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APPLICATION OF FUZZY LOGIC FOR POWER MANAGEMENT IN HYBRID VEHICLES

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Abstract. The increasing number of cars may be causing serious effects to the environment and to humans, such as pollution, global warming, and depletion of oil reserves, among others. This situation encourages the research for new energy forms and devices with higher energy efficiency. The adoption of hybrid propulsion technology has contributed, considerably, to reducing gases such as oxides of carbon, nitrogen and sulfur and the reduction of particulate materials. Beyond, the hybrid electric vehicle (HEV) maintains the characteristics attributed to conventional vehicles such as performance, safety and reliability. The term "hybrid" derives from the combination of two or more power sources, and the most common combination is through of an internal combustion engine (ICE), commonly used in conventional vehicles, together with the battery and electric motor (EM) used in EVs (Electric Vehicles). In general, the main reason to use electric hybrid architecture is the additional degree of freedom due to the presence of an additional energy source, which implies that, at each instant, the power required by the vehicle can be provided by one of these sources, or a combination of both. Choose the correct combination is usually a complex task. For a HEV present satisfactory operation (performance and emission reduction) is important that the architecture and components of HEVs are optimized, and occurs an appropriate choice of power management strategy. In this work is carried out the development and analysis of power management strategies in a HEV to minimize its fuel consumption and consequently emissions. Is developed one management strategy using fuzzy systems, and its results is analyzed varying the vehicle mass. The results of this work allow to view when it is triggered each propulsion system, and to analyze the consumption of fuel for each power management strategy.

1 INTRODUCTION

The hybrid electric vehicles (HEVs) are becoming, in recent times, an alternative and a solution to the problems faced by urban society. Problems such as high consumption of oil-based fuels and the exhaust of greenhouse gases are reduced with the implementation of the technology used in hybrid vehicles. These factors imply that all manufacturers will, eventually, have a hybrid vehicle in the near future (Bucherl et al., 2008).

Hybrid vehicles have as main feature the union of two or more power generation systems, such as internal combustion engines (ICE) coupled with electric motors (EM) or fuel cells. Comparing to a classic vehicle, the hybrid one is more complex. The large number of settings allows the division into two main groups: series hybrids and parallel hybrids. In a series hybrid, a ICE turns a generator that power the batteries and/or directly the EM. In a parallel hybrid, the ICE or the EM propels the vehicle, or both together, generally the EM also work as a generator when not used for traction, to charge the batteries.

In order to obtain the maximum efficiency in HEV, the main control strategy is to select the propulsion force (ICE or EM) depending on the load. The ICE has a low efficiency at low load, for transient regimes and for idling. For the full loads and high speed, the engine has the maximum efficiency. The control strategy for the HEV is trying to avoid these regimes by using the control algorithms to manage the energy sources in order to minimize the fuel consumption and the emissions (Ehsani et al., 2004).

HEV with a proper control, will consume less fuel. In this case, the vehicle autonomy will be double and the emissions will be lower because of the transients and idling regimes elimination. According Serrao and Rizzoni (2008), the hybridization advantages consist essentially in recovering potential and kinetic energy that would otherwise be dissipated in the brakes, and in operating the engine in its highest-efficiency region.

Powell and Pilutti (1994) have used a combination of several controllers, one for every section of the vehicle, due to the highly nonlinear system. The fuel consumption was relatively high. Sacks and Cox (1999) have proposed neuro adaptive controllers; the major advantage is the robustness to different driving and road conditions. Lee and Sul (1998) have used fuzzy systems, a fuzzy predictive controller with nine rules for converting the driver's commands to appropriate torques and another fuzzy controller with 25 rules.

Ippolito et al. (2003) have used fuzzy c-means, along with genetic algorithms, for power-flow management in different driving cycles of hybrid vehicles. In their method,there is a need for some off-line training for the controller, but they have achieved relatively low fuel consumption and smooth simulation results. Thus this paper present the control design based on artificial intelligence, the neuro-fuzzy type. With this control is possible to combine the ease of adding knowledge to the fuzzy logic of the problem and offered relatively low computational cost of the neural network approach to solve various problems.

