Preprints of the 20th World Congress
The International Federation of Automatic Control
Toulouse, France, July 9-14, 2017

Hierarchical and Adaptive Neuro-Fuzzy Control for Intelligent Energy Management in Hybrid Electric Vehicles ⋆

Elkhatib Kamal, Lounis Adouane, Rustem Abdrakhmanov and Nadir Ouddah

Institut Pascal / IMobS3, UCA/SIGMA UMR CNRS 6602, Clermont-Ferrand, France. e-mail: Firstname.Lastname@uca.fr

Abstract: This work is concerned with the minimization of total energy consumption (summation of electric battery and fuel) of hybrid hydraulic-electric vehicles through an energy management combined approach incorporating elements of fuzzy logic, neural network and rule-based algorithms. In this paper, the global vehicle effciency is calculated by considering electrical motor, battery, engine, hydraulic pump, hydraulic motor and the transmission. An adaptive fuzzy neural algorithm is embedded in the vehicle with a fuzzy mode-switching control strategy along with proposed fuzzy tuning controllers to achieve real time control. In addition, a new formula is developed to update the proposed fuzzy controller. An intelligent hierarchical hybrid controller strategy is employed with several advantages: (i) proposed strategy does not depend on the a priori knowledge of the driving event, which makes it suitable to be implemented online; (ii) it can be easily implemented in real time based on fuzzy rule-based strategy containing five operation modes; (iii) rate of charge of the battery is limited to minimize aging effects; (iv) engine is operated near its optimal range. The effectiveness of the overall proposed architecture is demonstrated under various conditions in MATLAB/Truckmaker simulations which show increased efficiency over Pontryagin's minimum principle. Offline and online control performance of the proposed approach are tested.

Keywords: Hybrid Electric Vehicle, Power Management Strategy, Hierarchical Control Architecture, Adaptive and Optimal Neuro-Fuzzy Controller.

1. INTRODUCTION

The problem of reducing the environment pollution in order to save the planet has become one of the most important challenges in the world. Besides, the worldwide crisis of the fossil fuel resources, which diminish at high rate, aggravates it. These two global aspects made the big industrial companies and the state governments invest increasingly into the alternative energy sources. The hybrid electric vehicles (HEV) promise a relevant solution with regard to the objectives of reducing the fuel consumption, as well as the decrease of the exhaust gazes emission Murphey (2008). The presence of additional power sources in the HEV introduces additional degrees of freedom in controlling the drivetrain, since at each time the drivers power request can be delivered by either one of the on-board energy sources or their combination. The additional degrees of freedom can be leveraged to reduce fuel consumption and pollutant emissions and also to optimize other possible cost such as battery life Li (2015). This task is performed by the energy management strategy which is the highest control layer of the drivetrains control strategy. Energy management strategies can be divided into numerical and analytical approaches. In numerical optimization methods like dynamic programming Ximing (2015), the global optimum is found numerically under the assumption of full knowledge of the future driving conditions. Unfortunately, the results obtained through dynamic programming cannot be implemented directly due to its high computational demands. To remedy this problem, approximated dynamic programming and stochastic dynamic programming Johannesson (2007), Moura (2011) had been suggested as possible solutions. Analytical optimization methods, on the other hand, use a mathematical problem formulation to find an analytical solution that makes the obtained solution faster than the purely numerical methods. Within this category, Pontryagin's Minimum Principle (PMP) based energy management strategy is introduced as an optimal control solution Panday (2016). This approach can only generate an optimal solution if implemented offline since in this case the driving cycle is supposed to be known in advance. In addition, rule-based strategies developed from heuristic ideas are widely used in HEVs applications Mashadi (2010), Mi (2011), Ying (2016), Kamal (2016) because they can be implemented easily in real-time, but creating these rules commonly requires engineering experience, large numbers of experimental results, etc., and have generally limited benefits for fuel economy. In order to improve the fuel economy of rule-based methods, the authors in Lihao (2016) directly adopted fuzzy rules instead of deterministic ones to improve the operational efficiency

⋆ This project is supported by the ADEME (Agence De l'Environnement et de la Matrise de l'Energie) for the National French program "Investissement d'Avenir", through BUSINOVA Evolution project, (http://www.businova.com/).

of vehicle system. In Duan (2003) the authors added a fuzzy algorithm for the rule-based method, to modify the rules. To further reduce fuel consumption, fuzzy controllers were further modified using particle swarm optimization Chen (2015), genetic algorithms Wu (2008), and machine learning algorithms Zhou (2013). Moreover, learning vector quantization using neural network Murphey (2011) or a fuzzy neural network Wu (2012) are used. The integrated fuzzy-neural-network system has the merits of both fuzzy systems Tian (2011) (human-like conditional rules which depend on knowledge of an expert or past experience) and Neural Networks (NN) Wang (1997) (learning and optimization abilities and connectionist structures).

