FUZZY CONTROL FOR HYBRID VEHICLE

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Abstract. *The Hybrid Vehicles (HEVs) are becoming, in recent times, one of the alternatives solutions of the problems faced by urban society. HEVs have as main feature the union of two or more power generation systems, such as internal combustion engines coupled with electric motors or fuels cells. There are several types of working models of HEV, for each traffic situation the choice of the system for power generation generates a better or worse efficiency. This work will be undertaken the parallel system, which electric motor is coupled directly to the wheels. Thus, this paper proposes a control system to improve the strategy of actuation of the motors of a hybrid vehicle. This paper will study the control of the energy source to find the best period of time of work of the electric motor and combustion engine. The control system will use as reference data of an urban cycle, verifying that the controller is able to manage the electrical and combustion engines for this traffic situations.*

Keywords*: hybrid vehicle, electric motor, engine, control*

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. According Bücherl *et al*., (2008), these factors imply that all manufacturers will, eventually, have a hybrid vehicle in the near future.

Hybrid vehicles have as a main feature the union of two or more power generation systems, such as internal combustion engines coupled with electric motors or fuel cells. Comparing to a classic vehicle, the hybrid one is more complex (about 25% complexity on hardware and more than double complexity on software). The large number of settings allows the division into two main groups: series hybrids and parallel hybrids.

In a series hybrid, a combustion engine turns a generator that powers the batteries and/or directly the electric motor. There is no mechanical coupling between the two types of motors. In a parallel hybrid the vehicle is propelled by the combustion engine, the electric motor or both together, generally the electric motor also works as a generator when not used for traction, to charge the batteries (Fig. 1).

In order to obtain the maximum efficiency of the hybrid vehicle the main control strategy is to select the propulsion force (engine or electric motor) depending on the load. The engine 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 hybrid vehicle 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 *el al.*, 2005).

Thus, a hybrid vehicle, with a proper control, will consume less fuel (about a half of a classic vehicle with similar engine characteristics). 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 *et al.* (2005), the hybridization advantages consist essentially in recovering potential and kinetic energy that would be dissipated in the brakes, and in operating the engine in its highest-efficiency region.

In order to fully realize the benefits of hybrid electric vehicles, HEV models are used as the first step in the design procedure to study and improve fuel economy, top speed and maximum acceleration. Therefore, accurate and flexible simulation tools, which will expedite the design processes for HEVs, are important. The simulation results will enable engineers to compare relative performances and come up with the better designs. In addition, computer modeling and simulation can be used to reduce the expense and length of design cycle of HEVs by testing configurations and energy management strategies before prototype construction begin.

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 (1998) have proposed neuro-adaptive controllers; the major advantage is the robustness to different driving and road conditions. Lee et al. (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 will 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.

Interest in simulating hybrid electric vehicles began to increase in the 1970's along side the development of several prototypes which were used to acquire a large amount of test data on the performance of hybrid drivetrains (Chang, 1978). Through a search of the relative papers dealing with computer software simulations for HEVs, we found that these simulation tools had varying capabilities in predicting vehicle performance in one or more areas, such as fuel economy, emissions, acceleration, and grade sustainability. Several computer simulations tools have been developed to predict hybrid drivetrain perfomance (Cole, 1993; Butler *et al.*, 1997).

