A MODEL FOR VEHICLE DYNAMIC SIMULATION WITH PID AND FUZZY LOGIC DRIVE CONTROLLERS

Ivan Arsie, Filippo Filippella, Cesare Pianese, Gianfranco Rizzo
Department of Mechanical Engineering, University of Salerno, Italy

Abstract

A computer code oriented to S.I. engine control and powertrain simulation is presented. The model predicts engine and driveline states, taking into account the dynamics of air and fuel flows into the intake manifold and the transient response of crankshaft, clutch, transmission gearing and vehicle. The whole model is integrated in the code O.D.E.C.S., now in use at Magneti Marelli, and is based on a hierarchical structure composed of different classes of models, ranging from black-box Neural Network to grey-box mean value models. By adopting the proposed approach, a satisfactory accuracy is achieved with limited computational demand, which makes the model suitable for the optimization of engine control strategies. Furthermore, in order to simulate the driver behavior during the assigned vehicle mission profile, two drive controllers have been implemented for throttle and brakes actuation, based on classical PID and fuzzy-logic theory. In the paper a detailed description of the whole driveline system is presented and the results achieved making use of both driver-behavior models are compared with respect to a set of arbitrary transient maneuvers and vehicle speed profiles.

Introduction

In order to satisfy the primary objective to develop vehicles with specified performance criteria, including acceleration, maneuverability and comfort and to comply with the more stringent environmental, energetic and economic constraints, the powertrain control represents one of the most important features to deal with during new automobiles design.

The use of additional actuation mechanisms for improving both engine performance and active vehicle safety (e.g. electronic throttle control, continuous variable transmission, traction control system) requires the design of an integrated control system for the whole powertrain. In order to reach this objective, simulation models are powerful tools for shortening the time required to design new control systems and reducing development costs [1]. Computer models reproducing engine and vehicle systems have been used since many years by automobile designers to estimate fuel economy and exhaust emissions and to aid for engine control strategy mapping [2], [3], [4]. These tools allow a relatively large spectrum of users to acquire knowledge on general vehicle performance data in a short time and at low cost without the difficulties related to the experimental activity. Generally, depending on accuracy and computational demand, a powertrain model can be used for several purposes: it can be used to supply general vehicle performance data or to assist design engineers in understanding the effects of newly configured components on engine or vehicle performance. And, of course, it can also be used for powertrain control system analysis in order to design the most suitable strategies. However, the achievement of this latter objective makes powertrain models alone not sufficient to speed up the development process. Thus the vehicle's dynamic behavior should be complemented by a realistic driver model which allows to reproduce with fidelity the effective vehicle maneuver with respect to a given mission profile (i.e. driving test cycle).

Model Approach

The powertrain has been modeled following a modular and hierarchical approach [5] and is the main body of the code O.D.E.C.S. which is implemented in Matlab/Simulink® in order to gain the benefits of an object-oriented graphical simulation environment [6]. Each physical subsystem has been described by either an independent block or library of sub-blocks, so that a part of the simulation model can be easily modified and reused by connecting the input / output signals of the selected objects. This approach, followed by several authors [7], [8], [9], [10], allows to analyze the effects of different S.I. engine control strategies making use of various powertrain configurations with different modeling accuracy depending on the phenomena to be analyzed. The flexibility and the ability to represent simply several configurations are target features for a powertrain system model which is oriented to reproduce different plants. Moreover, the adoption of an object oriented approach makes the model to be user-friendly and easily integrated in other system identification programs.

The Air-Fuel flow dynamics in the intake manifold is described by means of mean value dynamic models. The driveline can be modeled by choosing between several dynamic systems with different complexity, taking into account clutch engaging, gear shifting, transmission and final axles deformations. Moreover, the code makes use of Neural Network models for engine torque and exhaust temperature and emissions estimation. A library of ECU sub-models is also available to test the effects of different strategies for fuel film compensation and feedback control systems based on UEGO or EGO lambda sensors.

Regarding to the driver modeling, two different models for throttle valve and brakes actuation are considered: the former is based on a classical PID controller whose feedback signal is the actual vehicle velocity, while the second is developed by means of a fuzzy-logic approach whose inputs are both the vehicle acceleration and the difference between actual and target velocity.

Model Description

In the Figure 1 a block diagram of the whole powertrain system model is sketched. The figure evidences the main sub models corresponding to the Air-Fuel manifold dynamics, to the engine torque-emissions and to the driveline module and the state, control and operating system variables. The ECU module accounts for control strategies for fuel metering, spark advance, electronic throttle and transmission actuation and is connected with the drive controller. In the next paragraphs each module will be described in detail, evidencing the adoption of the mentioned hybrid approach in modeling the different physical subsystems.