In this work, the design and analysis of a novel Intelligent Hierarchical Hybrid Controller Strategy (IHHCS) for Hybrid Hydraulic-Electric Vehicles (HHEVs) is presented. The primary objective is to develop a practical, reliable and implementable intelligent control strategy, which can manage the power distribution among different energy sources to maximize the hybrid vehicle's overall efficiency. This hybrid strategy minimizes the total energy consumption (summation of electric battery and fuel) and it can be employed for both offline and online scenarios. The proposed strategy consists of three control level based on neural network, fuzzy logic and rule based optimization. An Intelligent Supervisory Switching Mode Controller (ISSMC) based on fuzzy logic in the third level, an Intelligent Power Distribution and Optimization Controller (IPDOC) based on optimal neural fuzzy logic strategy in the second level and Local Fuzzy tuning Proportional-Integral-Derivative Controllers (LFPIDC) in the first level. We compare MATLAB/Truckmaker simulations with alternative frameworks existing in the literature based on PMP Panday (2016) in order to demonstrate the advantages of our methodology.

The results of this paper support that the proposed strategy is capable of: (i) being applied to various types of HEV; (ii) an accurate and reliable model of the studied bus (i.e., BUSINOVA) is design by MATLAB/Truckmaker software; (iii) reducing fuel consumption by optimizing switching control modes; (iv) increasing global vehicle efficiency; (v) being implemented in real-time; (vi) reducing the number of rules needed in fuzzy control; (vii) being used either offline or online; (viii) maintaining the engine near its optimal operating range; (ix) keeping State Of Charge (SOC) within the range which promotes battery longevity.

The paper is organized as follows. The overall HHEVs description and modeling is given in section 2. In section 3, the proposed intelligent hierarchical hybrid controller structure is developed. Simulation results and comparative analysis by MATLAB/Truckmaker simulator are presented in section 4. Finally, the conclusions and future prospects are presented in section 5.

2. MODELING OF THE HYBRID BUS

The aim of this section is to modeling based on Truckmaker software and illustrate the architecture and the mathematical model of the studied system, i.e., BUSINOVA hybrid bus, developed by SAFRA company (cf. Figure 1). This bus is composed of an Electric Motor (EM), a Hydraulic Motor (HM), an Internal Combustion Engine (ICE) and battery as the propulsion powertrain system of the vehicle.

Fig. 1. BUSINOVA hybrid bus.

2.1 *Hybrid bus powertrain architecture*

The model of the studied hybrid bus is based on a series-parallel power-split hybrid architecture Bayindir (2011). A simple block diagram of the power flows in the bus is shown in Figure 2. The EM and HM are both directly connected

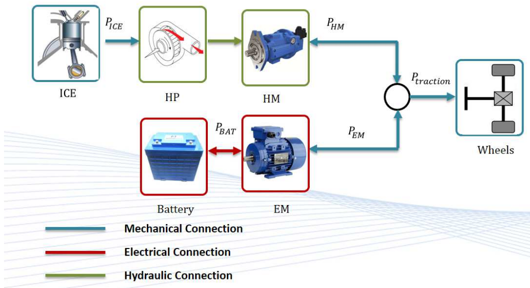

Fig. 2. Block diagram of the powertrain power flows. (ICE: Internal Combustion Engine, HP: Hydraulic Pump, HM: Hydraulic Motor, EM: Electric Motor)

to the transmission and can ensure simultaneously or independently the traction of the bus. On the other hand, the ICE is coupled to a Hydraulic Pump (HP) for driving the HM, and therefore allowing the ICE load shifting.

The rotational speeds of the HM and the EM are imposed by the wheels speed in proportion to the reduction ratios of HM and EM respectively. Moreover, the rotational speed ω_{HM} and the torque T_{HM} are expressed as follows:

$$\begin{cases} \omega_{HM}\left(T_{ICE}, D_{HM}\right) = \dfrac{D_{HP}.\eta_{v_{HM}}.\omega_{ICE}}{D_{HM}.\eta_{v_{HP}}} \\ T_{HM}\left(T_{ICE}, D_{HM}\right) = \dfrac{D_{HM}.\eta_{m_{HM}}.T_{ICE}}{D_{HP}.\eta_{m_{HP}}} \end{cases} \quad (1)$$

where ω_{ICE}, T_{ICE} are respectively rotational speed and torque of the ICE, and D_{HM}, D_{HP}, $\eta_{m_{HM}}$, $\eta_{m_{HP}}$, $\eta_{v_{HM}}$, $\eta_{v_{HP}}$ are respectively displacement, mechanical efficiency and volumetric efficiency of the HM and the HP.

The BUSINOVA can operate according to the modes described below:

- the propulsion is fully supplied by the EM (mode 1),
- the bus is actuated by the HM via the ICE (mode 2),
- the mode 3 implies the hybrid operation of the EM and the HM via ICE,
- the recharge of the electric battery via ICE (mode 4),
- the regenerative braking (mode 5)- the part of the kinetic energy during braking phase is recuperated to charge the electric battery.