The target this work is the application of fuzzy logic for development of power management strategies (PMS) in a HEV power to minimize its fuel consumption. The power management using fuzzy logic uses rules, and the analysis is done changing of vehicle mass. In the simulations, it is used the urban cycle driving standard Brazilian, NBR6601. The results of this work allow to view when each propulsion system is triggered and to analyze the fuel consumption for the power management strategy proposed.

2 FUZZY-BASED CONTROL STRATEGIES

The fuzzy logic is closer in spirit to human thinking and natural language than conventional logical systems. This provides a means of converting a linguistic control strategy based on expert knowledge into an automatic control strategy (Zadeh, 1965). The ability of fuzzy logic to handle imprecise and inconsistent real-world data made it suitable for a wide variety of applications.

In particular, the methodology of the fuzzy logic controller (FLC) appears very useful when the process are too complex for analysis by conventional quantitative techniques or when the available sources of information are interpreted qualitatively, inexactly, or with uncertainty (Mamdani, 1974). Thus fuzzy logic control may be viewed as a step toward a rapprochement between conventional precise mathematical control and human - like decision making.

One of the major problems in use of the fuzzy logic control is the difficulty of choice and design of membership functions for the system problem. A systematic procedure for choosing the type of membership function and the ranges of variables in the universe of discourse is still not available. Tuning of the fuzzy controller by trial and error is often necessary to get a satisfactory performance.

However, the neural networks have the capability of identification of a system by which the characteristic features of a system can be extracted from the input and output data. This learning capability of the neural network can be combined with the control capabilities of a fuzzy logic system resulting in a neuro-fuzzy inference system. Recently an adaptive neuro-fuzzy inference system (ANFIS) has been proposed which has been shown to have very good data prediction capabilities (Jang, 1993).

System modeling based on conventional mathematical tools is not well suited for dealing with ill - defined and uncertain systems. By contrast, a fuzzy inference system employing fuzzy 'if - then' rules can model the qualitative of human knowledge and reasoning processes without employing precise quantitative analyses. Takagi and Sugeno were the first to systematically explore fuzzy modeling or fuzzy identification (Mamdani, 1974). However, even today, no standard methods exist for transforming human knowledge or experience into the rule base and database of a fuzzy inference system.

The is a need for effective methods for tuning the membership functions (MF's) so as to minimize the output error measure or maximize performance index. It it was suggested by Jang (1993) that an architecture called adaptive network - based fuzzy inference system or adaptive neuro-fuzzy inference system can be used effectively for tuning the membership functions. ANFIS can serve as a basis for constructing a set of fuzzy 'if -then' rules with appropriate membership functions to generate the stipulated input-output pairs.

Fundamentally, ANFIS is about taking an initial fuzzy inference (FIS) system and tuning it with a back propagation algorithm based on the collection of input-output data. In principle, if the size of available input-output data is large enough, then the fine-tuning of the membership functions are applicable (or even necessary). Since the human determined membership functions are subject to the differences from person to person and from time to time; they are rarely optimal in terms of reproducing desired outputs.

However, if the data set is too small, then it probably does not contain enough information of the system under consideration. In this situation, the human-determined membership functions represent important knowledge obtained through human experts experiences and it might not be reflected in the data set; therefore the membership functions should be kept fixed throughout the learning process.

Interestingly enough, if the membership functions are fixed and only the consequent part is adjusted, the ANFIS can be viewed as a functional-link network, where the "enhanced representation" of the input variables are achieved by the membership functions. This "enhanced representation" which takes advantage of human knowledge are apparently more insight-revealing than the functional expansion and the tensor (outerproduct) models. By fine-tuning the membership functions, we actually make this "enhanced representation" also adaptive (Jang, 1993).