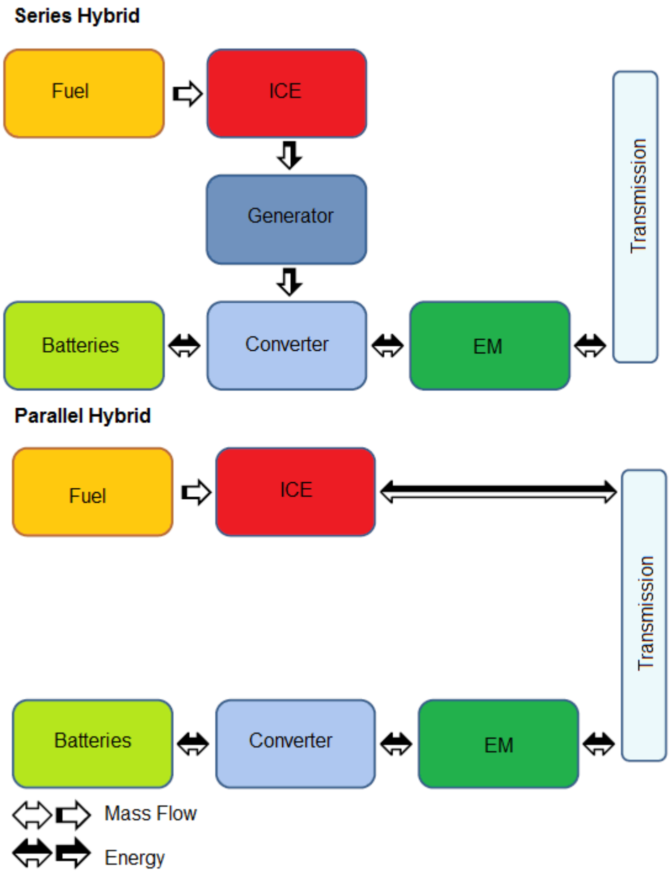

Figure 1. Series and Parallel settings (Souza and Dedini, 2009)

In this context, this work focuses the study of the control system in a HEV, so who is the best period of work of electric motors and combustion engines. For this, the control system will use as references the urban cycle, verifying that the controller is able to manage the electric motors and combustion engines for this urban cycle.

2. THE DRIVE CYCLE

A driving cycle represents the way the vehicle is driven during a trip and the road characteristics. In the simplest case, it is defined as a sequence of vehicle speed (and therefore acceleration) and road grade. Together with some vehicle characteristics, this completely defines the road load, i.e., the force that the vehicle needs to exchange with the road during the driving cycle. The road load is, in fact, the sum of several terms:

- inertia, i.e. force needed to accelerate the vehicle;
- grade force, needed to overcome the slope of the road;
- rolling resistance, due to the contact between the tire and road, bearing losses etc.;
- aerodynamic drag.

It is important to point out that each term is a function of both the driving cycle (speed, acceleration, grade) and the vehicle (mass, coefficients of aerodynamic and rolling resistance). For this reason, the fuel consumption of a vehicle must always be specified in reference to a specific driving cycle. On the other hand, given a driving cycle, the absolute value of the road load and also the relative magnitude of its components depend on the vehicle characteristics.

These driving cycles are designed to be representative of urban and extra-urban driving conditions, and reproduce measures of vehicle speed in real roads. Some of them and the test procedures have been recently updated to better suit modern vehicles, following criticism towards the previous regulation (Serrao *et al.*, 2005)

Even with the current improvements, the regulatory cycles should be considered a comparison tool rather than a prediction tool. In fact, it is not possible to predict how a vehicle will be driven, since each vehicle has a different usage pattern and each driver his or her own driving style. In order to obtain more realistic estimations of real-world fuel consumption for a specific vehicle, vehicle manufacturers may develop their own testing cycles.

In the case of hybrid vehicles, estimating the actual driving cycles becomes an even more important task, because the actual fuel consumption is affected by the supervisory control strategy implemented, which is tuned using simulations based on the estimated driving cycles.

3. CONTROL STRATEGY - THE LOGIC NEURO-FUZZY

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 (Takagi and Sugeno, 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 (Rojer, 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 (Takagi and Sugeno, 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 Rojer (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 (Rojer, 1993).

3.1 Implementation

The control system proposed in this paper was implemented in Simulink / Matlab. First, we used a set of rules drawn up by expert knowledge. The rules were drawn up so that when the vehicle speed is above 60 km / h only the combustion engine is working, and when the vehicle speed is below 60 km / h combustion engine is responsible for 20% of the final speed of the vehicle, and the electric motors for 80% of the final speed of the vehicle, so there is a great fuel economy considering urban cycles. The logic used in powering of the electric motor and combustion engine is shown in the Fig. 2. This logic was developed using the speed and the acceleration of the vehicle.