2.2 Dynamical model

This part is dedicated to the dynamical equations describing the bus. The purpose of the dynamical model is to have a realistic global behavior of the bus in order to validate the proposed energy management techniques. To describe it in a generic manner, assume that the bus is moving up the slope of θ degree (cf. Figure 3). The origin of the coordinates is situated in the Center of Mass (CoM). It is supposed that CoM of the bus is in its geometric center. Projecting the vectors of the forces to x-axis (the bus is moving along x-axis in the positive direction, with the velocity v and acceleration $a_x = a$), the following expressions of the forces acting on the bus is obtained (cf. Figure 3):

$$F_{tr} - F_{rr} - F_{ad} - F_g - F_{brake} = (M + M_{eq})a \quad (2)$$

where F_{tr} traction force, F_{rr} rolling resistance, F_{ad} aerodynamic force, F_g gravity force, F_{brake} mechanical brake force, M bus weight, M_{eq} equivalent mass of rotating parts, a bus acceleration. In this modeling it is assumed that all the masses M (which include curb mass of the bus and passengers' mass) are homogeneously distributed in order to consider that the CoM is in the geometric center of the bus. To produce a bus acceleration, it is necessary to take into account the moments of inertia of the rotating components (e.g., rotor of the EM, crankshaft of the ICE, driving axle, etc.). It is done by introducing the equivalent mass M_{eq} of the rotating components:

$$M_{eq} = \frac{i_g \eta_{pt} J_{rot}}{r^2} \quad (3)$$

where i_g gear ratio, η_{pt} powertrain efficiency, J_{rot} total inertia of the rotating components in the transmission, and r the wheel radius Cheng (2007).

The traction force F_{tr} is linked to the torque produced by the powertrain T_{pt} via gear ratio i_g, powertrain efficiency η_{pt}. Expanding the dynamical equation (2), the following relation is obtained:

$$a = \frac{dv}{dt} = \frac{1}{M + M_{eq}} H \quad (4)$$

with

$$H = \frac{i_g \eta_{pt} T_{pt}}{r} - \mu_{rr} F_N sign(v) - \frac{1}{2}\rho A C_d (v + v_{wind})^2 - Mg\sin(\theta) - \frac{T_{brake}}{r} \quad (5)$$

where:

- T_{pt}: output powertrain torque from the gearbox,
- μ_{rr}: rolling resistance coefficient, $F_N = Mg cos(\theta)$ normal force, g gravity acceleration, θ slope angle, v bus speed,
- ρ: the air density, A the frontal area of the bus, C_d drag coefficient, v_{wind} wind speed,
- T_{brake}: the brake torque provided by the bus mechanical brake system.

3. PROPOSED INTELLIGENT HIERARCHICAL HYBRID CONTROLLER STRATEGY (IHHCS)

In this section, an IHHCS structure is proposed which is capable of meeting various objectives including optimized power flow management, maintaining high operational efficiency of the ICE, and balancing EM and battery charge to maximize the global vehicle efficiency. The first block of the proposed IHHCS (cf. Figure 4) is a driver command interpreter which converts the driver inputs from the brake and accelerator pedals to required torque.

This proposed strategy consists of three control levels as shown in Figure 4. The third level has been developed by fuzzy strategy to decides which operating mode or combination of modes would be most efficient (cf. section 3.1). At the second level (cf. section 3.2), an advanced IPDOC has been developed for power splitting which decides the optimal combination of power sharing between different energy sources to maximize overall vehicle efficiency. In section 3.3, a LFPIDC is used to track the set points of EM and HM via the ICE generated at the second level, in order to reach peak performance and acceptable operation indexes while taking in consideration of the dynamic behavior of EM, ICE and HM. The proposed strategy can be used for both offline and online scenarios. Offline scenario implies that the information about the future driving cycle and the environment (road profile, vehicle weight, etc.) is fully known, whereas for the online scenarios this information is obtained in real time. In this paper, we will focus more on level 2 and level 3 (cf. section 3.1 and 3.2). In the diagram below (cf. Figure 4), PCVE is the Produced and Consumed Vehicle Energy, T_{demand} is the total torque demand required to drive the vehicle (it is also defined by the global torque set point), $T_{ICE,SP}$ is the ICE torque set point and $T_{EM,SP}$ is the EM torque set point.

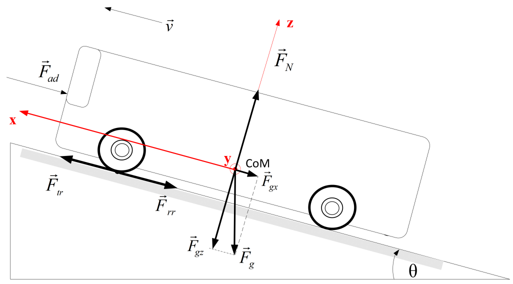

Fig. 3. Forces acting on the bus.

