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Statistical Learning Controller for the energy management in a Fuel Cell Electric Vehicle

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Abstract— **This paper considers a high efficiency energy management control strategy for a hybrid fuel cell vehicle. The proposed switching architecture consists of a bank of neural network based controllers designed using statistical learning theory. The use of different power sources and the presence of different constraints make the power management problem highly nonlinear. Probabilistic and statistical learning methods are used to design the weights of a neural network and the switching strategy is used to implement different controllers designed on the considered operative conditions. The proposed controller increases the efficiency of the whole system and reduces the fuel consumption during a given path. Numerical results are obtained using the model of a real hybrid car, "*Smile*" developed by FAAM, using a stack of fuel cells as the primary power source in addition to ultracapacitors and a lithium battery pack. The results are compared with those of a single neural network based controller and the perfomance is shown to be satisfactory in terms of fuel consumption and the efficiency of the whole system.**

I. INTRODUCTION

In recent years, pollution problems and the increasing cost of fuel have pushed the car companies to study alternatives to the inefficient and polluting internal combustion vehicles. The increase in the size and weight of passenger cars have made those standard vehicles more polluting and expensive ([4]). Electric Vehicles (EVs) are the most efficient zero-emission vehicles on the market. Unfortunately, the long recharge time, the lower amount of energy stored, the lower performance, and the higher cost compared with similar internal-combustion vehicles have limited the acceptance of these cars in the current car market. Hybrid Electric Vehicles (HEVs) are considered a compromise between the two extremes of thermal and electric vehicles. HEVs actually combine the efficiency of electric cars with the high autonomy of conventional vehicles and are considered a potential solution to the pollution problem. The combination of electric motors with various storage elements (i.e. fuel cell, thermal engine, ultracapacitors, etc..) brought about more complex systems, as well as different control strategies to manage the vehicle powertrain ([13]).

Hybrid vehicle controllers are based on a supervisor that chooses, in the presence of different constraints, the best power path to satisfy the power demands of the drive line, while minimizing the fuel consumption and the production of polluting gases. Various solutions were developed in the literature in order to achieve different performances: Dynamic Programming and Quadratic Programming are used to minimize the fuel consumption over all paths ([11], [12], [14]). Heuristic controllers, based on Boolean of fuzzy logic rules, are used to minimize the fuel consumption using different vehicular variables such as torque demand or car speed ([9], [12]). Artificial neural networks have also been used to achieve various performance objectives during different driving cycles ([10], [9]). An alternative solution to analytical optimization approaches is provided by statistical learning methods ([15]). In a previous work ([17]), we used statistical learning to train the weights of a single Neural Network based controller to minimize a performance index. In this paper, a switching architecture is implemented and a bank of neural network based controllers are trained using Statistical Learning Theory (SLT). The switching architecture is designed to work in four different operating conditions: acceleration, constant speed, stand-by, and regenerative brake, that are obtained by analyzing the power demand in a given HEV. Statistical learning theory is used to choose the networks' weights of each neural network based controller in order to reduce the fuel consumption (hydrogen) during sample paths. The resulting controller is applied to a Fuel Cell Electric Vehicle (FCEV) called "*Smile*" and produced by FAAM S.p.A. (Italy). The vehicle has a fuel cell stack, that convert hydrogen to electric power using hydrogen as the primary power source. A buffer of energy in the powertrain is provided by the lithium battery pack and ultracapacitors. The performance of the proposed controller is evaluated via numerical simulation and compared with the results obtained in our earlier paper ([17]). The paper is organized as follows. In Section II the powertrain and main power devices are described. The details of the Switching Neural Network based Controller (SNNC) are discussed in Section III, while statistical learning theory is presented in Section IV. The results of the numerical simulations and a comparative analysis between the SNNC and a single Neural Network based Controller (NNC) are reported in Section V, and the paper concludes with comments on the performance of the proposed controller and an analysis of future work.

