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Intelligent Energy Management Strategy based on Artificial Neural Fuzzy for Hybrid Vehicle

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***Abstract*—This paper proposes an intelligent energy management strategy for a hydraulic-electric hybrid vehicle in order to minimize its total energy consumption. It proposes first to model the vehicle total energy consumption and investigates the minimization of an expended energy function, formulated as the sum of electrical energy provided by the on-board batteries and consumed fuel. More precisely, it is proposed in this paper an intelligent controller which shows its capabilities of increasing the overall vehicle energy efficiency and therefore minimizing total energy consumption. The proposed strategy consists of an advanced supervisory controller at the highest level (third) which corresponds to a fuzzy system deciding the most appropriate operating mode of the system. In the second level, an intelligent optimal control strategy is developed based on neuro-fuzzy logic. Then, in the first level, there are local fuzzy controllers to regulate vehicle subsystems set points to reach the best operational performance. The advantage of the proposed strategy could be summarized as follows: (i) it can be implemented online; (ii) reduces total energy consumption compared with several traditional methods. The proposed strategy validations are performed using a mix of automotive TruckMaker and MATLAB/Simulink developed software on several (standard or not) driving cycles.**

***Index Terms*—Hybrid Vehicle; Power Management Strategy; Hierarchical Control Architecture; Adaptive and Optimal Neuro-Fuzzy Controller.**

NOMENCLATURE

- IHHCS: Intelligent Hierarchical and Hybrid Controller Strategy.
- ISSMC: Intelligent Supervisory Switching Mode Controller.
- IPDOC: Intelligent Power Distribution and Optimization Controller.
- LFPIDC: Local Fuzzy Tuning Proportional-Integral-Derivative Controllers.
- ICE, HM, HP and EM: Internal Combustion Engine, Hydraulic Motor, Hydraulic Pump and Electric Motor.
- SOC: State Of Charge.
- ANN: Artificial Neural Network.
- LAA: Learning Adaptive Algorithm.
- PCVE: Produced and Consumed Vehicle.

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- FMC: Fuzzy Management Controller.
- ω_{ICE}: Rotational speed of the ICE.
- D_{HM}, D_{HP}, $\eta_{m_{HM}}$, $\eta_{m_{HP}}$, $\eta_{v_{HM}}$ and $\eta_{v_{HP}}$: Displacement, mechanical efficiency and volumetric efficiency of the HM and the HP, respectively.
- F_{tr}, F_{rr}, F_{ad}, F_g and F_{brake}: Traction force, rolling resistance, aerodynamic force, gravity force and mechanical brake force, respectively.
- M, M_{eq} and a: bus weight, equivalent mass of rotating parts and bus acceleration, respectively.
- i_g, η_{pt}, J_{rot} and r: Gear ratio, powertrain efficiency, total inertia of the rotating components in the transmission and radius of the wheel, respectively.
- $\Delta\Omega_i^k$, ζ^k: Correction value for Ω_i^k and learning rate at instant k.
- y_j^k and $\hat{y}_j^k$: j^{th} calculated and desired outputs.
- N: Number of training iterations.
- T_{actual}^k: Total actual wheel torque.
- η_{opt} and η_{hev}: Optimal and the actual efficiency of the hybrid vehicle, respectively.
- T_{pt}: Output powertrain torque from the gearbox.
- μ_{rr}, F_N, g, θ, v: Rolling resistance coefficient, normal force, gravity acceleration, slope angle, bus speed, respectively.
- ρ, A, C_d, v_{wind} : Air density, the frontal area of the bus, drag coefficient and wind speed, respectively.
- T_{brake}: Brake torque provided by the bus mechanical brake system.
- T_{ICE}, T_{HM}, T_{EM}: ICE, HM, EM torque, respectively.
- P_{ICE}, P_{HM}, P_{EM}: ICE, HM and EM consumed power, respectively.
- $T_{ICE,SP}$, $T_{EM,SP}$: ICE and EM torque set point, respectively.
- $\dot{m}_{fuel}$: Fuel flow rate of the ICE.
- Q_{LHV}: Lower heating value of a used fuel.
- ω_{EM}, T_{demand}: EM current speed and torque demand, respectively.
- $\sigma_{ICE,j1}$ and $\sigma_{EM,i1}$, $\sigma_{ICE,j2}$ and $\sigma_{EM,i2}$: Mean and the standard deviation of the Gaussian Membership Functions (GMF) of the output variable for the ICE and the EM. $m_{ICE,j}$ and $m_{EM,i}$: Inferred weights of the j^{th} and i^{th} output membership function for the ICE and the EM.

I. INTRODUCTION

THE sustainable development of the automotive industry is faced to a dual challenges: energy exhaustion and environment pollution. There has been an urgent need to effectively improve energy efficiency and reduce energy consumption.

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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 [1] due to efficiency of the conversion and density limits of the low power of electric motors and batteries [2]. The presence of additional power sources in the HEV introduces additional degrees of freedom in controlling the drivetrain, since at each time the driver 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 costs function such as battery life [3]. Vehicle fuel consumption is not only related to the performance of the vehicle itself but also it is closely related to energy power management for a given velocity profile [4]-[20] and driver behavior optimization [21]-[24]. A correlative research study confirmed that Power Management Optimization (PMO) on HEV can reduce fuel consumption [4]-[20], and it is also conducive to reducing emissions. Thus, PMO proves to be an effective measure to achieve reduction of fuel consumption, which is one of the important focuses for automobile energy savings.

The authors in [4] has investigated the use of dynamic programming to formulate global optimum numerically for reducing fuel consumption under the assumption of full knowledge of the future driving conditions. Unfortunately, the obtained results through dynamic programming cannot be implemented directly due to its high computational demands. To remedy this problem, approximated dynamic programming [5] and stochastic dynamic programming [6] had been suggested as possible solutions. Analytical optimization methods, on the other hand, use a mathematical problem formulation to find an explicit solution that makes the obtained solution faster than a purely numerical methods. Within this category, Pontryagin's minimum principle based Energy Management Strategy (EMS) is introduced as an optimal control solution [7]. This approach can only generate an optimal solution if implemented offline since in this case the future driving conditions are supposed to be known in prior. For online implementation, authors in [8], [9] have proposed a generic framework of online EMS for HEVs is proposed, where an Estimation Distribution Algorithm (EDA) is used for on-line (i.e., real-time) optimization of the power-split strategy. It includes several control strategies for managing battery State-Of-Charge (SOC). Rule-based energy management control strategies have been widely used in practical HEV energy management systems due to the fact that the algorithms are easy to implement in real time. Rule-based EMS for HEV are proposed in [10]-[12] in order to split the power demand between the engine and the battery. In [13],[14] authors use a rule-based controller based on StateFlow (SF) toolbox and they proposed a proper supervisory environment for a complex structure of control. The problem of this method is that it needs highly engineering experience, extensive experimental data, etc. to create these rules. In addition, it gives limited benefits for fuel economy. To overcome this problem, a fuzzy inference system is added to rule-based strategy in [15], [16]. The advantages of fuzzy system are: simple enough to be implemented in real time applications, use of linguistic variables and ease to model nonlinearity and uncertainty but as main drawback fuzzy system alone is not adaptive to large modification of the system modelling. This problem can be solved by using the Genetic Algorithms (GA) [17] to optimize the membership functions of the fuzzy controller for several problems while using appropriate fitness function. Random convergence of solutions is the major disadvantage of GA. In addition, the optimization algorithm is generally highly time consuming, therefore, many of the problem statements do not prefer GA for optimizing their respective function. To overcome this problem and to reduce fuel consumption, Artificial Neural Network (ANN) is introduced in [18]-[20]. ANN are good learning but are generally considered as black boxes.