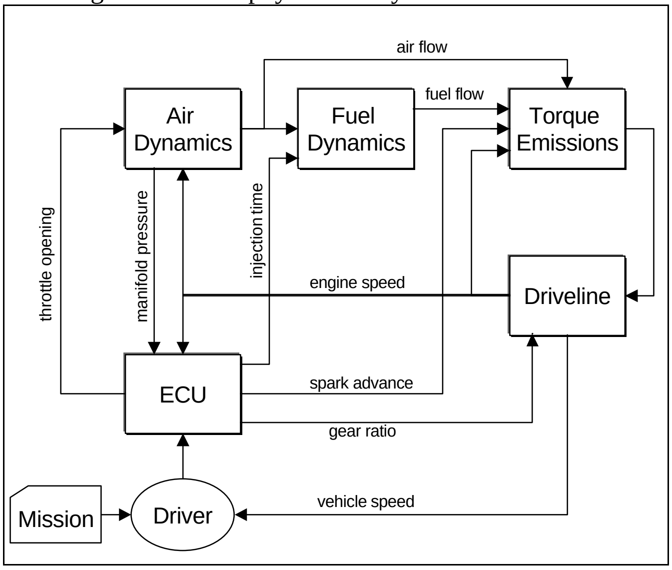

Figure 1 – Block diagram of the vehicle-powertrain simulation model.

Intake Manifold

In order to design a tool to be used for powertrain system control application, a precise estimation of air and fuel dynamics into the intake manifold has to be performed within a wide range of engine operating conditions. Typically, this goal is achieved with acceptable precision by means of zero dimensional mean value models, neglecting the unsteady fluctuations due to periodic phenomena. This solution guarantees a detailed description of system behavior within the frequency spectrum of interest for control application, with limited computational resources [2]. The intake manifold block is composed of two dynamic subsystems represented by a set of ordinary differential equations. The air dynamics block computes the air flow rates through the throttle body and the engine port, while the fuel dynamics model describes the effects due to the two phases fuel flow into the manifold (i.e. fuel wall wetting and evaporation). The ratio between air and fuel port flow rates is then used to compute engine torque and emissions. For an accurate description of the intake manifold dynamic models the reader is addressed to previous papers [4], [6] and to the bibliografy [2], [11], [12], [13], [14], [15], [16], [17].

In-Cylinder Process

Due to the quoted exigencies of computational time and precision, the in-cylinder processes for torque and emissions estimation have been described making use of black-box models, based on the synthesis of steady-state experimental data [4]. The effects due to powertrain dynamics and engine control strategies are considered by means of the input signals (engine speed, air mass flow, AFR and spark advance) derived from the intake manifold and driveline dynamic models and ECU module.

The black box models formerly implemented in the code O.D.E.C.S. were based on regressions and interpolation techniques [4]. They have been replaced by a Neural Network models structure in order to overcome the limitations coming out from the use of the previous approach. The Neural Networks, well suited for non linear phenomena modeling, are able to deal with high uncertainty input level or noised data and allow to operate outside their range of training experience with a reduced number of experimental data compared with regression based model system. A detailed description of Neural Network approach is beyond the scope of the paper; for a detailed analysis of the present application, the reader is addressed to previous papers [6], [20] and to the specific literature [21], [22].

Driveline

The driveline model describes the rotational dynamics of engine, clutch, transmission, final drive and wheels, for a servoactuated layshaft transmission powertrain. Depending on the required accuracy and computational demand, different approaches can be adopted for the driveline simulation, corresponding to rigid or elastic systems with two or more degrees of freedom. For the purposes of the proposed powertrain model the driveline has been described by two rigid bodies connected by a friction transmission for modeling the clutch engaging effect during gear shift or standing start. This configuration does not account for axle deformation and cannot be used for jerking or comfort analysis. However, the limited number of states speeds up the simulation making it suitable for analyses on the general vehicle behavior with respect to given transients and control strategies [18], [19].

In order to account for clutch engaging and disengaging maneuvers, the driveline rigid model has two degrees of freedom corresponding to the angular position of the engine equivalent flywheel Θ_E and the angular position of the vehicle equivalent flywheel Θ_V [6]. In Figure 2 a reference scheme of the model is sketched. The driveline is then represented by a two states dynamic system reduced to the engine crankshaft:

$$-(\boldsymbol{Y_E} + \boldsymbol{SW}2\cdot\boldsymbol{Y_V})\ddot{\Theta}_{\boldsymbol{E}} + \boldsymbol{T_E} - \boldsymbol{T_{cl}}\cdot\boldsymbol{SW}1 - \boldsymbol{T_R}\cdot\boldsymbol{SW}2 = 0 \quad (1)$$

$$-(\boldsymbol{Y_V} + \boldsymbol{SW}2\cdot\boldsymbol{Y_E})\ddot{\Theta}_{\boldsymbol{V}} + \boldsymbol{T_{cl}}\cdot\boldsymbol{SW}1 + \boldsymbol{T_E}\cdot\boldsymbol{SW}2 - \boldsymbol{T_R} = 0 \quad (2)$$

where Y_E and Y_V are the equivalent engine and vehicle inertia, T_E is the engine torque and T_R is the load torque due to aerodynamic and advancing resistance.