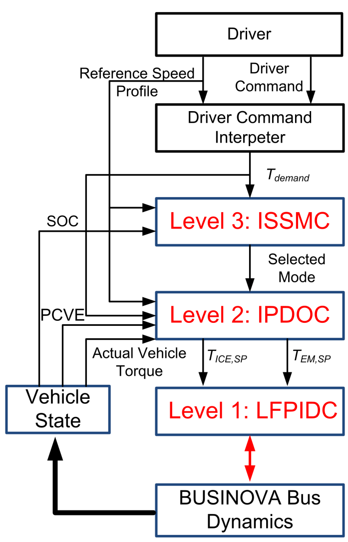

Fig. 4. IHHCS for HHEVs distributed generation system.

3.1 Intelligent Supervisory Switching Mode Controller (Level 3: ISSMC)

As mentioned in section 2.3, there are five modes of operation. In order to improve the HHEVs operation, the proposed ISSMC based on fuzzy logic and rule based, has to decide which operating mode (or combination of them) is appropriate. Many parameters (such as the value of SOC for the battery, vehicle power required, vehicle speed and maximum power supplied by the battery, etc.) must be considered to choose the most efficient operation mode to manage and optimize power flow. Based on the available output torque, the pedal position is converted into torque demand (T_{demand}). If $T_{demand}<0$, the driver intends to decelerate the vehicle. Therefore, regenerative braking mode is chosen. But, if $T_{demand}>0$, the requiring torque is split between EM or/and HM via ICE. In the proposed algorithm, modes 1, 2, 3, and 4 are selected by fuzzy logic and mode 5 is selected by traditional logic. Fuzzy logic is well suited for selecting between modes 1, 2, 3 and 4, since the range or boundary is vague and not clearly specified due to the actual state of the vehicle (masse, velocity, etc.) for these modes. The ISSMC input variables are Vehicle Speed (VS), T_{demand} and SOC and its output variable is the operation mode (Mode). We use Gaussian Membership Functions (GMF) and Centre-of-Gravity (COG) defuzzication to calculate the output fuzzy signal, the advantage of this method is its simplicity in reducing the complexity of the calculations Lihao (2016). Some of the fuzzy rules of the ISSMC are shown in Table 1, where RN is the rule number, L is the Low and H is the High. The fuzzy rule is constructed from 27 individual fuzzy rules.

Table 1. Some examples of fuzzy rules used by the ISSMC level.

RN	T_{demand}	SOC	VS	Mode
1	L	H	H	Mode1
2	H	L	L	Mode2
.	.	.	.	.
.	.	.	.	.
27	L	L	L	Mode4

3.2 Intelligent Power Distribution and Optimization Controller (Level 2: IPDOC)

Once level 3 has selected the appropriate mode, this level of control manages and optimizes the power distribution between the two different sources based on new proposed formula to update the proposed fuzzy controller. Therefore, the mode of operation is considered as an input for the second level of control. There are five input variables at this control level: actual vehicle torque for the Learning Adaptive Algorithm (LAA) block and mode of operation with the same three inputs of the third level (speed of the vehicle, torque demand, SOC) for the Fuzzy Management Controller (FMC) block. The two output variables of level 2 are $T_{ICE,SP}$ and $T_{EM,SP}$. This level consists of three blocks. The FMC block splits the required torque between EM or/and HM via ICE (cf. section 3.2.1). The proposed LAA block based on a neural network is used to update FMC parameters. The Global Vehicle Actual and Optimal Efficiency Calculation Algorithm (GVAOECA) block is used to calculate the total actual and the optimal efficiency for the vehicle based on the elementary efficiencies of the EM, battery, ICE, HP, HM and transmission. The main contributions of this level are: (i) optimize the power distribution between EM or/and HM via ICE; (ii) tune the optimal parameters of the fuzzy controller based on neural network optimization; (iii) find the best combination of power distribution between different energy sources and maximize hybrid vehicle overall efficiency; (iv) optimize centers and widths of membership functions while taking into account the system constraints, speed profile and road slope; (v) and generates the set point for the first level. The block diagram of the proposed level 2 block is presented in Figure 5.

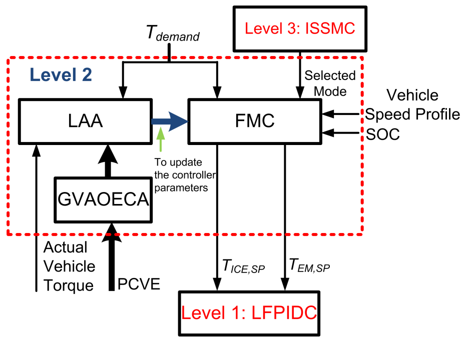

Fig. 5. Block diagram of the proposed level 2.