One of the main objectives of this paper is the development and experimental verification of such control framework to minimize the energy consumption based on the merging of two paradigms (ANN and fuzzy system) to inserts their advantages and avoids their disadvantages. In order to study and develop an efficient and reliable EMS forHydraulic-Electric Hybrid Vehicle (HHEV), a precise vehicle modelling is desirable. The studied vehicle is a hybrid bus, based on a series-parallel power-split hybrid architecture. This hybrid bus is called BUSINOVA and is developed by SAFRA Company (cf. Figures 1 and 2). BUSINOVA is composed of Electric Motor (EM), Internal Combustion Engine (ICE), Hydraulic Motor (HM), and battery as the propulsion powertrain system of the vehicle. The EM and HM motors are both directly connected 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. This gives a big number of working modes for the bus which increase the combinations of optimizing its energy management.

The contributions of this work are twofold: The primary objective is to investigate and to propose a reliable model of the studied HHEV, corresponding to the BUSINOVA bus based on a mix of IPG automotive TruckMaker and MATLAB/Simulink software (cf. section II and section IV). This software has been chosen because it allows reliable and dynamic simulation of the overall bus and its different embedded and interconnected sub-systems (such us: EM, HM, ICE, HP and battery). The second main contribution corresponds to the proposition of an overall Intelligent Hierarchical and Hybrid Controller Strategy (IHHCS), (cf. section III), in order to enhance the bus energy efficiency, leading therefore to minimize the total energy consumption (summation of electric energy and fuel energy). The overall proposed control and EMS is compared with alternative frameworks existing in the literature based on Optimal Fuzzy Logic Control (OFLC) [16] and SF [13] in order to demonstrate the advantages of the proposed methodology (cf. section IV). The results of this paper support that the proposed strategy is capable of: (i) being applied to various types of hybrid vehicles; (ii) reducing total energy consumption compared with several traditional methods; (iii) increasing global vehicle efficiency; (iv) being implemented in real-time; (v) reducing the number of rules needed in fuzzy control; (vi) keeping SOC within the range which promotes battery longevity. Therefore, this paper, will provide both a novel model and novel approach for an advanced energy management system of hybrid vehicles.

The paper is organized as follows. The overall HHEV's description and modeling is given in section II. In section III, the proposed intelligent hierarchical hybrid controller structure is developed. Section IV. is dedicated to explain a power management strategy based on StateFlow, which corresponds to one of the comparative methods used in this paper. Simulation results and comparative analysis using IPG automotive TruckMaker simulator are presented in section V. Finally, the conclusions and future prospects are presented in section VI.

II. MODELING OF THE HYBRID BUS

The aim of this section is to model the studied system, i.e., BUSINOVA hybrid bus, developed by SAFRA Company (cf. Figure 1). It is emphasized also in this section the use of TruckMaker/Matlab software in order to have precise simulations. This software will allow us to illustrate the efficiency of the proposed IHHCS (cf. section V). The studied hybrid bus is composed of an EM, a HM, a ICE and battery as the propulsion powertrain system of the vehicle.

Fig. 1. BUSINOVA hybrid bus.

A. Hybrid bus powertrain architecture

The model of the studied hybrid bus is based on a series-parallel power-split hybrid architecture [25]. A simple block diagram of the power flows in the bus is shown in Figure 2. The EM and HM are both directly connected to the transmission and can ensure simultaneously or independently the traction of the bus. On the other hand, the ICE is coupled to a HP for driving the HM, and therefore allowing the ICE load shifting.

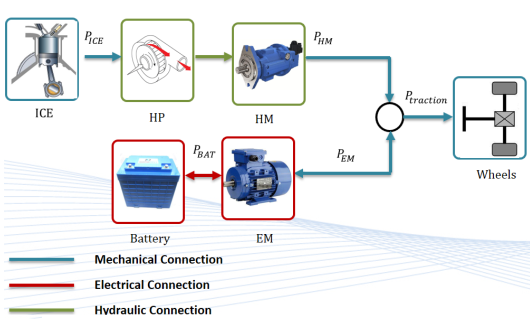

Fig. 2. Block diagram of the powertrain power flows. (ICE: Internal Combustion Engine, HP: Hydraulic Pump, HM: Hydraulic Motor, EM: Electric Motor, P_{ICE}: Consumed fuel power, P_{HM}: Hydraulic motor power and P_{EM}: Consumed electrical power.)

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:

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

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 specification parameters of the ICE, HM, HP and the traction EM used in BUSINOVA are given respectively in the Tables V and VI (cf. Appendix).

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.

B. Dynamical model

This part is dedicated to the dynamical equations describing the bus. The parameters used for the vehicle modeling is presented in the Table VII in the appendix. The purpose of the dynamical model is to have a realistic global behavior of the bus in order to validate the proposed energy management technique. 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:

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

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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 [26].

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:

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

with

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

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

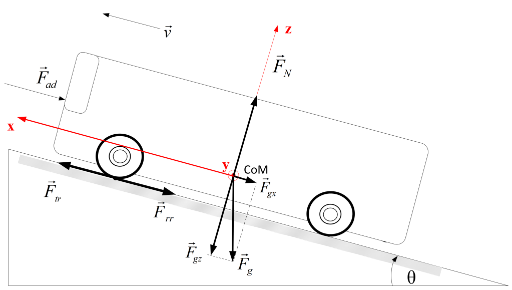

Fig. 3. Forces acting on the bus.