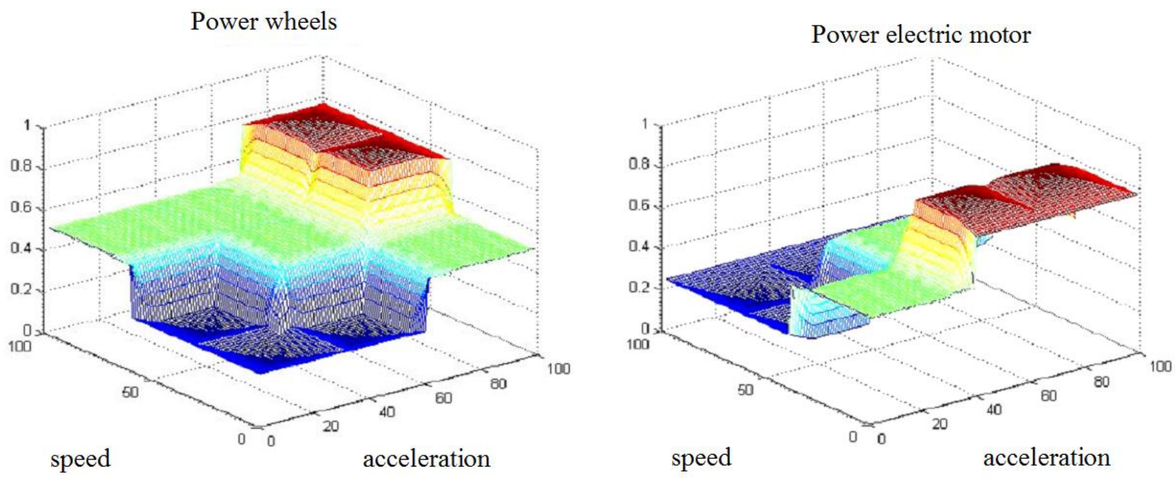

Figure 2. Logic used to drive the electric motor and combustion engine.

Second controller implemented was developed based on the results obtained by the rules, because through the activation of the electric motors and engine resulting from the rule, it was possible to train a neural network. Figure 3 (a) shows the fuzzy rules implemented for the internal combustion engine, and Fig. 3 (b) shows the fuzzy rules implemented to the electric motor. Thus, the neuro-fuzzy controller was implemented with the help of the MATLAB ANFIS. Table 1 shows the linguistic variables used in the neuro-fuzzy controller and the Tab. 2 shows the rules of the fuzzy controller.

Table 1. Linguistic variables used in the neuro-fuzzy controller.

Variable	Name	Variable	Name
NG	Large negative	PG	Large positive
NB	Medium negative	PM	Medium positive
NP	Small negative	PP	Small positive
ZE	Zero		

Table 2. Rules of the fuzzy controller.

	dE							
E		NG	NM	NP	ZE	PP	PM	PG
	NG	NG	NG	NG	NG	NM	NP	ZE
	NM	NM	NM	NM	NM	NP	ZE	PP
	NP	NM	NM	NM	NP	ZE	PP	PM
	ZE	NM	NM	NP	ZE	PP	PM	PM
	PP	NM	NP	ZE	PP	PM	PM	PM
	PM	NP	ZE	PP	PM	PM	PM	PG
	PG	ZE	PP	PM	PM	PM	PG	PG