II. FUEL CELL ELECTRIC VEHICLE

Fuel cells (FCs) are electrochemical devices that convert the chemical energy of Hydrogen directly into electric energy without any combustion byproducts. The combination of fuel cells and electric batteries allows us to design clean (zero emission) and high efficiency vehicles. As shown in figure 1, the configuration of the FCEV powertrain consists of a

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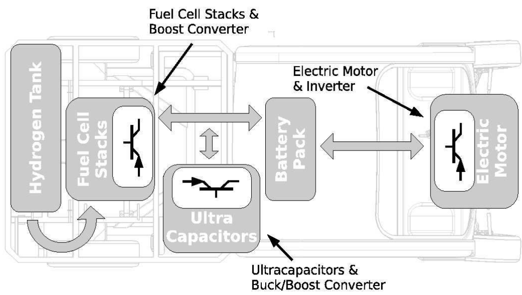

Fig. 1. Powertrain scheme of a fuel cell electric vehicle

battery pack, a fuel cell stack (PEM), an ultracapacitor bank and an inverter that provides power to the electric motor. The fuel cell stack, by a dc/dc converter (Boost), is in parallel with the battery and the supercapacitors bank are connected to the power bus by a Buck/Boost converter. Note that while a boost converter allows us to push power from the fuel cell stack to the battery, the Buck/Boost converter works in both directions. The fuel cell stack provides the main power to the vehicle while the ultracapacitors and the lithium battery pack supply and receive power, during acceleration and braking, respectively. Finally, the inverter converts the DC voltage into an AC voltage used to drive the motor. Along a given path, the amount of power required by the vehicle is provided by the different power devices as described by the following equation:

$$P_t(t) = P_{fc}(t) + P_{uc}(t) + P_{bat}(t). \tag{1}$$

where $P_t(t)$ is the power required by the inverter at each time instant, and $P_{fc}(t)$, $P_{uc}(t)$ and $P_{bat}(t)$ are the power portions provided by the fuel cell, the ultracapacitors, and the battery pack, respectively. The low-level control architecture of the power devices is shown in figure (II), where $I_{fc}(kT)$ and $V_{fc}(kT)$ are the current and voltage provided by the fuel cell, $I^{fc}_{ref}(kT)$ is the reference signal for $Controller_1$ and represents the current required to the fuel cell stack. $I_{bs}(kT)$ is the current output of the Boost converter. The hydrogen consumption $\Delta h(kT)$ is a nonlinear function of the fuel cell current $I_{fc}(kT)$. $I_{uc}(kT)$ and $V_{uc}(kT)$ are the current and voltage of the ultracapacitors, $I^{uc}_{ref}(kT)$ is the amount of current required by the ultracapacitors while $I_{bb}(kT)$ is the current output of the Buck/Boost. $I_{bat}(kT)$ and $V_{bat}(kT)$ are the current and the voltage of the battery packs, respectively. All the devices are modelled using a linear approximation as described in ([17]). The power provided by the fuel cell stack is controlled by the boost converter. The current provided by this device is set up by $Controller_1$, using the reference signal $I^{fc}_{ref}(kT)$. Another device (the Buck/Boost converter) is used to push and pull power from the ultracapacitors to the battery pack. The reference signal $I^{uc}_{ref}(kT)$ is the current required to the ultracapacitors bank and is controlled by $Controller_2$. A complete analysis of the model is provided in ([7]). By using an intelligent control strategy to generate the two control inputs, $I^{fc}_{ref}(kT)$ and $I^{uc}_{ref}(kT)$, it is possible to obtain a reduction in the fuel consumption (hydrogen) while achieving other performance objectives.