C. HHEV Design using TruckMaker

TruckMaker[1] software (cf. Figure 4) is a highly reliable and precise software for modelling and controlling heavy vehicles (it is used by important international companies throughout the world). This software can be used even independently or with MATLAB/Simulink and its key features are given in the following: The software is plug and play, allows for model data customization and for power train configuration customization. In addition, it has an easy Graphical User Interface (GUI) to modify the parameters of the studied HHEV. TruckMaker software can be used for:

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

To perform a simulation in TruckMaker, it is just like on a real test drive, it is needed to define a vehicle, the tires, the powertrain, a driver, a test track and a maneuver that the driver should complete. In TruckMaker, there is a model for each of these requirements. The combination of these models forms a global TestRun. Hence, the model of the studied bus is implemented by using TruckMaker software (cf. Figure 4). Since all the BUSINOVA model parameters are defined on the TruckMaker GUI. BUSINOVA simulink subsystem blocks are then generated automatically by TruckMaker. If any modification is needed, the user can change the parameters from the GUI or add new blocks on MATLAB/Simulink to define new modeling functions that are not included in TruckMaker software.

[1]Developed by IPG Automotive German Company.

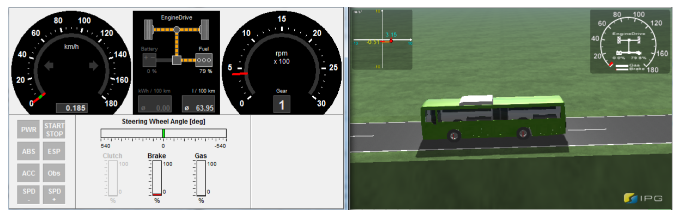

Fig. 4. TruckMaker vehicle.

As far as possible, each component of the TruckMaker simulator should correspond to an actual component on the studied BUSINOVA bus. Tables VII, V and VI in the appendix indicate the specification of the studied hybrid vehicle.

III. PROPOSED INTELLIGENT HIERARCHICAL HYBRID CONTROLLER STRATEGY (IHHCS)

After the definition of the BUSINOVA bus model, the aim of this section is to make the focus on the proposed IHHCS, embedded in the bus in order to minimize its total energy consumption while maximizing the global vehicle efficiency. Therefore, 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 5) corresponds to a driver command interpreter which converts the driver inputs from the brake and accelerator pedals to the required torque to apply at the wheels level in order to track the desired velocity profile as accurately as possible.

This proposed strategy consists of three control levels as shown in Figure 5. An Intelligent Supervisory Switching Mode Controller (ISSMC) based on fuzzy logic is developed in the third level (the highest level) that is capable of managing all of the possible bus operation modes (cf. section III.A). At the second level (cf. section III.B), an advanced Intelligent Power Distribution and Optimization Controller (IPDOC) has been developed for power splitting which decides the optimal combination of power sharing between different energy sources to maximize the overall vehicle efficiency. In section III.C, a Local Fuzzy tuning Proportional-Integral-Derivative Controllers (LFPIDC) is used to regulate the set points of EM and HM via ICE, to give a good tracking control performance. In this paper, we will focus more on level 3 and level 2 (cf. respectively, section III.A and III.B).

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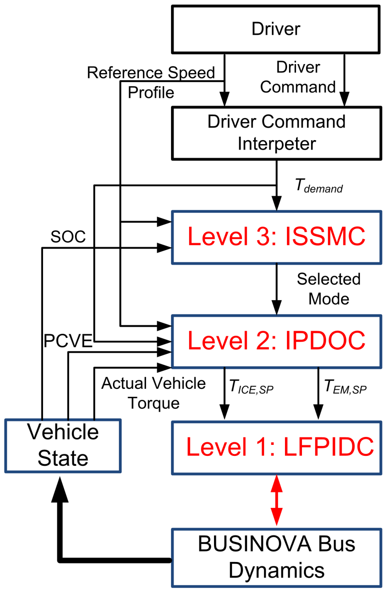

Fig. 5. Developed IHHCS for BUSINOVA bus distributed generation system. In this figure the following acronym are used: PCVE is the Produced and Consumed Vehicle, T_{demand} is the torque demand, $T_{ICE,SP}$ and $T_{EM,SP}$ are the ICE and EM torque set point, respectively.

A. *Intelligent Supervisory Switching Mode Controller (Level 3: ISSMC)*

As mentioned in section II.A, there are five modes of operation. In order to improve the HHEV operation, the proposed ISSMC based on fuzzy logic 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 the 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 Boolean 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 Reference Speed (RS) profile, T_{demand} and SOC, and its output variable is the operation mode (Mode). We use Gaussian Membership Functions (GMF) in the premise parts (input variables) and consequent parts (output variables) as given in Figure 6 and Center 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 [27]. The actual physical values for the input variables are defined as the following: reference speed is from 0 Km/h to 75.65 Km/h, T_{demand} is from 0 Nm to 1170 Nm, and SOC is from 0% to 100%. The selected Bus operating modes are based on the fuzzy rules (cf. Table I),as example, when the battery SOC is high, speed are high speed condition and the torque demand is less than the EM torque, therefore EM can drive the vehicle, etc., where RN is the rule number. The fuzzy rule is constructed from 27 individual fuzzy rules.

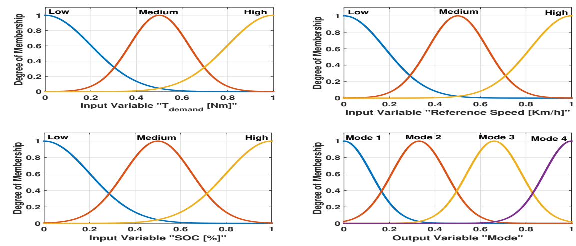

Fig. 6. Input and output variables membership functions.

TABLE I
SOME EXAMPLES OF FUZZY RULES USED BY THE ISSMC.

RN	T_{demand}	SOC	RS	Mode
1	Low	High	High	Mode1
2	High	Low	Low	Mode2
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
27	Low	Low	Low	Mode4

B. *Intelligent Power Distribution and Optimization Controller (Level 2: IPDOC)*

An integrated neuro-fuzzy system is proposed in second level which has the advantages of both fuzzy systems and ANN. The block diagram of the proposed level 2 is presented in Figure 7. This level consists of two blocks: Learning Adaptive Algorithm (LAA) block and Fuzzy Management Controller (FMC) block. 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 one input for this level beside other six input variables: Produced and Consumed Vehicle (PCVE) and actual vehicle torque for the LAA block and the same three inputs of the third level (reference speed profile, T_{demand}, SOC) for the FMC block, while there are two output variables are ICE and EM torque set points $T_{ICE,SP}$ and $T_{EM,SP}$, respectively. The FMC block splits the required torque between EM or/and HM via ICE (cf. section III.B.1) based on the fuzzy logic and generates the $T_{ICE,SP}$ and $T_{EM,SP}$ to the first level (LFPIDC). The proposed LAA block based on a neural network is used to update weights of the FCM output variables. The total actual and the optimal efficiency for the vehicle are calculated based on the elementary efficiencies of the EM, battery, ICE, HP, HM and transmission. The main contribution of this level are: (i) find the best combination of power distribution between different energy sources and maximize hybrid vehicle overall efficiency; (ii) tune the optimal parameters of the fuzzy controller based on ANN optimization; (iii) and generates the set point for the first level.