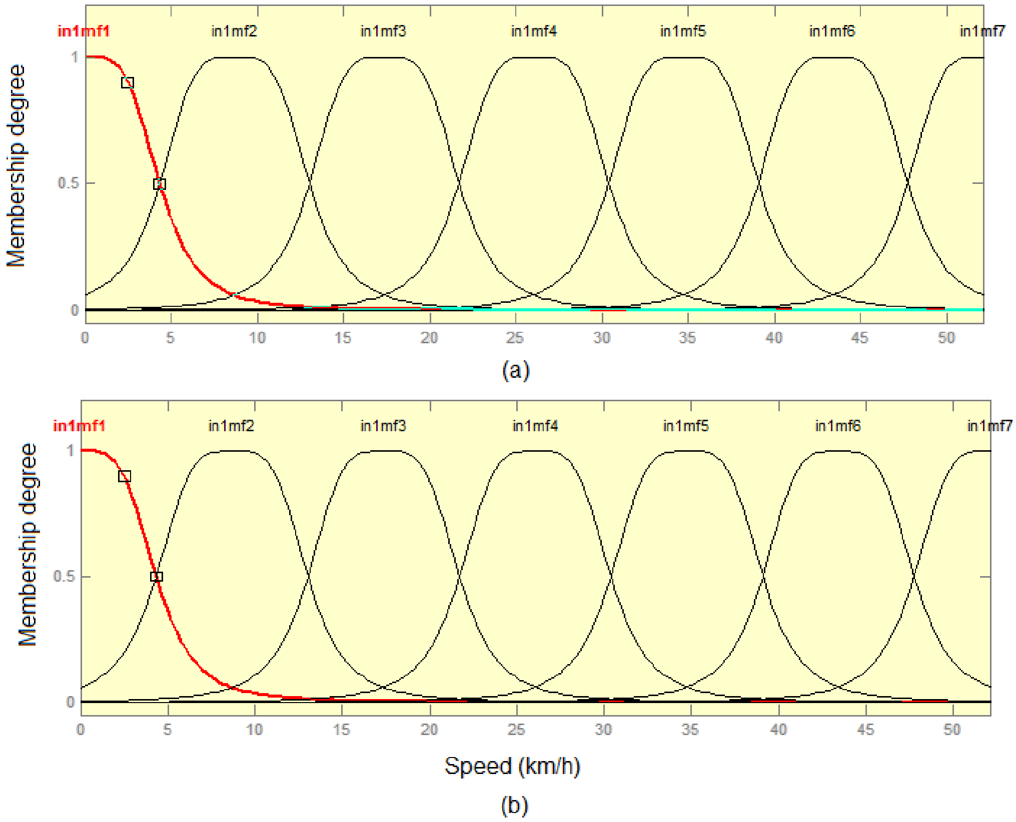

Figure 3. Set of Fuzzy Rules implemented for the neuro-fuzzy controller

4. SIMULATION AND RESULTS

The simulation was carried out in Simulink / Matlab due to ease of deployment of vehicle components. The first step was the construction of simulation modeling of vehicle dynamics. The modeling of vehicle dynamics in Simulink / Matlab was represented by the Longitudinal Vehicle Dynamics block.

After completing the modeling of vehicle dynamics in Simulink, the next step is the preparation of the control system. Both electric motors and internal combustion engine takes as input the desired speed in km/h, so this will be the output of the control system. Through of the Fig. 4 can view the block diagram implemented.

4.1. DC Motor Model

In part of the electric motors of a hybrid vehicle, we used two electric motors 5 Hp DC, each inserted into a wheel rear axle. The speed provided by each electric motor was then multiplied by the radius of the tire, and thus feeding the block modeling of the tire, where the resulting force fed the Longitudinal Vehicle Dynamics block, on the strength back.

The electric motor has been described as a function of some constant and due to its mechanical and electrical parts as shown in Fig. 5.

The PID control has three separate controls whose outputs are summed to determine a single output signal. PID stands for Proportional, Integral, and Derivative. It is a purely reactive control as it only responds to the system error. Fig. 6 shows a classical PID control. In this work was used a PID to control the velocity of the DC motor and also the ICE motor.

4.2. ICE Motor Model

The combustion engine used in this simulation is given by the block Gasoline Engine, whose output is connected to a variable transmission. The speed of transmission output variable is multiplied by the radius of the tire and into the block on the modeling of the tire. This model represents the behavior of the tire for a given speed, the output is the force of the tire that feeds the Longitudinal Vehicle Dynamics block, on the power front. Unlike traditional automatic gearboxes, the continuously variable type does not have a gearbox with a number of gears, which means the absence of sprockets that are interconnected. The most commom type of CVT operates on an ingenious pulley system that allows an infinite variability between the highest gear and the lowest same with discrete steps without changing gears.

Also for control the velocity of the ICE motor was used a PID and in this simulation was consider a automatic transmission (Fig. 7).