Proposed Fuzzy Management Controller (FCM)
The design of the FMC must achieve two objectives. One is to make the ICE and EM operate at suitable points to increase overall system efficiency, and the second is to make the control strategy become more concise and convenient. It has four inputs variables and two outputs variables. The rules of the proposed fuzzy controller would be modified by observing the control surfaces determined by the inputs and outputs. In addition, from the simulation results, the rules of the fuzzy controller can be also modified. Some of the fuzzy rules are shown in Table 2. The input variables are splitted into two levels (cfa. level 2 and 3) so as to reduce the number of the fuzzy rules, from 74 rules to 27(which decrease the rules combination and thus the analysis complexity).

Table 2. Some examples of the used fuzzy rules of FMC.

RN	Mode	T_{demand}	SOC	VS	$T_{EM,SP}$	$T_{ICE,SP}$
1	Mode 1	H	H	H	H	L
2	Mode 2	H	L	L	L	H
.	.	.	.	.	.	.
.	.	.	.	.	.	.
27	Mode 3	H	H	H	Mid	Mid

The proposed FMC inferred output for the ICE torque (T_{ICE}) and EM torque (T_{EM}) based on COG given by,

$$T_{ICE} = \frac{\sum_{j=1}^{c} m_{ICE,j}\sigma_{ICE,j1}\sigma_{ICE,j2}}{\sum_{j=1}^{n} m_{ICE,j}\sigma_{ICE,j2}} \tag{6}$$

$$T_{EM} = \frac{\sum_{i=1}^{c} m_{EM,i}\sigma_{EM,i1}\sigma_{EM,i2}}{\sum_{i=1}^{c} m_{EM,i}\sigma_{EM,i2}} \tag{7}$$

where, $\sigma_{ICE,j1}$ and $\sigma_{EM,i1}$, $\sigma_{ICE,j2}$ and $\sigma_{EM,i2}$ are the mean and the standard deviation of the GMF of the output variable for the ICE and the EM, respectively, which are two adjustable parameter, $m_{ICE,j}$ and $m_{EM,i}$ are the inferred weights of the $j^{th}$and i^{th} output membership function for the ICE and the EM, respectively, c is the number of fuzzy rules. The mean and the standard deviation of the output variable are optimize based on the proposed LAA presented in the following section.

Proposed Learning Adaptive Algorithm (LAA)
This section presents in details the proposed algorithm in order to ensure the learning adaptive algorithm working with the FMC block. In order to optimize the output of the proposed FMC based on NN. We first identify the parameter sets involved in the premise and consequence control logic, and use Theorem below to updates the parameter value.

Theorem: The parameters required by the FMC, shown in equations (6) and (7) are updated by the proposed LAA, if the mean and the standard deviation of the membership function satisfy the following:

$$\sigma_{ij1}^{k+1} = \sigma_{ij1}^{k} - \zeta^k \sum_{k=t+1}^{t+s} \sum_{j=1}^{N} \left(e_{ed}^k \mu_{td,ij} + e_{eff}^k \mu_{eff,ij} \right) \quad (8)$$

$$\sigma_{ij2}^{k+1} = \sigma_{ij2}^{k} - \zeta^k \sum_{k=t+1}^{t+s} \sum_{j=1}^{N} \left(e_{ed}^k \mu_{td,ij} + e_{eff}^k \mu_{eff,ij} \right) \quad (9)$$

where, σ_{ij1} is $\sigma_{ICE,j1}$ and $\sigma_{EM,i1}$ for (6) and (7), and σ_{ij2} is $\sigma_{ICE,j2}$ and $\sigma_{EM,i2}$ for (6) and (7) which are the mean and the standard deviation of the GMF for ICE and the EM, respectively. e_{td} and e_{eff} are the error functions for the torque demand and the vehicle total efficiency which are defined in (17). $\mu_{td,ij}$ and $\mu_{eff,ij}$ are the weights of the i^{th} rule for the j^{th} training pattern defined in (16). ζ^k is the learning rate defined in (14). k the iteration index. t is the trailing edge of the moving time-window over which the prediction error is minimized and s is the window of learning. For off-line learning we select $t = 1$ and $s = P$; where P is the size of the training set, which is usually much larger than the largest multi-step-ahead prediction horizon needed in practice Gupta (2015). The prediction accuracy deteriorates very quickly with increasing P. For on-line learning, s can be selected to be sufficiently large so as to include the largest possible prediction horizon Gupta (2015).

