Efficient Experimental Energy Management Operating for FC/Battery/SC Vehicles via Hybrid Artificial Neural Networks-Passivity Based Control

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Abstract**—** Nowadays, the energy management of multisource hybrid systems is becoming an interesting and challenging topic for many researchers. The judicious choice of the energy management strategy not only allows for the best distribution of energy between the different sources, but also reduces the system's consumption, increases the life span of the used sources and fulfills the energy demand that affects the autonomy of the electric vehicle (EV). A novel hybrid control strategy based on the interconnection and damping assignment passivity-based control (IDA-PBC) technique is proposed while considering the battery State of Charge (SOC) and the hydrogen level operating conditions. PBC is a very powerful nonlinear technique, which uses important system information such as the system energy information. The Artificial Neural Network (ANN) is used for defining the appropriate references for the proposed controller to properly share the load power demand among the sources. Consequently, the proposed nonlinear control enables dispatching the requested power/energy among sources under source limitations. The real time experimental results demonstrate the enhanced efficiency of the hybridized ANN together with the IDA-PBC control. This work proposes a complete study and solution, from modeling, control, stability proof, simulation to practical validation. New constraints are emerging in anticipation of the real-time use of FC hybrid systems. These constraints and objectives are mainly related to the limitations of energy resources and the minimization of hydrogen consumption. The supervision of hydrogen level and battery SOC resources are proposed by using ANN, which gives the battery current and/or SC set point to the control loops. Experimentation works have validated the feasibility of this optimization technique.

Keywords**—** *Energy management, Hybrid system, Passivity based control, Artificial neural network.*

Nomenclature

L_{FC}	FC inductance
V_{FC}	FC voltage
i_{FC}	FC current
$\bar{\imath}_{FC}$	FC current value at equilibrium
V_{DC}	Load voltage
i_{DC}	DC bus current
V_d	Desired DC bus voltage
C_{DC}	DC bus capacitance
L_{DC}	DC bus inductance
L_{SC}	SC converter inductance
C_{SC}	SC capacitance
i_{SC}	SC current
V_{SC}	SC voltage reference
i_B	Battery current
V_B	Battery voltage
e_B	Battery E.M.F (ElectroMotive-Force)

r_B	Battery internal resistance
L_B	Battery converter inductance
V_L	Load voltage
L_L	load inductance
E_L	Load Electromotive Force
R_L	Load resistance
r	Control design damping parameter
$\bar{u}_1, \bar{u}_2, \bar{u}_3$	Equilibrium control variables
u_1, u_2, u_3	Controller signals
P_{FC}	FC power
P_{SC}	SC power
P_B	Battery power
P_{load}	Load power

I. INTRODUCTION

The increase in human mobility has been accompanied with a rapid growth rate in the worldwide car number [1]. The conventional vehicle is considered the most polluting fuel consumer in the world. The rapid development of the traditional vehicle market results in environmental problems and source limitation constraints [2][3]. The priority is no longer only to satisfy the excessive demand for mobility but also to reduce the consumption of fossil fuels and subsequently to limit the greenhouse gas effects [3]. In recent decades, great research efforts have been witnessed to propose new transport solutions targeting the reduction of gas emissions. Recently, hybrid electric vehicles (HEVs) based on fuel cells (FCs), are becoming an attractive technology [4]. The proper energy management in HEVs improves the H_2 fuel economy. Hydrogen is a very promising solution thanks to its high energy density compared to other polluting sources such as gasoline and diesel. Meanwhile, hydrogen use is neither toxic nor polluting fuel. It has zero emissions as its reaction in FC generates only water [5][6]. In such FC-HEV, the batteries can be the embedded storage system. However, their problems linked to the autonomy, life time and recharging duration are still open research challenges deeply considered [7]. The storage of electrical energy can be enhanced by supercapacitors (SCs) [8][9]. However, each of these storage systems has its own advantages in terms of energy, mass power, lifetime, cyclability, safety and cost, which are all key criteria for viable vehicle applications [10][5]. The combination of two (or more) sources of electrical storage, with complementary characteristics, for example battery with SC option is used for increasing the HEVs autonomy and life time [11],[12]. In this research, the mixed storage system is used to overcome the shortcomings of using each electrical storage source separately and to combine their advantages for obtaining adequate compromise in all considered criteria [13][14]. This work focuses on studying HEV with multisource system: FC as the main source and the hybrid auxiliary energy storage systems of batteries and SCs. The FC and SC provide the power demand in steady state and transient states respectively. The battery can be used in either steady or transient states besides the startup phase. The main energy is provided by the FC and can be helped by the battery.

Hybrid energy systems present an up-to-date topic for both scientists and engineers. In [15], the authors have studied the impact of the storage devices on the performance and the economy of the hybrid FC/battery/SC EV. The optimal sizing of the storage system has been performed. The energy management considering the battery lifespan using its degradation models has been considered [15]. In [16], the hybrid FC/batteries/SC for tramway applications has been discussed. The control strategy has been proposed based on the combination of fuzzy logic and Haar wavelet transform for sharing the flow among the sources. The real driving cycle has been used for evaluating the proposed control. The results have confirmed its technical validity. In [17], the authors have studied the powertrain configuration constituted of FC, battery and SC inside the tramway. The FC has acted as the main source. The battery has been used in different phases: the start-up, the acceleration and the absorption of the power generated during braking. The SC has been operated only during power peaks beyond the operation of FCs and batteries. The energy management strategy has been chosen to minimize the hydrogen consumption. During simulation analysis, a real driving cycle of the tramway has been treated. An average FC efficiency of 60.9% has been reached. In [12], the main energy source was the FC. The hybridization in energy and power has been considered using battery and SC as storage devices. According to the intrinsic energy characteristics of each source, the energy distribution strategy has been selected. High-power density of the SC has enabled the DC bus voltage to work properly. The battery presents higher energy source compared to the SC. Batteries have led to maintain constant average energy for the SC to keep it charged. The FC, due to its' auxiliaries slow dynamics [2][18], has been considered to maintain the charge of the battery pack. The experimental studies performed on a small-scale test bench have led to satisfactory results. In [19], the energy management has been studied for FC, battery and SC taking into account the lifetime of the storage devices. In order to extend the lifespan of the storage modules, the current regulation become necessary. Therefore, the references of the battery and the FC have been controlled at certain values while maintaining stable DC output voltage. The model predictive control (MPC) has enabled producing the reference current for each converter. The experimental results have shown how efficient was the MPC in controlling the currents of the battery and FC besides maintaining the DC bus voltage in accordance with the reference values. In [20], the authors have developed the energy management strategy to control the instantaneous power distribution between FC/Battery/SC while considering the frequency decomposition of the energy demand cycle [21][20]. The strategy used in [20] has maintained the charging state of the storage devices at acceptable levels to guarantee the reliability during the overall system operation. The simulation results have demonstrated the efficiency of the energy management strategy. The proposed hybrid source has enabled with both standing unpredictable load dynamics in different operation modes and to satisfying the inherent characteristics of the sources, such as the current limits of the FC and the slow dynamics of its auxiliaries. Thus, the FC system should be used in the most efficient operating region. In [22], hybrid power system containing FC, batteries and SCs has been presented. The aim of the chosen energy management strategy is to reduce the total hydrogen consumption and slow down the performance degradation of the FC. The chosen technique is called Salp Swarm Algorithm (SSA). It takes into consideration the limits of each energy source used for the load demand. This is achieved by the fact that batteries and SCs provide the maximum energy. A comparative study has been given to show the efficiency of the proposed SSA-based energy management technique. In [23], the hybrid optimal energy management based on support vector machine with pass filter for the hybrid FC system. The objectives of this study has been developped to improve the performance of the hybrid system designated to ship application while decreasing the systems's energy consumption and increasing the lifetime of the device. The comparative study with different methods has concluded the efficient performance of the chosen energy management in terms of dynamic performance where the fluctuation at power and energy yield levels have been eliminated. All these results improve the efficiency and energy quality. The authors of [24] have proposed simulation works on the hybrid energy management using nonlinear controller using the super twisting sliding mode and optimal control based on fuzzy logic. These technics have been applied for FC/battery/SC system for key objectives, such as: i) reduce the hydrogen consumption and, ii) use of maximum SOC of storage system. An impartial comparison with other approaches in the literature has validated the efficiency of the used methods and the stability of system has been justified using the Lyapunov approach [24]. Table.1 presents a comparison of the proposed research with previous hybrid controller in the literature for the energy management of multisource FC system.