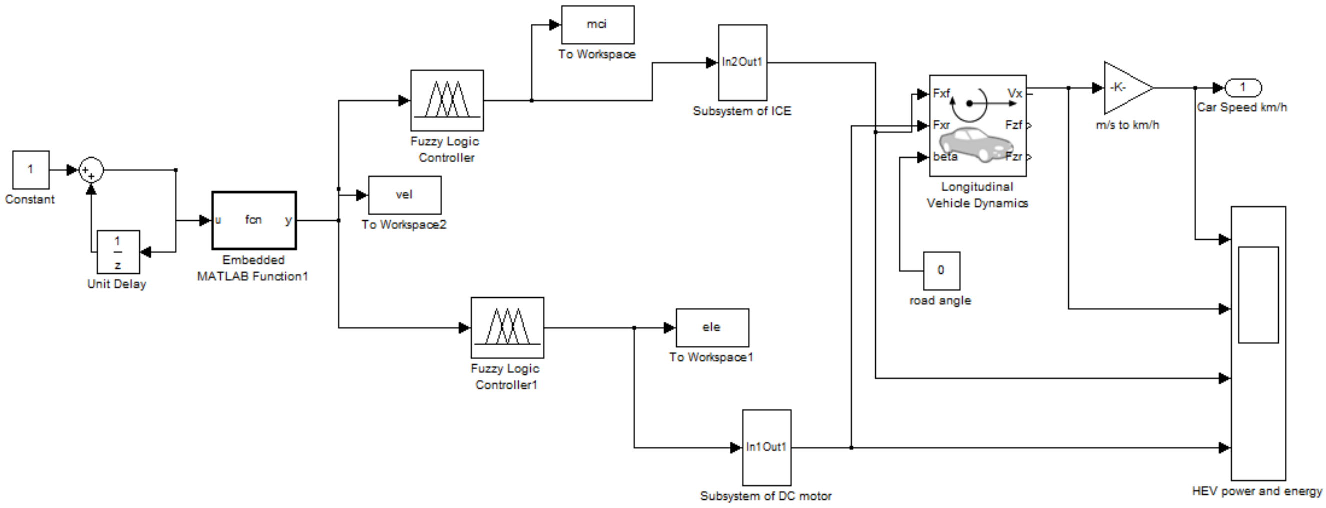

Figure 4. Block diagram of the proposed simulation.

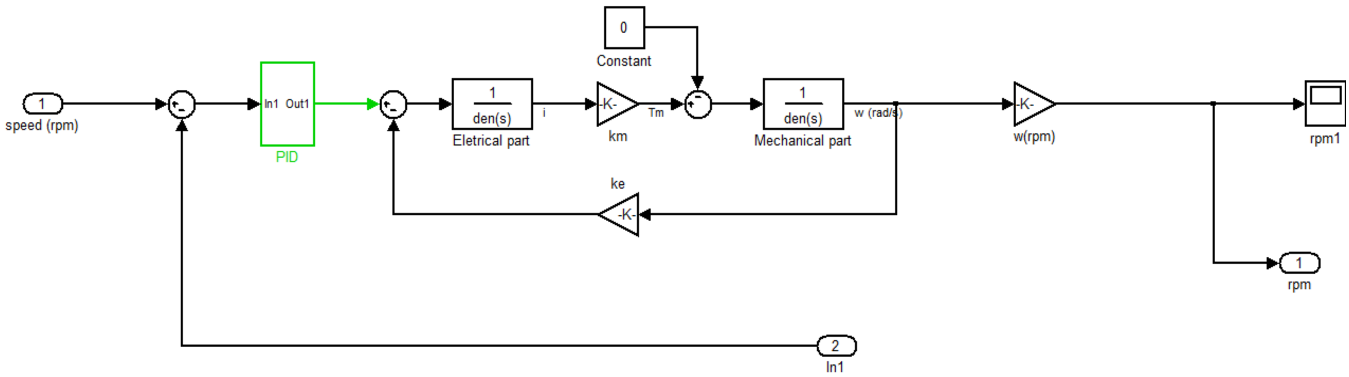

Figure 5. DC motor model

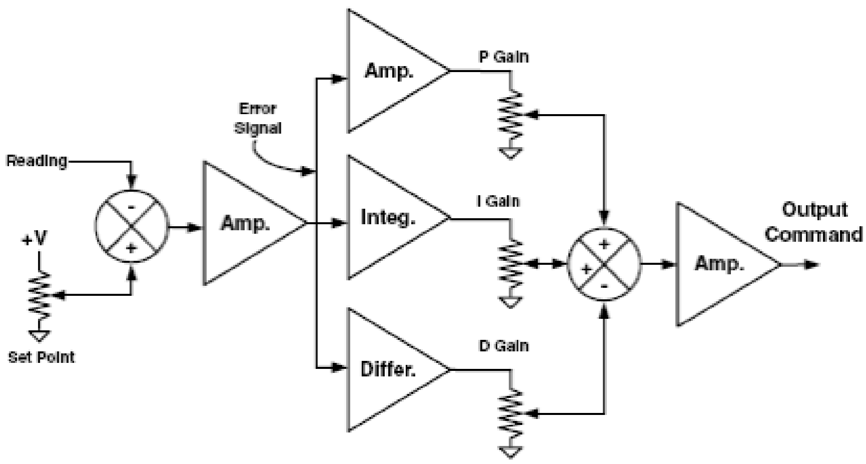

Figure 6. Classical PID Control (Holland, 2006)