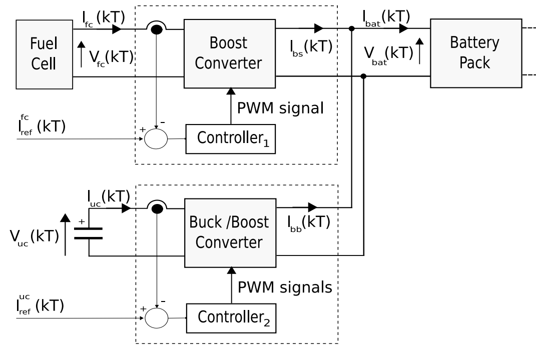

Fig. 2. Low level control architecture of the FCs current $I_{fc}(T)$ and utracapacitors current $I_{uc}(T)$ in a FCEV

III. Switching Neural Network based Control

As described earlier, a major aim of this paper is to develop a switching control system that integrates with the low-level control architecture in order to reduce the fuel consumption along a given path. In order to achieve this objective, a bank of neural network based controllers and a switching strategy are proposed in order to generate the two control inputs $I^{uc}_{ref}(kT)$ and $I^{fc}_{ref}(kT)$ used as reference signals in the low level architecture. In figure 3 the acquired data of an experimental test is presented. The particular shape of the data suggests dividing the trajectory into four different regions associated with four different drive configurations. Region 1 is associated with a low power request by the vehicle. In this case, the velocity of the vehicle is low, and the requested power is low (stand-by mode) or negavite (short regenerative brakes). Region 2 may be associated with a hard regenerative task because the vehicle's velocity is high and the power is highly negative. Region 3 is defined for a high vehicle speed and a low request of power. This region is associated with a constant speed path. Finally, Region 4 is associated with an accelerating or an uphill path. In this case, the vehicle velocity is low with a corresponding large amount of power request. The continuous lines in figure 3 are plotted to divide the data into the four regions. The dashed lines are hysteresis thresholds to avoid the continuous switching between two different regions. Points in figure 3 depend only on the power request and the vehicle velocity and are thus functions of the drive path and the drive action. For this reason, the data plotted in figure 3 presents the collection of different drive paths (city path, extra-urban path, et. al.), with different drivers. The control inputs $I^{fc}_{ref}(kT)$ and $I^{uc}_{ref}(kT)$ can only change the management of the power in the powertrain but they do not affect the power request, and therefore have no effect on the stability of the system.

The closed-loop system is shown in figure 4, where $P_t(kT)$ is the requested power by the vehicle along the desired path, $V(kT)$ is the vehicle velocity and $P^y_t(kT)$ is the generated power by the three power devices. The number μ is the selected neural network based controller at time

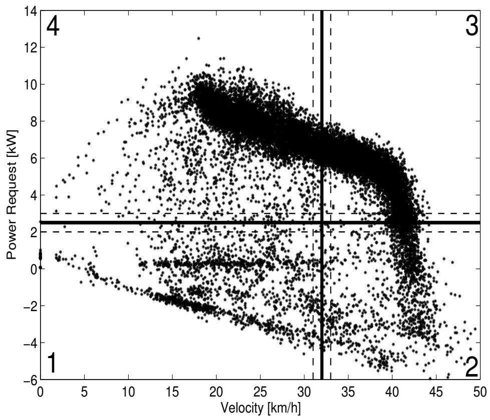

Fig. 3. The power versus velocity in a general drive path

kT as generated by the $Supervisor$, and may only assume the values $\mu = \{1, 2, 3, 4\}$. The outputs of the radial basis function (RBF) neural network may be expressed as:

$$I^{fc}_{ref}(kT) = \mathbf{\Theta}^{fc^T}_{\mu} \boldsymbol{\phi}(\boldsymbol{\kappa}(kT)) \quad (2)$$

$$I^{uc}_{ref}(kT) = \mathbf{\Theta}^{uc^T}_{\mu} \boldsymbol{\phi}(\boldsymbol{\kappa}(kT)) \quad (3)$$