Table 1: Comparative analysis with the multi-source FC-based energy management studies existed literature

reference	**Energy management**	**Specific parameters**	**Description**
[23]	Low pass filter and support vector machine	- SOC of Storage system - Validation by simulation	Improve power system dynamic performance and prolong the FC lifetime. Simulation results validate the approach in terms of deleting the power fluctuation. The stability proof and experimental validation are missed to validate the chosen method efficacity.
[24]	Fuzzy super twisting sliding mode	- Nonlinear method	Storage source supervision in terms of SOC of battery and SC to maintain the DC bus voltage

		- SOC of battery and SC are considered - Validation by simulation - Stability proof	to decrease the hydrogen consumption. The stability proof is given by Lyapunov approach. Validation by the simulation of proposed methods with the existing approaches. Limitations here are the lack of experimental validation and the consideration of the remaining hydrogen level.
[51] [52]	IDA-PBC+HJB	- Nonlinear method - H_2 level, SOC of battery and SC - Stability proof - Validation by simulation and experimental tests - Optimization of the shared energy using Hamilton Jacobi Bellman method (HJB) - Online method, no need to know the driving cycle	SOC of storage systems and H2 level are considered. Limitation of this approach is that HJB optimal control is quite hard to solve since that the optimization needs the resolution of the analytical partial differential equations.
This paper	IDA-PBC + ANN	- Nonlinear method - H_2 level, battery SOC are considered for the energy sharing management - Stability proof is given - Validation by simulation and experimental tests - Online method, no need to know the driving cycle -	Modeling, control, stability proof (Lyapunov stability), simulation then until practical validation are studied. Limitations of energy resources are considered to share the energy and the minimization of hydrogen consumption are the key of our study. One limitation of this approach is that it needs a dataset for the training process

When combining FC/battery/SC as a hybrid system, the SC is used for compensating the power peaks during short time as in [25],[26]. The battery is used in steady state supporting the FC when this later cannot provide alone the requested load, as proposed in [27],[28]. In faulty FC systems as in [28], the battery role is provided the power difference between the load power and FC power to cover the demanded power. The present work deals with the control and energy management of a full electric hybrid vehicle considering the battery SOC and the FC hydrogen level. The major contribution of this study is the use of nonlinear control on the hybrid system based on Interconnection and Damping Assignment-Passivity Based Control (IDA-PBC) with stability proof along with Artificial Neural Networks (ANN) for managing the power distribution by defining the best current references under source limitations. The combination of ANN with the IDA-PBC enables the optimal energy distribution among the HEV's sources while considering the SOC and hydrogen level of both battery and FC respectively.

The remainder of this scientific paper is organized as: the hybrid power source structure using FC, battery and SC supplying the load is described in Section II. The main objectives of this study and the mathematical system representation are defined in the same section. Afterwards, the problem formulation and the IDA-PBC controller are designed in Section III. Sections IV is devoted to explain the ANN methodology used for providing the most appropriate current reference for energy management. In Section V, the experimental set-up is illustrated and the experimental results are discussed. Section VI is assigned to highlight the conclusions and perspectives of this work.

II. HYBRID POWER SOURCE STUCTURE AND PROBLEM FORMULATION

The system under study contains the DC bus, the FC as main source and the unidirectional DC/DC boost converter to maintain the DC bus voltage at its desired voltage. In addition, the storage system composed of battery and SC are connected to the DC bus through a current reversible DC/DC buck-boost for each. The 8th order state space equations of the overall system is mentionned in [29]. The overall structure of the hybrid FC/Battery/SC system is illustrated in Fig.1. The parametes of the FC, battery, SC and converters are listed in the appendix. The overall state space equations of the system are comprehensively deduced from [29].

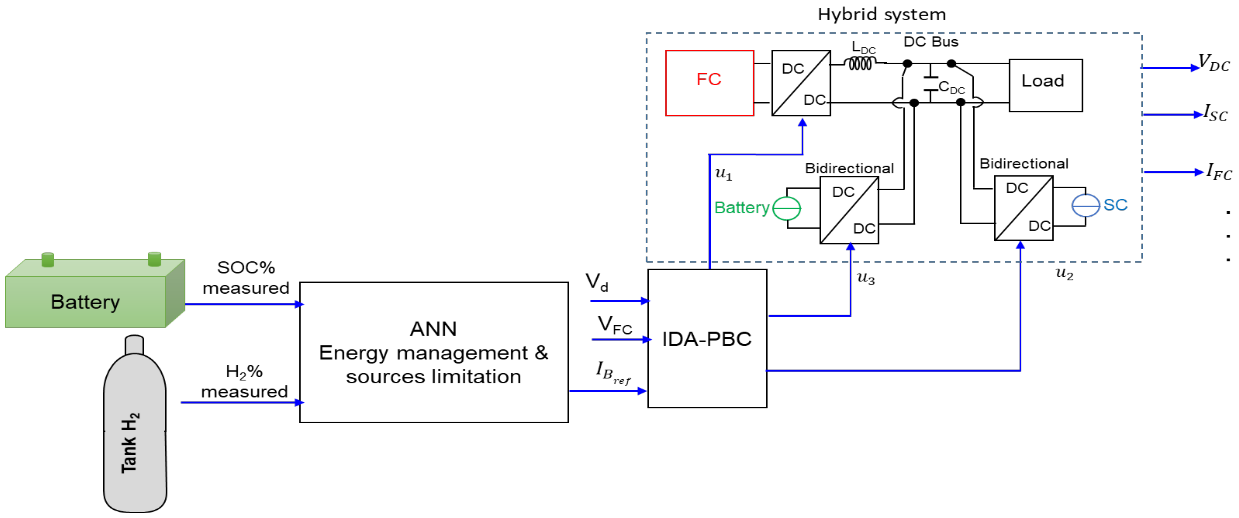


Fig. 1. Hybrid structure of the controlled electrical vehicle by IDA-PBC and ANN.

The originality of this study is the use of ANN for determining the desired battery current I_{Bref} considering the sources limitations such as the battery SOC and H_2 level in the hydrogen tank. The I_{Bref} obtained through ANN is entered together with FC measured voltage V_{FC} and the imposed DC bus voltage reference V_d into the IDA-PBC strategy to calculate the three converters control laws (u_1, u_2, u_3). These control variables will be introduced in Eq. 1 to obtain the different simulated variables as V_{DC}, I_{FC}, I_{SC}.

The 8th order hybrid system's set of state space equations is:

$$\begin{cases} \dfrac{dV_s}{dt} = \dfrac{1}{C_s}[(1-u_1)i_{FC} - i_{DC}] \\ \dfrac{di_{FC}}{dt} = \dfrac{1}{L_{FC}}[V_{FC} - (1-u_1)V_s] \\ \dfrac{dV_{DC}}{dt} = \dfrac{1}{C_{DC}}[i_{DC} - i_L + (1-u_2)i_{SC} + (1-u_3)i_B] \\ \dfrac{di_{DC}}{dt} = \dfrac{1}{L_{DC}}[V_s - V_{DC}] \\ \dfrac{dV_{SC}}{dt} = \dfrac{-1}{C_{SC}}i_{SC} \\ \dfrac{di_{SC}}{dt} = \dfrac{1}{L_{SC}}[V_{SC} - (1-u_2)V_{DC}] \\ \dfrac{di_B}{dt} = \dfrac{1}{L_B}[V_B - (1-u_3)V_{DC}] \\ \dfrac{di_L}{dt} = \dfrac{1}{L_L}[-R_L i_L + V_L] \end{cases} \quad (1)$$

where the state variables are defined as:

$$x = [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8]^T = [V_s, i_{FC}, V_{DC}, i_{DC}, V_{SC}, i_{SC}, i_B, i_L]^T$$

V_{FC} is given by the static model of Larminie et Dicks [30] and $V_B = e_B - r_B i_B$.