3 IMPLEMENTATION OF POWER MANAGEMENT STRATEGIES

The PMS are developed and analyzed through co-simulation between the multibody dynamics program Adams™ and Simulink/Matlab ™ . In this work, the Simulink/Matlab is used to simulate the vehicle components such as: EM, ICE, transmission system, battery and the power management system. The multibody dynamics program Adams is used for simulating the vehicle inertia.

3.1 Vehicle longitudinal dynamic

According to the methodology proposed by Gillespie (1992), to a conventional vehicle powered only by the ICE, the traction force required (F_x) is given by Eq. (1), where N_{tf} is the gear ratio, I_e is the engine inertia, I_t is the transmission inertia, I_d is the differential inertia, N_f is gear ratio of the differential, I_w wheel inertia, a_x longitudinal acceleration of the vehicle and r tire radius.

As EMs are coupled directly to the rear wheels of the vehicle becomes necessary to know the power demand on the wheels and not the ICE to one for that the correct management of the two propulsion sources is conducted.

$$F_x = \frac{T_e N_{tf}}{r} - ((I_e + I_t)N_{tf}^2 + I_d N_f^2 + I_w)\frac{a_x}{r^2} \tag{1}$$

The vehicle wheel torque (T_r) due to the engine torque (T_e) is given by Eq. (2).

$$T_r = T_e N_{tf} \eta_{tf} \tag{2}$$

Replacing the Eq. (2) in the Eq. (1), obtained the Eq. (3). Equation (4) describes the behavior of the vehicle accelerating on a flat track, where M is the vehicle mass [kg].

$$F_x = \frac{T_r}{r} = ((I_e + I_t)N_{tf}^2 + I_d N_f^2 + I_w)\frac{a_x}{r^2} \tag{3}$$

$$T_r = r(D_A + R_x + M a_x + \frac{((I_e + It)N_{tf}^2 + I_d N f^2 + I_w)a_x}{r^2}) \tag{4}$$

Because of the rear wheels EMs are not coupled to the transmission system, the term refers to efficiency is disregarded in calculating the tensile force required at the wheels, which are considered only after of the power demand division between the ICE and the EMs, applied an efficiency factor for each power source (EM or ICE).

After calculation of the required torque (T_r) at the vehicle wheels, the management system makes decisions on which system to use to propel the vehicle. The portion of the torque allocated to the ICE to be divided by the efficiency factor of the system transmission (η_{tf}) and the gear ratio as shown in Eq. (5), where T_{ICE} is the portion of the required torque of ICE and the Tr_{ICE} is the portion of the required torque of ICE on the wheel of the vehicle.

$$T_{ICE} = \frac{Tr_{ICE}}{\eta_{tf} N_{tf}} \tag{5}$$

In the case of the portion of torque provided by the EMs wheel is obtained by dividing the required torque on the wheel by efficiency of EMs (η_{EM}) as shown in the Eq. (6), where T_{EM} is the portion of the required torque of EMs and the Tr_{EM} is the portion of the required torque of ICE on the wheel of the vehicle.

$$T_{EM} = \frac{Tr_{EM}}{\eta_{EM}} \tag{6}$$

The torque required by the management system T_{ICE} and T_{EM} is compared with the torque available on the respective curves as a function of rotation for each propulsion system type, in which the available torque at the vehicle wheels (T_d) is the sum of the torques provided by the EMs and by the ICE as shown in Eq. (7), where Td_{EM} is the torque given by the curve of the EM and Td_{ICE} is the torque given by the curve of the ICE. And the available vehicle acceleration (a_d) is given by Eq. (8), where R_a is the aerodynamic resistance and R_r is the rolling resistance.

$$T_d = Td_{ICE} N_{tf} \eta_{tf} + Td_{EM} \eta_{EM} \tag{7}$$

$$a_d = \frac{\frac{T_d}{r} - R_a - R_r}{M + \frac{(I_e + I_t) N_{tf}^2 + I_d N_f^2 + I_w}{r^2}} \tag{8}$$

3.2 Engine model

The powertrain is the system responsible for the generation of power through the transmission system originate the driving forces on the driving wheels. For conventional vehicles it is common to find in the literature characterization of the ICE by means of curves of power and torque versus rotation speed as set by Rizoulis et al. (2000).