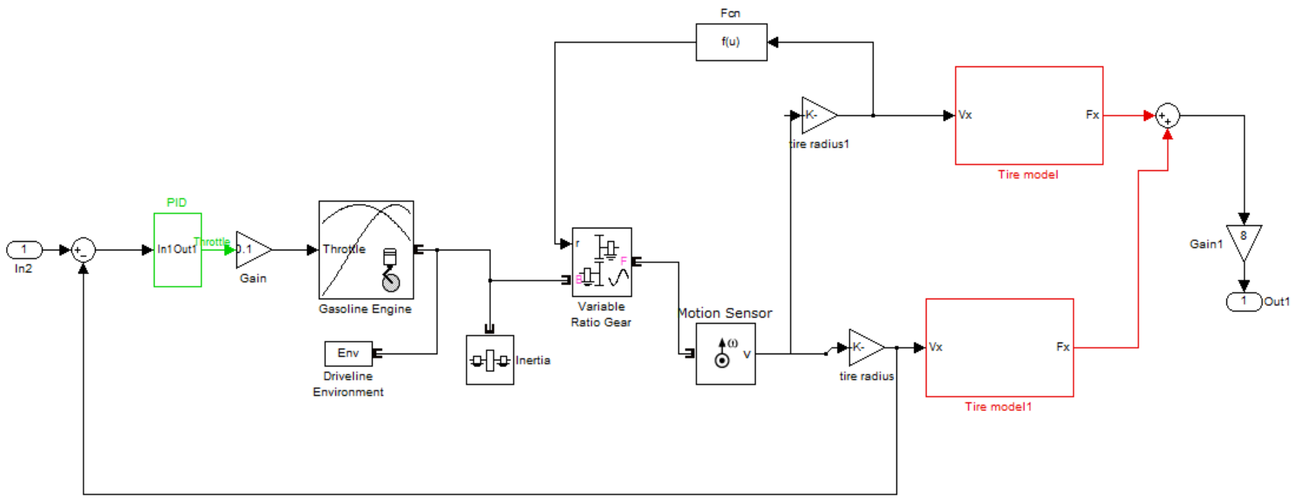

Figure 7. Ice Motor Model

4.3. Tire Model

There are many different mathematical models for a tire, here we use the magic formula because this model has a precise answer and parameters that can be improved for each type of tire. The magic formula was developed during the second half of the 1980s by the Technological University of Delft in cooperation with "Volvo Car Corporation". The magic formula developed by Pacejka, and it is widely used for empirical models and simulations. The magic formula can be used in modeling to calculate the tire forces and moments applied and there are several versions of this magic formula developed over these years of study. Over the years, the magic formula was further strengthened. Published by Pacejka and Bakker (1993) the general formula, which calculates the longitudinal force, the lateral force and the aligning torque in function of slip angle or longitudinal slip, is:

$$y(x) = D\sin\left[C\arctan\left\{Bx - E(Bx - \arctan Bx)\right\}\right] \tag{1}$$

with:

$$Y(x) = y(x) + S_v \tag{2}$$

$$x = X + S_h \tag{3}$$

Where $Y(x)$ represents the forces or the moment and X denotes the slip angle or the longitudinal slip. The coefficient B is called a stiffness factor, C is the shape factor, D is the peak factor and E is the curvature factor. S_v and S_h is vertical and horizontal displacement.

4.4. Results

The urban cycle is shown in Fig. 8; for a better analysis and visualization was consider only the beginning of the urban cycle. Consider a time of 120 seconds for the simulation, the result can be seen in Fig. 9. Also it was consider just this period because of training time when use a neuro-fuzzy. Figure 9 shows that the vehicle has the same velocity behavior of the urban cycle input. Thus the control system controls the motor turning on and off each one according with the velocity input. Because of the training time also was implementing the fuzzy rules to help in the function. Figure 10 shows the behavior of the electric motor through the action of neuro-fuzzy control.

One problem of this method is the rules used, because the approximation and the design of the membership was done using a triangular model and the answer was not the same. In this model if the input is constant and the variation in the time is slow the rules work very well. Thus correct rules are very important to have a satisfactory control function.

