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A Novel Intelligent Energy Management Strategy Based on Combination of Multi Methods for a Hybrid Electric Vehicle

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ABSTRACT

Based on the problems caused by today conventional vehicles, much attention has been put on the fuel cell vehicles researches. However, using a fuel cell system is not adequate alone in transportation applications, because the load power profile includes transient that is not compatible with the fuel cell dynamic. To resolve this problem, hybridization of the fuel cell and energy storage devices such as batteries and ultra-capacitors are usually applied. This article has studied a hybrid electric vehicle comprising a fuel cell system and battery pack. Energy management strategy is one of the essential issues in hybrid electric vehicles designing, for power optimal distribution as well as, improving both the fuel economy and the performance of vehicle's components. In this paper, an optimal hierarchical strategy has been proposed based on the load power prediction and intelligent controlling to achieve an optimal distribution of energy between the vehicle's power sources; and, to ensure reasonable performance of the vehicle's components. For load power prediction, a new method is presented that is based on Takagi – Sugeno fuzzy model trained by an improved differential evolutionary algorithm with an objective function formulated by support vector machine. A combination of empirical mode decomposition (EMD) algorithm capabilities, fuzzy logic controller, supervisory switching technique and improved differential evolution algorithm is used to design the proposed energy management strategy. The proposed strategy is assessed in the UDDS Standard drive cycle. Simulation results show that the proposed control strategy can fulfill all the requirements of an optimal energy management.

KEYWORDS

Hybrid Electric Vehicle, Fuzzy Logic Controller, support Vector Machine, Empirical Mode Decomposition, supervisory Switching Control, Improved Differential Evolution Algorithm.

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1. INTRODUCTION

In recent years, due to increasing concerns in energy crisis and environmental pollution, extensive researches have been done on fuel cell (FC) vehicles as a viable alternative for today conventional vehicles [1]. Despite significant advances in the fuel cell technology, technological limitations such as low efficiency at low power demand and slow transmission rate of power at transient positions are existed [2]. These cases have resulted that the fuel cell system should not be used alone in the hybrid electric vehicles in order to meet power demand, especially in start-up and transient times. Compared to the fuel cells, batteries have higher power density that can provide necessary load power immediately in transient position [3]. Also based on the fact that fuel cells have no energy recovery capability, hybridization of the fuel cell and batteries is one of the most important requirements of fuel cell vehicles. In hybrid configuration of FC and battery, FC system and battery pack are sized to meet the continuous and transient power load profile, respectively. The hybridization of fuel cell and battery has remarkable results including: reduction in fuel consumption, and downsizing of FC. Many published papers such as [4]-[5]-[6]-[7] proposed a structure consists of FC and battery (as energy storage system) for hybrid electric vehicle configuration. Designing an energy management strategy is an important and inevitable matter in hybrid electric vehicles, due to the distinct nature of FC and battery dynamics [8]. Many different energy management techniques have been proposed in the literature. In many studies on the hybrid electric vehicles, according to the nonlinear dynamic of the system, parametric sensitivity to environmental factors, load complexity and system uncertainty are the basic of energy management strategy on intelligent controllers. Among the intelligent control strategies, fuzzy logic control (FLC),has a central role in the intelligent strstegies due to its independence of mathematical modeling and training procedure [9]. In [9-16]the FLC was used to design energy management strategy in hybrid electric vehicles. Intelligent energy management strategies in [1-3]and[8-10] were designed based on the distinctive nature and dynamic of the power source. Although in afore mentioned papers, the FC lifetime problem and its optimum performance have been studied better than the control strategies presented in [11]-[12]-[13]-[14]-[15]-[16]. But the problem of fuel economy and the overall system efficiency has not been well investigated. Furthermore the proper states of FC shutdown and starting were not well examind. Another weakness of their strategies is their problem of being online, although they have been introduced as real-time approaches.Evidence of this asseveration is that, in the mentioned strategies the used load power information requires previous data of the management problem.

In real-time energy management strategies it is not possible to achieve an optimal solution for the problem of energy management in a hybrid electric vehicle due to the lack of driving cycle recognition. Most of the proposed methods carry out from the control process based on a background of vehicle propelling or traffic information that causes the vehicle's performance to be mostly inappropriate. Hence, gaining driving cycle information and its proper estimation is very important in the field of energy management study [17]. In this paper, a comprehensive and real-time energy management strategy is presented. In the proposed strategy, a hybrid algorithm is designed to predict the vehicle load power profile. Also, the empirical mode decomposition (EMD) algorithm is applied to produce fuel cell reference power signal from the predicted load power profile. Fuzzy logic controller and improved differential evolutionary (IDE) algorithm are employed to optimal control of power. The supervisory switching technique is used to determine the appropriate status (on / off) of the fuel cell system. The proposed strategy is developed in a FC/ battery hybrid vehicle.

The goal of designing the proposed strategy is to optimally distribute power among the power sources (fuel cell and battery), reduce fuel consumption, increase overall system efficiency and improve the lifetime and performance of the hybrid system components.

This paper is organized as follows. In section1, the configuration of the vehicle components is described. In section2, the proposed strategy and its applied techniques are described.In section 3, the simulation process and its results are discussed. finally section 4 concludes the paper

2. Driving Structure Of The Hybrid Electric Vehicle

The hybrid electric vehicles have different structures, but generally a hybrid vehicle is formed of a power plant, an energy storage system, and a power transmission system. Usually a parallel connection of a FC, energy storage system and DC-DC converters is chosen because it increases system capabilities [11].

A propulsion structure of FC/ battery is shown in Fig. 1. In this structure, the FC system as the main power source acts and the battery pack is considered as the auxiliary power source. The advantage of this system is that the battery system can provide transient power and is capable to recover brake energy.

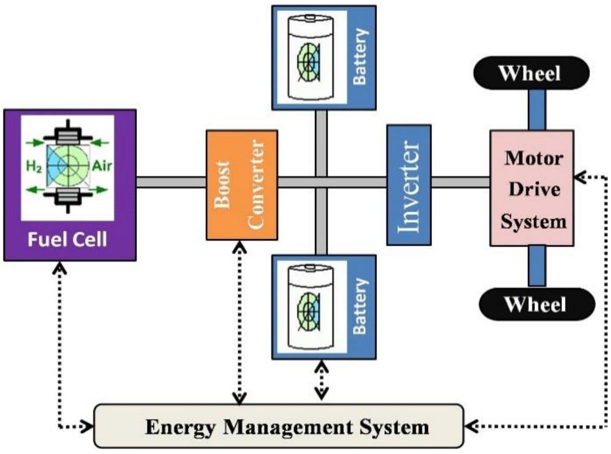

Fig. 1. Architecture of the FCHEV

A. Modeling Of The Hev

In this paper, the "Advisor" software is employed to model the hybrid vehicle's components. This software is developed by the American National Renewable Energy Laboratory. Advisor is a set of model files, data and scripts to use in Matlab/Simulink environment for vehicle simulation [11]. This software simulates the dynamic performance of vehicles in a variety of different power train systems with varied sizes.

The feature of this software is that all of its models and files are open to user to allow users to access the original creation and changes files and models.

Instead, attaining the actual and accurate results of this software relies heavily on the skill of users in vehicle modeling and simulation process. The studied hybrid vehicle model in Advisor is shown in Fig. 2. As mentioned before the modeling details and relationships among the components are available and open to users. So, modeling of hybrid vehicle components is not described in this paper. Table 1 describes the characteristics of the underlying vehicle and its power components.

3. The Proposed Energy Management Strategy

In the FC/ battery hybrid vehicles a comprehensive energy management strategy must be considered to optimize the distribution of power flow between power sources with consideration of distinctive dynamical feature

In this section, a management strategy based on fuzzy logic controller, empirical mode decomposition, improved differential evolution algorithm and supervisory switching control is designed.