Due to the high complexity of operating a ICE involving control throttle, in this work, it was chosen to use a three-dimensional map of the throttle position versus rotational speed versus torque for represent the ICE model.

3.3 Electric motor model

EM was modeled according to the dynamic equations for a DC electric machine with independent field. Through the Eq.(9), which represents the direct relationship between the armature current (I_a) and the electrical torque developed by the rotor through torque constant (K_T), and the union of this with the Eq. (10) and Eq. (11) is possible to construct a block diagram equivalent for modeling the EM as represented by the Fig. (1), where V_t is the armature voltage, r_a is the armature resistance, L_a is armature inductance, J is the inertia, and the D is the damping constant.

$$T_{el} = K_T I_a \tag{9}$$

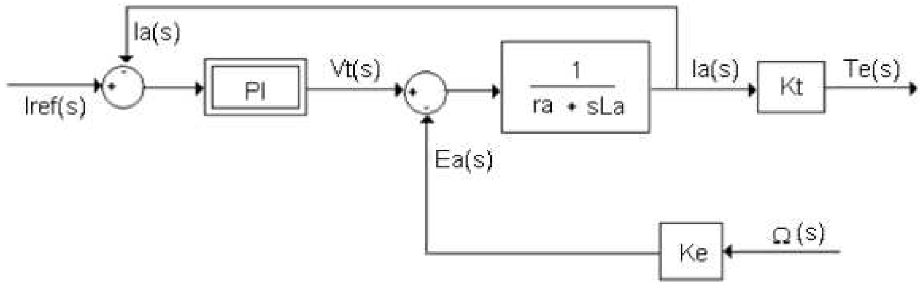

Figure 1: Block diagram of the electrical and dynamic equations for DC motor with independent field.

$$I_a(s) = \frac{(V_t(s) - E_a(s))}{(r_a + sL_a)} \tag{10}$$

$$\omega(s) = \frac{(T_{el}(s) - T_{carga}(s))}{(D + sJ)} \tag{11}$$

Based on the study by Waltermann (1996), and as shown in Fig.1, a controller uses proportional and integral (PI) for generating the voltage value of the armature circuit $V_t(s)$ of Eq. 10. The input of this controller is the error obtained from the difference between the current value of the armature current and its reference value ($I_{ref}(s)$) desired.

The current ($I_{ref}(s)$) is defined as the direct demand of the armature current required for the traction motor is able to meet the demand of power required by the driver. This control becomes necessary in the most convenient point for the machine operation, when the $I_a(s)$ is equal to $I_ref(s)$. In this situation, the integrative component of the controller is necessary for the EM error has zero current situations of regime, ie, when $V_t(s)$ is constant.

$$\omega = \frac{V_{el} N \eta}{r} \tag{12}$$

The torque of EM (T_{EM}) produced is then used for calculating the longitudinal acceleration and hence the vehicle velocity. The vehicle velocity and the motor speed (ω) are related by Eq. (12). Where: $V_{vel} \cong$ vehicle longitudinal velocity and the η is the electric motor efficiency. Thus, it was obtained ω calculating *fcem*(back EMF) of the armature circuit.

The EM traction is able to act as a generator during vehicle braking, the proposed model shows 100% efficiency for electric machine operating as a motor and as a generator.

3.4 Battery model

The battery used as a source of energy for Parallel HEV is the lead acid type and the model was built for convenience online code. The model inputs are the battery power demand (P_b) of PMS, the depth of discharge (DoD) and the total charge removed (CR_n).

DoD and CR_n are feedback to the actual battery model to control the charging and discharging energy at each instant of the simulation. The main output of this model is the power available from battery (Pot) to the traction system.

