_{fc,min} \leq P_{fc}(k) \leq P_{fc,max}$$

$$P_{sse,min} \leq P_{sse}(k) \leq P_{sse,max} \tag{8}$$

$$(\triangle P_{fc,min} + P_{fc}(k)) \leq P_{fc}(k+1) \leq (\triangle P_{fc,max} + P_{fc}(k))$$

$$SoE_{min} \leq SoE(k) \leq SoE_{max}$$

In the next subsections, three optimization strategies (DP, MPC and ECMS) are proposed to compute the optimal fuel cell power that minimizes the hydrogen consumption subject to SoE dynamics and the imposed constraints.

B. Dynamic programming

Dynamic programming involves the recursive resolution of the optimization problem (7)-(8) backwards in time, by applying Bellman's optimality principle [11]. Hence, considering the SoE dynamics defined in (4), the final value of the SSE energy $SoE(T_{cycle})$ will be equal to its initial value $SoE(t_0)(= SoE_{ref})$. Here, a graph's resolution [11] is adopted, which is elaborated in 3 steps.

• Step 1

An admissible space $\Omega(k)$ of $SoE(k)$ variations at each sampling instant is defined, that allows to minimize the computation time, without considering all possible values of $SoE(k)$ in the interval $[SoE_{min}, SoE_{max}]$:

$$\Omega(k) = \Omega_{min}(SoE)(k) : \triangle x : \Omega_{max}(SoE)(k) \tag{9}$$

where

$$\Omega_{max}(SoE)(k) = \max(SoE_{b,max}, SoE_{f,max}, SoE_{max}))$$
$$\Omega_{min}(SoE)(k) = \min(SoE_{b,min}, SoE_{f,min}, SoE_{min}))$$

and $\triangle x$ is the state space sampling step.

The forward and backward evolutions of SoE dynamics are calculated using the following relations:

$$\begin{cases} SoE_{f,max}(k+1) = SoE_{f,max}(k) - \min(\frac{P_{load}(k) - \eta_b P_{fc}(k)}{\eta_{rp}E_{sse,max}}) \\ SoE_{f,min}(k+1) = SoE_{f,min}(k) - \max(\frac{P_{load}(k) - \eta_b P_{fc}(k)}{\eta_{rp}E_{sse,max}}) \end{cases} \tag{10}$$

$k = 0 : T_{cycle} - 1$

$$\begin{cases} SoE_{b,max}(k) = SoE_{b,max}(k+1) + \max(\frac{P_{load}(k) - \eta_b P_{fc}(k)}{\eta_{rp}E_{sse,max}}) \\ SoE_{b,min}(k) = SoE_{b,min}(k+1) + \min(\frac{P_{load}(k) - \eta_b P_{fc}(k)}{\eta_{rp}E_{sse,max}}) \end{cases} \tag{11}$$

$k = T_{cycle} - 1 : -1 : 0$

• Step 2

The resolution algorithm, given by Algorithm 1, analyzes all the admissible trajectories of $SoE(k)$ inside $\Omega(k)$ and computes the optimal values of FC power. Once these values are determined for the whole driving cycle, they are stored in a look-up table. Also, an indices look-up table is obtained that allows to find the minimum cost trajectory inside the look-up table containing the optimal values of P_{fc}.

Algorithm 1. Dynamic Programming: off-line resolution

1. $N_t = \frac{T_{cycle} - t_0}{\triangle t}$;
2. **for** $k = N_t : -1 : 1$
3. $\Omega_k = \Omega_{min}(SoE)(k) : \triangle x : \Omega_{max}(SoE)(k)$;

$\Omega_{k-1} = \Omega_{min}(SoE)(k-1) : \triangle x : \Omega_{max}(SoE)(k-1)$;
$c_k \leftarrow length(\Omega_k)$;
$c_{k-1} \leftarrow length(\Omega_{k-1})$;
for $i = 1 : c_{k-1}$
for $j = 1 : c_k$
$cost(j) = \phi_{H_2}(i \rightarrow j) + cost_k(j)$
$cost_k(j)$ is the total cost that leads the state $SoE^j \in \Omega_k$ to the final value $SoE(T_{cycle})$
$\phi_{H_2}(i \rightarrow j)$ is the cost that leads the state $SoE^i \in \Omega_{k-1}$ to $SoE^j \in \Omega_k$
end for
Find minimum of $cost(1 : c_k)$ and save it on $cost_{k-1}(i)$
end for
end for

- Step 3

Using the indices look-up table and Algorithm 2, the optimal power sequence is found and applied to system (4).