Proof. The proof can be given as the following. Assume the objective function given by,

$$E^k = \frac{1}{2} \sum_{j=1}^{N} (y_j^k - \hat{y}_j^k)^2 \quad (10)$$

where y_j^k and $\hat{y}_j^k$ are the j^{th} calculated output and desired output, respectively, N is the number of training iterations. From equations (6) and (7), the calculated output y_j is a function of consequent parts (Ω_i) given by,

$$y_j = \sum_{i=1}^{c} \mu_{ij} \Omega_i \quad \text{with:} \quad \sum_{i=1}^{c} \mu_{ij} = 1 \quad 1 \leq j \leq N \quad (11)$$

where Ω_i is the consequent part of the i^{th} rule. For a moving window of s points in a system with N outputs to be predicted, the following objective function is optimized:

$$\xi(t) \equiv \sum_{k=t+1}^{t+s} E^{t,k} = \frac{1}{2} \sum_{k=t+1}^{t+s} \sum_{j=1}^{N} (y_j^{k/t} - \hat{y}_j^k)^2 \quad (12)$$

where the error $E^{t,k}$ depends both on the location of the window and the prediction point within the window. The objective of the proposed learning strategy is to minimize the objective function (10). To simplify the expressions, the variable t is omitted from the equations. Using a gradient-descent method, the NN weights are updated using the partial differential equation.

$$\Delta\Omega_i \equiv -\zeta^k \sum_{k=t+1}^{t+s} \left(\frac{\partial E^k}{\partial \Omega_i} \right) \quad (13)$$

where $\Delta\Omega_i^k$ is the correction value for Ω_i^k at instant k, ζ^k is the learning rate at instant k given by,

$$\zeta^{k+1} = \left\| \frac{\Delta\Omega^k}{\Delta\Omega^{k-1}} \right\| \zeta^k \quad (14)$$

where $\|\bullet\|$ denotes the norm value. In view of the prediction error defined by (12) and from (10), the error gradient with respect to the weights can be obtained by using the Chain rule **?**. Chain rule is used to calculate the derivative of the composition of two or more functions. From (10), (11) and (12), we obtain,

$$\Delta\Omega_i = -\zeta^k \sum_{k=t+1}^{t+s} \sum_{j=1}^{N} (y_j^k - \hat{y}_j^k) \mu_{ij}^k \quad (15)$$

As mentioned in Jain (1988), μ_{ij} could be computed to minimize the objective function expressed by (10) as follows;

$$\mu_{ij}^k \equiv \left[\sum_{g=1}^{c} \left(\frac{e_{ij}^k}{e_{gj}^k} \right)^2 \right]^{-1} \quad 1 \leq i \leq c \quad , \quad 1 \leq j \leq N \quad (16)$$

where e_{ij} (e_{gj}) is the error between the j^{th} desired output of the system and the output data of real system of the i^{th} rule with the j^{th} (g^{th}) input data. For the studied HHEV, we consider the error functions defined as the following,

$$e_{td}^k = T_{demand}^k - T_{actual}^k \quad ; \quad e_{eff}^k = \eta_{opt} - \eta_{hev} \quad (17)$$

where T_{demand}^k is the total torque demand required to drive the vehicle, T_{actual}^k is the total actual wheel torque, η_{opt} and η_{hev} are the optimal and the actual efficiency of the hybrid vehicle, respectively. A sub-objective of the overall optimization algorithm consists to maximize the efficiency of the hybrid vehicle (18).

$$\eta_{hev} = \frac{\int_0^{dc} P_{hev}}{\int_0^{dc} P_{ICE} + \int_0^{dc} P_{EM}} \quad (18)$$

where dc is the driving cycle interval length, P_{hev} is the power supplied into the vehicle, P_{ICE} is the power consumed by the ICE, P_{EM} is the power consumed by the EM and supplied by the battery, with $P_{EM} = I_{bat}V_{bat}$, where I_{bat} and V_{bat} are the battery current and voltage, respectively. From equations (10) and (17), the total objective function given by,

$$E^k = \frac{1}{2} \sum_{j=1}^{N} [(e_{td}^k)^2 + (e_{eff}^k)^2] \quad (19)$$

Consequently, as a result of the learning strategy, the algorithm adapts parameters of strategy to minimize the objective function and maximize the total vehicle efficiency. In this paper, we choose the highest theoretical efficiency of the EM and the ICE, which are of about 0.9 and 0.34, respectively, but in the future work, we will calculate it based on the EM and the ICE current optimal efficiency. From equation (13), the parameters of the proposed FMC with proposed LAA using the following,

$$\sigma_{ij1}^{k+1} = \sigma_{ij1}^{k} + \Delta\sigma_{ij1}^{k}, \quad \sigma_{ij2}^{k+1} = \sigma_{ij2}^{k} + \Delta\sigma_{ij2}^{k} \qquad (20)$$

where σ_{ij1}^{k} and σ_{ij2}^{k} are the mean and the standard deviation of the function which are adjustable parameters of the jth membership function of the i^{th} fuzzy rule. Based on equations (15), (17), and (19), we can re-write the mean and the standard deviation of the GMF which given in (20) as equations (8) and (9) which given in the Theorem. From the derived theorem, it can be seen that a novel hybrid algorithm is proposed to create a fuzzy neural network, which takes the effect of the vehicle dynamics into consideration, since the learning strategy is based on the global vehicle efficiency and the required torque.