The electric power balance of the HEV should satisfy Eq. 2:

$$P_{FC} + P_B + P_{SC} = P_{Load} \quad (2)$$

The main objectives of this study are as following: (1) apply the IDA-PBC method to control the hybrid multisource system. (2) the battery SOC and H_2 quantity are subject to source limitation. (3) use ANN method for choosing of the best battery current reference under different (here ANN will decide if battery should contribute? How much? or should be recharged). (4) control the DC bus voltage to track its reference V_d. (5) FC supplies the load demand at the steady state phases. (6) SC delivers or absorbs the transient power. (7) battery provides the steady state energy (or power) when the FC cannot satisfy alone the load demand. In this condition, the battery needs to be recharged by the FC when it is discharged.

The equilibrium trajectories are computed in order to achieve the objectives, therefore:

$$x = [\bar{x}_1, \bar{x}_2, \bar{x}_3, \bar{x}_4, \bar{x}_5, \bar{x}_6, \bar{x}_7, \bar{x}_8]^T = \left[V_d, \bar{x}_2, V_d, \bar{x}_4, \bar{x}_5, 0, \bar{x}_7, \frac{V_d}{R_L}\right]^T$$

An implicit objective of the proposed structure is to recover the energy to charge the SC. Hence, the choice of the SC equilibrium voltage is its nominal value ($\bar{x}_5 = 24V$). The desired voltage of DC bus ($\bar{x}_2$) is supposed equal to 42V. $\bar{x}_4$ and $\bar{x}_7$ are defined according to the assigned role to the battery.

After simple calculations, the equilibrium control signals can be calculated as:

$$\bar{u} = [\bar{u}_1, \bar{u}_2, \bar{u}_3]^T = \left[\frac{V_{FC}}{V_d}, \frac{V_{SC}}{V_d}, \frac{e_B - r_B\bar{x}_7}{V_d}\right]^T \quad (3)$$

In this paper, the battery SOC is among the important parameters to be considered. The desired battery current is obtained through ANN. Eq. 4 is used to estimate the battery SOC (Coulometric Estimator):

$$SOC = SOC_0 - \int \frac{i_B}{Q_n} dt \quad (4)$$

where, SOC_0 is the initial battery SOC, i_B is the battery current and Q_n is the nominal battery capacity.

The battery SOC, as an input to the ANN along with the H_2 level, is used for determining the battery current reference. In addition, when the battery is fully charged, it can help the FC to provide power in steady state to reduce the dependency on FC and H_2 consumption. If FC is faulty, the battery is used according to its SOC level allowing a continuous service in a degraded mode.

III. PROPOSED CONTROL FOR THE HYBRID POWER SOURCES

Port Control Hamiltonian (PCH) technique is considered as a real-time nonlinear control approach. Since nineties, PCH has become an interesting method to control electrical, mechanical and electromechanical systems. In this study, PCH representation is chosen in order to have an efficient energy control for the hybrid multisource system [31]. System modeling in PCH form allows covering a large set of physical systems and capture important structural properties [8], [32]. For the PCH closed loop representation, the desired closed loop energy function is:

$$H_d = \frac{1}{2}\tilde{x}^T Q \tilde{x} \tag{5}$$

In Eq. 5, $\tilde{x} = x - \bar{x}$ is defined as the new state variable vector expressed in terms of error dynamics (difference between each variable and its equilibrium value/trajectory).

$Q = diag\{C_S; L_{FC}; C_{DC};\ L_{DC}; C_{SC}; L_{SC}; L_B; L_L\}$ is a diagonal constant matrix

The new error dynamic vector as function of the gradient of the desired energy function (Eq. 5) can be expressed as:

$$\dot{\tilde{x}} = [J(\mu) - R]\nabla H_d + A_i(\bar{x}, \mu) \tag{6}$$

with

and $$\nabla H_d = [C_S\tilde{x}_1; L_{FC}\tilde{x}_2 ; C_{DC}\tilde{x}_3;\ L_{DC}\tilde{x}_4; C_{SC}\tilde{x}_5; L_{SC}\tilde{x}_6; L_B\tilde{x}_7; L_L\tilde{x}_8]^T$$

$$J(\mu) - R = \begin{bmatrix} 0 & \frac{\mu_1}{C_S L_{FC}} & 0 & \frac{-1}{C_S L_{DC}} & 0 & 0 & 0 & 0 \\ \frac{-\mu_1}{C_S L_{FC}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{C_{DC} L_{DC}} & 0 & \frac{\mu_2}{C_{DC} L_{SC}} & \frac{\mu_3}{C_{DC} L_B} & \frac{-1}{C_{DC} L_L} \\ \frac{1}{C_S L_{DC}} & 0 & \frac{-1}{C_{DC} L_{DC}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{-1}{C_{SC} L_{SC}} & 0 & 0 \\ 0 & 0 & \frac{-\mu_2}{C_{DC} L_{SC}} & 0 & \frac{1}{C_{SC} L_{SC}} & 0 & 0 & 0 \\ 0 & 0 & \frac{-\mu_3}{C_{DC} L_B} & 0 & 0 & 0 & \frac{-r_B}{L_B^2} & 0 \\ 0 & 0 & \frac{1}{C_{DC} L_L} & 0 & 0 & 0 & 0 & \frac{-R_L}{L_L^2} \end{bmatrix} \qquad A_i(\bar{x}, \mu) = \begin{bmatrix} \frac{\bar{x}_2}{C_S}\left(\mu_1 - \bar{\mu}_1\right) \\ \frac{-V_d}{L_{FC}}\left(\mu_1 - \bar{\mu}_1\right) \\ \frac{\bar{x}_7}{C_{DC}}\left(\mu_3 - \bar{\mu}_3\right) \\ 0 \\ 0 \\ \frac{-V_d}{L_{SC}}\left(\mu_2 - \bar{\mu}_2\right) \\ \frac{-V_d}{L_B}\left(\mu_3 - \bar{\mu}_3\right) \\ 0 \end{bmatrix}$$

$J(\mu) = -J^T(\mu)$ is a skew symmetric matrix of $n \times n$ dimension representing the interconnection between the states and $R = R^T \geq 0$ is a positive semi-definite symmetric matrix defining the natural damping of the system.

The proposed control laws are:

$$\begin{cases} u_1 = \bar{u}_1 \\ u_2 = \bar{u}_{SC} - r\tilde{x}_6 \\ u_3 = \bar{u}_3 \end{cases} \tag{7}$$

with r is a positive design parameter.

<u>Proposition:</u> The origin of the closed loop PCH system in Eq. 6, with the control laws defined by Eq. 7 and Eq. 3 with the radially unbounded energy function Eq. 5, is globally stable.

Demonstration: The closed loop dynamic of the PCH system Eq. 6 with the control laws in Eq. 7 and Eq. 3 with the radially unbounded energy function Eq. 5 is expressed by

$$\dot{\tilde{x}} = [J(\mu) - R']\nabla H_d \tag{9}$$

with $R' = diag\left\{0; 0; 0; 0; 0; r; \frac{r_B}{L_B^2}; \frac{R_L}{L_L^2}\right\} = R'^T \geq 0$

The derivative of the desired energy function Eq. 5 during the trajectory of Eq. 9 is non-positive, as:

$$\dot{H}_d = \nabla H_d^T \dot{\tilde{x}} = -\nabla H_d^T R' \nabla H_d \leq 0$$

Consequently, the desired energy (Eq 5) is playing the role of the Lyapunov function which is proved to be non-positive. Therefor, the new state variables are all globally stable towards the origin. Hence, the original state variable are globally stable towards their equilibrium/trajectory references.