Algorithm 2. On-line implementation

for $k = 1 : N_t$
Find $P_{fc,optimal}(k)$
Compute $SoE(k+1)$ using equation (4) and $P_{fc,optimal}(k)$
end for

C. Equivalent consumption minimization strategy

The principle of equivalent consumption minimization strategy (ECMS) derives from the conversion of the energy stored in the SSE into fuel consumption. The equivalence is made by introducing a positive conversion factor λ [$\text{gram} \cdot \text{J}^{-1}$]. Thus, the equivalent fuel consumption γ_{eq} is defined as:

$$\gamma_{eq}(k) = \phi_{H_2}(k) + \lambda P_{sse}(k) \tag{12}$$

Using the power balance equation:

$$P_{fc}(k) = \frac{P_{load}(k) - \eta_{rp} P_{sse}(k)}{\eta_b} \tag{13}$$

and the relation (2), the optimization problem minimizing γ_{eq} is formulated as follows:

$$\min_{P_{sse}(k)} \beta_2 P_{sse}^2(k) + \beta_1 P_{sse}(k) + \beta_0 + \lambda(k) P_{sse}(k) \tag{14}$$

with: $\beta_2 = a_2 \frac{\eta_{rp}^2}{\eta_b^2}$, $\beta_1 = -\frac{\eta_{rp}}{\eta_b}(2\frac{a_2}{\eta_b} P_{load} + a_1)$ and $\beta_0 = \frac{a_2}{\eta_b^2} P_{load}^2 + \frac{a_1}{\eta_b} P_{load} + a_0$.

The ECMS computes the instantaneous optimal value $P_{sse,optimal}(k)$ using the current value of the power demand, while $P_{fc,optimal}(k)$ is determined using equation (13). The choice of parameter λ influences the SSE charge and discharge processes over the driving cycle. In the literature, several approaches have been considered [23] to balance the SSE energy level during the cycle, such that the $SoE(k)$ lies between the boundary values and the same SSE energy capacity is obtained at the beginning and at the end of the cycle. Here, the conversion factor is chosen as a proportional controller $\lambda(k) = s_0 + s_1(SoE_{ref} - SoE(k))$ [23], where s_0 and s_1 represent equivalence factors. Their values are tuned in function of the driving cycle and usually are adapted to driving conditions (acceleration phase, breaking phase, road slope).

D. Model Predictive Control

Model predictive control (MPC) strategy consists in computing an optimal sequence of the input variable that minimizes a cost function over a finite prediction horizon N_p with respect to a prediction model and constraints imposed on the model input and states. The optimal sequence is determined at each sampling instant and according to the receding horizon policy, only the first element of the sequence is applied to the system. Then, the procedure is repeated using the updated state.

Let us define the extended state vector: $x_e(k) = [SoE(k), P_{fc}(k-1)]'$ and the fuel cell power variation between two successive sampling instants: $\triangle P_{fc}(k) = P_{fc}(k) - P_{fc}(k-1)$.