3.3 Local Fuzzy Tuning Proportional-Integral-Derivative Controllers (Level1: LFPIDC)

The objective at this level is to regulate the set points of EM and HM via ICE, to give a good control tracking performance. As mentioned before, level 2 (cf. section 3.2) permits to manage optimally the power distribution between the different sources during operation mode, while sending out reference torque signals to each individual hybrid vehicle subsystem (e.g., ICE, EM, battery, etc.), level 1 with LFPIDC ensures that this reference torque signals are tracked as accurate as possible. In addition, the low level control strategy based on LFPIDC has the ability to keep the hybrid vehicle system states stable even in the presence of uncertainties. In this level, torques of the EM and the ICE are controlled by a PID-fuzzy logic based controller Ohri (2015). The purpose of this section is to study the adaptive tuning of a fuzzy PID controller, which combines the traditional PID controller and fuzzy control algorithm. The initial PID controller parameters are calculated using Ziegler-Nichols step response method, then these parameters are optimized by fuzzy tuning. Compared to work done on fuzzy PID controllers given in Ohri (2015), the proposed LFPIDC gives better performance for special processes (nonlinear, highly uncertainties and unsteady behavior).

4. SIMULATION RESULTS AND DISCUSSION

To verify the control performance of the proposed overall control and optimal energy management strategy, simulation results under different variable road slope conditions, with a simulator based on MATLAB/Truckmaker are used. In order to develop a new controller and to evaluate its performance, an accurate and reliable model of the vehicle is required. For implementing and testing the proposed strategy, a realistic model of the BUSINOVA bus is needed. The model is implemented by using TruckMaker software (cf. Figure 6). Its key features are given as the following: The software is plug and play, allows model data customization and power train configuration customization. In addition, it has an easy graphical user interface. TruckMaker software has been used for:

- Fuel consumption evaluation, fuel economy, emissions, and vehicle drivability.
- Simulation of a single component and simulation of a component in the loop.
- Software in the loop.

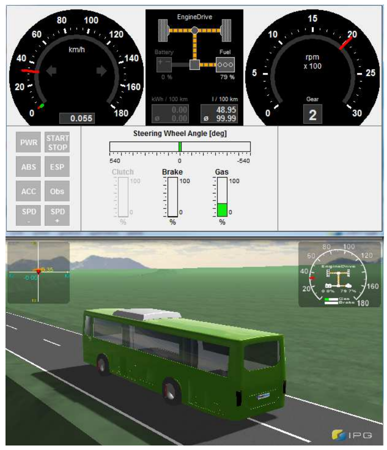

Fig. 6. TruckMaker test platform.

To prove the effectiveness of the proposed overall control architecture for optimal energy management, proposed strategy is compared with PMP strategy already existing in the literature Panday (2016). The desired and the actual bus speed profile is shown in Figure 7. Figure 8 shows the driver torque demand and the required wheel torque for the proposed energy management strategy and PMP strategy Panday (2016).

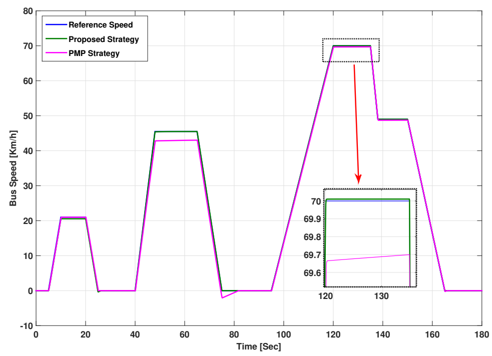

Fig. 7. Output vehicle speed for proposed energy management strategy and PMP strategy Panday (2016).

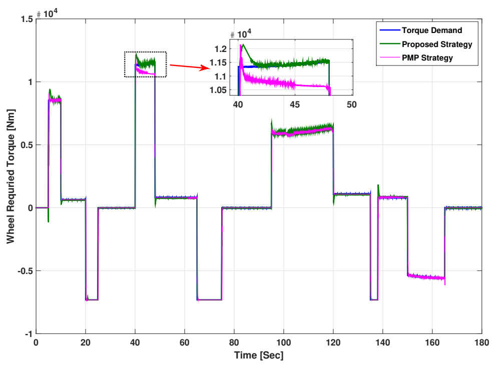

Fig. 8. Wheel required torque [Nm] for proposed energy management strategy and PMP strategy Panday (2016).

For the simulation runs, the initial SOC, driving cycle and all other parameters remain the same. From Figures 7 and 8, it may be seen that the vehicle output speed and required wheel torque of the vehicle are similar to the set point of the drive cycle for the proposed energy management strategy, on the other hand, the PMP strategy Panday (2016) cannot give good responses. Figure 9 depicts the progress of SOC (from initial to final state) using proposed strategy and PMP strategy Panday (2016). This information may be used to make appropriate control decisions to improve fuel economy.