The clutch torque T_{cl} is given in input, considering a linear shape during the engaging and disengaging maneuvers, and assuming a constant friction coefficient *m*.

The logical switches *SW1* and *SW2* are alternatively activated depending on engine and vehicle rotational speeds and actual clutch torque:

$$\dot{\Theta}_E = \dot{\Theta}_V \;\; and \;\; T_{cl} \geq \max(T_E, T_R) \Rightarrow \begin{matrix} SW1=0 \\ SW2=1 \end{matrix} \qquad (3)$$

$$\dot{\Theta}_E \neq \dot{\Theta}_V \;\; or \;\; T_{cl} < \max(T_E, T_R) \Rightarrow \begin{matrix} SW1=1 \\ SW2=0 \end{matrix} \qquad (4)$$

Three states of the clutch are then modeled depending on the clutch torque T_{cl} and on the switches (*SW1* and *SW2*): engaged, slipping and disengaged [6].

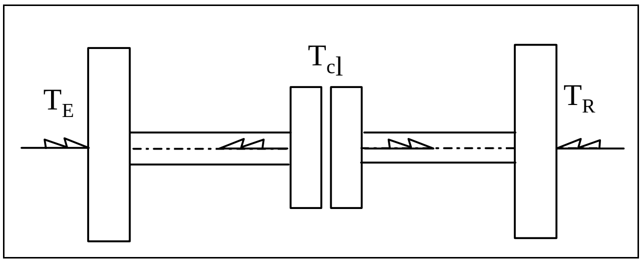

Figure 2 – Reference scheme of the driveline rigid model with two degrees of freedom.

Ecu

An engine control unit module (ECU) has been developed in order to simulate the effects of different control strategies.

The main objective concerns with Air-Fuel ratio control in order to guarantee optimum catalyst performance, especially in throttle transients because of the different dynamics of air and fuel flow [2], [3], [4], [11], [13], [14], [15], [16]. According to this goal the ECU module library offers a selection of several engine control strategies, which are mainly composed of a closed loop lambda control and a model based fuel film compensation.

Following the philosophy adopted in a modern engine, the fuel metering is performed into several steps: a base fuel calculation, a correction imposed by a lambda control loop and a fuel film compensation. The base fuel calculation is determined by the air mass flow to the engine estimated by the filling-emptying model described above or eventually by a look up table from engine sensor measurements (manifold pressure and engine speed).

An active lambda PI feedback control is then incorporated, simulating the AFR signal from a digital (HEGO) or continuous (UEGO) exhaust Air-Fuel sensor, accounting for engine cycle and exhaust transport delay, and sensor response [12].

Driver Model

In order to simulate a realistic mission profile, the knowledge of human control behavior is required. The powertrain model alone is not sufficient to reproduce with fidelity the transient maneuver corresponding to a given speed mission profile, (i.e. test driving cycle) since the actuation of both throttle valve and brakes is dependent upon physical and psychological factors, as well as the demand of the driving situation. Though the behavior of the driver is theoretically known, mathematical descriptions have not been sufficiently realistic yet. Several approaches have been proposed in the literature, among others three techniques have been used addressing to classical control, fuzzy logic or a combination of them [23], [24], [25]. The classical PID controller performs a robust tracking of a reference mission profile, but does not behave like a human driver. On the other hand driver models based on fuzzy logic theory address to human behavior but, they can only model part of the driver's cognitive process [23]. A more realistic hybrid model has been recently proposed by Kiencke et al. [25], which describes the complete cognitive process of the human operator by means of a combination of discrete event theory and classical control theory.

In the proposed vehicle model, the control of the longitudinal dynamics is performed adopting two different approaches based on classical control theory (PID) and fuzzy logic theory. In order to reproduce both acceleration or deceleration transients, the controllers operate alternatively on throttle valve or brakes. The PID controller takes as input the desired and the actual speed while for the fuzzy controller the actual acceleration is also processed. The location of the driver controller within the whole powertrain model is shown in the block diagram in Figure 1. The figure evidences the input/output connection with the desired data (mission block), the feedback signal (vehicle speed and acceleration) and the throttle valve and brakes actuation (ECU block).