The state-space representation of the prediction model has the following expression:

$$\begin{cases} x_e(k+1) = A x_e(k) + B \triangle P_{fc}(k) + D P_{load}(k) \\ y(k) = C x_e(k) \end{cases} \tag{15}$$

with: $A = \begin{pmatrix} 1 & \frac{\eta_b \triangle t}{\eta_{rp} E_{see,max}} \\ 0 & 1 \end{pmatrix}$; $B = \begin{pmatrix} \frac{\eta_b \triangle t}{\eta_{rp} E_{see,max}} \\ 1 \end{pmatrix}$

$$D = \begin{pmatrix} \frac{-\triangle t}{\eta_{rp} E_{see,max}} \\ 0 \end{pmatrix}; C = \begin{pmatrix} 1 & 0 \end{pmatrix}$$

The optimization problem is formulated as a tracking problem, where the cost function to be minimized consists of the error between the $SoE(k)$ and its reference value SoE_{ref}, and of the variation $\triangle P_{fc}(k)$:

$$\min_{\triangle P_{fc}(k)} \sum_{i=1}^{N_p} \|Q(y(k+i) - y_{ref}(k+i))\|_2 + \|R \triangle P_{fc}(k+i-1)\|_2 \tag{16}$$

subject to: state-space model (15)

$$x_{e,min} \leq x_e(k) \leq x_{e,max}$$

$$\triangle P_{fc,min} \leq \triangle P_{fc}(k) \leq \triangle P_{fc,max}$$

where Q and R are weight matrices.

Considering the following sequence to be optimized $\triangle \overline{P_{fc}}(k) = [\triangle P_{fc}(k), \cdots, \triangle P_{fc}(k+N_p-1)]'$ and the power demand sequence $\overline{P_{load}}(k) = [P_{load}(k), \cdots, P_{load}(k+N_p-1)]'$, the quadratic optimization problem (16) can be rewritten in the following form:

$$\min_{\triangle \overline{P_{fc}}(k)} 0.5 \triangle \overline{P_{fc}}(k)' H \triangle \overline{P_{fc}}(k) + (x_e(k)' F_1 + \overline{P_{load}}(k)' F_2 + [SoE_{ref}, *] F_3) \triangle \overline{P_{fc}}(k) \tag{17}$$

subject to:

$$\Gamma \triangle \overline{P_{fc}}(k) \leq X_{e,max} - \Phi x_e(k) - \Psi \overline{P_{load}}(k)$$

$$\mathit{\Gamma} \triangle \overline{P_{fc}}(k) \leq -X_{e,min} + \mathit{\Phi} x_e(k) + \mathit{\Psi} \overline{P_{load}}(k)$$
$$\triangle P_{fc,min} \leq \triangle P_{fc}(k+i) \leq \triangle P_{fc,max},\ i = 0 : N_p - 1$$

where $X_{e,max} = [x_{e,max}, \cdots, x_{e,max}]'$, $X_{e,min} = [x_{e,min}, \cdots, x_{e,min}]'$, $x_{e,max} = [SoE_{max}, P_{fc,max}]$ and $x_{e,min} = [SoE_{min}, P_{fc,min}]$.

The matrices H, F_1, F_2, F_3, $\mathit{\Phi}$, $\mathit{\Gamma}$ and $\mathit{\Psi}$ are defined as follows:

$$H = \mathit{\Gamma}' \overline{Q} \mathit{\Gamma} + \overline{R}; \qquad F_1 = \mathit{\Phi}' \overline{Q} \mathit{\Gamma}; \qquad F_2 = \mathit{\Psi}' \overline{Q} \mathit{\Gamma};$$
$$F_3 = -\begin{pmatrix} I_2 & I_2 & \cdots & I_2 \end{pmatrix} \overline{Q} \mathit{\Gamma}; \ \mathit{\Phi} = \begin{pmatrix} A & A^2 & \cdots & A_e^{N_p} \end{pmatrix}';$$
$$\mathit{\Gamma} = \begin{pmatrix} B & 0 & . & 0 \\ AB & B & . & 0 \\ . & . & . & . \\ . & . & . & . \\ A^{N_p-1}B & . & . & B \end{pmatrix}; \mathit{\Psi} = \begin{pmatrix} D & 0 & . & 0 \\ AD & D & . & 0 \\ . & . & . & . \\ . & . & . & . \\ A^{N_p-1}D & . & . & D \end{pmatrix} \quad (18)$$

with: $\overline{Q} = \text{diag}(C^T QC, \cdots, C^T QC); \overline{R} = \text{diag}(R, \cdots, R)$. Therefore, the resolution of the optimization problem (17)-(18) requires the knowledge or the estimation of the power demand over the prediction horizon. At each sampling instant, the supervisor system computes the optimal sequence $\triangle \overline{P_{fc}}^*(k)$ and uses its first element $\triangle P_{fc}^*(k)$ to determine the optimal power $P_{fc,optimal}$ that the fuel cell should provide. Then, using equation (13), the optimal SSE power $P_{sse,optimal}$ is calculated.