The bases of the proposed strategy is established on the fuzzy logic. A schematic diagram of the proposed strategy is shown in Fig. 3.

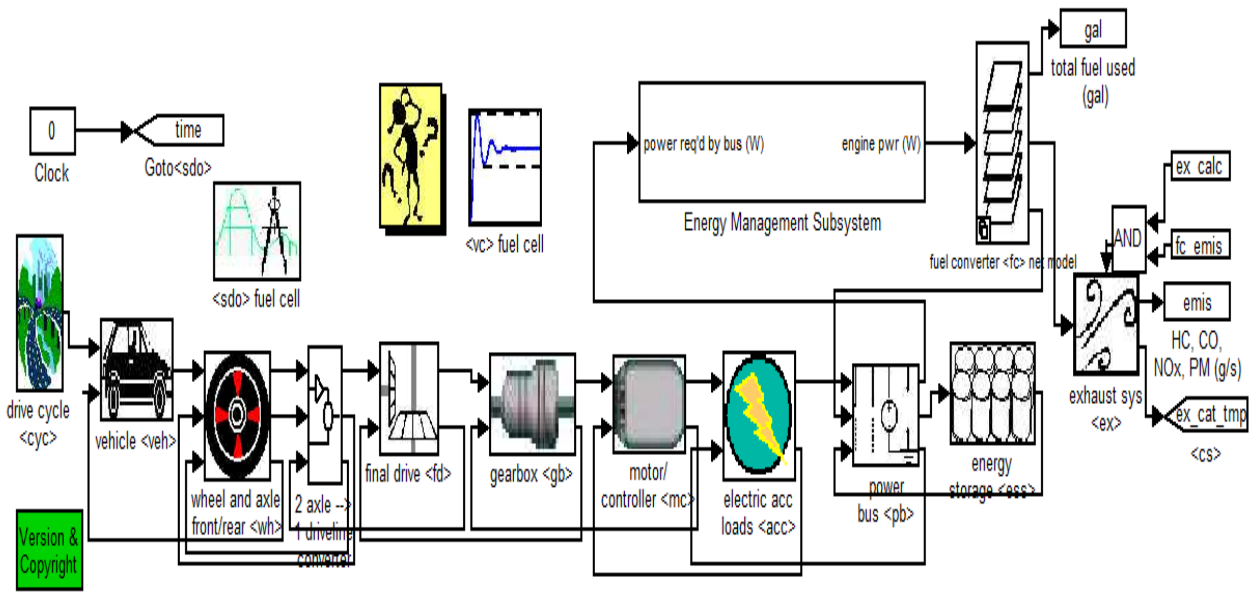

Fig. 2. Architecture of the FCHEV

TABLE 1. SPECIFICATIONS OF THE ELECTRICAL AND MECHANICAL COMPONENTS OF THE HEV

Vehicle specification:			
Total mass (kg)	1380	Coefficient of rolling drag	0.009
Frontal area (m2)	2.0	Coefficient of aerodynamic drag	0.335
Wheel rolling radius (m)			
Motor specification:			
Maximum power (kW)	75	Maximum speed (rpm)	6283
Rated voltage (V)	320	Average efficiency (%)	60
Fuel cell system specification:			
Type Average efficiency (%)	PEMFC 56	Maximum net power(kW) Minimum power (kW)	50 5
Battery specification:			
Maximum discharging rate	5C	Number	25
Rated voltage (V)	308	Capacity (Ah)	2.5

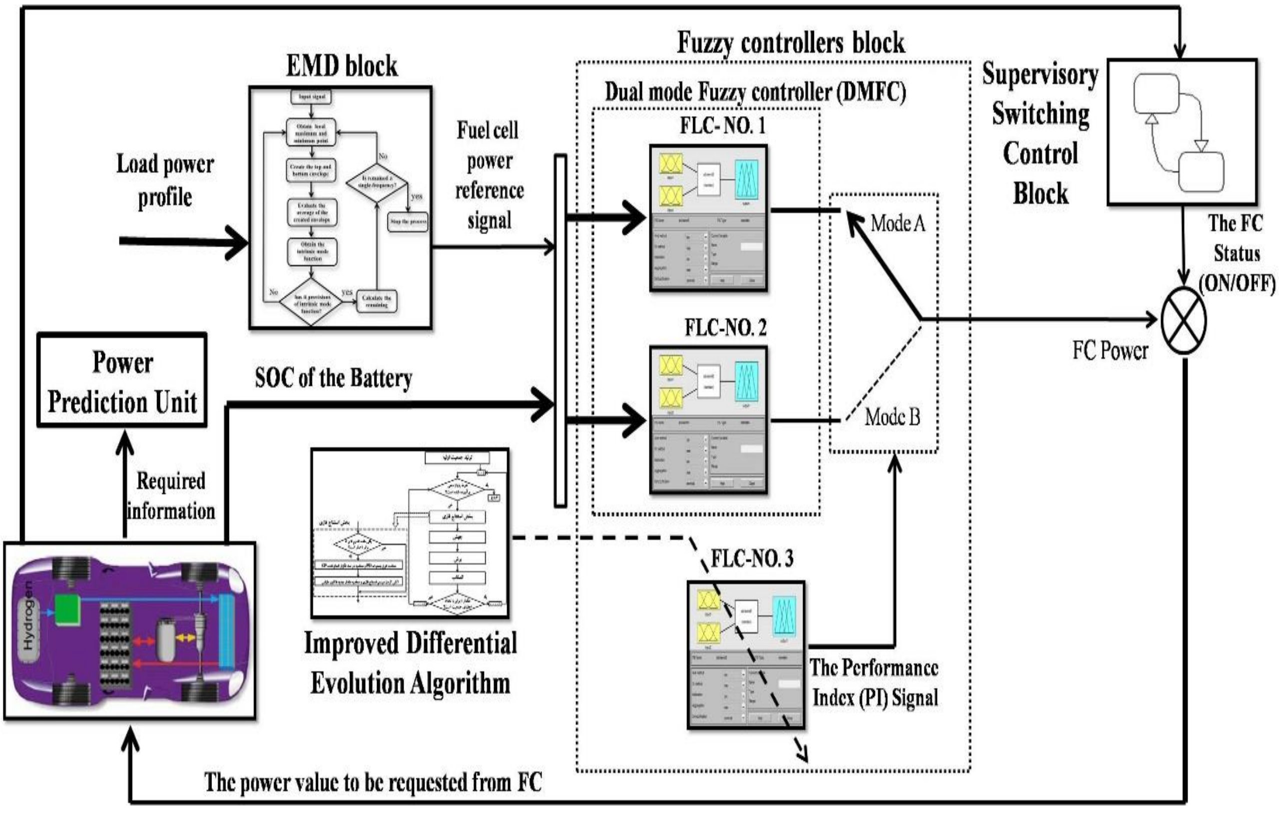

Fig. 3. Proposed energy management diagram

As can be seen in Fig. 3, a signal is provided as a reference power signal for the fuel cell system in the EMD block. This signal is low frequency part of the load power signal that has transient-free nature. The fuzzy block is included of three fuzzy controllers (FLC-No.1, FLC-N0.2 and FLC-No.3). A dual mode fuzzy controller (DMFC) is existed in this block that its operating mode is determined by another fuzzy controller (FLC-No.3). The task of these fuzzy controllers is to determine the appropriate requested power value of the FC system. In the supervisory switching control block, the appropriate status of FC activity (turn on or shutdown) is investigated. To improve the performance of the proposed strategy an improved evolutionary algorithm is used to tune parameters of the membership functions of the FLC-No.3. The employed techniques in the proposed strategy are described,below

A. Load Power Prediction

Identification and estimation of the driving cycle patterns in the real action of a hybrid electric vehicle is difficult and has its own specific complexities. This matter usually causes the impossibility of driving pattern identification directly, due to plenitude of the driving patterns and multiplicity of affecting parameters [17].