As already mentioned, the PID controller takes as input the error between desired and actual vehicle speed and as output the fraction of throttle opening or brake torque. The controller has been designed, according to the classical feedback control theory, tuning the controller gains with the Ziegler-Nichols method [26].

Regarding to the structure of the Fuzzy Logic controller it takes two inputs corresponding to the error between the desired and the actual vehicle speed, and the actual vehicle acceleration and one output corresponding to the fraction of throttle opening or brake force alternatively. The controller has been designed with seven membership functions for the first input and the output and five membership functions for the second input, all ranging from negative large to positive large values, as it is shown in Figure 3. The fuzzy inference process is based on the Mamdani method assuming the Fuzzy logical operator ‘AND’ (i.e. minimum operator). For the defuzzification the center of gravity method has been applied [27].

The figure 3 evidences that for the second input and the output, equidistant triangular-shaped membership functions have been defined; while, for the first input, in order to obtain a smoother control for limited excursions around the reference speed, the membership functions have been concentrated around the steady state condition (i.e. zero velocity error). Regarding to the output membership functions it is worth to notice that positive and negative values correspond to an action on the throttle valve and the brake pedal respectively. The rule set reported in Table I summarizes the controller output, reflecting the experience of the driver. An example of how the fuzzy controller interprets driver’s behavior is the following: in case that the vehicle speed is greater than the reference speed and the vehicle is already decelerating, then an experienced driver would not brake hard but would just keep the throttle closed or eventually would brake only gently. This behavior is reflected by the rules in the lower right corner in Table I.

Table I – Rule base for Fuzzy controller

Acc.	A	O	ST	C	MC	MC	HC	HC
	LA	MO	O	ST	C	MC	MC	HC
	ST	HO	MO	O	ST	C	MC	HC
Dec.	LD	HO	MO	MO	O	ST	C	MC
	D	HO	HO	MO	MO	O	ST	C
		HS	MS	S	ST	F	MF	HF
		Slow				Fast		

Membership functions legend			
HS	High Slow	LDec	Low Deceleration
MS	Medium Slow	LAcc	Low Acc.
S	Slow	Acc	Acceleration
F	Fast	HC	High Close
MF	Medium Fast	MC	Medium Close
HF	High Fast	MO	Medium Open
Dec	Deceleration	HO	High Open

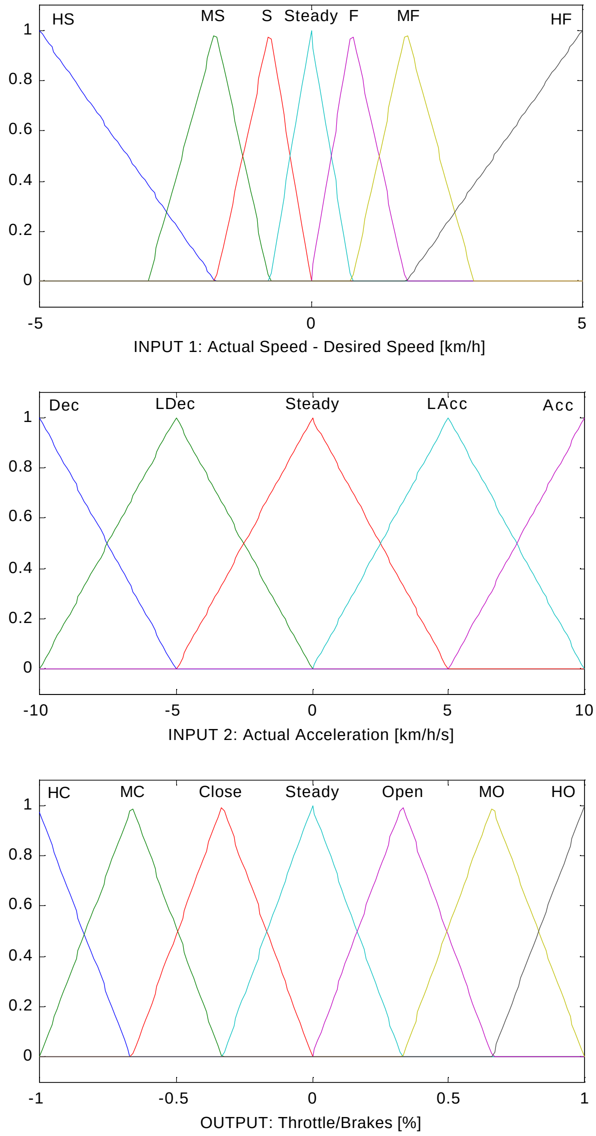

Figure 3 – Membership functions for controller inputs and output.

Vehicle Maneuvers

The proposed powertrain model can be used to perform three different kinds of engine-vehicle maneuvers depending upon the analysis to be carried out:

1. Simulation of wide open/close throttle transients with fixed gear ratio.
2. Simulation of powertrain transient during up/down gear shift and different throttle actuation.
3. Simulation of vehicle transient maneuver assuming a velocity mission profile.