IV. Simulation results

The analyzed optimization-based strategies are applied to a FC/SSE system of an electric vehicle and their performances are evaluated in simulation using the Artemis driving cycle. The considered secondary storage element is a supercapacitor with a maximal energy capacity of $E_{sse,max} = 150$ [kJ]. The vehicle parameters are given in Table I. Fig. 3 shows the velocity and power demand corresponding to Artemis cycle. The power demand has been derived using equation (5) and a road slope α of 5% between $t \in [400, 600]$ s and 0 otherwise. The limits and the parameters of the multi-source system are presented in Table II.

The DP algorithm was performed for an admissible space of SoE defined with a state space sampling $\triangle x = 0.001$ and a sampling time $\triangle t = 1s$. The optimal FC power over the whole cycle is illustrated in Fig. 4(a). The algorithm guarantees that the state of energy of SSE stays in the admissible space in the presence of constraints (positive P_{fc}, limited $\triangle P_{fc}$) and that the initial value of SSE energy is obtained at the end of the cycle ($SoE(T_{cycle}) = SoE(t_0)$), as shown in Fig. 4(b). The ECMS optimization problem (14) was solved using the equivalence factors $s_0, s_1 \in [1.5, 2] \cdot 10^{-5}$. Fig. 5 shows the fuel cell power and the state of energy obtained with ECMS approach. At the end of the driving cycle, the energy stored in the SSE approximates the initial value with an error of 3.8%.

The MPC strategy has been implemented using the prediction horizon $N_p = 20$, the weight matrices $Q = 10^5$, $R = 10^5$ and the lower/upper bounds of P_{fc}, $\triangle P_{fc}$ and SoE given in Table II. To demonstrate the potential of this optimization strategy, the power load profile has been considered to be known over the prediction horizon, assumption that can be removed by estimating the power demand. Fig. 6 shows that the constraints on the FC power and SoE are satisfied. In this case, a 3% error between the final and the initial values of SoE is obtained.

TABLE I
Vehicle Parameters

M [kg]	S [m^2]	C_x	ρ_{air} [kg · m^{-3}]	g [m · s^{-2}]	C_r
1500	2.5	0.3	1.225	9.8	0.01

TABLE II
Multi-source System Limits and Parameters

$P_{fc,max} = 35$ [kW]	$\triangle P_{fc,max} = 4$ [kW]	$\eta_b = 0.95$
$P_{fc,min} = 0$ [kW]	$\triangle P_{fc,min} = -4$ [kW]	$\eta_{rp} = 1$
$P_{sse,max} = 10$ [kW]	$SoE_{min} = 0.25$	
$P_{sse,min} = -10$ [kW]	$SoE_{max} = 1$	

The performances of the proposed energy management strategies are compared in terms of hydrogen mass consumption. Table III illustrates the fuel consumption and the fuel economy determined using the analyzed optimization methods. Also, the fuel consumption in the absence of the additional storage element is provided.

The on-line approaches (ECMS and MPC) yield close sub-optimal results concerning the fuel consumption, compared to the DP optimal result. Although, the fuel economy percentage obtained using MPC is promising in comparison to the value determined using ECMS. However, the MPC provides an optimistic result due to the assumption of a known power demand over the optimization window. On the other hand, the drawback of ECMS is the lack of an accurate method to determine s_0, s_1 parameters. Still, the main advantage of the on-line methods is the low computation complexity that eases their real-time implementation.