IV. Artificial Neural Networks

The development of ANN and their applications in different engineering sectors become fundamental challenges. The ANN has been considered in simulation, control, forecasting and laboratory establishments. The ANN, mainly inspired by biological neural networks, is widely used in solving various classification and forecasting problems. Although the ANN has the ability to deal with various features, its major disadvantage is still the necessity of huge information amount for training, and its need to powerful computing resource. Inci et al. have impartially discussed the different power transmission architectures and control strategies for attaining the desired efficiency. The FCEV technological perspectives and challenges comprehensively introduced both for Full and Hybrid FCEVs [33].

The deep ANN-based model has been used for predicting the tank-to-wheel CO_2 emissions. The correlations between the HEV design parameters has been reached. The prediction model data management has been properly performed [34]. From the results, the model can be further efficiently used for optimal (Internal Combustion Engine) ICE-based HEV designs. In [35], the energy management strategy (EMS) hybrid FC/UC vehicular system has been developed based on a combined wavelet transform/ANN for controlling the power distribution while operating the FC and SC during steady state and transient conditions respectively. The PEMFC parameter identification has been proposed an improved Elman ANN optimized by a hybrid optimizer based on the world cup optimization (WCO) combined to the fluid Search Optimization (FSO) [36].

Recently, different research studies have considered ANN in either/both controlling multisource systems or/and defining appropriate energy management procedures to maintain and ensure continuous efficient operation.

The authors of [37] have proposed the efficient optimal energy management operation of hybrid power system (HPS) using Artificial Intelligent (AI) controllers. The HPS has comprised both Wind Turbines (WTs) and the PV panels as primary Renewable Energy Sources (RESs) besides both FCs and Gas Micro-Turbines (GMTs) as Backup Sources (BKUSs). To avoid the undesired negative impacts on the HPS functionality because of the RESs intermittency, the Hydrogen Storage System (HSS) has been integrated into the system [37]. To enforce this idea, the authors in [38] have maximized the exploited wind power to benefit from the wide range of the wind speed. Thus, the combined MPPT-Pitch angle control has been developed via a single low-cost circuit based on ANN. This combination has allowed the Permanent Magnet Synchronous Generator (PMSG) to operate at the optimal speed for extracting the maximum power [38]. The authors of [39] have evaluated the Hydrogen fueling station as a way to commercialize hydrogen energy through FCs, particularly in the automotive sector. Techno-economic analysis of hydrogen refueling station powered by wind/PV hybrid power system in Izmir-Cesme region in Turkey has been performed. This analysis has been carried out to develop the hydrogen refueling station for 25 FC EVs daily [39]. The study of [40] has focused on developing a software application to compare the MPPT algorithms for PV systems. The considered real time working conditions (solar irradiance and ambient temperature) have based on four PV different models (B-model) [40]. In [41], the authors have proposed the hybrid adaptive control approach for solar photovoltaic and FC system fed Voltage Source Converter (VSC) [41]. The authors of [41] have focused on analyzed the ever-increasing demand for fossil fuels and environmental issues over the last few decades. The authors have proposed hydrogen as a viable and promising alternative fuel option to Internal Combustion (IC) engines.

The use of H_2 alternative fuel would result in bridging the contemporary gap to the long-term FC based power train roadmap [41]. The authors of [42] have presented the robust neural network adaptive control for Polymer Electrolyte Membrane (PEM) FCs. Due to inherent nonlinearities in PEMFC dynamics and variations of the system parameters, the linear control with fixed gains may be insignificant for PEMFC systems. Therefore, the adaptive neural network control with feedback linearization has been developed [42]. Moreover, the authors of [43] have estimated the output power and the efficiency of the Axial Flux Permanent Magnet Synchronous Generator (AFPMSG). The present tool can be used for estimating data for the characterization of the machines. It can be beneficial for the applications where a nonlinear relationship among the power generation, generator efficiency, speed and load has been required [43]. The authors of [44] have investigated the unsorted nature of electrical energy. The energy generation-consumption balance should be ensured to avoid power system frequency deviation problems. Therefore, dynamic neural network has been used for the prediction of daily power consumption. The suitability and the performance of the proposed approach have been verified with simulations on load data collected from French transmission system operator website [44]. The authors of [45] have developed the ANN control strategy for Solid Oxide Fuel Cell (SOFC) to meet the demand of public utility buildings where electricity demand has been predicted [45]. Furthermore, in [46], the authors have presented the cost-benefit analysis methodology of stand-alone storage plants operating under market conditions through price arbitrage for both pumped hydropower plant and hydrogen storage plant. The results have shown that the pumped hydropower plant was profitable, whereas the hydrogen storage plant project was not economically viable without additional supports. Thus, possible economic incentives resulting in a profitable hydrogen storage plant have been examined [46]. In addition, the authors of [47] have studied the possibility to eliminate pollution resulted by burning fossil fuels. Since the analytical model, expressing FCs' characteristics was not accurate in comparison with the real system's performance. The robust and dynamic model for FCs became necessary. The authors have studied the optimized model for Proton-Exchange Membrane Fuel Cell (PEMFC) integrated into electric bicycle that consists of a 250 W FC, battery pack, DC/DC convertor, electric motor and Electric Control Unit (ECU) [47]. Moreover, in [48], the moth-flame optimizer (MFO) approach to improve the power extraction from the Solid Oxide Fuel Cell (SOFC) through defining the model optimal parameters. The cell model has been identified via trained ANN using experimental dataset. The results have illustrated the enhanced output power extraction using the proposed hybrid ANN-MFO technique. The authors of [49] have studied the multi-objectives energy management for microgrids considering random EV charging. To attain such objective, forecasting has been employed to the charging EV loads. The ANN hybridized with deep learning has been considered for reaching an efficient forecasting operation and better convergence [42].

In this paper, the ANN is originally employed to obtain the battery reference current. To enable more convenient energy management operation for the FC/battery/SC system, the current through the battery should be estimated with sufficient accuracy. After defining a pool of experimental measurements that illustrates the relation between the different inputs (SOC, H_2, t) and the current output I_{Bref}, the ANN can be simply used for specifying the current reference for any operation condition. However, the use of ANN requires more expertise particularly for ANN training process to avoid simulation/calculation time consumption. To cope with the high variability of the experimental measurements and to eliminate any undesired ones, it is possible to propose a strategy that imposes weighting criteria to improve the measurements classification. In this paper, the authors sought to circumvent the problem of unnecessary measurements through developing the ANN methodology to provide the most appropriate current reference for the energy management in the FC/battery/SC system.

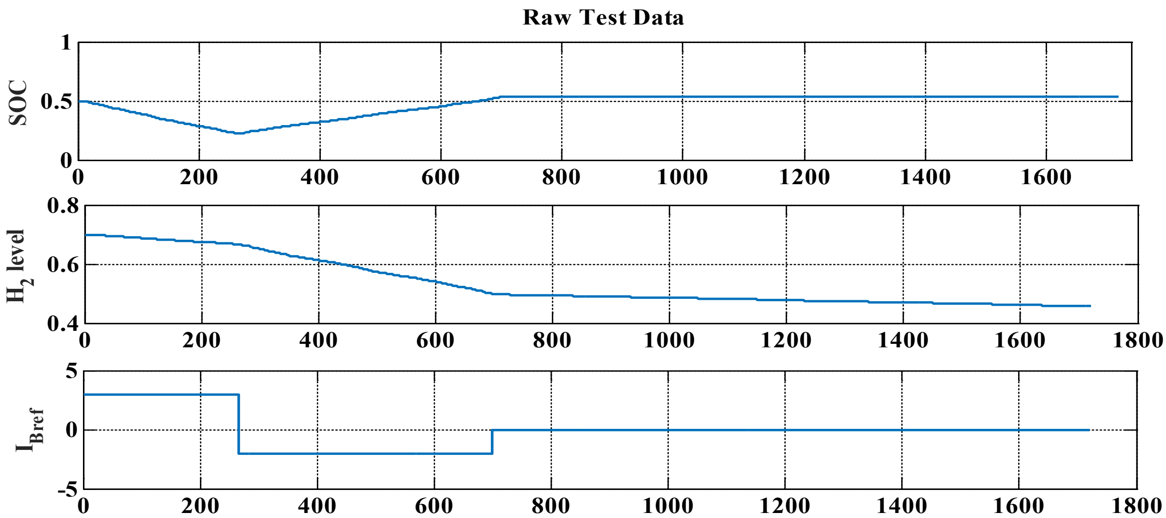


Fig. 2. ANN raw test data

Fig. 2 depicts the ANN raw test data. Both plots, the battery SOC and the H_2 level represent the input to the ANN while I_{Bref} shows the target (defined by expert users) that ANN tries to emulate. The current I_{Bref} varies between 3 constant values over 3 intervals. Its value is 3 when SOC degrades from the initial value 0.5 down to 0.2 and H_2 level goes down slowly below its initial value 0.7. Then, I_{Bref} reaches the value -2 when the SOC increases from 0 to slightly more than its initial value and H_2 level decreases with larger slop than in first interval until reaching 0.5. In the third interval, I_{Bref} becomes 0 when H_2 level becomes less than 0.5 and SOC becomes constant to a steady final value.