Different combinations of these three simulations can be performed in order to simulate more complex transients such as standard driving test (FTP, ECE). For detailed analysis, the first two simulations are oriented to evaluate the effects of different control strategies on specific engine/vehicle variables (e.g. AFR control or clutch-gear shift maneuver). In these cases the input signals are given by throttle or throttle-gear actuation profiles respectively. The latter kind of simulation, which has been considered for the purposes of the present work, is oriented to global performance analyses and to the optimization of engine maps with respect to a given mission profile. In order to compare the performance of the two proposed drive controllers three different mission profile have been simulated: a slight and a strong acceleration transient with fixed gear, and a driving test cycle (ECE cycle) including starting and stopping maneuvers.

Figure 4a shows the simulated throttle profile for the slight acceleration maneuver plotted in Figure 4b. In this latter figure the resulting vehicle speed is also shown for both PID and Fuzzy controller. Both driver models exhibit satisfactory and comparable level of accuracy in following the fixed vehicle velocity target with a time delay of about 0.4 seconds. Such a limited delay is in accordance with the human driver behavior during experimental driving test cycle. It is worth to note that due to the simple speed mission profile, the throttle valve actuation is sufficiently smooth without opening/closing spikes.

In the second simulation, an instantaneous acceleration transient is imposed, as it is shown in Figures 5b. In this case a slight difference in the throttle actuation profile can be noticed in Figures 5a, though the simulated vehicle velocities exhibit almost the same transient response with both controllers. These figures evidence that the Fuzzy controller reproduces slightly better the driver behavior since it actuates an early throttle closing maneuver once the vehicle is approaching the target speed. The throttle shape also evidences the effects due to the different control models: PID control is smoother than the fuzzy one, reflecting the event based approach of this latter.

Since the proposed powertrain model is mainly oriented to the design and the optimization of engine/vehicle control strategies with respect to standard driving test cycle, the simulation of one module of the ECE cycle has been performed and the results are shown in Figures 6a-b-c. The standard test imposes the vehicle speed mission shown in Figure 6c, starting from vehicle at rest and scheduling the gear position along the transient as shown in the figure. The figures show the throttle opening, the brake torque and the vehicle speed for both controllers, evidencing a satisfactory precision in matching the target velocity with negligible errors. Regarding to throttle opening and brake torque, both controllers actuate comparable maneuvers with local spikes for the fuzzy controller, due its previously quoted event based definition. In Figures 7a-b the simulated fuel consumption and exhaust emissions are also plotted for the PID controller only, as an example of the performance evaluation to be considered for the control strategy optimization; comparable performance have been found with the fuzzy logic controller.

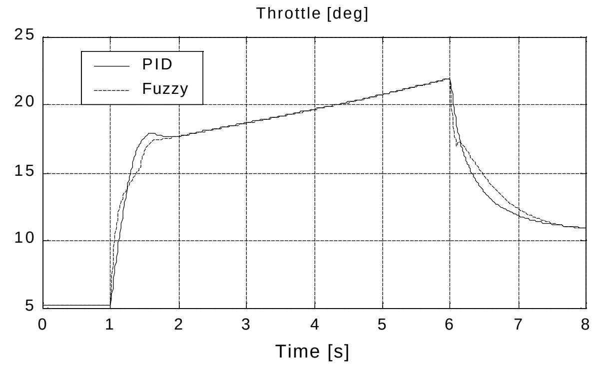

Figure 4a – Simulation results for a slight acceleration with PID and Fuzzy Logic controller. Throttle maneuver.

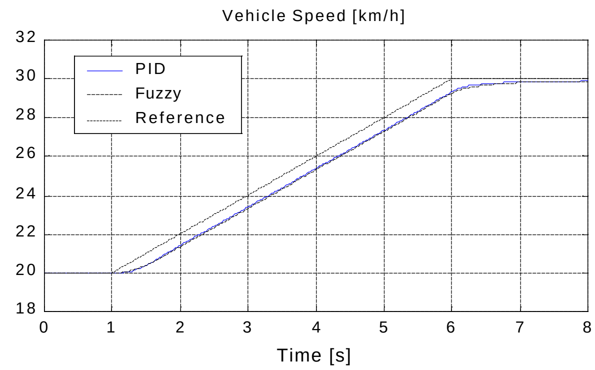

Figure 4b – Simulation results for a slight acceleration with PID and Fuzzy Logic controller. Actual and reference speed.