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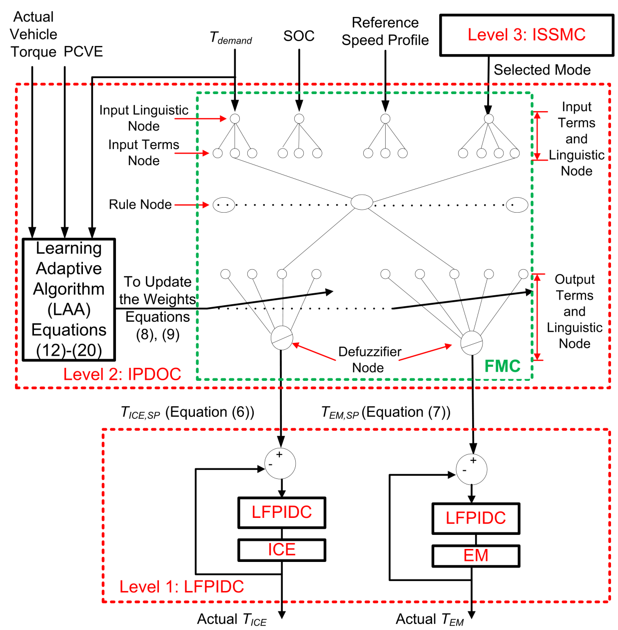

Fig. 7. Block diagram of the proposed level 2.

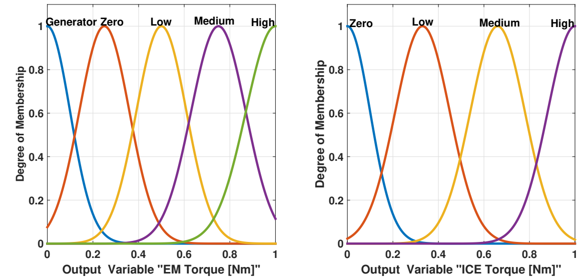

Fig. 8. Initial GMF of the FMC output variables.

TABLE II
SOME EXAMPLES OF THE USED FUZZY RULES OF FMC.

RN	Mode	T_{demand}	SOC	RS	$T_{EM,SP}$	$T_{ICE,SP}$
1	Mode 1	High	High	High	High	Low
2	Mode 2	High	Low	Low	Low	High
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
27	Mode 3	High	High	High	Medium	Medium

1) Proposed Fuzzy Management Controller (FMC): The design of the FMC must achieve two objectives. One is to make the ICE and EM operate at suitable working points to increase the overall system efficiency, and the second is to make the control strategy becomes more concise and convenient. FMC block is proposed based on the fuzzy logic control to manage the power distribution between the two different sources and generates the $T_{ICE,SP}$ and $T_{EM,SP}$ to the LFPIDC level. It consists of two outputs ($T_{ICE,SP}$ and $T_{EM,SP}$) (cf. Figure 7). The actual physical varaibles for the ouput variables as the following, EM torque range from -600 Nm to 660 Nm and ICE torque range from 0 Nm to 343 Nm. Some of the fuzzy rules are shown in Table II. The proposed FMC inferred output for the ICE torque (T_{ICE}) and EM torque (T_{EM}) based on COG are given by,

$$T_{ICE} = \frac{\sum_{j=1}^{c} m_{ICE,j}\sigma_{ICE,j1}\sigma_{ICE,j2}}{\sum_{j=1}^{c} m_{ICE,j}\sigma_{ICE,j2}} \qquad (6)$$

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

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 parameters; $m_{ICE,j}$ 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 optimized based on the proposed LAA which is presented in the following section.

2) Proposed Learning Adaptive Algorithm (LAA): LAA is developed based on neural networks to optimize the mean and the standard deviation of the FMC output variable. In this method, error between the desired output of the system and the output data of real system is used to correct (update) the GMF weights for proposed FMC. Consequently, this algorithm adapts parameters of FCM strategy based on the below Theorem to minimize the objective function (20) (cf. Figure 11) and to maximize the total vehicle efficiency. The total actual efficiency for the vehicle are calculated based on the elementary efficiencies of the EM, battery, ICE, HP, HM and transmission.

Theorem: FMC parameters which are given in (6) and (7) are optimized by the proposed LAA, if the mean and the standard deviation of the GMF satisfy the following:

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

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

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, $\mu_{td,ij}$ and $\mu_{eff,ij}$ are the weights of the i^{th} rule for the j^{th} training pattern, ζ^k is the learning rate, 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 [28]. 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 [28].

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

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

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,

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

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:

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

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 ANN weights are updated using the partial differential equation.

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

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,

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

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[2] [29]. Chain rule is used to calculate the derivative of the composition of two or more functions. From (10), (11) and (12), we obtain,

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

As mentioned in [30], μ_{ij} could be computed to minimize the objective function expressed by (10) as follows,

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

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,

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

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).

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

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. The fuel consumption rate $\dot{m}_{fuel}$ is transformed into equivalent consumed engine power P_{ICE}:

$$P_{ICE} = \dot{m}_{fuel}Q_{LHV} \tag{19}$$

where Q_{LHV} is lower heating value of the used fuel. For diesel $Q_{LHV} = 43MJ/kg$. From equations (10) and (17), the total objective function is given by,

$$E^k = \frac{1}{2}\sum_{j=1}^{N}[(e_{td}^k)^2 + (e_{eff}^k)^2] \tag{20}$$

Based on (13), the mean and the standard deviation of the GMF for proposed FMC with proposed LAA are given by,

$$\sigma_{ij1}^{k+1} = \sigma_{ij1}^k + \Delta\sigma_{ij1}^k, \qquad \sigma_{ij2}^{k+1} = \sigma_{ij2}^k + \Delta\sigma_{ij2}^k \tag{21}$$

where σ_{ij1}^k and σ_{ij2}^k are the mean and the standard deviation of the function which are adjustable parameters of the j^{th} membership function of the i^{th} fuzzy rule. Based on equations (15), (17) and (20), the mean and the standard deviation of the GMF which are given in (21) can be rewritten as (8) and (9) which are given in the Theorem.

From the derived theorem, it can be seen that a novel hybrid algorithm was proposed to create a neural fuzzy system, which takes the effect of the vehicle dynamics in consideration, since the learning strategy is based on the global vehicle efficiency and the required torque.