where $\mathbf{\Theta}^{fc}$ and $\mathbf{\Theta}^{uc}$ are the matrix weight vectors of the RBF network; each column of the matrix $\mathbf{\Theta}^{fc}_{\mu}$ and $\mathbf{\Theta}^{uc}_{\mu}$ is related with a given operating condition. The vector $\boldsymbol{\phi}(\boldsymbol{\kappa}(kT)) \in \mathbb{R}^n$ is Gaussian and defined as

$$\phi_i(\boldsymbol{\kappa}(kT)) = exp\left(-\frac{\|\boldsymbol{\kappa}(kT) - \boldsymbol{c}_i\|^2}{\sigma_i^2}\right),\ i = 1, 2, \cdots, n \quad (4)$$

where n is the number of nodes, $\boldsymbol{c}_i \in \mathbb{R}^n$ are the centers of the basis functions and σ_i are scaling or "width" parameters ([16]). The input vector $\boldsymbol{\kappa}(kT)$ is defined in this paper as:

$$\boldsymbol{\kappa}(kT) = [SoC_{bat}(kT)\ SoC_{uc}(kT)\ P_{fc}(kT)\ P_t(kT)]^T \quad (5)$$

where $SoC_{bat}(kT)$ and $SoC_{fc}(kT)$ are two numbers ranging between 0 and 1 and are proportional to the state of charge of the battery and the ultracapacitors, respectively (0 when the device is empty, 1 when the device is full charged). The signals $P_t(kT)$ and $P_{fc}(kT)$ denote the power functions defined in (1). In the proposed approach, the matrix of the weight vectors $\mathbf{\Theta}^{fc}$ and $\mathbf{\Theta}^{uc}$ are designed using statistical learning theory.

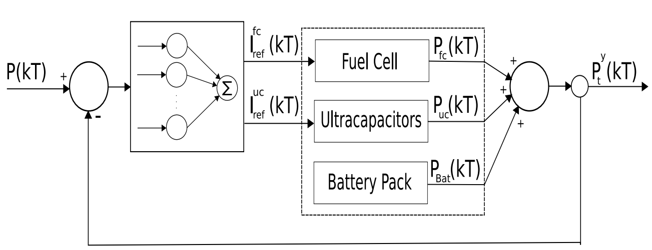

Fig. 4. Closed-loop scheme for the complete powertrain system

IV. Statistical Learning theory

A general supervised learning problem was considered in ([5]). Assume there is a system producing input/output pairs (x, y). Moreover, assume that each input is distributed according to a probability measure $F(x)$ (fixed but unknown), and that y is returned according to a conditional distribution $F(y|x)$ (also fixed but unknown). Consider a "learning machine" capable of implementing a set of functions $f_k(x) \in \mathcal{F}$, and that this learning machine is presented with a training set of N independent and identically distributed (i.i.d.) samples $(\mathbf{x}, \mathbf{y}) = (x_1, y_1), ...(x_N, y_N)$ distributed according to $F(x, y)$. Then, given a function $L(y, f_k(x))$, that measures the loss or discrepancy between the real system response y and the function $f_k(x)$, the problem is to use the information contained in $(\mathbf{x}, \mathbf{y})$ to choose f_k such that the risk functional

$$R(f_k(x)) = \int L(y, f_k(x))dF(x, y) \quad (6)$$

can be minimized, trying to reproduce the behavior of the real system with the learning machine $f_k(x)$. This problem is difficult to solve directly. First, there is the already mentioned lack of knowledge of $F(x)$ and $F(y|x)$. Moreover it may be difficult to come up with the actual form of $f_k(x)$ such that the response of the system is exactly reproduced. Instead, an approximation of the real $f_k(x)$ is estimated ([6]). This optimization problem is then reformulated as follows. Given a desired accuracy $\epsilon > 0$ and confidence parameter $\delta \in (0, 1)$, find an estimate $\hat{f}_k(x)$ of $f_k(x)$ such that

$$\sup_{F(x,y)} Pr\{R(\hat{f}_k(x)) \geq \inf_{\mathcal{F}} R(f_k(x)) + \epsilon\} \leq \delta. \quad (7)$$

or in other words, $R(f_k(x))$ is within ϵ (small) of $\inf_{f_k} R(f_k(x))$ with probability $1 - \delta$ (high). To formalize this concept, the following definition is considered:

Definition 1 (Approximate Near Minimum): Given $R(f) = R(f_k(x))$, $\epsilon > 0$ and $\delta \in (0, 1)$, a number $R_0 \in R$ is said to be an approximate near minimum of $R(f)$ to accuracy ϵ and confidence $1 - \delta$ if

$$Pr\{|R_0 - \inf_{\mathcal{F}} R(f)| \leq \epsilon\} \geq 1 - \delta \quad (8)$$

Another important concept in optimization via randomized algorithms is the so called "*level*" ([2], [1]). Loosely speaking, the "*level*" describes a set of potential solutions that may not be represented in the sample taken for optimization. If the size of this set is large, the optimization may not be valid, since the sample is not representative of the family of possible solutions. On the other hand, if this set can be guaranteed to be small, then there will be a small probability of finding another solution that provides considerably better performance than those found during the sampling. Combining the level with the confidence a new type of minimum is defined, where the objective of high accuracy (ϵ) is replaced by that of low probability of not finding the best solution (α).

A. Statistical Learning theory applied to the energy management in a FCEV

Statistical learning theory may be used to solve the optimization problem when it is difficult to find an analytical solution. In this paper, Statistical learning theory is used to designing a SNNC and to reduce the fuel consumption in a FCEV. In the following, the original optimization problem is reformulated as a statistical learning one. Consider the performance index $J(\cdot)$ related to the fuel consumption

$$\begin{aligned} J(\mathbf{\Theta}_\mu^{fc}, \mathbf{\Theta}_\mu^{uc}, KT) &= \alpha_1 \sum_{j=0}^{K} \Delta h(\mathbf{\Theta}_\mu^{fc}, \mathbf{\Theta}_\mu^{uc}, jT)T \\ &+ \alpha_2 |SoC_{bat}(t_0) - SoC_{bat}(t_1)| \\ &+ \alpha_3 |SoC_{uc}(t_0) - SoC_{uc}(t_1)| \quad (9) \end{aligned}$$

where K is the number of the samples required, $\Delta h(\cdot)$ is the fuel consumption function which depends on $I_{ref}^{fc}(kT)$ and $I_{ref}^{uc}(kT)$ and by (2) and (3) it is a function of $\mathbf{\Theta}_\mu^{fc}$ and $\mathbf{\Theta}_\mu^{uc}$. The terms $|SoC_{bat}(t_0) - SoC_{bat}(t_1)|$ and $|SoC_{uc}(t_0) - SoC_{uc}(t_1)|$ are used to obtain at the end of the path the same initial amount of energy stored in the power devices, and α_1, α_2 and α_3 are three design parameters. The minimum of the performance index $J(\cdot)$ is achieved by the optimal weight vectors $\mathbf{\Theta}_\mu^{fc}$ and $\mathbf{\Theta}_\mu^{uc}$ for each operating condition according to statistical learning theory. Note that instead of looking for a solution $J^*(\cdot)$ that guarantees that the cost function (9) achieves its exact minimum, an approximate $J_0(\cdot)$ is calculated. The number of samples needed to guarantee that the solution is sufficiently close to the optimal solution are based on results that may be found in [2]. The minimum value of the performance index is

$$J^* = \min_{\Upsilon \in \mathbb{R}^{2n}} J(\Upsilon) = J(\Upsilon^*), \quad (10)$$

the optimal solution for the system. Denote by $\{\hat{\Upsilon}\}$ the set of the weight samples $\{\hat{\Upsilon}_1, ... \hat{\Upsilon}_N\}$, with $\hat{\Upsilon}_i = (\mathbf{\Theta}_-^{fc}, \mathbf{\Theta}_-^{uc})$, let

$$J_0 = \min_{1 \le i \le \cdot N} J(\hat{\Upsilon}_i) = J(\hat{\Upsilon}_0), \quad (11)$$

be the minimum performance value for the system over the set of vectors $\{\hat{\Upsilon}\}$. We then have the following result (see [2]).