So, in attention to the aim of the controlling problem that is related to vehicle's energy topic,in this paper the estimation value of the requested power from the vehicle at any moment is used. In recent years, the use of the fuzzy models for modeling, prediction and time series analysis has grown significantly and now these models are important tools for time-series prediction. The proof of the theory about the all-purpose approximation feature of the fuzzy models has been presented in recent decades [18]. In this paper, the Takagi-Sugeno fuzzy type is used to fuzzy systems model the load power prediction problem. This model is trained by an improved differential evolutionary (IDE) algorithm further an, inspiration of the support vector machine (SVM) is used for its fitness function.

The training flowchart of the Takagi-Sugeno model (prediction model) is shown in Fig. 4. The inputs of the prediction model are

1- The vehicle speed.

2- The exerted torque on the vehicle's front wheels.

The output of the prediction model is the required power of the power supplies of vehicle i.e. the load power.

B. Takagi-Sugeno Fuzzy Model[ ]

In this paper, the Takagi-Sugeno fuzzy model (for simplicity T-S model) is used to load power prediction due to its ability as a powerful tool for system identification.

For simplicity of discussion, a multi-input and single-output (MISO) system is considered. The general form of T-S model with n input variables and r rules is as follows [18]:

$$R_i : \text{if } X_1 \text{ is } A_{i1} \text{ and} \dots X_n \text{ is } A_{in} \text{ then } y_i = p_{i1}X_1 + \dots + p_{in}X_n + p_{i(n+1)} \quad (1)$$

where R_i denotes the i-th rule, X_j represent the j - th input variable, A_{ij} represents the fuzzy membership function belong to the i- th rule and j- th input variable, Y_i represents the output of the i- th rule which is usually expressed as a first order polynomial and P_{i1}, P_{i2}, ..., $P_{i(n+1)}$ are parameters related to the polynomial.

A variety of membership functions in T-S model is existed. The function that is used here, is a Gaussian function. The grade of membership function of variable "x" is calculated

$$\mu(X) = \exp\left(\frac{(X - C)^2}{2\,\sigma^2}\right) \quad (2)$$

where c and are the center and the standard deviations of the membership function ($\mu(.)$).

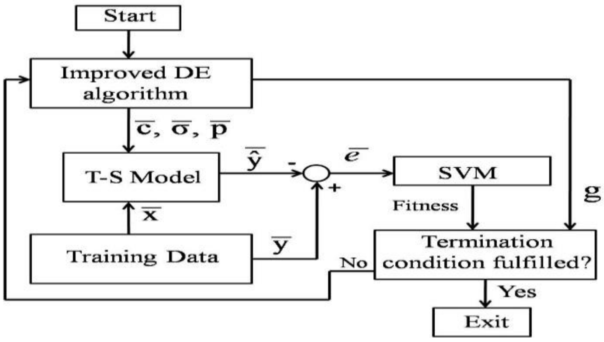

Fig. 4. The training flowchart of T-S model

C. Support Vector Machine Formulation[ ]

In each regression problem, training data are given. The goal of support vector regression (SVR) is to find the functional that its estimation error is less than and be flat as possible. Assume the used function in SVR is linear as it can

$$y = f(x) = \langle w, x \rangle - b \quad (3)$$

where represents the inner product, W is the weight vector or slope vector defined at space, and b is a scalar. Therefore, a prerequisite for training data estimation with error less than ε by the function $f(x)$ can be written

$$\begin{cases} y_i - \langle w, x_i \rangle + b_i \le \varepsilon \\ \langle w, x_i \rangle - b - y_i \le \varepsilon \end{cases} , \quad i = 1, 2, \dots, m \quad (4)$$

The condition to have a flat Estimation is equivalent to have a low slope. To achieve this goal, the square norm of the gradient vector i.e. $\|w\|^2$ must be minimized in the optimization process [19].

Owning the mentioned contents, it is required to solve the following optimization problem for a SVR model development as in [20]. (5)

Find w and b to minimize $\|w\|^2$

$$\text{subject to} \begin{cases} y_i - \langle w, x_i \rangle + b_i \le \varepsilon \\ \langle w, x_i \rangle - b - y_i \le \varepsilon \end{cases} , \quad i = 1, 2, \dots, m$$

If it is not possible to create a SVR model by using the function $f(x)$ with approximation error less than ε, the optimization constraints changes

$$\begin{cases} y_i - \langle w, x_i \rangle + b_i \le \varepsilon + \xi_i \\ \langle w, x_i \rangle - b - y_i \le \varepsilon + \xi_i^* \end{cases}, \ i = 1, 2, ..., m \tag{6}$$

where $\{\xi_i\}_{i=1, 2, ..., m}$ and $\{\xi_i^*\}_{i=1, 2, ..., m}$ are positive parameters and to reduce these parameters, a factor of ensemble of these parameters in the optimization objective function is added. Thus the optimization problem can be expressed

$$\text{find w and b to minimize } \|w\|^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*)$$
$$\text{subject to } \begin{cases} y_i - \langle w, x_i \rangle + b \le \varepsilon + \xi_i \\ \langle w, x_i \rangle - b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{7}$$

Thus, the model training process can be written as the following optimization problem:

$$\text{find } \{\overline{C_i}\}_{i=1, 2, ..., n}, \{\overline{\sigma_i}\}_{i=1, 2, ..., n}, \{\overline{P_i}\}_{i=1, 2, ..., n}, \overline{\xi} \text{ and } \overline{\xi^*} \text{ to minimize } C\sum_{i=1}^{m}(\xi_i + \xi_i^*)$$
$$\text{subject to } \begin{cases} y_i - \langle w, x_i \rangle + b \le \varepsilon + \xi_i \\ \langle w, x_i \rangle - b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{8}$$

where $\{\overline{C_i}\}_{i=1,2, ..., n}$, $\{\overline{\sigma_i}\}_{i=1, 2, ..., n}$, $\{\overline{P_i}\}_{i=1, 2, ..., n}$ are the centers of the membership functions, standard deviation of the membership functions and parameters related to the output polynomial respectively in each rule of the T-S model. To train the fuzzy model, an improved differential evolution (IDE) algorithm is used.

Observation of optimization problem constraints, a penalty function is defined

$$\text{penalty}(\bar{e}, \bar{\xi}, \overline{\xi^*}) = \text{penalty}(\bar{e}, \bar{\xi}) + \text{penalty}(-\bar{e}, \overline{\xi^*}) \tag{9}$$

The pseudo-code of the penalty (., .) function is shown in Fig. 5.

In the optimization process, the algorithm tries to produce parameters in order to minimize the objective function values

$$\text{Fitness}(\bar{e}, \bar{\xi}, \overline{\xi^*}, \overline{w}) = c_2 \text{ penalty}(\bar{e}, \bar{\xi}, \overline{\xi^*}) + ... \ c\sum(\bar{\xi}(i) + \overline{\xi^*}(i)) \tag{10}$$

```
function [out] = penfunc (ē, ξ̄)
out = 0 ;
for i = 1: m
    if (e (i) ≻ ε + ξ̄(i))
        out = out + (e (i) - ε - ξ̄ (i) );
        end
      end
      end
```

Fig. 5. Architecture of the FCHEV

The first term of this equation is related to constraints observance whose value shall rise when constraints not observed. And, the minimization of the second term leads to the error band to be narrowed [21].

D. Improved Differential Evolution Algorithm

The original DE algorithm keeps all its parameters constant in the optimization process. However, the necessity of the parameters change in the optimization process has proved[22]. The relationship between performance and the control parameters of evolutionary algorithms is very complex that is not completely understood [23].

One of the most important tools for understanding and analyzing complex environment is fuzzy logic. Therefore, the fuzzy inference system can be used to control the DE parameters. Since the most important controlling parameter in the DE algorithm is the scale factor (F), in the proposed algorithm the control parameters such as crossover constant (CR) and population size (NP) are considered constant and on the factor scale (F) is concentrated.