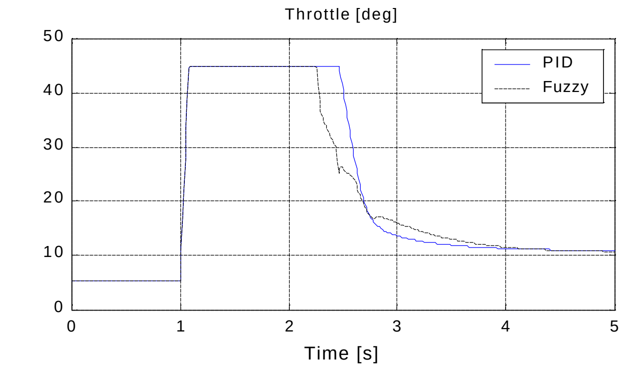

Figure 5a – Simulation results for a strong acceleration with PID and Fuzzy Logic controller. Throttle maneuver.

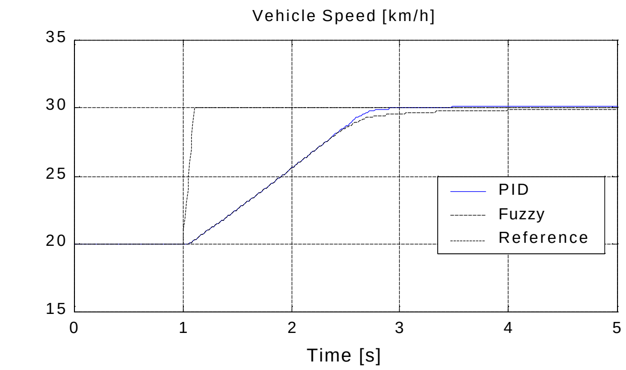

Figure 5b – Simulation results for a strong acceleration with PID and Fuzzy Logic controller. Actual and reference vehicle speed.

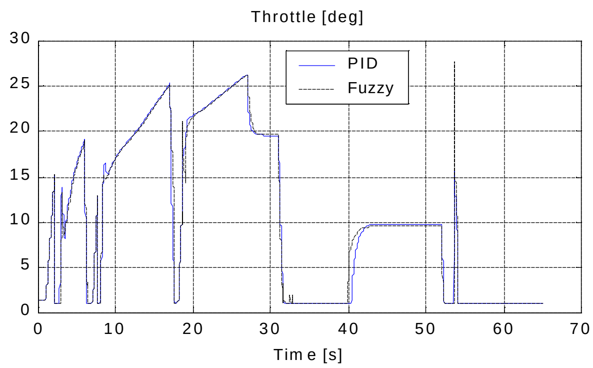

Figure 6a – Simulation results for a module of ECE test cycle with PID and Fuzzy Logic controller. Throttle maneuver.

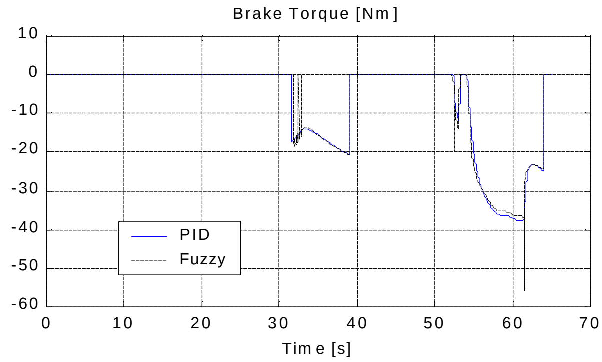

Figure 6b – Simulation results for a module of ECE test cycle with PID and Fuzzy Logic controller. Actual and reference speed.

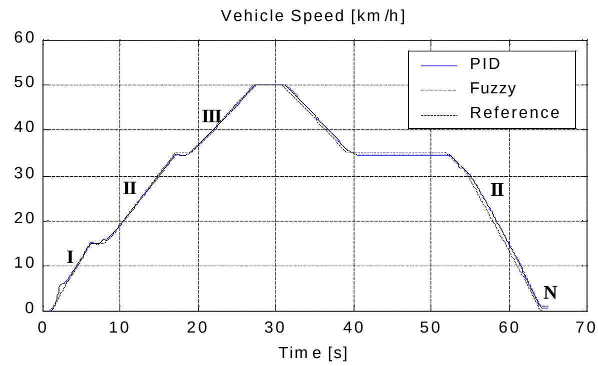

Figure 6c – Simulation results for a module of ECE test cycle with PID and Fuzzy Logic controller. Actual and reference speed.