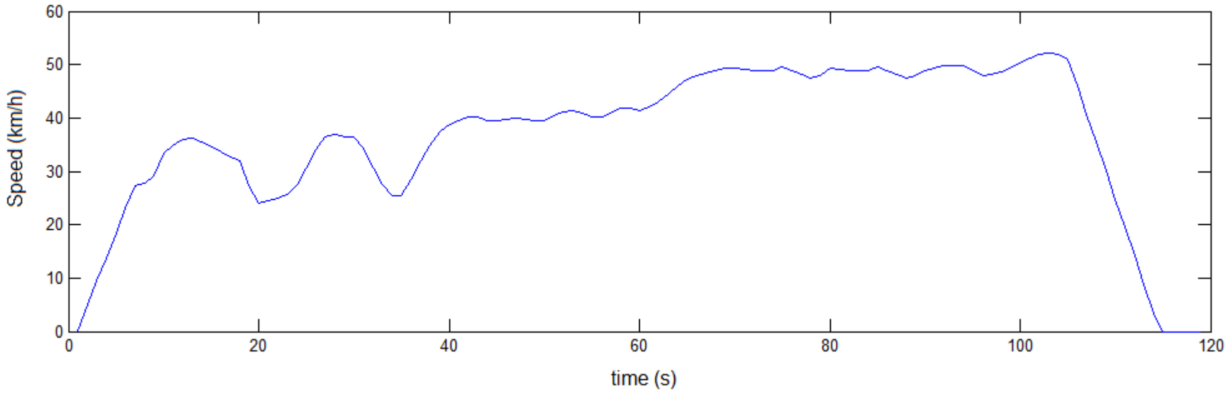

Figure 8. Urban Cycle

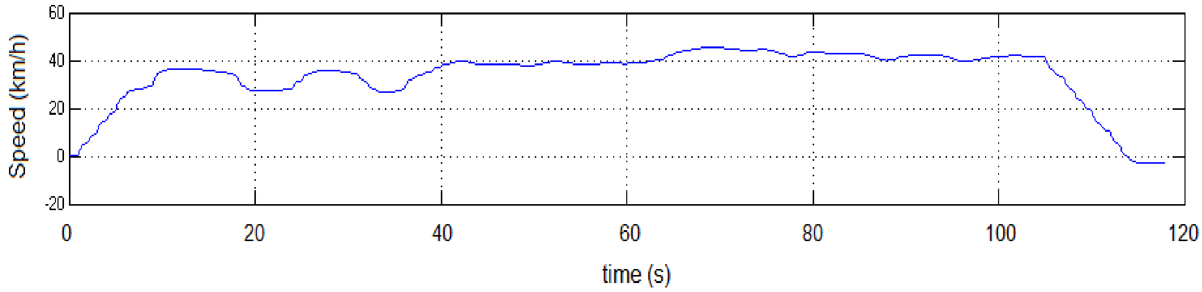

Figure 9. Speed Vehicle using Neuro-Fuzzy

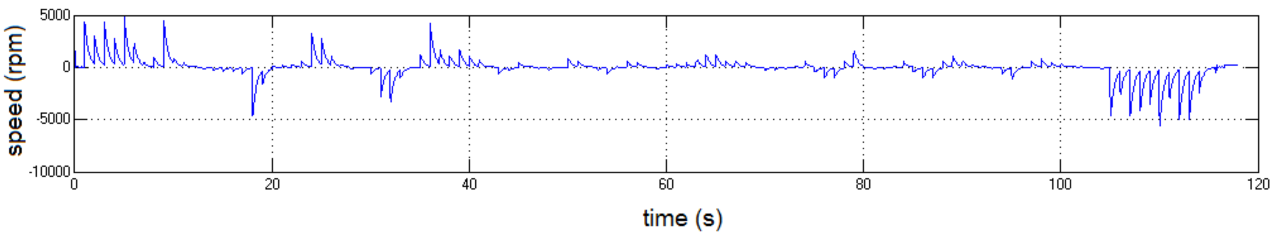

Figure 10. Behavior of the Electric Motor

5. CONCLUSIONS

The main goal of this paper was to develop the control system for operating the motors in hybrid vehicle. For this, a fuzzy rules was created and it was possible to visualized and understand the behavior of the control system taking into account every situation trafficking.

Thus to test this control, it was implemented in Simulink / Matlab. The control system of the hybrid vehicle showed a satisfactory response, whose driver also showed a desired behavior. With this result, it was possible to design a neuro-fuzzy controller, that showed a favorable control for this system.

For future work other drivers should be tested in order to analyze their behavior, even if the answer to the neuro-fuzzy controller is satisfactory. And finally, it is interesting that the control system proposed in this paper is implemented on a vehicle so that their actual behavior is observed. Through modeling of the vehicle is easier implement other controllers and thus have a complete integration of control and sensor fusion.

6. ACKNOWLEDGEMENTS

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