In the original version of the DE algorithm, the F parameter is a scalar, but in the improved version this is considered as a vector with size D.D is dimension of the problem. Two points of view are intended to describe the state of DE's population: population diversity (PD) and generation percentage (GP) so far performed. PD and GP are the inputs of the fuzzy inference system to control the scale factor (F). PD in j-the dimension i.e. is given using the following equation:

$$PDj = \frac{1}{NP\,(X_j^{max} - X_j^{min})}\sum_{i=1}^{NP}\sqrt{(X_{i,j} - X_{B\,j})^2} \tag{11}$$

where X_j^{max} and X_j^{min} are the maximum and minimum vector of the population in the j-the dimension, respectively. NP and X_{Bj} are the population size and the best population vector in the j-the dimension, respectively. GP is easily calculated from the following equation:

$$GP = \frac{G}{G_{max}} \tag{12}$$

where G is the number of generations so far performed and G_{max} is the maximum number of generation of the algorithm. Obviously, the range of PD, GP can be in the interval [0, 1].

The membership functions of the Scale factor in the fuzzy inference system are shown in Fig. 6. Fuzzy membership functions related to the PD and GP are the same given in Fig. 6. The output of the fuzzy inference system is scale factor and its range is [0, 1].

The rule base of the fuzzy inference system is manually adjusted based on the experience. The fuzzy rule base is shown in Table 2 [24].

The flowchart of IDE is shown in Fig. 7. According to this flowchart, the algorithm returns a certain number of iterations (parameter c) into the fuzzy inference section that allows users to reduce the calculations if necessary.

It is noteworthy that fuzzy inference system is fired as the problem dimension each time getting into the fuzzy

TABLE 2. THE RULE BASE OF THE FUZZY INFERENCE SYSTEM IN THE IDE

Output	***Input 1***			
	VL	***L***	***M***	***H***
Input 2				
VL	*VH*	-----	*M*	*H*
L	*VH*	*H*	-----	*M*
M	*H*	*H*	*M*	-----
H	*H*	*M*	*L*	-----
VH	*M*	*M*	*VL*	-----

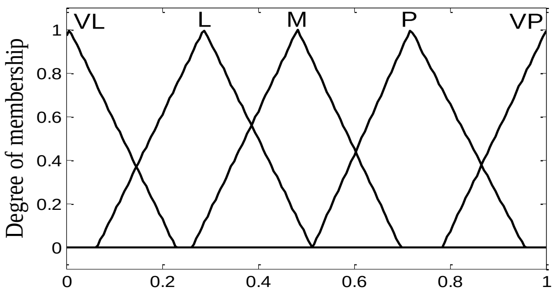

Fig. 6. The membership functions of the Scale factor in the fuzzy inference system

Inference section. Therefore, the calculation content may rise if the problem's dimension is high.

To reduce the calculation content, the scale factor can be considered as a scalar (as stated in the original version) and population diversity can be computed

$$PD = \frac{\sum_{j=1}^{NP} PD_j}{NP} \tag{13}$$

where PD_j is calculated according to (11) and NP is population number. The fuzzy inference system is then fired only once in each time entering into fuzzy section.

E. Empirical Mode Decomposition

A nonlinear wave can be composed of various frequency components. One simple technique to separate single-frequency component from the original waveform

Each Single-frequency component obtained of EMD is called intrinsic mode function [20]. The steps to obtain intrinsic mode functions from a waveform as low-frequency components are separated in each step and this process continues until the highest frequency component remain. A waveform that can only be regarded as an intrinsic mode function must have the following conditions simultaneously [26].

- Extreme points are equal to the number of zero crossing points.
- At any point, the average value of the top and bottom envelope of the curve must be zero.

Fig. 8 shows the EMD algorithm. Further details of the algorithm are given in [26]. In this paper, the EMD algorithm is used to decompose load signal into different frequency components. Both low and high frequency signals are aggregated. Finally, two signals with low and high frequencies are produced. Due to slow dynamic nature of the fuel cell, the low frequencies signal can be considered as a reference signal to FC power following [1]. The FC reference power signal obtained by the EMD algorithm has a restricted gradient that this feature causes to improve FC lifetime, due to avoid of rapid power changes in this power supply [9].

On the other hand, battery system can afford to provide transient power demand due to its ability to response very quickly.

Therefore, an optimal power management algorithm is resulted. The reason of EMD algorithm usage is to consider the lifetime problem of FC in the proposed strategy. Rapid load demand changes in actual driving cycles insert a significant negative impact on the fuel cell