3.5 Management strategy based fuzzy

Fuzzy systems are known to approach the computational decision of human decision. A major feature is the independence of mathematical modeling and the ability to approach complex nonlinear models. The fuzzy systems were quite suitable for the control of HEVs. The fuzzy systems based on PMS was used to control the power supplied by the propulsion systems based on power demand and the depth of discharge of the battery.

For adjusting the membership functions, as the number of functions used as well as the intervals for which were defined in their respective universes of discourse, were performed preliminary tests using results from rule-based strategy. The purpose of these tests was the reduction of fuel consumption compared with strategies based on rules. In this context, linguistic variables, which represent the fuzzy sets of inputs for PMS in question were determined as follows:

- Demand power (P_{dem}): this input variable was specified in the universe of discourse between -20000 and 60000 W, with set of terms NM (negative medium), LN (low negative), Z (zero) , L (low), M (medium) and H (high) represented by their respective sets fuzzy. The limits of the universe of discourse for this variable were obtained from the maximum and minimum values assumed by the power demand of the vehicle in operation in urban cycle.

- Depth of discharge of the battery (DoD): is specified in the universe of discourse between 0 and 1, with a set of terms VL (very low) , L (low), M (medium) and H (high) represented by their respective sets fuzzy. The limits for the universe of discourse are the same for which DoD is defined in the battery model.

- Request braking (T_{req}): This variable was specified in the universe of discourse between -5000 and 0, with sets of terms represented by their respective sets fuzzy. The limit of the universe of discourse defined, in this case, is the limit of braking required by HEVs added the safety margin.

Linguistic variables which represent the outputs fuzzy sets to PMS based on fuzzy is:

- Electric motor power (P_{em}): This output variable is specified in the universe of discourse between -8000 and 7500 W with set of terms NC (negative constant), N (negative), Z (zero), P (positive) and PC (positive constant) represented by their respective sets fuzzy. Similar to other variables, the limits of the universe of discourse for this variable were obtained from the maximum and minimum values that the electric motor can take over its operation.

- Engine power combustion (P_{ice}) was specified in the universe of discourse between 0 and 55000 W be the limit of operation of ICE, with term set Z (zero), L (low), ML (medium low), M (medium) and H (high) represented by their respective sets fuzzy.

- Power battery (P_b): This output variable is specified the same way as the electric motor, the universe of discourse between -8000 e $7500W$, since the battery must provide the same power as the required by the electric motor. In this same way of the EM, the output variable is set of terms NC (negative constant), N (negative), Z (zero), P (positive) and PC (positive constant) represented by their respective sets fuzzy.

- Braking torque (T_{brak}): This output variable corresponding to variable input braking request (B_{req}), for this variable output responds in proportion to the input variable related to it, this case B_{req}. Thus, this output variable is specified in the universe of discourse between -5000 and 0.

For the validation of the fuzzy inference process is necessary to map the knowledge related to the system studied by the fuzzy rules. These rules can be implemented from the expert knowledge of the process being described in linguistic form using the If-Then structure. Therefore, the process of knowledge expressed by the rules is given as follows by Tab.(1).

Table 1: Set of rules fuzzy for power management in HEV.

P_{dem}	DoD	P_{EM}	P_{ICE}	P_b
L	M	P	Z	P
H	B	PC	M	PC
H	H	Z	H	Z
MN	H	NC	Z	NC
MN	M	NC	Z	Z
LN	H	N	Z	N
LN	L	N	Z	Z
Z	L	Z	Z	Z
Z	L	Z	Z	Z
Z	H	Z	Z	Z
L	VL	P	Z	P
H	M	P	Z	P
H	VL	PC	H	PC
L	H	Z	ML	NC
L	M	Z	ML	NC
LN	VL	N	Z	Z
M	L	P	ML	P
M	M	P	ML	P
M	H	Z	M	Z
M	VL	P	ML	P
L	L	P	Z	P
NM	L	P	Z	P
LN	M	N	Z	N

The rules were drawn up so that the DoD kept the value around its maximum equal to 0.45. In this PMS was chosen using the operator Mandani which is to find the relation of inference through minimum values between the input and output of the system.