Fig. 3 shows that the ANN error is slightly close to 0 during the simulation intervals. Although the error is bounded between 0 and -0.05 during the test, the error rarely reaches -1 or 2. In Fig. 4, the mean square error (MSE) has been used for depicting the ANN model performance. The best validation performance reaches 0.00029195 (≈ 1.7% root MSE) at epoch 124 before entering overfitting stage where validation error starts increasing while train test is still decreasing. It is noted that the validation and test errors are smaller than the train ones.

From Fig.5, the Gradient plot shows that updating the weights is going on along epochs. However, it is bounded as the gradient value is about 0.192 at epoch 130 and the proposed ANN continues learning effectively. The Momentum constant is gradually decreased during the training process both for converging to a solution and for preventing the oscillations in weights values. The validation plot indicates that after 6 consecutive epochs training stops as performance is expected to become worse if training proceeds. In Fig.6, the Regression plot of ANN model reflects high precision (i.e. adequate degree of closeness) between the ANN output and the target (~0.0038 average difference between output and target). Recall that target only takes 3 values: 3, -2, 1.

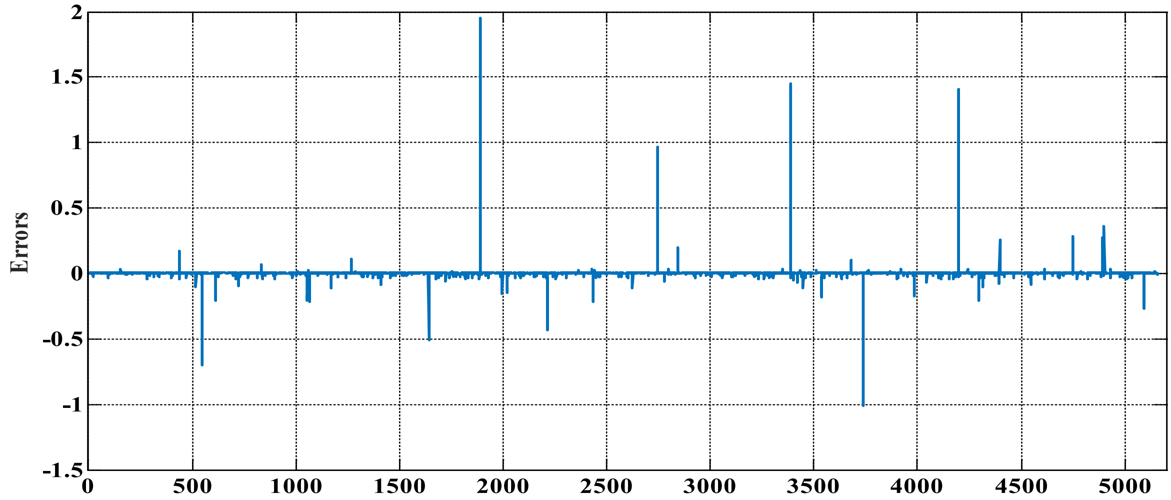


Fig.3. ANN error

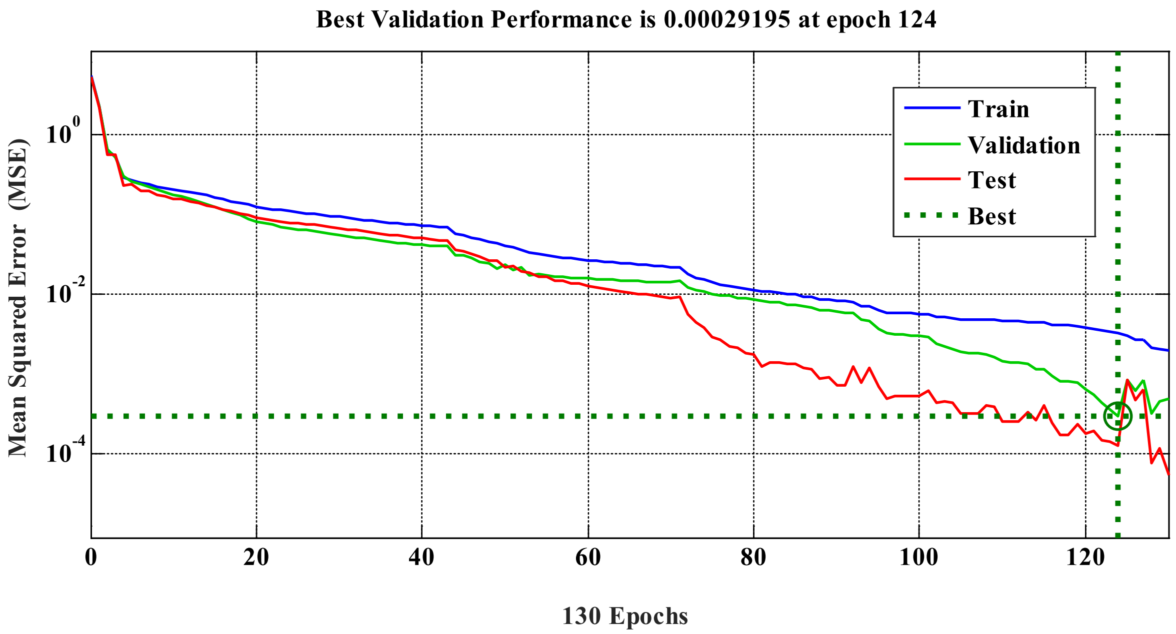


Fig.4. ANN performance measure.

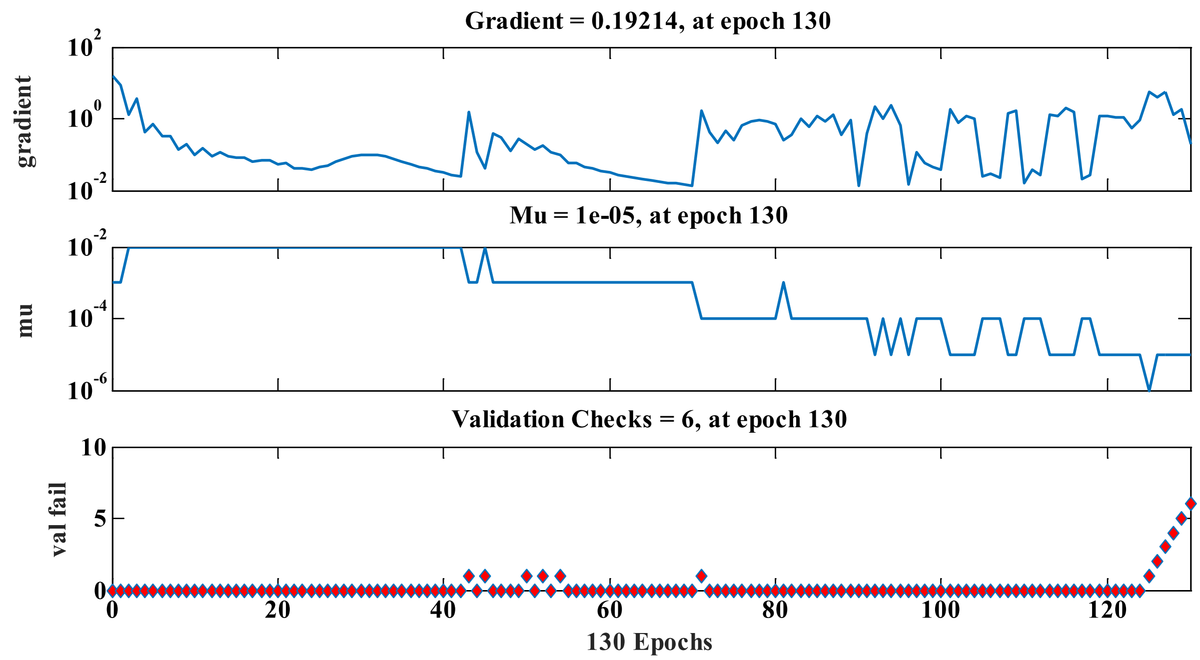


Fig.5. ANN model training state.