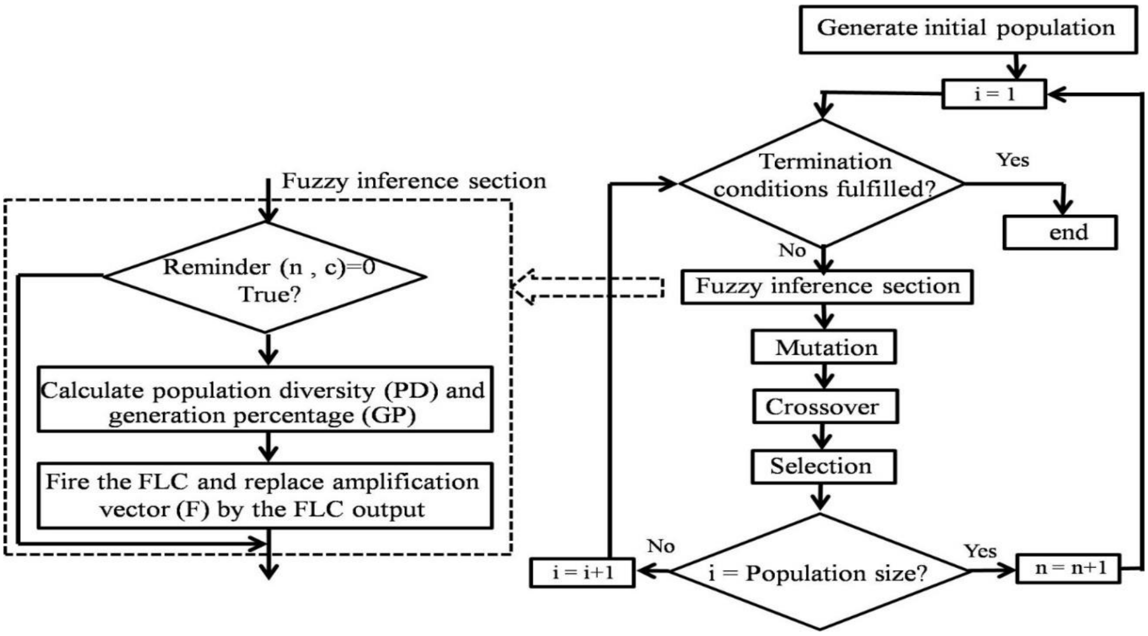

Fig. 7. The flowchart of the IDE algorithm

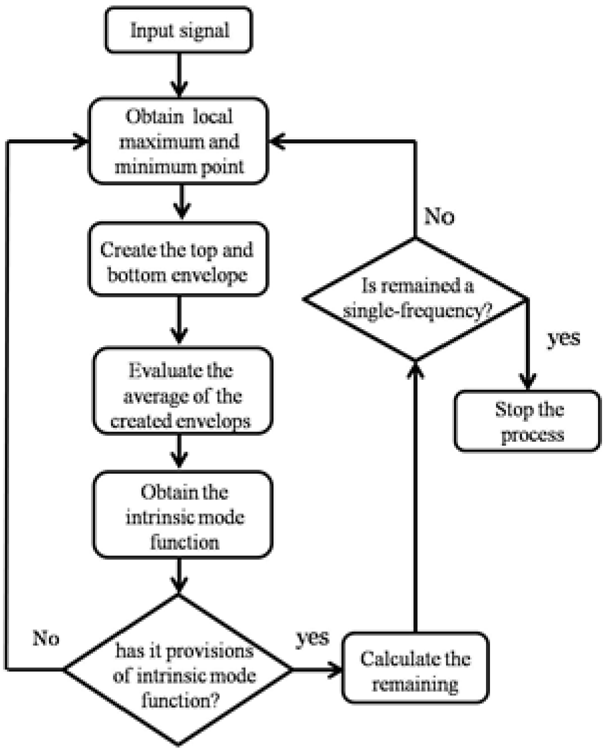

Fig. 8. The flowchart of the EMD algorithm

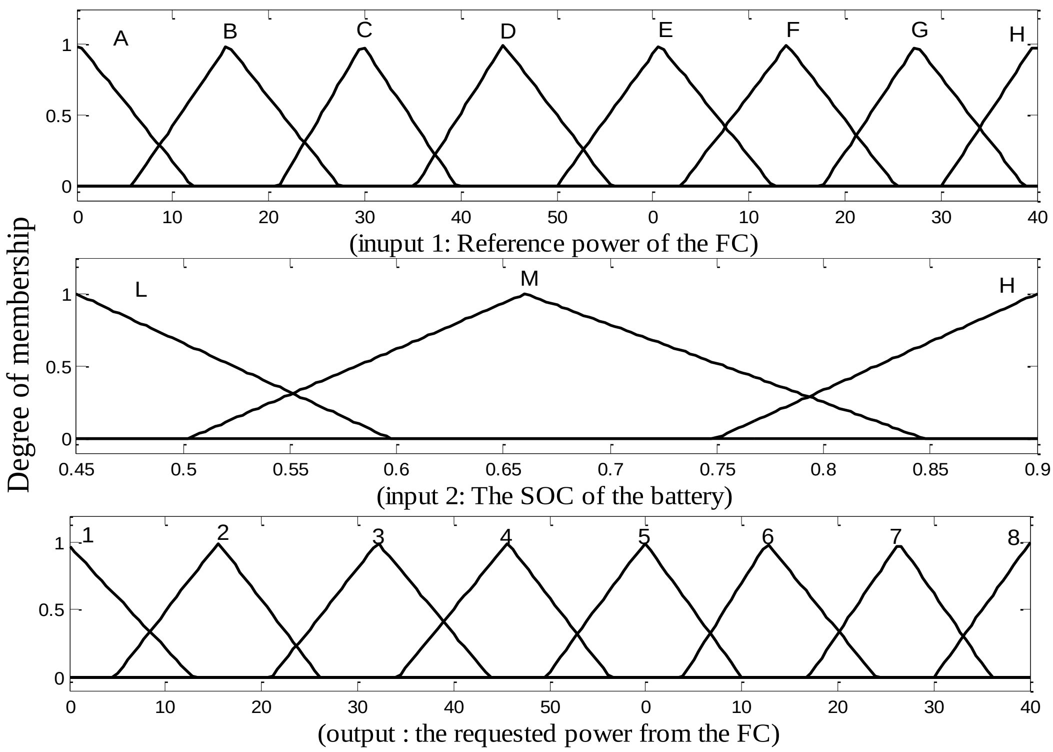

Fig. 9. Fuzzy membership functions of the FLC-No.1

Membrane. Since the FC lifetime is an essential factor for the HEV's economy, this technique could provide a potential solution to the FC's lifetime problem.

F. Fuzzy Logic Control Block

Since the performance of a system can be improved by dual mode controlling technique [27], a dual-mode fuzzy controller is designed in this section to determine the requested power from the FC system. The control inputs of the dual-mode fuzzy controller are

1) The FC reference power signal produced by the EMD algorithm,

2) The state of charge (SOC) of the battery pack.

Charge sustaining of the battery in an optimal range is one of the important indices of a hybrid vehicle performance [1]. The fulfillment of this performance index can guarantee both brake energy recovery and system response to transient load changes.

The desired range of SOC is defined

$$SOC_{min} \leq SOC \leq SOC_{max} \tag{14}$$

where and are the lower and upper limits of the battery SOC, respectively, in this paper, they are considered 0.4 and 0.8.

This dual mode fuzzy controller acts in mode A as long as the performance index (PI) signal is larger than the switching limit of the controller. Otherwise ,it operates in mode B.

The only difference between these two fuzzy controllers in the dual mode controller is their fuzzy membership functions in output variable. The membership functions of the FLC-No.1 are shown in Fig. 6. The input membership functions of the FLC-No.2 are the same as the FLC-No.1

The output variable membership functions of the FLC-No.2 are shown in Fig. 7. The fuzzy rule base of both FLC-No.1 and FLC-No.2 are given in Table 2.

The control objectives in the dual mode control process are: to maintain battery's SOC, reduce fuel starvation in FC, extract optimal power for FC and improve generally the overall performance of the system.

Determination the operating mode of the DMFLC is done by a fuzzy decision-making system. The output of this fuzzy system is the performance index (PI) signal ,which is a function:

1) difference between the produced FC power and the load demand mean.

2) difference between the battery SOC and a desired reference value (0.7).

According to the selected input variables of the FLC-No.3, the PI signal is produced to meet the following

TABLE 3. THE RULE BASE OF THE FLC-NO.1 AND THE FLC-NO.2

Output	***Input 1***		
	L	***M***	***H***
Input 2			
A	*2*	*1*	*1*
B	*3*	*2*	*1*
C	*4*	*3*	*2*
D	*5*	*4*	*3*
E	*6*	*5*	*4*
F	*7*	*6*	*5*
G	*8*	*7*	*6*
H	*8*	*8*	*7*

Objectives:

- The FC power variations will be slow and include the load power demand mean in order to improve the FC performance and its lifetime.
- The SOC of the battery pack remains in a desired range.

Membership functions of the input and output variables are considered equal in the FLC-No.3. Their only difference is the domain of these variables. Membership functions of the FLC-N0.3 are shown in Fig. 8.

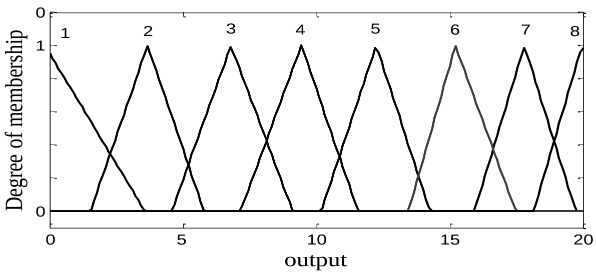

Fig. 10. Membership functions of the FLC- No.2 output

The values of the parameters of a, b and c for fuzzy variables in the FLC-No.3 are presented in Table 3. The rule base of the FLC-No.3 is listed in Table 4.

TABLE 4. THE VALUES OF THE MEMBERSHIP FUNCTIONS OF THE FLC-NO.3

	A		
Input 1	*-20000*	*0*	*20000*
Input 2	*-0.5*	*0*	*0.5*
Output	*0*	*0.5*	*1*

G. Supervisory Switching Control

In the proposed strategy, the role of the supervisory switching control is determining the FC activity status ;i.e., at what situations the FC system should operate to generate electric power and/ or should be shut down. The purpose of this control step is reducing the working hour of the FC system since the conventional FC's lifetime for transport applications are less than 2000 hours [14]. So, respecting to the high cost of FC system, it is essentially necessary to control the FC activity time. Several conditions are existed for moving between the two states (turn on/ shut down) of the FC.

TABLE 5. THE RULE BASE OF THE FLC-NO.3

Output	***Input 1***		
	Mf1	***Mf2***	***Mf3***
Input 2			
Mf1	*Mf1*	*Mf1*	*Mf1*
Mf2	*Mf1*	*Mf2*	*Mf3*
Mf3	*Mf2*	*Mf2*	*Mf3*
Mf4	*Mf3*	*Mf3*	*Mf4*

As default, the FC system has been shut down. Necessary conditions to state changing of FC are described in Table 5.