Theorem 1 (Minimum number of input samples): The minimum number of samples N that guarantee that J_0 is a probable near minimum to level α and confidence δ of J^* is

$$N \ge \frac{\ln(1/\delta)}{\ln(1/(1-\alpha))} \ . \quad (12)$$

V. Numerical Results

Numerical tests of the proposed controller have been performed on a model of a Fuel Cell Electric Vehicle (FCEV) called "*Smile*" developed by FAAM of Monterubbiano (Italy). Vehicle "*Smile*" is a commercial vehicle that requires a main power of 5 kW and which has a maximum velocity of 50 Km/h. The vehicle uses hydrogen (that is converted to electric power by a fuel cell stack) as its primary source and ultracapacitors for an energy buffer as shown in figure (I). The fuel cell stack is produced by "*Hydrogenics*^{TM}" and the Boost converter is a custom made device. The module provides 12 kW of maximum power, with a current ranging between 0 to 300 A and the operating voltage ranging from 40 to 55 V. A complete description of the mathematical model and the identification phase are reported in ([7], [17]).

The ultracapacitors are produced by *Maxwell Technologies*^{TM} . The module has 165 F of capacity and a voltage ranging between 24.3 and 48.6 V. In order to avoid damage to this power device, $Controlloer_2$ works under the constraint that the capacitor voltage is in the required range. The State of Charge (SoC) is a variable that represents the charged state of the device, and is represented by a number between 0 to 1. The Battery pack is composed of 19 lithium polymer cells produced by $Kokam$, each with a nominal voltage of 3.7 V and 70 Ah each one. The nominal battery pack voltage is 70.3 V. Different constraints are considered for the battery pack. The State of charge (SoC) of the battery ranges between 0 to 1. In fact, the battery may not be completely discharged or over charged. The minimum and maximum battery pack voltage are 51.3V and 79.8V, respectively. The maximum current provided by the battery is limited to 200A but may reach a peak of 700A, while the maximum current provided to the battery is limited to -100 A.

The total power amount $P_t(kT)$ is obtained from the request of power during a given drive test. The drive test is chosen to be representative of a typical drive condition. For this reason, different road conditions (uphill, downhill, and flat), different velocities, and different drive conditions (speedup, brake) are considered. Two different drive tests are used here: the first is used to design the weight vectors, while the second was chosen to test the proposed controller. In figure (6), the vehicle velocity (top) and the request of power (bottom) are shown as a function of time during the training phase. figure (7) shows the power path used to verify the performance of the proposed control. The switching neural network based controller was designed off line, using statistical learning theory as described in the previous paragraph. The whole control scheme was put in the closed-loop system, shown in figure 4, and the SLT used to choose the neural network weights. The size of the RBFN is chosen to be as small as possible, while covering all the input space spanned by the input vector $\boldsymbol{\kappa}(kT)$. Therefore, the hidden layer is chosen to have 27 nodes to cover the input space spanned by the input vector $\boldsymbol{\kappa}(kT)$. The two weight matrices $\mathbf{\Theta}^{fc}$ and $\mathbf{\Theta}^{uc}$ are designed to generate, using the switching signal generated by the supervisor, the two control inputs $I_{ref}^{fc}(kT)$ and $I_{ref}^{uc}(kT)$. The values of α and δ in 1 are chosen to be 0.01 and 10^{-3}, respectively. This leads to the number of samples $N = 688$. figure 5 shows the switching control signal generated using the required power and the velocity of the vehicle (see figure 3). figure 8 shows the control inputs generated by the neural network controller using the second path described in figure (7). Note that $I^{fc}_{ref}(t)$ takes on positive values only because the fuel cell stack is a power generator, while the reference signal for the ultracapacitors $I^{uc}_{ref}(t)$ may be positive or negative. In figures 9, 10 and 11 the behaviors of the voltage (top) and the current (bottom) during the drive path are reported. The figures show that all the defined constraints are satisfied. In figure 12, the states of charge of the battery pack and of the ultracapacitors are shown. The figures clearly show that the two power devices are used as power buffers, and that the final amount of energy is almost the same as the starting one. Therefore, all the energy required during the drive path is provided by the fuel cell. In Table I, a comparision between the SNNC controller and the NNC controller (described in [17]) is provided. Using a different control strategy, and without modifying any hardware device, our approach allows us to achieve the same performance while reducing the fuel consumption. A fuel reduction of 3.84% may seem too small for one car, but considering the large number of the cars, the overall reduction is indeed large.