The last step (defuzzification) is required in the replacement of this region by a single fuzzy value that acts as the controller output. For this, it was used the maximum area of the first region fuzzy result and determined the output value of the point at which the degree of relevance reaches the first maximum value.

4 RESULTS

In this section, the PMS developed for HEV are analyzed by observing of the fuel consumption. The fuel consumption is analyzed using an implemented algorithm that performs the estimation by the consumption map, and also by the consumption map dispersion is shown in relation to specific consumption and the rotational torque corresponding ICE.

The total mass of the vehicle is initially 980 kg (mass of the vehicle, driver and fuel tank). Analyses of PMS in relation to change of vehicle mass shall be made by taking an extra mass arising by adding passengers in HEVs. Thus, values for the total mass of HEVs will be used with 1120 kg, considering the vehicle mass, fuel tank, driver, electric motor and battery; and the mass of 1260 kg for HEVs will add 2 passengers and 1400 kg add 4 passengers.

For comparative purposes analyzed is the first result of the conventional vehicle. Figure (2) shows the dispersion of the specific consumption with respect to the engine speed, torque and the corresponding consumption map ICE. Thus, it can be seen that the consumption map for the conventional vehicle has regions of low efficiency, with the goal of PMS reducing these regions of the map of the graph consumption, which results in fuel economy. In this case, the amount of fuel used changing vehicle mass can to be seen in the Tab.(2):

Table 2: Fuel consumption for the conventional vehicle due to variation in their total mass.

Vehicle Mass	Consumption	km/l
980	0.66	18.10
1120	0.673	17.83
1260	0.69	17.39

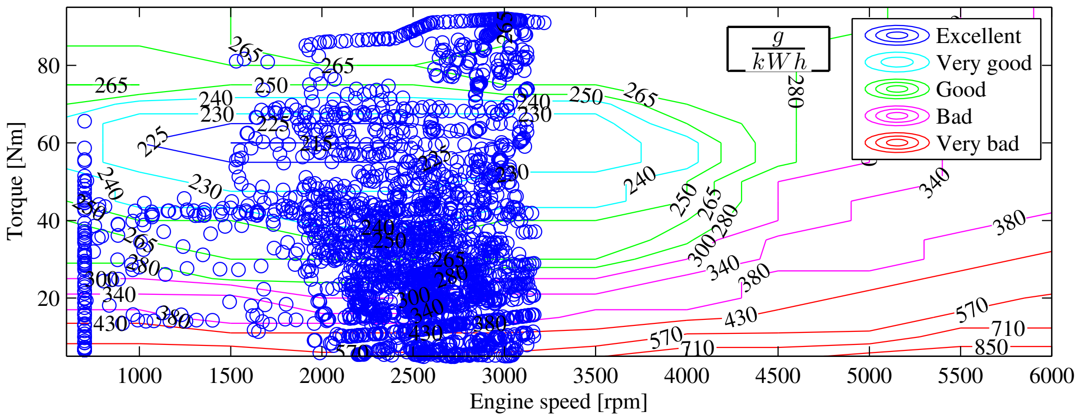

Figure 2: Dispersion of the specific consumption for the conventional vehicle.

Using the PMS of fuzzy logic, the fuel consumption can to be seen in Tab.(3) for each considered vehicle mass. The consumption increases when the mass of HEVs is increased, but compared to conventional vehicle analyzed so far, this has a better economy fuel, a fact that can be better understood when seen in Fig. (3) that shows the dispersion of the specific consumer consumption map. Through this figure we can see that ICE operates in a region of lower specific fuel consumption, thus justifying the economy fuel. Thus, PMS based on fuzzy can manage more effectively the various sources of HEV propulsion, which emphasizes the ability of fuzzy systems to make decisions.

Table 3: The fuel consumption of HEVs with EGP-based fuzzy

Vehicle Mass	Consumption	km/l
1120	0.4439	27.03
1260	0.4629	25.92
1400	0.481	24.94

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