C. Local Fuzzy Tuning Proportional-Integral-Derivative Controllers (Level 1: LFPIDC)

In this level, fuzzy logic tuning PID is proposed based on [31], [32] for the EM and HM via ICE (cf. Figure 7). Since this paper focuses more on Level 3 and 2, only few details of this level are given. This level corresponds to an adaptive PID controller, based on fuzzy logic inference system to compute its parameters. It corresponds thus to a combination of 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

[2]The chain rule is a formula for computing the derivative of the composition of two or more functions.

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the works done on fuzzy PID controllers given in [31], [32], the proposed LFPIDC gives better performance for special processes (nonlinear, highly uncertain and unsteady behavior).

IV. Power Management Strategy Based on StateFlow

As we explained in section II.A, there are five possible operating modes. The SF strategy that is used is a rule-based controller [10]-[12], [13], [14]. The energy management will only use reference speed profile, T_{demand}, SOC to calculate the appropriate operating mode. According to T_{demand}, the operation of this controller is divided into five modes. We use the charge sustaining policy which assure that the (SOC) stay within preset lower (SOC_{min}) and upper (SOC_{max}) bounds. This policy is chosen for efficient battery operation as well as to prevent battery depletion or damage power split strategy. The various operating modes are selected based on the following set of rules:

- If battery SOC is greater than the lower limit (SOC_{min}) and T_{demand} can be provided by battery then the vehicle is only operated in Electric mode.
- If the battery SOC is above the lower limit (SOC_{min}) and the use of ICE alone cannot be in efficient operating point, then ICE and EM both provide the requested power in a way that the ICE is as near as possible of best operating point imposed by the transmission and the EM supply the rest of torque demand.
- If the T_{demand} requested by the driver is negative, and the battery SOC is maximal then the mechanical braking is engaged. The controller state machine is implemented using Simulink/ StateFlow (Level 3: cf. Figure 9).

In the second level, Power Management Strategy (PMS) based on rule based and mathematical formula for power splitting between EM and HM via ICE is designed. This level is activated according to the decision made in level 3. Finally in the first level (LFPIDC) corresponds to the same than what is given in subsection III.C. Some examples of switching conditions between the modes are given in the Table III, NA means that TEM or TICE is not depend on T_{demand}.

Some examples of switching conditions between the modes are given in the Table III, NA means that T_{EM} or T_{ICE} is not depend on T_{demand}.

TABLE III
Some examples of the SF switching conditions.

T_{demand}	SOC (100%)	T_{EM}	T_{ICE}	Mode
>0	>60%	$>T_{demand}$	NA	Mode 1
>0	<30%	NA	NA	Mode 2
>0	>30%	NA	$<T_{demand}$	Mode 3
>0	<60%	NA	$>T_{demand}$	Mode 4
<0	<90%	NA	NA	Mode 5

V. Simulation Results and Discussion

To verify the BUSINOVA bus model and the control performance of the proposed overall control and optimal energy management strategy, simulation results under different

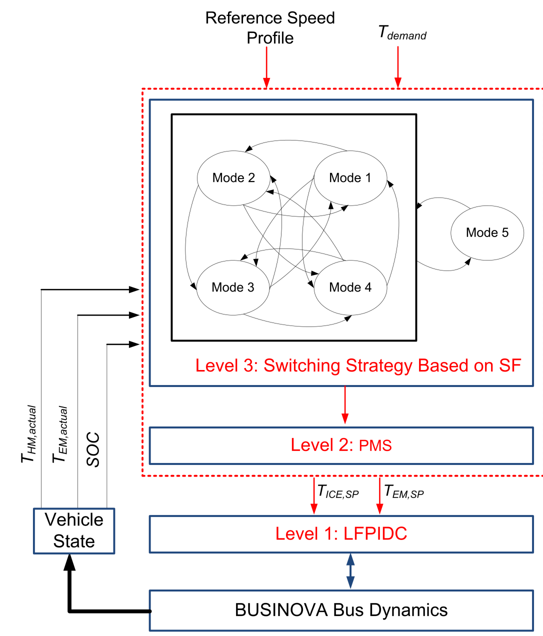

Fig. 9. Power management strategy based on the SF for BUSINOVA bus.

driving cycles and variable road slopes, with a simulator based on IPG automotive TruckMaker are used. In order to develop and to evaluate the performance of the proposed overall energy management strategy (called IHHCS (cf. section III)), a realistic model of the studied Hydraulic-Electric Hybrid bus is used (cf. Section II) and implemented using TruckMaker/MATLAB simulator (cf. Section II.C). The actual physical HHEV parameters are listed in Tables VII to VI (cf. Appendix). In this section, three simulations and discussions to demonstrate the effectiveness of the proposed IHHCS are presented. The first simulation compares the control surface of the proposed strategy and SF based strategy. In the second simulation, the effectiveness of the proposed overall control architecture is highlighted and a comparison with different well known strategy (e.g., OFLC (Optimal Fuzzy Logic Control) and also SF (StateFlow)) are discussed. The third simulation validates the proposed strategy for different standard driving cycles to illustrate the reliability of the proposed control architecture.

A. Simulation 1: Control surface of the proposed Fuzzy Strategy and its Comparison with StateFlow Approach

In this section, simple PMS based on the rule-based controller SF [10]-[12], [13], [14] is briefly described in order to give some comparisons with the proposed strategy based on fuzzy logic inference system. In addition, the resultant EM torque for both SF and the proposed strategy are highlighted under different conditions. The resultant EM torque for the proposed strategy and SF strategy under different bus navigation conditions are given in Figure 10 (left) and (right), respectively, which shows that the proposed strategy is more smoothing than the SF strategy. Therefore, according to the control surface and the knowledge of the expertise, the rules of the fuzzy controller can be modified to give more smoothing for the proposed strategy. Figure 10 shows the control surfaces

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of the torque set point for the EM as a percentage w.r.t. the global torque set point (T_{demand}) and SOC using proposed fuzzy strategy and SF.

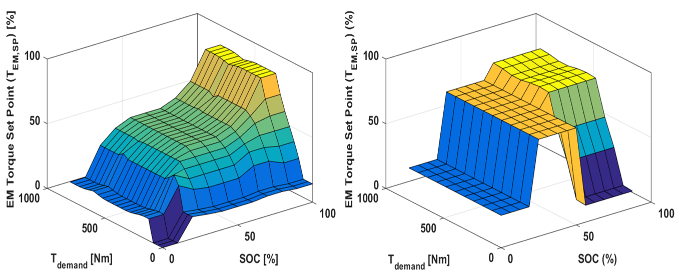

Fig. 10. Control surfaces of EM torque set point with global torque set point (T_{demand}) and SOC using proposed strategy (left) and Stateflow (right).