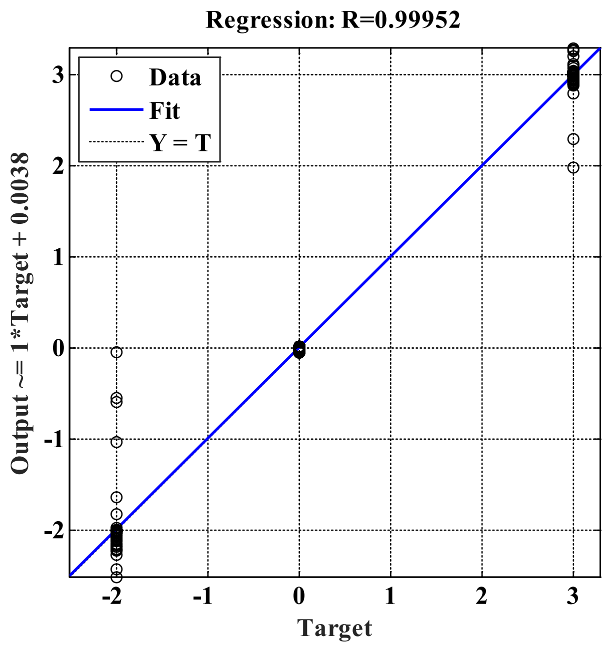


Fig.6. Regression plot of ANN model.

V. Experimental Set-up, Results and Discussion

The experimental tests are performed at the Hydrogen Research Institute at Trois Rivières University, Quebec Canada to validate the IDA-PBC proposed control. The test bench is illustrated in Fig.7 and is composed of (a) three Zahn converters, (b) DC bus capacitor, (c) Horizon PEMFC, (d) the fuses are used for limiting the current t to 20A to protect the experimental platform, (e) three Lithium-Cadmium (Li-Cd)batteries connected in series, (f) two modules of Maxwell SC, (g) LEM transducers and voltage probes to measure voltages and currents of sources, (j) programmable load to emulate the traction subsystem. As only positive powers are provided by the load, the regenerative braking is not considered. The mechanical braking is accounted for braking phases. The developed platform allows the validation of the control portability at real time besides the energy management. The experimental validation has been performed using the system parameters given in Table I of [26] in addition of using of the Li-Cd battery packs with 36V [50][50][49][47][46][45][44][43][42][41][40][39][38].

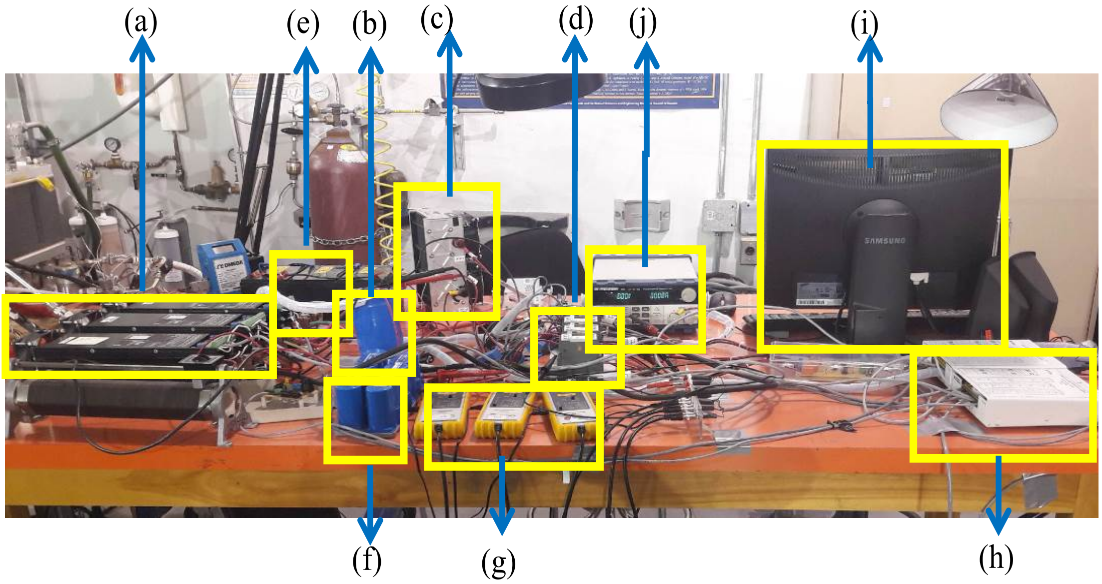
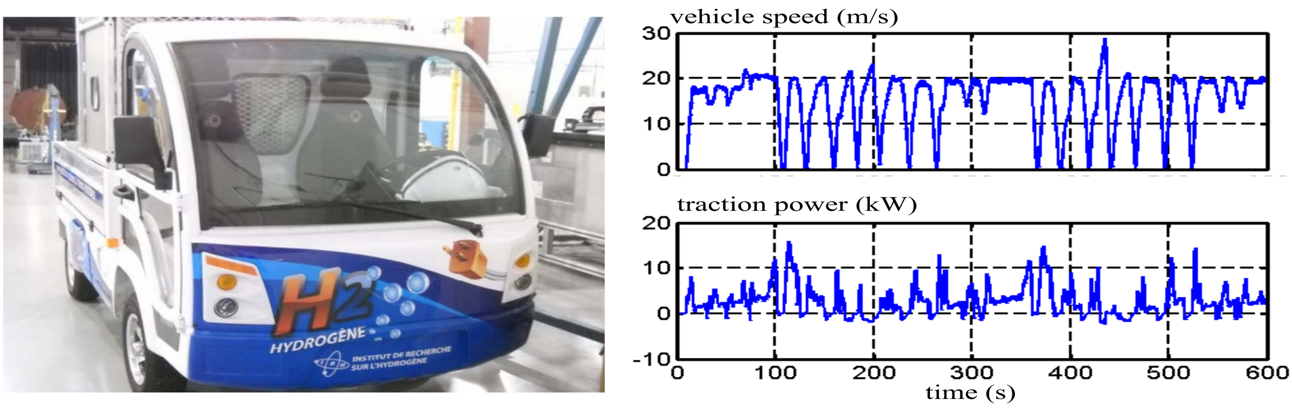


Fig.7. Test bench: (a) Converters; (b) DC bus; (c) FC; (d) fuses; (e) three Li-Cd battery; (f) SC modules; (g) sensors; (h) data acquisition system; (i) control unit; (j) programmable load.

The experimental results are obtained using a reduced scale power of the real operating profile of the hybrid Nemo EV the Hydrogen Research Institute as shown in Fig.8.a). The driving cycle of [26], depicted in Fig.8.b), is used for Nemo vehicle at Trois Rivières University Canada during the driving test around the campus, where the power peaks around 15kW is saved. Consequently, the proposed hybrid FC/battery/SC system must satisfy the power request in each phase. In this paper, the programmable load is used for reproducing the driving cycle with a reduction scale of 1/60. Furthermore, this load does not consider the negative power demand.