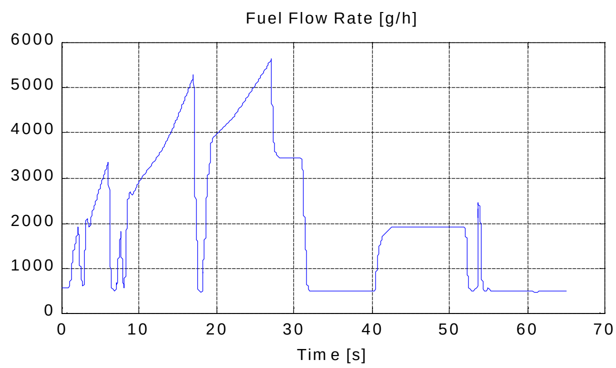

Figure 7a – Simulation results for a module of ECE test cycle with PID controller. Fuel consumption.

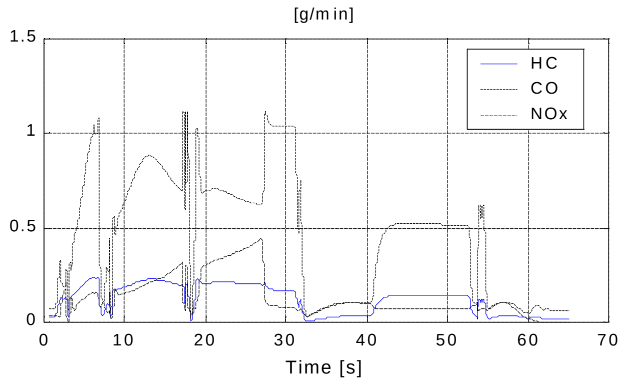

Figure 7b – Simulation results for a module of ECE test cycle with PID controller. Exhaust Emissions.

The presented results have shown almost the same performance for PID and Fuzzy Controller; the target speed has been matched with acceptable accuracy and the actuated throttle profiles exhibit comparable behavior in simple and complex transient maneuvers. In both cases the throttle profiles have been maintained sufficiently smooth, apart from some very fast transients where the fuzzy controller has showed the occurrence of opening/closing spikes. Therefore, further work is required in order to improve the fuzzy controller performance and this goal will be accomplished by an appropriate tuning of the rules [27] instead of the heuristic approach adopted for the current application which results in a less smoothed behavior.

The performed simulations confirm that both drive controllers can be adequate to reproduce the behavior of a standard skilled driver in 'normal' environment condition for any given driving test. Nevertheless, it has to be pointed out that fuzzy logic controller is more flexible than the PID for simulating the behavior of different driver types on different test courses, with a variety of curves and road condition (dry, wet). This objective can be achieved by considering the different stages of information processing in humans, which according with Kiencke et al. [23], [25], can be described by means of a series of function blocks responsible for signal perception, decision and response selection and response execution.

Conclusions

A powertrain model with two drive controllers based on classical control (PID) and fuzzy Logic theory has been presented. The powertrain model accounts for the dynamic behavior of the whole engine-driveline-vehicle system and is suitable for the analysis and the optimization of control strategies. An hybrid approach has been followed in defining each sub-model, ranging from black-box models based on Neural Networks for estimating torque and exhaust emissions for a S.I. Engine (HC, CO, NO_x), to a set of mean value dynamic sub-models for the description of mixture dynamics in the intake manifold. Moreover a two states clutch model has been designed to simulate gear up/down-shift maneuvers.

However, in order to optimize engine control strategies with respect to fuel consumption and exhaust emissions, the powertrain model alone is not sufficient. Thus, the design of a drive controller has been performed to reproduce the driver behavior during the transient maneuver.

The two proposed drive controllers have been tested for three different vehicle speed missions: two acceleration maneuvers and one module of the ECE driving test schedule. In all cases, both controllers have shown a satisfactory accuracy in following the target mission with an acceptable smoothness in the actuated throttle maneuver. However further improvements will be carried out on the fuzzy logic controller in order to simulate the behavior of different driver types with respect to different environment conditions and test courses.

Acknowledgements

The present research has been funded on Magneti Marelli – Powertrain Control Division financial support. Part of the activity has been supported by Campania Regional Government Project (POP 5.4.2).

The driveline models have been designed in cooperation with M. Russo, R. Russo, V. Ciaravola and M. Cuoco at D.I.M.E. - University of Naples "Federico II".

References

[1] Moskwa J.J., Munns S.A., Rubin Z.J., "The Development of Vehicular Powertrain System Modeling Methodologies: Philosophy and Implementation", *SAE paper* No. 971089, 1997.

[2] Hendricks E. and Sorenson S.C., "SI Engine Controls and Mean Value Engine Modelling", *SAE paper* No. 910258, 1991.

[3] Moskwa J.J. and Hedrick J.K., "Modeling and validation of automotive engines for control algorithm development", *Transaction of ASME J. of Dynamic System, Measurement and Control*, Vol. 114, pp. 228-285, June 1992.