In addition, as the learning rate (14) is updated online, the ANN weights (13) will also be updated after every data input to minimize the error function in order to ensure quick convergence speed toward the sub-optimal controller parameters. The experiment results show that the proposed strategy has performed a good prediction results as well as running time (cf. average objective function error in Figure 11). From Figure 11, it can be seen that, there are two jumps at instant 40 sec and 95 sec, these are due to abrupt change of the acceleration (given by the velocity set point, cf. Figure 12). Nevertheless, it is to be noted that the average error will always decrease until reaching (at 150 sec) the global optimal controller parameters of Level 2. In the following simulation 2, the overall performance for the proposed strategy related to the energy consumption are given and compared to different other strategies in the literature.

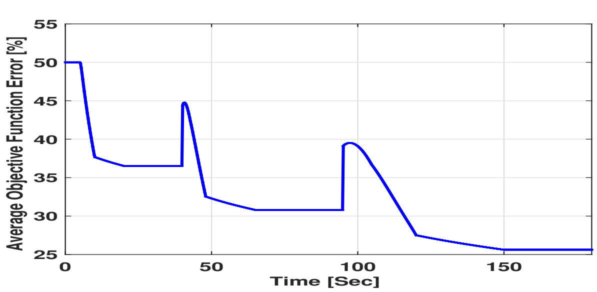

Fig. 11. Average objective function error for the proposed strategy.

B. Simulation 2: Proposed Overall Control Architecture for Complete HHEV Simulation

To prove the effectiveness of the proposed overall control architecture for optimal energy management, IHHCS is compared with OFLC [16] and SF [13] methods already existing in the literature. In order to implement and measuring the performance of these strategies system, BUSINOVA bus model has been selected. The vehicle model parameters used for the simulation are given in the appendix. These strategies are implemented in IPG automotive TruckMaker vehicle simulation software. For simulation runs, the initial state of charge, driving cycle, all other parameters and constrains conditions are the same. The desired and the actual bus speed profile is shown in Figure 12. Figure 13 shows the driver torque demand and the required wheel torque for the proposed IHHCS, OFLC and SF strategies.

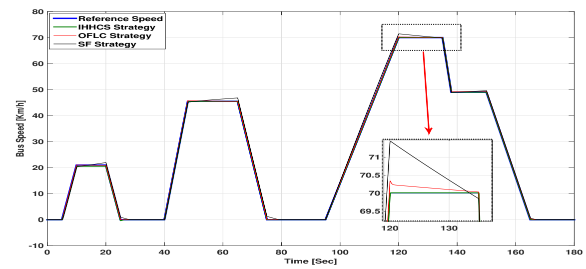

Fig. 12. Comparisons between reference speed and actual vehicle speed [Km/h] for the proposed IHHCS strategy w.r.t. OFLC and SF.

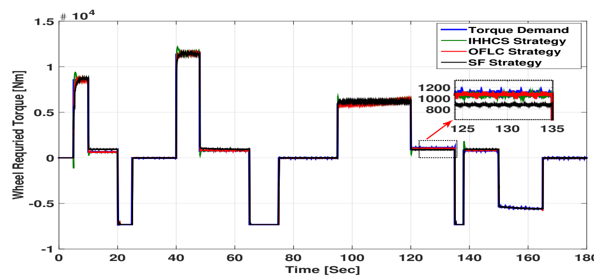

Fig. 13. Comparisons between reference torque and actual vehicle torque [Nm] for the proposed IHHCS strategy w.r.t. OFLC and SF.

From Figure 12 it is seen that the vehicle output speed of the vehicle is similar to the set point of the drive cycle for the proposed IHHCS, OFLC and SF strategies. In addition, from Figure 13, it can be seen that, all the strategies give the total torque demand, but each strategy generates different optimal set point for EM and HM via ICE to satisfy this target, so it consume different electrical energy and fuel energy. To eliminate the sudden change of the torque and obtain smoother dynamic we need to use PID controller, since the PID controller implemented in the inner control loop smoothes out any sudden changes in the fuzzy control output signals, which is particularly important at low speeds [33]. Figure 14 depicts the progress of SOC (from initial to final state) using IHHCS strategy, OFLC and SF.

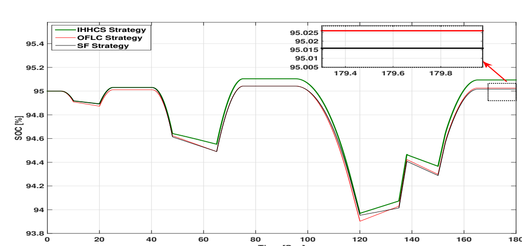

Fig. 14. SOC [%] profiles for the proposed IHHCS strategy w.r.t. OFLC and SF.

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From Figure 14, it is seen that the SOC values begin at 0.9500 for IHHCS, OFLC and SF strategy. SOC is finished at 0.9510 using the proposed IHHCS strategy. The net fluctuation is 0.0010. With OFLC, the SOC value finish at 0.9528. The net fluctuation is 0.0028. With SF, the SOC value finish at 0.95015. Therefore, we can see that during the driving cycle, the SOC level is kept higher when using IHHCS strategy, instead of using OFLC and SF. Energy consumed by the ICE [KJ] for the IHHCS, OFLC and SF are given in Figure 15.

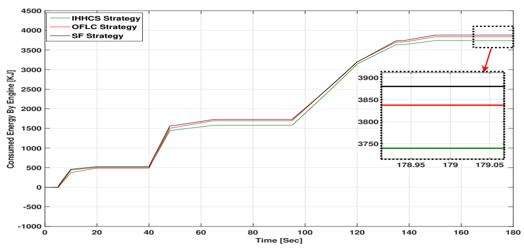

Fig. 15. Consumed energy by ICE [KJ] for the proposed IHHCS strategy w.r.t. OFLC and SF.

Total consumed energy by the vehicle for these controllers is given in Figure 16 which shows that the IHHCS strategy is better w.r.t. to OFLC and SF controllers for reducing total consumed energy (fuel consumption and battery discharge), which increases the efficiency of the vehicle.

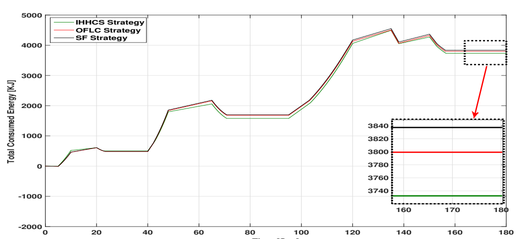

Fig. 16. Total energy consumed by the vehicle [KJ] for the proposed IHHCS strategy w.r.t. OFLC and SF.

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 IV, where FEC is the Fuel Energy Consumption by ICE [KJ].

TABLE IV
COMPARISON OF RESULTS FOR PROPOSED IHHCS, OFLC AND SF STRATEGIES.