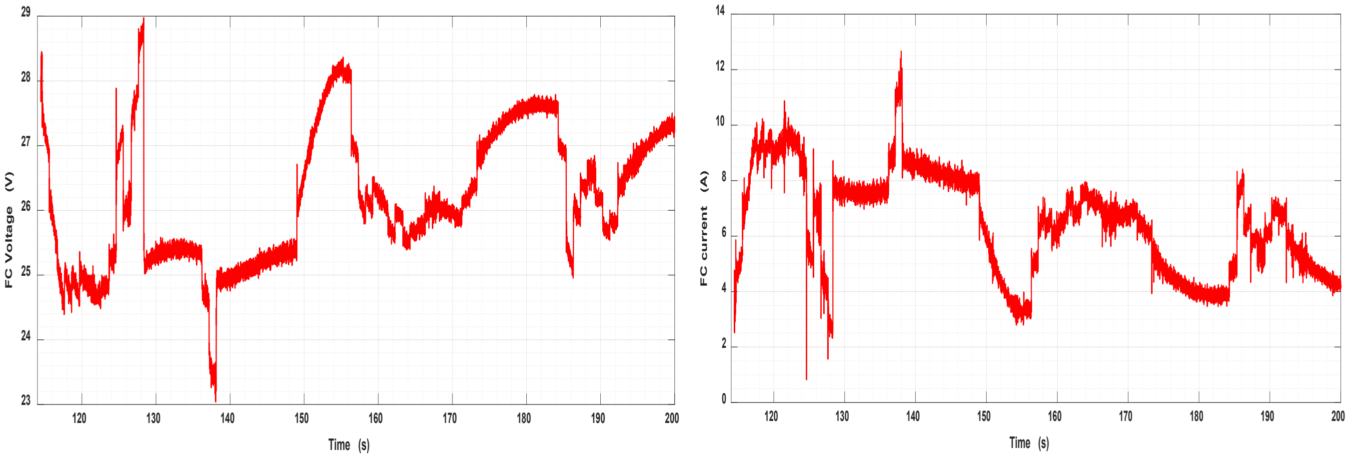
a) nemo EV b) driving cycle

Fig.8. Nemo Electric vehicle and its full-scale road driving cycle.

Experimental results obtained for hybrid FC/battery/SC multi-sources multi-converters system. The current and voltage dynamic behavior are presented and discussed for each source.

- Electrical behavior of FC source

  Fig.9 illustrates the experimental time current and voltage time response of FC. The FC current in Fig.9 (b) achieves the maximum value of 13A at 136s. The FC voltage Fig.9 (a) varies according to the current imposed on it. It is also clear that the FC has a slow behavior compared to the SC (Fig.11).

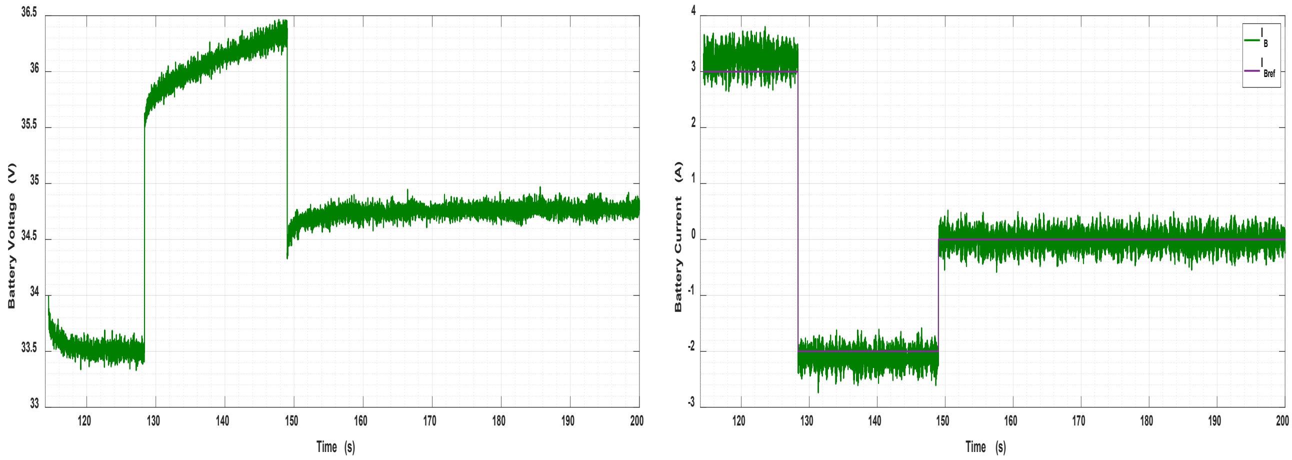


(a) FC voltage (b) FC current

Fig.9. Experimental results of FC voltage and current

- Electrical behavior of battery source

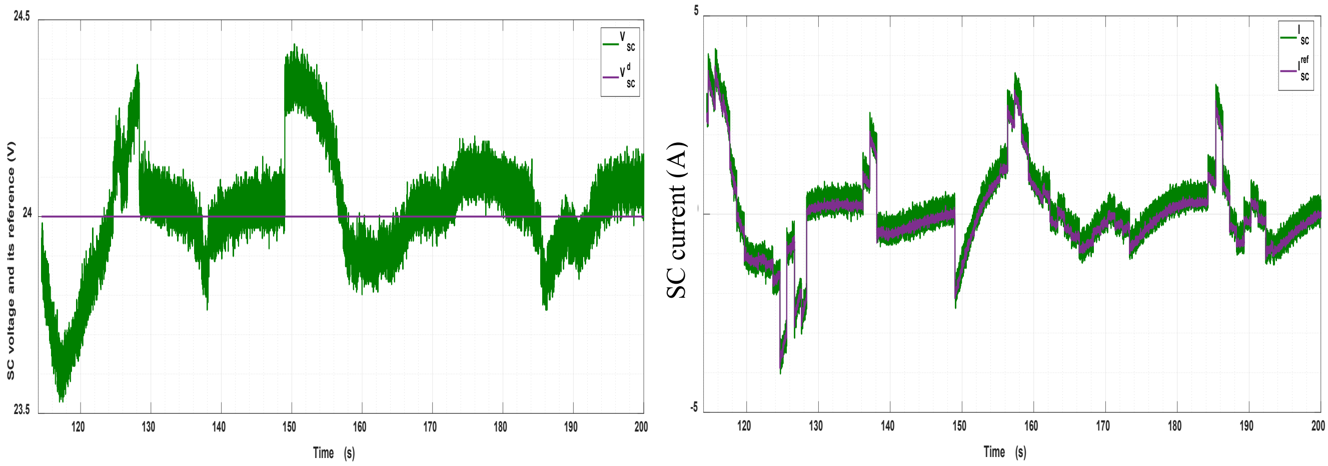
The curves in Fig.10 represent the battery current and voltage. The curve of the battery current and its reference in Fig.10(b) shows that the battery current tracks well its set point with overshoots of about ±0.2A and this during the whole cycle. From Fig. 10(b), one can notice different modes of battery operation. The battery current in the time interval [100s-125s], the battery provides energy to the load, its current is about 3A. On the other hand, During [130s-150s], the battery current is negative (-2A) → the battery is in charging mode. . The battery voltage is shown in Fig.10 (a), where it is observed that it is between 36.5 V and 33.5V in the time interval [125s-150s]. When the battery is solicited to supply the load. For example in the period [100s-125s], its voltage decreases from 34.9V to 33.5V. Whereas in the interval [125s-150s], the battery is recharged in by the FC and its voltage increases from 35.5V to 36.5V. Outside these periods, the battery voltage is around 34.8V.



(a) Battery voltage (b) Battery current and its reference

Fig.10. Experimental results of battery voltage and current

- Electrical behavior of SC source



(a) SC voltage and its response (b) SC current and its reference

Fig.11. Experimental results of SC voltage and current

Fig.11 depicts the dynamic response of the SC current and voltage and their references. Through Fig.11 (b), the SC current tracks accurantely its reference at all time. The SC current reference presented in Fig.11 (b) is obtained suing the ANN method. This is showing that the SC current is perfectly tracking its reference with almost zero error. Concerning the SC voltage in Fig.11 (a), the desired SC voltage is of 24V and SC voltage returns to its initial value of 24V (mind that there is a zoom on this figure, consequently, the variation of the SC voltage is quite low).