TABLE 6. TABLE6 SHIFT CONDITIONS IN THE STATE MACHINE

the conditions to start up FC	*Load power should be positive and the battery's SOC should be less than the minimum desired value.* *Load power should be positive and the requested power of FC be more than the minimum FC power and the time of being inactive also should be more than 3 minutes.* *Load power should be more than the maximum battery power.* *SOC should be less than SOC_{min} and also the minimum FC power value be less than the difference between the load power and the maximum charging power of battery.*
the conditions to Shut down FC	*Load power should be negative and the minimum FC power be more than the difference between the load power and the maximum charging power of battery.* *Load power should be less than the maximum battery power and the requested power of FC be lower than the its minimum value and the battery SOC be more than the SOC_{max}*

H. Optimization Problem Ormulation

The fuzzy controller was used in [9-16] to design HEV's energy management strategy. However, one of the disadvantages that fuzzy theory face to, is that membership functions parameters such as width and standard deviation are independent of the designed fuzzy rules [16]. Therefore, there is no guarantee for excellent performance of the developed fuzzy system, particularly to control HEV that has lots of uncertainties. So the search for an optimal method of fuzzy variables can be crucial in improving the control performance. Many papers such as [15] - [28] - [29] - [30] used evolutionary algorithm to optimize the variables of fuzzy controller in HEVs.

In this paper, the improved differential evolution algorithm is used to search the optimal coefficients of membership functions parameters of the FLC-No.3 variables. Since in this controller the membership functions of the input and output variables are selected Gaussian type, the optimization parameters with respect to (2) are the centers (c) and widths (σ). Optimization parameters and their lower and upper limits are given in Table 7. The objective function of the optimization problem consists of two performance criteria stated by two weighting factors

$$f(\Delta SOC, Fuel_{com}) = (w_1 \times \Delta SOC) + (w_2 \times Fuel_{com}) \quad (15)$$

where is the SOC fluctuation that can be represented as:

$$\Delta SOC = SOC_{final} - SOC_{initial} \quad (16)$$

where and are SOC value of the final and initial time in driving cycle, respectively. Represents consumed fuel per gallon (4 liters). Weighting coefficients of w1 and w2 are intended to be 1000 and 1, respectively. These weighting coefficients are to value the effects of optimization terms. Here is negligible with respect to the amount of consumed fuel, so the weighting coefficient of it is 1000. Optimal values of optimization variables are presented in Table 7.

4. Validation Process

In this section, the validation process of the proposed strategy is performed. The proposed strategy has been implemented on a FC/ battery hybrid vehicle in order to verify the improvement of the performance and economical indices. To compare and demonstrate the effectiveness of the proposed strategy, three pre-designed strategies are used. The three strategies include default control strategy existed in Advisor software, and the fuzzy logic control based strategy presented in [11].

These relevant simulations have been implemented in Advisor software.

A. Simulation Parameters

Standard driving cycles can be used to evaluate the dynamic response of a designed control strategy [8].

In this paper, the Urban Dynamometer Driving Schedule (UDDS), used commonly in the literature, is employed. The UDDS cycle parameters are shown in Table 8.

The Advisor default values have been utilized to set the sizes of vehicle Parameters. Therefore, the degree of hybridization (DOH) is 51.6%. The DOH is defined as [31]:

$$DOH = \frac{P_{ESS\text{-}rated}}{P_{total}} \quad (17)$$

where electric power is can be delivered by ESS and is the total power that can be delivered by ESS and FC.

TABLE 7. TABLE8 SPECIFICATIONS OF THE UDDS DRIVING CYCLE

Time [S]	*1369*
Distance [miles]	*7.45*
Max. speed [mph]	*56.7*
Avg. speed [mph]	*19.58*
Max. accel [ft.$(s^2)^{-1}$]	*4.84*
Max. decal [ft.$(s^2)^{-1}$]	*-4.84*
Avg. accel [ft.$(s^2)^{-1}$]	*1.66*
Avg. decal [ft.$(s^2)^{-1}$]	*-1.9*
Idle time [S]	*259*

B. Simulation Results

The simulation results related to the load power prediction are shown in Fig. 11. As shown in this figure, the load power is predicted as good as expected. The reference power signal of the FC system obtained by the EMD algorithm is shown in Fig. 12. As can be seen from Fig. 12, this signal is empty of any suddenly changes in power values. So considering this signal as a tracking reference, the FC power profile can be a useful step to enhance the performance and extend its lifetime. Fig. 13 shows variations of the FC Power in the driving cycle duration. As can be seen in this figure,variations of FC power are slow and transient-free by the proposed EMS as expected. As the FC power rises, it is expected that the FC current increases in order to provide requested power.

FC current is proportional to the fuel consumption i.e. sudden increase of the current leads to fuel starvation and also having a negative impact on FC membrane. Therfore, the fuel cell lifetime can be increased by the proposed strategy.

Consumed fuel (hydrogen) flow rate of FC system is shown in Fig. 14. The amounts of the consumed fuel per gallon (4 liters) are shown in Fig. 15. The power variation of the battery is shown in Fig. 16. One of the goals of the proposed strategy is to allocate load power transients to the battery. The fulfillment of this goal can be seen with respect to Fig. 16. Fig. 17 shows the SOC variations of the battery pack with respect to the load changes. As Fig. 17 shows, the SOC variations will remain in a desired range. Variations of the vehicle speed during the driving cycle are shown in

TABLE 8. TABLE7 OPTIMAL VALUES OF THE FLC-NO.3 PARAMETERS

The output of the FLC-No.3				*The second input of the FLC-No.3*				*The first input of the FLC-No.3*			
Optimal Value	***Upper limit***	***Lower limit***	***parameter***	***Optimal Value***	***Upper Limit***	***Lower limit***	***Parameter***	***Optimal Value***	***Upper limit***	***Lower limit***	***Parameter***
0.045	*0.122*	*0.007*	$\sigma_{3,1}$	*0.022*	*0.11*	*0.007*	$\sigma_{2,1}$	*391.84*	*4710*	*380*	$\sigma_{1,1}$
0.021	*0.061*	*0.007*	$\sigma_{3,2}$	*0.012*	*0.0683*	*0.007*	$\sigma_{2,2}$	*2320.6*	*2470*	*380*	$\sigma_{1,2}$
0.043	*0.068*	*0.007*	$\sigma_{3,3}$	*0.021*	*0.07*	*0.007*	$\sigma_{2,3}$	*2033.28*	*2680*	*380*	$\sigma_{1,3}$
0.073	*0.118*	*0.007*	$\sigma_{3,4}$	*0.079*	*0.13*	*0.007*	$\sigma_{2,4}$	*2424.06*	*4560*	*380*	$\sigma_{1,4}$