Control Strategy	FEC by ICE [KJ]	SOC [100%]
SF	3835	95∼95.015
OFLC	3800	95∼95.028
IHHCS	3732	95∼95.100

From Table IV, with the initial SOC, driving cycle, all other parameters and constrains conditions are the same, it is seen that the proposed IHHCS kept SOC higher than OFLC and SF and reduce the fuel consumption up to 1.79% and 3% compared to OFLC and SF methods, respectively.

From Figures 12 to 16, 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 SF strategy. 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. It is emphasized in Table IV that the proposed strategy significantly reduce the fuel consumption by the ICE [KJ], which shows the effectiveness of the strategy applied on the BUSINOVA bus. Three standard cycle conditions are selected in simulation 3 for testing vehicle performance.

C. Simulation 3: Proposed Strategy Validation over Different Driving Cycles

Indeed, to validate better the proposed strategy, several Standard Driving Cycles (SDC), commonly used in the literature have been used. Among them for instance the Federal Test Procedure (FTP-75) (cf. Figure 21) or the modified version of FTP-75 which is known as Highway Fuel Economy Test (HWFET) (cf. Figure 25). These two SDC are used for representing the American Driving Cycle and the European standard New European Driving Cycles (NEDC) (cf. Figure 17), which are widely used in the literature for simulationas well as for actual experiments.

Figures 17, 21, 25, 18, 22 and 26 depict the trajectories of bus velocity, and the torque under the NEDC, FTP-75 and HWFET drive cycles, respectively. It is seen that the output speed and torque of the vehicle is similar to the reference speed profile and the torque demand of these drive cycles.

The main goal of the proposed strategy is to minimize the total energy consumption of the vehicle over the complete drive cycle and increase the efficiency of the vehicle. Figures 19, 23 and 27 show the total energy consumption by the vehicle during the NEDC, FTP-75 and HWFET complete cycles, respectively.

Average objective function error for the three driving cycles NEDC, FTP-75 and HWFET are given in Figures 20, 24 and 28, respectively. It is found that the average error will always decrease which show the effectiveness of the proposed strategy. In addition, the proposed strategy can be applied to the power assignment for HHEVs even if the future driving cycle is unknown.

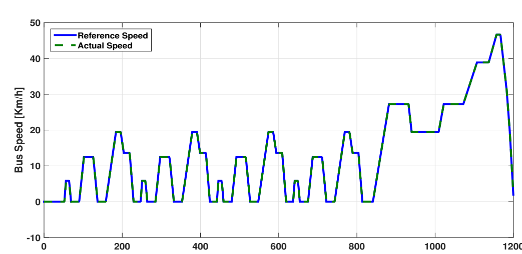

Fig. 17. Comparisons between reference speed and actual vehicle speed [Km/h] for proposed strategy over NEDC cycle.

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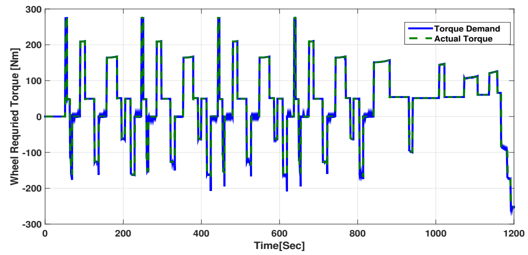

Fig. 18. Comparisons between reference torque and actual vehicle torque [Nm] for proposed strategy over NEDC cycle.

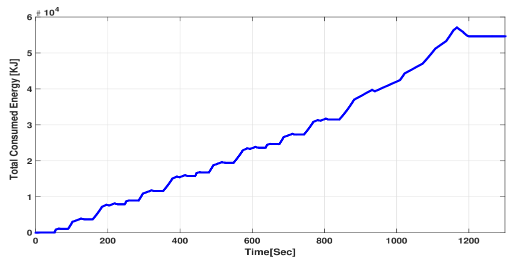

Fig. 19. Total energy consumed by the vehicle [KJ] for proposed strategy over NEDC cycle.

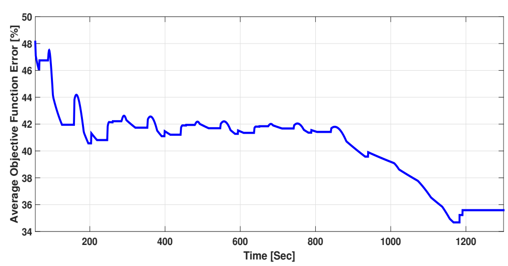

Fig. 20. Average objective function error for the proposed strategy over NEDC cycle.

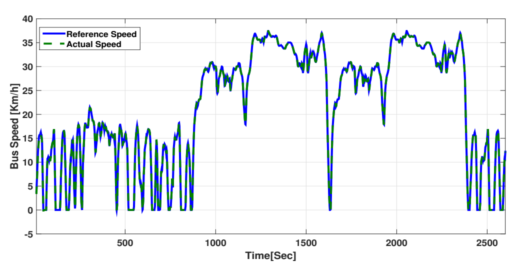

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Fig. 21. Comparisons between reference speed and actual vehicle speed [Km/h] for proposed strategy over FTP-75 cycle.

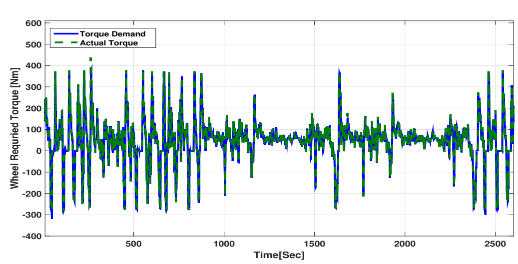

Fig. 22. Comparisons between reference torque and actual vehicle torque [Nm] for proposed strategy over FTP-75 cycle.

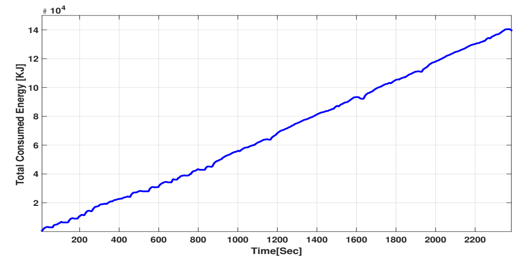

Fig. 23. Total energy consumed by the vehicle [KJ] for proposed strategy over FTP-75 cycle.

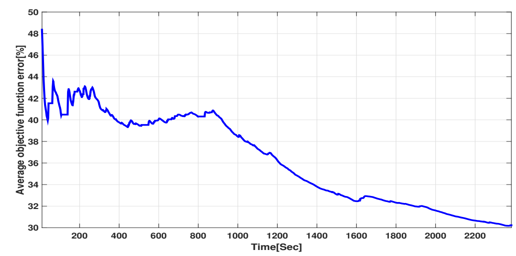

Fig. 24. Average objective function error for the proposed strategy over FTP-75 cycle.