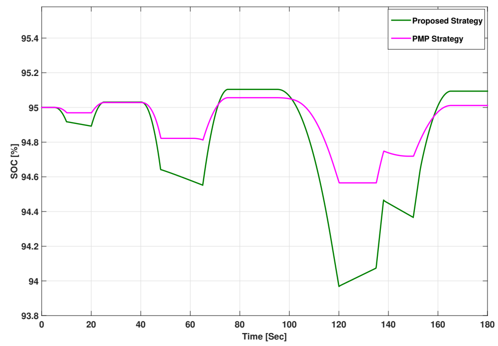

Fig. 9. SOC profiles for proposed energy management strategy and PMP strategy Panday (2016).

The proposed, the SOC values begin at 0.95 and finish at 0.951, but with PMP strategy Panday (2016), SOC values begin at 0.95 and finish at 0.95011. The net fluctuation is 0.00011. Therefore, we can see that during the driving cycle, the SOC level is kept higher when using proposed strategy, instead of using PMP strategy Panday (2016). Energy consumed by the ICE [KJ] for the online proposed strategy and PMP strategy Panday (2016) are given in Figure 10.

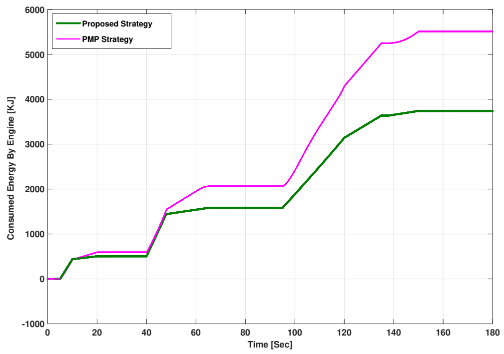

Fig. 10. Consumed energy by ICE [KJ] for proposed energy management strategy and PMP strategy Panday (2016).

Total energy consumed by the vehicle for these controllers is given in Figure 11 which shows that the proposed energy management strategy is better w.r.t. to PMP strategy Panday (2016) controllers for reducing total energy consumed (fuel consumption and battery discharge), which increases the efficiency of the vehicle.

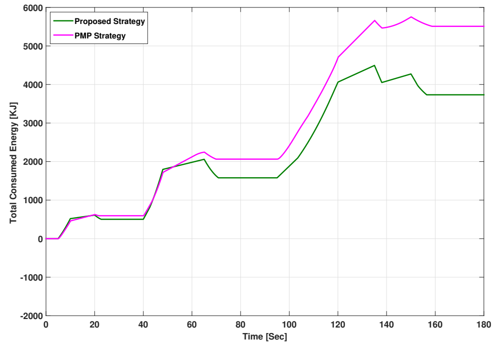

Fig. 11. Total energy consumed by the vehicle [KJ] for proposed strategy and PMP strategy Panday (2016).

To have a more specific comparative analysis, the variation of SOC, and the total energy consumption for a typical driving cycle are shown in Table 3, where FEC is the Fuel Energy Consumption by ICE (KJ).

Table 3. Comparison of results for proposed IHHCS and PMP Panday (2016) strategies.

Control Strategy	FEC by ICE (KJ)	**SOC (100%)**
PMP	5510	95∼95.011
IHHCS	3732	95∼95.100

From Table 3, it is seen that the proposed IHHCS kept SOC higher than PMP Panday (2016) and reduce the fuel consumption up to 30% compared to PMP method Panday (2016).
From Figures 7 to 11, simulation results indicate that the proposed online energy management control method can achieve increased energy efficiency. From the simulation results, it can be seen that the proposed IHHCS and OFLC based energy management method can achieve better energy efficiency compared with traditional SF and PMP strategies. In addition, we observe that, all power sources (battery and the ICE) can be operated within their desired working ranges while satisfying the load demand.

5. CONCLUSIONS AND PROSPECTS

The paper has presented a methodology to design an online implementable strategy based on the fuzzy neural control theory. In this paper, an IHHCS strategy to manage the power splitting within a HHEVs is presented. It can be easily implemented in real time because it does not need prior information about future driving conditions and can online self-tune the parameters of the proposed fuzzy controller to adapt to changing conditions. The proposed IHHCS consists of three control levels. The first level uses fuzzy PID to track the set points of EM and ICE. At the second level power source splitting decisions are made between the EM and ICE based on adaptive NN fuzzy strategy. Finally, the third level has been developed by fuzzy strategy to decide the optimal mode of operation. Through simulation, the following have been verified; (i) an accurate and reliable model of the BUSINOVA bus is designed by TruckMaker software; (ii) the proposed fuzzy logic controller is used to effectively split the torque

between EM and HM via ICE; (iii) the proposed fuzzy controller parameters are found by optimization; (iv) an online learning control strategy based on fuzzy neural-learning has been proposed to minimize the fuel consumption for a HHEVs and maximize the global vehicle efficiency; (v) it can be used for both offline and online; (vi) rate of charge of the battery is limited to minimize aging effects; (vii) ICE is operated near its optimal range;(viii) keeping SOC within the range which promotes battery longevity. Finally, a simulation was provided and the designed controller was proved good performance.
It is planned in near future to implement the overall proposed control strategy on the actual BUSINOVA platform.

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