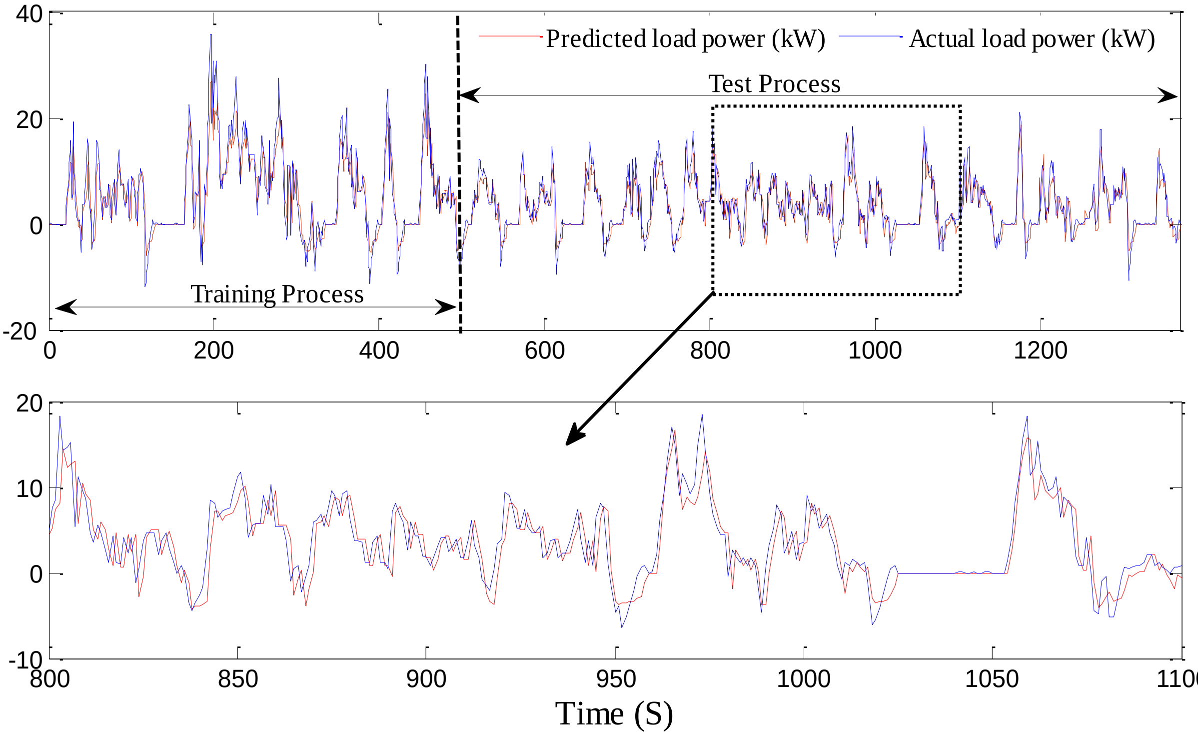

Fig. 11. Load power prediction result

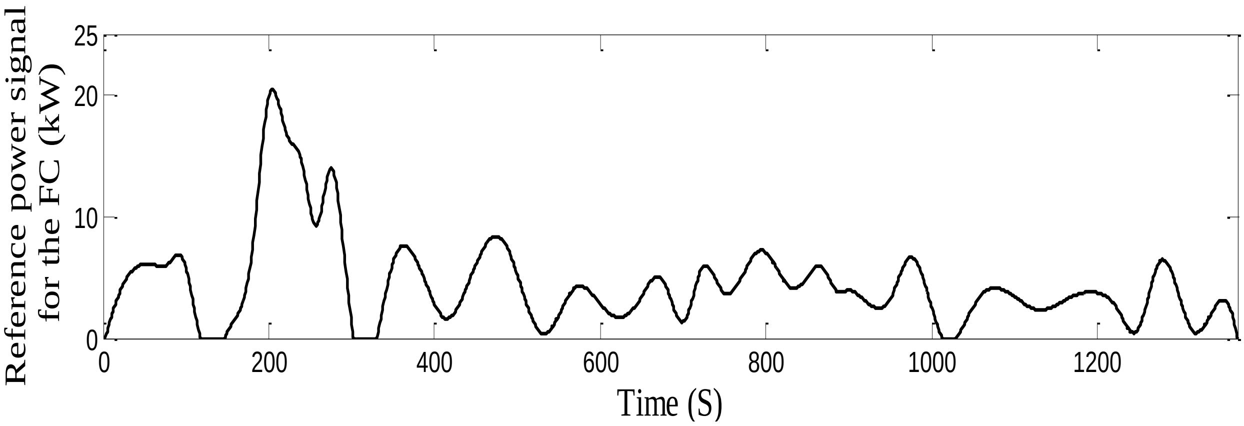

Fig. 12. Reference power signal for the FC system

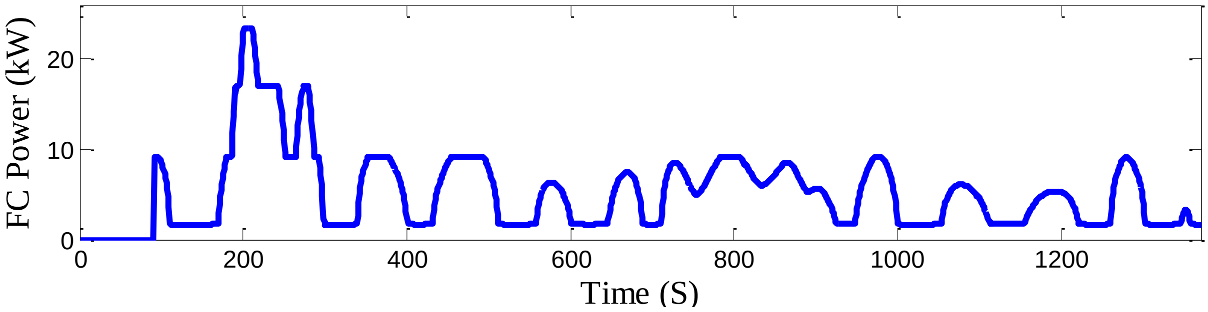

Fig. 13. The output power of the FC

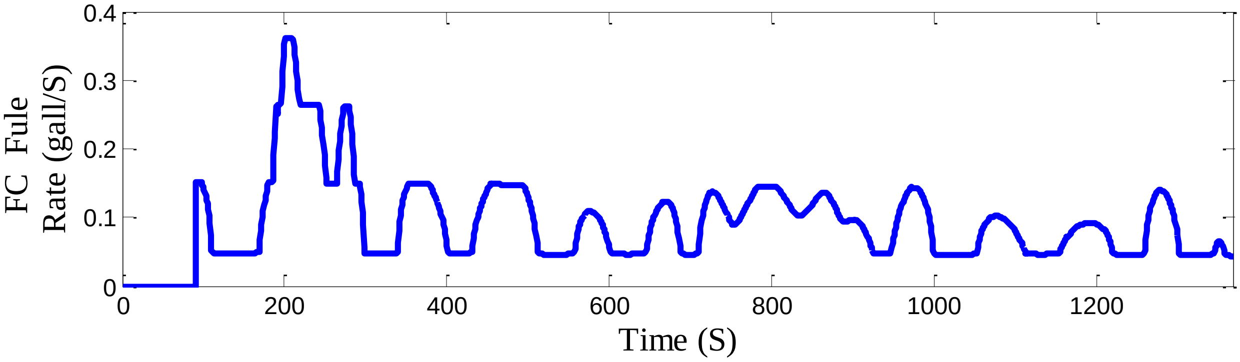

Fig. 14. The rate of the consumed fuel in the FC

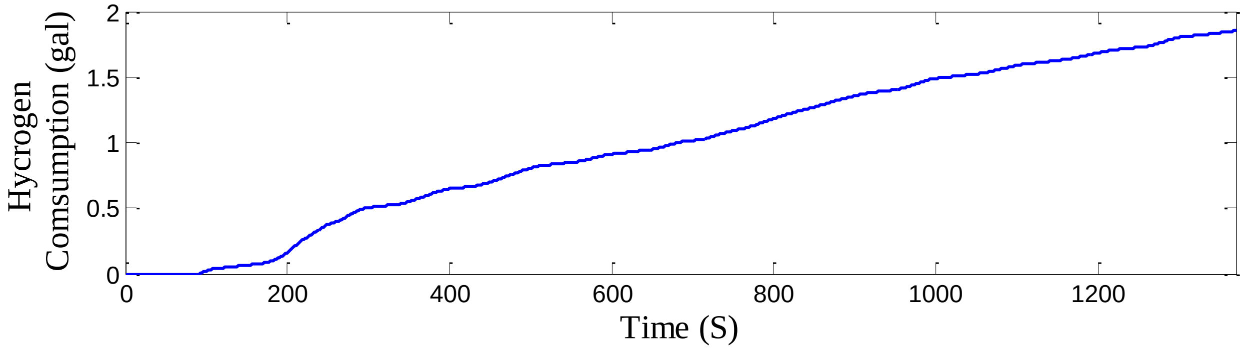

Fig. 15. The cumulative function of the consumed fuel

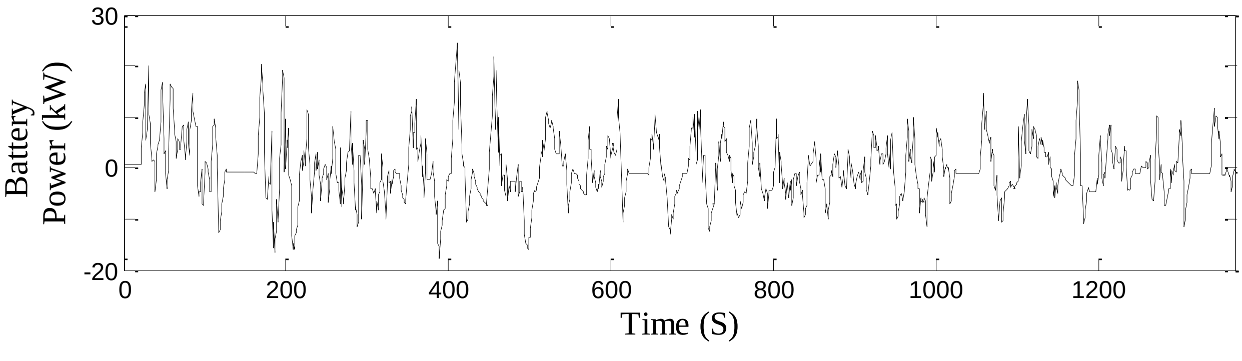

Fig. 16. The output power of the battery pack

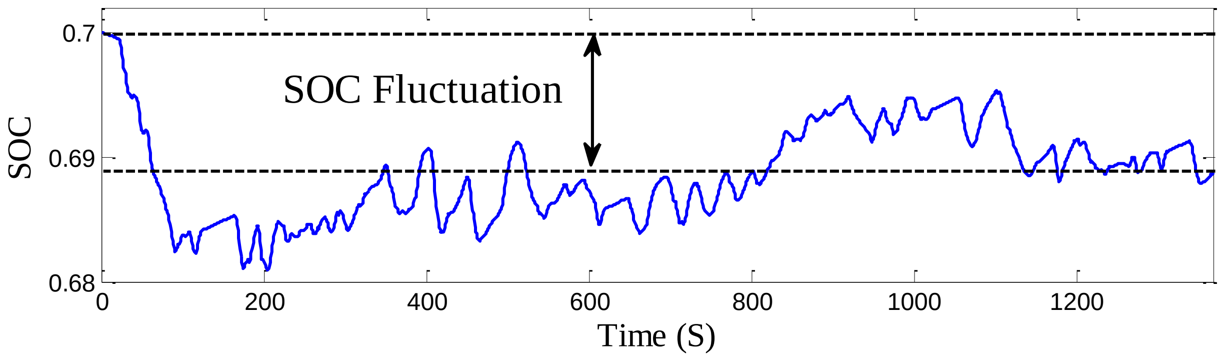

Fig. 17. Soc variation

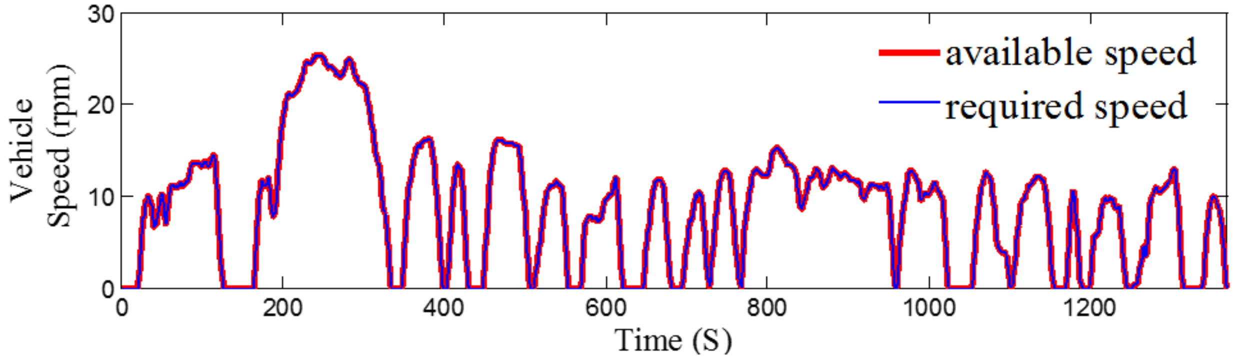

Fig. 18. The variation of the vehicle speed

TABLE 9.

TABLE 10. COMPARISON OF PERFORMANCE INDICES IN DIFFERENT CONTROL STRATEGIES

Performance Index	*Default Control*	*Fuzzy Control*	*Proposed Control*
Fuel Economy (mpg)	*3.1*	*3.2*	*4*
Gasoline Equivalent	*46.1*	*46.7*	*59. 4*
Overall System Efficiency	*0.149*	*0.149*	*0.163*
SOC Fluctuation	*0.0904*	*0.0837*	*-0.0113*

TABLE 11. THE REPORT OF ENERGY USAGE IN DIFFERENT CONTROL STRATEGIES

Energy Usage	*Default Control*	*Fuzzy Control*	*Proposed Control*
Aerodynamic loss (W)	*1056*	*1056*	*1056*
Rolling loss (W)	*1461*	*1461*	*1461*
Power of Fuel In (W)	*19507*	*19288*	*15139*
Energy stored (W)	*2590*	*2397*	*-309*

Fig. 18. It is clear from Fig. 18 that vehicle is able to track the required speed of the UDDS driving cycle.

In Table 9 some performance Criteria are listed that are studied in the HEV's energy management strategy discussion. In this table the performance inds of the proposed strategy are compared with three other strategies that are mentioned previously.

Table 9 confirms that the proposed control strategy is indeed effective in fuel economy under three driving patterns. By comparing the results of SOC deviations, it is clear that, the SOC deviation of the proposed strategy is less than other strategies. One of the evaluation criteria for energy management strategies is their capability to maintain the SOC of energy storage devices. In other words, the desired strategy is the one that have the same SOC at the beginning and the end of the cycle.