- DC bus voltage

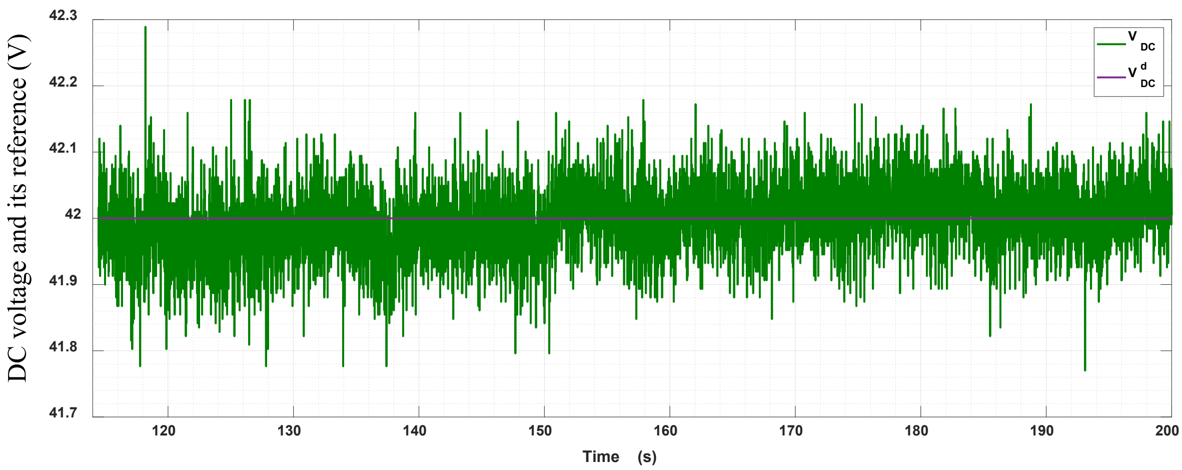


Fig.12. Experimental result of the DC bus voltage and the desired DC bus voltage

The proposed control using IDA-PBC shows its efficiency while maintaining constant the DC bus voltage at 42V, as shown in Fig.12. However, the experimental DC bus voltage is somehow noisiness because the real system is faced to the disruption as measurement noises (mind also that here, a zoom on this figure is adopted and the noise is not so large). Furthermore, this voltage fluactes in acceptable set of voltage, less then 0.3V and the oscillation arround of the desired DC voltage seems to have a constante frequency.From Figure 12 , the DC bus voltage follows well the imposed reference with suitable observed overshoots. This allows us to conclude that the proposed approach (IDA-PBC+ANN) for this study has satisfied one of the objectives of the control which is the stabilization of the DC bus output voltage around its desired value in order to show which source is used and at which time of the cycle depending on its SOC.

- Powers of the sources

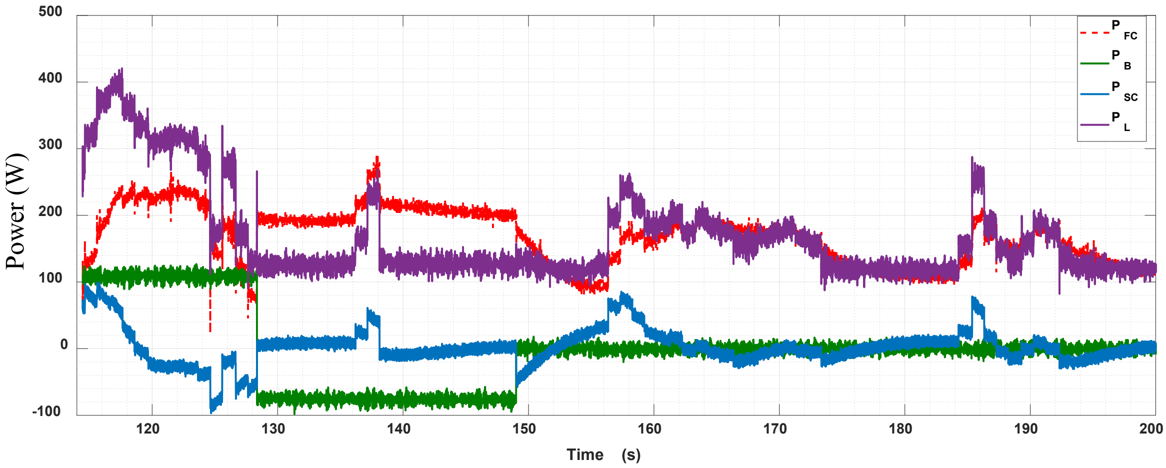


Fig.13. Load sources powers

From Fig.13, the Load power P_L is equal to the sum of the FC power P_{FC}, Battery power P_B and SC power P_{SC} during all the operating period. The FC power is always positive and having an almost smooth behavior. Furthermore, the traction power achieves 400W that corresponds to the limit of real traction power of 12 kW, considering the scale reduction of 1/60. Fig.13 illustrates the proposed scenario where the FC supplies the load demand during the steady state helped with the battery and SC in transient phases. Furthermore, the battery can play a complementary role to the FC supplying the load in the startup for example. The SC is devoted to absorb and/or supply the energy demand during transient phases.

From Fig.13, several scenarios have been demonstrated. The first scenario from t=114s to 128s, where the load demand power is mainly satisfied by the FC supported by the storage devices (battery and SC). The second scenario from t=128s to 149s, the battery is recharged and the FC ensures the load demand plus the battery charging.. The SC covers the transient phases. From t=149s to 197s, the FC supplies alone the load demand at steady state phase and SC ensures the transient phases, while the battery is not considered for this objective. From Fig.13, the load demand is appropriately supplied at all time during the driving cycle that concludes the efficiency of the proposed control. Therefore, depending on the battery SOC, the battery can help the FC meeting the load demand when the hydrogen level drops, for example. For more details, the reader can have a look to the work of [51], [52] , which uses the passivity with the optimal control based on the Hamiltonian Jacobi Bellman for FC hybrid system.

VI. CONCLUSIONS AND PERSPECTIVES

This paper discusses the energy management in hybrid FC/battery/SC for EV applications. Its major objective is to explicit energy management control strategy for the hybrid system composed of the FC as the main source and reversible sources (battery and supercapacitors) as auxiliary sources. This system is dedicated to traction in the FC electric vehicles, while taking into consideration the source constraints, namely the battery SOC and hydrogen quantity at the FC level. In this regard, the hybrid association architecture studied is composed of a FC linked to the DC bus via a boost converter. The storage devices are connected to the DC bus through DC/DC buck/boost converters. These converters aim to regulate the DC bus voltage and manage the power transfer to and from the load. Among the different energy management and techniques used in FC electric vehicles, authors are providing in this article a combination between the ANN and PBC to control and manage the energy of this multisource system considering the source limitation and providing the stability proof. The use of the ANN makes it possible to generate the battery reference current while depending on its SOC as well as the hydrogen remaining quantity in the tank realizing then the energy management between the sources. The role of the IDA-PBC control is to modify the damping matrix of the Hamiltonian studied system to force the battery current to follow its reference generated by the ANN technique. The IDA-PBC and the ANN techniques are combined to ensure at the same time, the hybrid system stability while providing adequate solution to dispatch the energy between sources considering the source limitations.

The experimental results using the proposed control shows adequate and satisfactory results. The stability proof is provided and the obtained results reflect exactly the proposed scenario. The experimental analysis shows that the proposed hybrid ANN control IDA-PBC can operate in real time with adequate tracking performance.

The future work will comprise the experimental validation of the proposed thermal management approach for enhancing the lifespan, cycle, efficiency and reliability of the EV. Furthermore, the multi-stacks FC system can be considered together with the battery under different parameter uncertainties. In addition, different advanced control methods can be applied to the system in order to obtain better dynamic performance.

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