TABLE I

FUEL CELL ELECTRIC VEHICLE PERFORMANCES

	NNC	SNNC	Improvement
Energy Provided	$9708.7\ kWh$	$9335.2\ kWh$	3.84%
Efficiency	41.20%	42.85%	1.65%

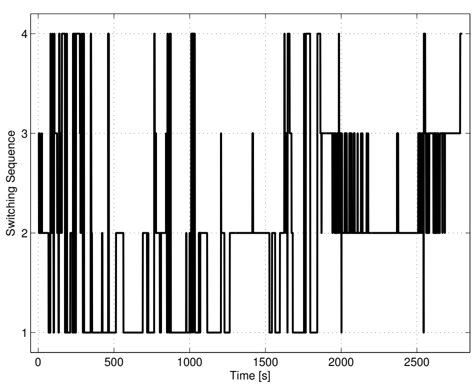

Fig. 5. The switching sequence provided by the supervisor.

VI. CONCLUSIONS

In this paper, the energy management problem for an FCEV is analyzed and solved using a SNNC designed by statistical learning theory (SLT). A switching control architecture is introduced to improve the performance of a NNC. Four different regions, depending on four different drive conditions, are used to design differents NNC using SLT. SLT was used to design the matrix of weight vectors of a SNNC with the aim to reduce the fuel consumption during a given path. Numerical simulations show an improvement of the performance compared with a single NNC. The use of a switching control instead of a single NNC is therefore a potential solution to reduce the fuel consumption in a FCEV. Our future work will focus on the implementation of this approach to the real vehicle "Smile" produced by FAAM. The possibility of using a clustering algorithm to choose the path regions may also lead to an improvement of the proposed work. The use of standard drive paths will be considered in future works.

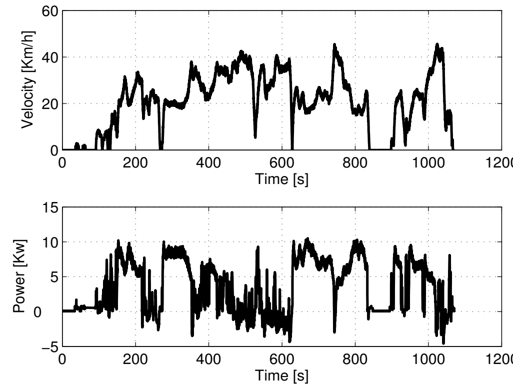

Fig. 6. Velocity and Power used for the training phase.

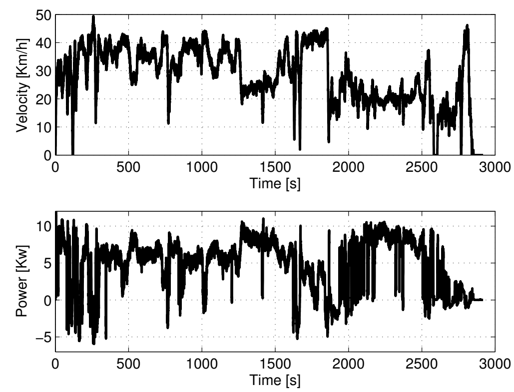

Fig. 7. Velocity and Power used to evaluate the performance of the proposed controller.