TABLE III
Energy management Strategies Comparison

Strategy	Fuel consumption [gram]	Fuel economy (%)
SSE omitted	78.93	-
DP	53.21	32.58%
ECMS	55.31	29.92 %
MPC	54.31	31.19 %

V. Conclusions

Energy management strategies have been analyzed for an electric vehicle with the aim of optimizing the global efficiency of the powertrain system, by minimizing the fuel consumption. On-line strategies, such as ECMS and MPC, have been evaluated using an urban driving cycle and have been compared to an optimal strategy (DP), that presents a high computational time and needs a large storage capacity for real-time application. The optimization strategies comparison has shown that the on-line approaches admit satisfying results

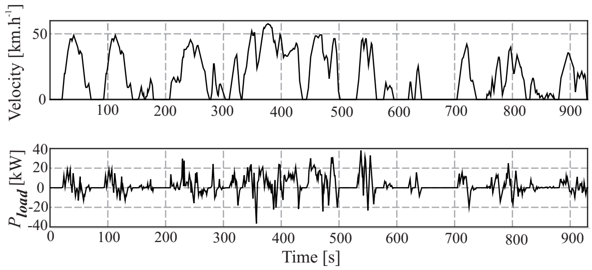

Fig. 3. Artemis driving cycle

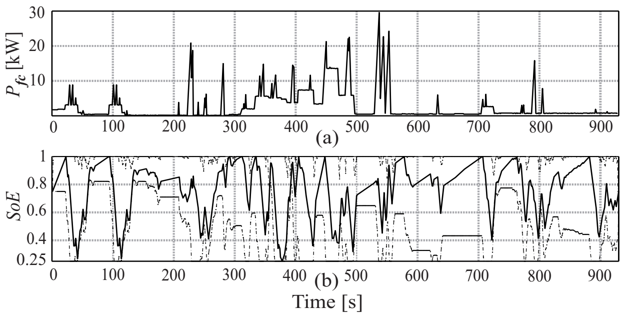

Fig. 4. DP: (a) Fuel cell power, (b) Supercapacitor sate of energy (SoE) (solid line), admissible space Ω (dash-dot line).

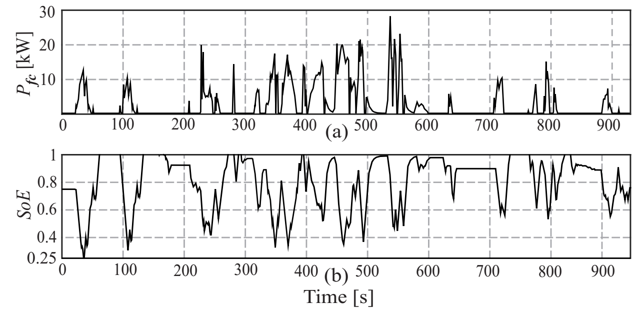

Fig. 5. ECMS: (a) Fuel cell power, (b) Supercapacitor sate of energy (SoE).

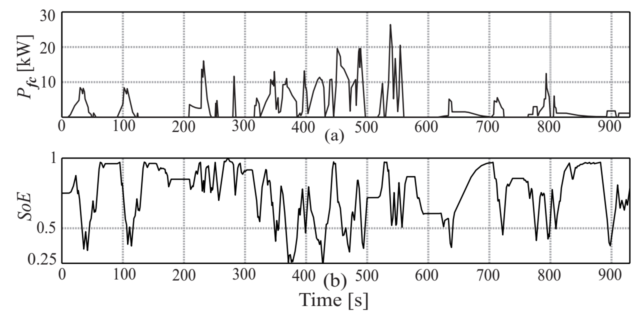

Fig. 6. MPC: (a) Fuel cell power, (b) Supercapacitor sate of energy (SoE).

in terms of fuel economy, computation complexity and ease of elaboration.

As perspectives of this work, the analyzed energy management strategies could be tested on a global model of the multi-source system that includes the fuel cell dynamics and the internal control loops of DC-DC power electronic devices used to interconnect the multiple energy/storage sources.

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