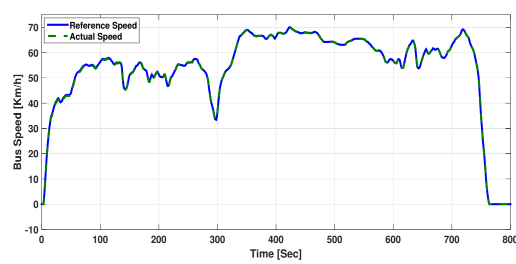

Fig. 25. Comparisons between reference speed and actual vehicle speed [Km/h] for proposed strategy over HWFET cycle.

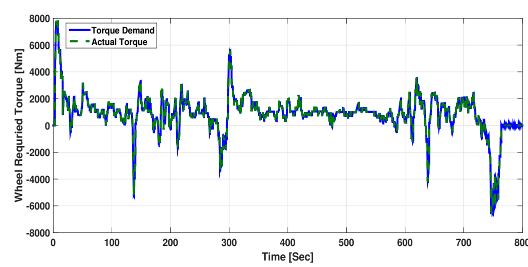

Fig. 26. Comparisons between reference torque and actual vehicle torque [Nm] for proposed strategy over HWFET cycle.

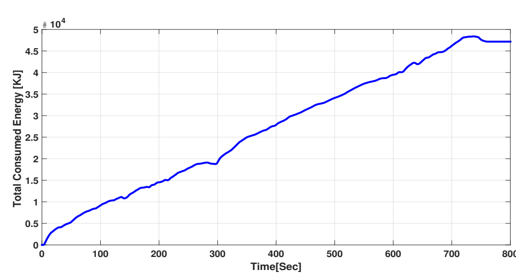

Fig. 27. Total energy consumed by the vehicle [KJ] for proposed strategy over HWFET cycle.

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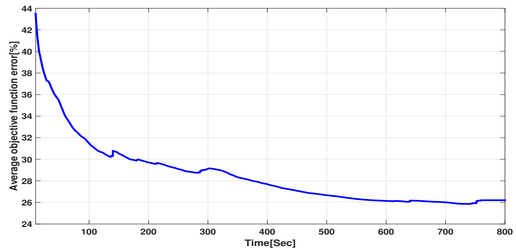

Fig. 28. Average objective function error for the proposed strategy over HWFET cycle.

From simulation 3 results, it is seen that the proposed strategy can satisfy the speed and power requirements for three standard cycle conditions and gives a good tracking performance even if the future driving cycle is unknown.
In summary, it can be seen that the BUSINOVA bus follows the trajectory of the reference inputs. Thus, if driving cycles are changed, the control effect of the proposed strategy remains as accurate as the results under NEDC, FTP-75 and HWFET cycles. Compared to OFLC and SF, the proposed strategy significantly reduce the fuel consumption, increase the energy efficiency and covers a wide range of driving conditions.

VI. Conclusions and Prospects

This paper discusses two important aspects of the control and optimization of hydraulic-electric hybrid vehicles power management. The first part of this work is dedicated to the development and validation of a dynamic BUSINOVA bus model using IPG automotive TruckMaker. This structure includes two energy sources: a battery and an ICE. The obtained results given in section V confirm the fidelity of the model under a variety of operating conditions. The second part of this paper focuses on minimizing total energy consumption, increasing energy efficiency, and thereby increasing total distance traversed between refueling. The value of the proposed methods are demonstrated under various driving schedules through comparison with other popular methods in the literature. The proposed architecture, composed by three control levels, has been implemented using real time power management strategy, named intelligent hierarchical and hybrid control strategy (IHHCS). This strategy consists of an advanced supervisory controller at the highest level (third) which corresponds to a fuzzy system deciding the most appropriate operating mode (or combination of modes) which would be the most efficient for the HHEV. In the second level, an Intelligent Power Distribution and Optimization Controller (IPDOC), based on neuro-fuzzy logic, has been developed for power splitting. This level takes into account the selected modes generated at the third level, and decides the optimal combination of power sharing between different energy sources to minimize the total energy and to maximize the overall HHEV efficiency. Finally, in the first level, a Local Fuzzy Tuning Proportional-Integral-Derivative Controllers (LFPIDC) has been 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 taken into consideration the dynamic behavior of EM, ICE and HM.
The obtained results confirm that, using the proposed approach: (i) the proposed strategy effectively splits the torque between EM and HM via ICE; (ii) mean and the standard deviation of the membership function of the fuzzy logic controller are optimized based on neural-network; (iii) total energy consumption is reduced compared with several traditional methods; (iv) global vehicle efficiency is improved as well as the total average distance traversable between refueling; (v) the strategy can be easily implemented in real time because it does not depend on prior information about future driving conditions; (vi) rate of charge of the battery can be limited to minimize aging effects.
Hence, this paper provides a novel model and approach for an advanced power management system of hybrid vehicles. It is planned in the near future to implement the overall proposed control strategy on the actual BUSINOVA platform.

VII. Appendix

In this appendix, we will present the parameters of the BUSINOVA bus used in IPG automotive TruckMaker. Where MIRP is Moment of Inertia of the Rotating Parts, RRC is the Rolling Resistance Coefficient, ADC is Air Drag Coefficient DLHV is the Diesel lower heat value and GAC is Gravity Aceleration.

TABLE V
Characteristics of the hydraulic motor and pump.

Specification	Value	
	Hydraulic motor	Hydraulic pump
Displacement [cm^3]	Variable - [22 - 110]	Fixed - 40
Max torque [Nm]	175 @100 bar	63.5@100 bar
Max speed [rpm]	3400	6100

TABLE VI
Parameters of the permanent magnet synchronous motor.

Specification	Value	Specification	Value
Nominal speed [RPM]	3240	Nominal current [A]	137
Nominal torque [Nm]	305	Maximum torque [Nm]	660
Nominal power [kW]	103	Maximum speed [RPM]	4000

TABLE VII
Parameters of the dynamic model of BUSINOVA bus and ICE.

Parameter	Value	Parameter	Value
Bus mass [kg]	13490	MIRP [kgm^2]	0.911
RRC	0.009	Wheel radius [m]	0.484
GAC [m/s^2]	9.81	Gear ratio	12.2
Frontal area [m^2]	6.7	Transmission efficiency	0.93
ADC	0.61	Air density [kg/m^3]	1.25
Max speed, [rpm]	2300	Max speed, [rpm]	2300
Max torque, [Nm]	343,8	Max output power [kW]	70.6
Displacement [mm^3]	82.2	Stroke [m]	0.107
C_1 [kPa]	101.5	DLHV [kJ/kg]	42946
Combustion efficiency	0.75	Diesel density [g/cm^3]	0.8355

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