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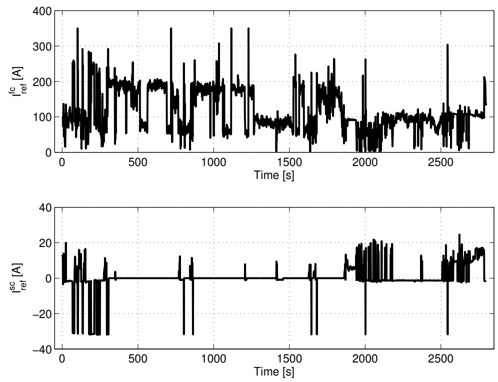

Fig. 8. Control input $I_{ref}^{fc}(t)$ and $I_{ref}^{uc}(t)$ generated by the neural network controller.

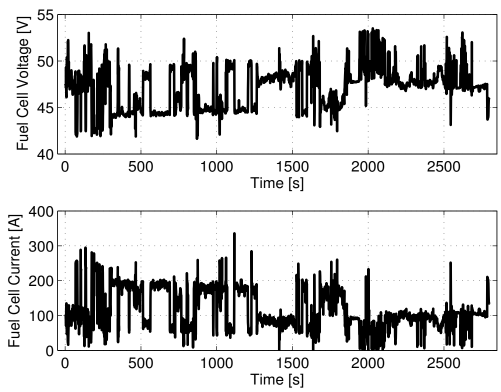

Fig. 9. Voltage and Current provide by the Fuel Cell Stack during the test.

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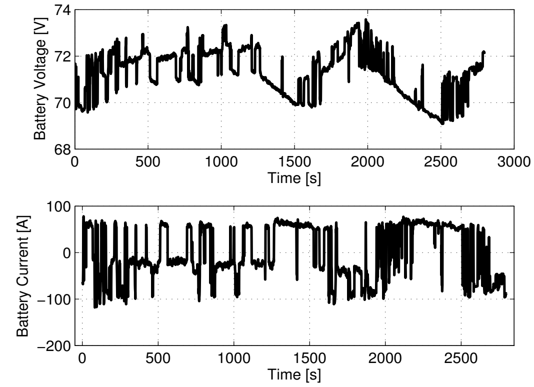

Fig. 10. Voltage and Current provide by the Battety during the test.

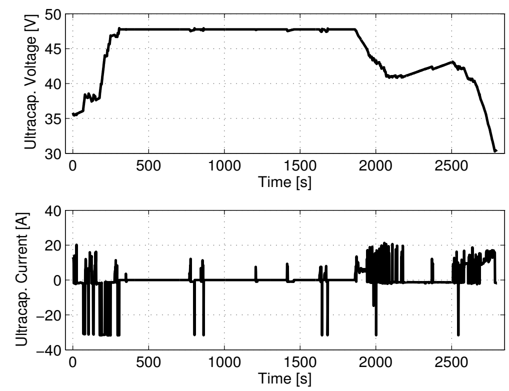

Fig. 11. Voltage and Current provide by the Ultracapacitors Bank during the test.

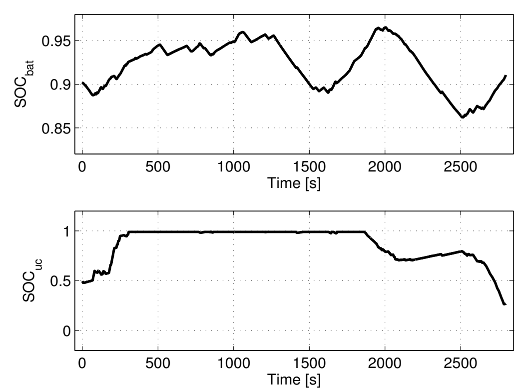

Fig. 12. State of Charge (SoC) of the Battery pack and Ultracapacitors, respectively.