[4] I. Arsie, F. De Franceschi, C. Pianese, G. Rizzo, "ODECS – A Computer Code for the Optimal Design of S.I. Engine Control Strategies", *SAE paper* No. 960359, in SP-1168, ISBN 1-56091-798-9, pp. 195-208, 1996.

[5] Arsie I., Pianese C., Rizzo G., "Models for the Prediction of Performance and Emissions in a Spark Ignition Engine - A Sequentially Structured Approach", *SAE Paper* No. 980779, in SP-1330, pp. 59-73, Pub. on SAE 1998 Transactions, 'Journal of Engines', Section 3, Vol. 106, ISBN 0-7680-0518-3, pp. 1065-1079, 1998.

[6] Arsie I., Pianese C., Rizzo G., Flora R., Serra G., "A Computer Code for S.I. Engine Control Powertrain

Simulation", *SAE Paper* No. 2000-01-0938, in SP-1501, ISSN 0148-7191, pp. 185-198, 2000.

[7] J.R. Wagner and J.S. Furry, "A Real Time Simulation Environment for the Verification of Automotive Electronic Controller Software", *Int. J. of Vehicle Design*, Vol. 13, No. 4, pp. 365-377, 1992.

[8] C.R. Ciesla and M.J. Jennings, "A Modular Approach to Powertrain Modeling and Shift Quality Analysis", *SAE paper* No. 950419, 1995.

[9] R.W. Weeks and J.J. Moskwa, "Automotive Engine Modeling for Real-Time Control using MATLAB/SIMULINK", *SAE paper* No. 950417, in SP-1080, pp.123-137, 1995.

[10] K.S. Hong, K.J. Yang, K. Lee, "An Object Oriented Modular Simulation Model for Integrated Gasoline Engine and Automatic Transmission Control", *SAE paper* No. 1999-01-0750, 1999.

[11] Hendricks E., Chevalier A., Jensen M., Sorenson S.C., Trumpy D. and Asik J., "Modelling of the Manifold Filling Dynamics", *SAE paper* No. 960037, 1996.

[12] Heywood J.B., "Internal Combustion Engine Fundamental", MC Graw Hill.

[13] Aquino C.F., "Transient A/F Control Characteristics of the 5 Liter Central Fuel Injection Engine", *SAE paper* No. 810494, 1981.

[14] Benninger N.F. and Plapp G., "Requirements and Performance of Engine Management Systems Under Transient Conditions", *SAE paper* No. 910083, 1991.

[15] Turin R.C., Geering H.P., "Model-Based Adaptive Fuel Control in an SI Engine", *SAE paper* No. 940374, 1994.

[16] Jones V.K., Ault B.A., Franklin J.F. and Powell J.D., "Identification and Air/Fuel Ratio Control of a SI Engine", *IEEE Transactions on "Control System Technology"*, Vol. 3, No. 1, pp. 14-21, March 1995.

[17] Arsie I, Pianese C., Rizzo G., "Identification of Manifold Two-Phase Fuel Flow Model in a Spark Ignition Engine with Kalman Filter and Least Square Methods", *7th IEEE Mediterranean Conference on "Control & Systems"*, Haifa, June 28-30,1999.

[18] Powell B.K., Bailey K.E., Cikanek S.R., "Dynamic modeling and Control of Hybrid Vehicle Powertrain Systems", *IEEE Control System*, Vol. 18, No. 5, October 1998.

[19] Ercole G., Mattiazzo G., Mauro S., Velardocchia M., "Co-operating Clutch and Engine Control for Servoactuated Shifting through Fuzzy Supervisor", *SAE paper* No. 1999-01-0746, 1999.

[20] Arsie I., Pianese C., Rizzo G., "Enhancement of Control Oriented Engine Models using Neural Network", *Proc. of the 6th IEEE Mediterranean Conference on "Control & Systems"*, Alghero, June 9-11, 1998.

[21] Hecht-Nielsen R., "Neurocomputing", Addison-Wesley, 1987.

[22] Patterson D.W., "Artificial Neural Networks - Theory and Applications", Prentice Hall, 1995.

[23] Kiencke U., Nielsen L., "Automotive Control Systems", Springer, 2000.

[24] Allen R.W., Rosenthal T.J., Hogue J.R., "Modeling and Simulation of Driver/Vehicle Interaction", *SAE paper* No. 960177, 1996.

[25] Kiencke U., Majjad R., Kramer S., "Modeling and Performance Analysis of a Hybrid Driver Model", *Control Engineering Practice*, Vol. 7, pp. 985-991, 1999.

[26] Franklin G.F., Powell J.D., Emami-Naeini A., "Feedback Control of Dynamic Systems", Addison-Wesley, 1994.

[27] Babuska R., "Fuzzy Modeling for Control", Kluwer Academic, 1998.