When a vehicle moves, the driving force provided by its power system is employed to overcome rolling resistance, grade resistance, aerodynamic resistance and accelerating resistance. In this paper, losses power of grade and acceleration resistances are neglected. Therefore, the overall system efficiency is calculated as:

$$\text{Overall System Efficiency} = \frac{P_{\text{Loss - aero}} + P_{\text{Loss - roll}}}{P_{\text{Fuel - in}} + P_{\text{ESS - stored}}} \qquad (18)$$

where $P_{\text{Loss - aero}}$ and $P_{\text{Loss - roll}}$ are both power losses, originated from the aerodynamic resistant and rolling resistant, respectively. is the net power obtained by the engine consumed fuel. is the stored power in energy storage systems at the drive cycle completion. During the vehicle moving, if the produced energy of the power sources becomes more than the required propelling energy, the surplus energy would stored in energy storage system. All the types of energy usage in the studied vehicle under different drive cycles are listed in Table 10.

From these results, it is clear that the proposed energy management strategy reduces the fuel consumption and also improves the system performance.

5. Conclusion

This paper presented an optimized hierarchical strategy based on several control techniques. The strategy was designed to distribute power between the power generation units of FC/ Battery hybrid electric vehicle power in order to meet its performance requirements. The main advantage of the proposed strategy was to meet a perfectly real time method. This proposed strategy could improve the vehicle components lifetime and ensure the reduction of fuel consumption cost. As observed in the simulation results, the proposed strategy could answer the controlling obligations such as charge sustaining of the battery, the overall system efficiency, fuel economy and etc. Therefore, the proposed strategy can be viewed as a new approach in advanced energy management system of the hybrid electric vehicles

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