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# OPTIMAL ENERGY MANAGEMENT IN A PARALLEL HYBRID VEHICLE

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## ABSTRACT

The paper focuses on the simulation, analysis and control of the energy flow in a parallel hybrid electric vehicle (HEV). HEVs operation is concerned with the on board conversion of chemical, electric and mechanic energy and its optimal control is essential in order to increase the global system efficiency.

A dynamic model is used to describe the driver-vehicle interaction for a generic transient and to simulate the vehicle driveline, the internal combustion engine (ICE) and the electric motor/generator (EM). A Genetic Algorithm has been implemented to design the rules of a fuzzy logic controller for the optimal management of the energy flow between EM and ICE, accounting for the battery state of charge (SOC) and the route typology (urban o extra-urban cycle).

The methodology has been applied for a standard driving ECE-EUDC cycle with a significant improvement of the fuel efficiency.

## NOMENCLATURE

| | |
|---|---|
| $B$ | Battery package. |
| $C$ | Electromagnetic clutch. |
| $c$ | Gaussian peak of the membership functions. |
| $C_s$ | [g/kWh] Specific fuel consumption. |
| $D$ | Differential gear. |
| $DB$ | Driver behavior model. |
| $DI$ | Driver Interpreter. |
| $DL$ | Driveline. |
| $ECU$ | Engine control unit. |
| $EM$ | Electric machine (Motor/Generator). |
| $GB$ | Gear box. |
| $ICE$ | Internal combustion engine. |
| $N$ | Number of membership functions. |
| $Pedal$ | Pedal actuator. |
| $P_{EM}$ | [W] Electric power. |
| $SOC$ | Battery state of charge. |
| $TC$ | Throttle controller. |
| $T_{EM}$ | [Nm] Torque delivered by the Electric Machine. |
| $T_{ICE}$ | [Nm] Torque delivered by the ICE. |
| $T_{Req,EM}$ | [Nm] Torque demanded to the EM. |
| $T_{Res}$ | [Nm] Resistant torque. |
| $TS$ | Torque splitter. |
| $I$ | [kg m$^2$] Momentum of inertia. |

## Greek symbols

| | |
|---|---|
| $\omega$ | [rad/s] Angular speed. |
| $\eta$ | Efficiency of the electric machine. |
| $\sigma$ | Standard deviation of the membership functs. |

## INTRODUCTION

In the last years the increasing interest for energetic and environmental problems has given a strong impulse toward the development of alternative propulsion systems for automotive applications. The hybrid electric vehicles (HEVs) seem to be a good and feasible solution from energetic-environing as well as industrial point of view. They are equipped with an electrical traction system, composed of a set of batteries and an electric motor/generator (EM) which is coupled with a standard internal combustion engine (ICE). Thus, HEVs present all the advantages of the electric traction (e.g. limited pollution and acoustic impact, significant energy saving, and improved drivability) together with the typical features of ICE such as high autonomy (Riley, 1994; Hochgraf et al. 1996; Powell et al., 1998; Nagasaka et al., 1998; Baumann et al., 1998; Guzzella and Amstutz, 1999).

Depending on the powertrain layout, two different HEVs configurations can be considered: series hybrid vehicles and parallel hybrid vehicles. In the series HEV, the ICE powers an

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electric generator for recharging the battery pack and the vehicle is powered by an electric motor. The ICE is sized for a mean load power and works at constant load with reduced pollutant emissions, high reliability and long working life. On the other hand, in this configuration the energy flows through a series of devices (ICE, generator, battery pack, electric motor, driveline) each with its own efficiency, resulting in a significant reduction of the powertrain global efficiency (Baumann et al., 1998)

In the parallel architecture, both ICE and EM are mechanically coupled to the transmission and can simultaneously power the vehicle. This configuration offers a major flexibility to different working conditions (i.e. driving cycle).

The dynamic model designed for simulating the on-board energy flow (i.e. mechanical, chemical, electrical) during arbitrary driving cycles, accounts for the following working modes:

[1] Electric mode: the vehicle is powered by the EM while the ICE is switched off. This mode is suitable for driving in urban areas where a great reduction of pollutant emissions is imposed.
[2] Hybrid mode: the EM works as motor and assists the ICE in powering the vehicle.
[3] Recharging mode: the ICE powers the EM which works as electric generator to charge the battery pack.
[4] Regenerative braking: during vehicle deceleration the EM works as a generator to charge the battery pack, thus converting the vehicle kinetic energy into electrical energy.

In the model, the above modes are selected as function of mission profile, urban or extra-urban route, battery state of charge (SOC) and engine / motor characteristics.

In the following the powertrain model and the energy control strategies are described together with the methodologies implemented for the control strategies optimization. In the results section, the simulation and optimization results, referred to the standard ECE-EUDC driving cycle are presented and discussed.

## SYSTEM CONFIGURATION

The powertrain of the parallel hybrid vehicle considered for the present study is sketched in Figure 1: the powertrain has a spark-ignition IC engine (4 cylinders with 16 valves and a displacement of 1242 $cm^3$) and an electric asynchronous three-phase motor/generator (30 kW); a lead-acid battery package is used for the electric energy storage. A cogged belt connects the thermal engine and the electric motor and an electromagnetic clutch decouples the engine from the drivetrain (Arsie et al. 1999). In order to focus the attention on the energy flow control strategy and to reduce the computational effort, the driveline has been simulated as a rigid body neglecting torsional elasticity and clutch dynamics (Arsie et al., 2000).

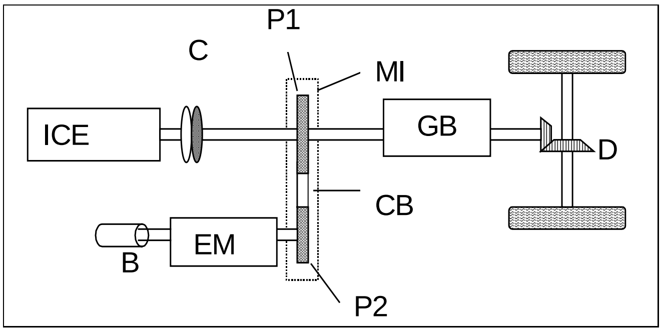



**Figure 1 - Parallel hybrid vehicle powertrain - ICE=Internal Combustion Engine; C= Electromagnetic Clutch; P1, P2=Pulleys; MI=Mechanical Interface; GB= Gear Box; D= Differential Gear; CB=Cogged Belt; EM=Electric Motor; B=Battery.**

## MODEL DESCRIPTION

In order to simulate the hybrid vehicle during a generic driving mission, the developed model describes the main powertrain components and simulates the driver behaviour in following the velocity target. A block diagram of the complete system is sketched in Figure 2 where all the main physical sub-models, the control tasks and the mechanical torque paths are shown. The Driver Behaviour (DB) model is based on the fuzzy logic and provides the actual gas pedal position in following the target velocity profile of the vehicle.

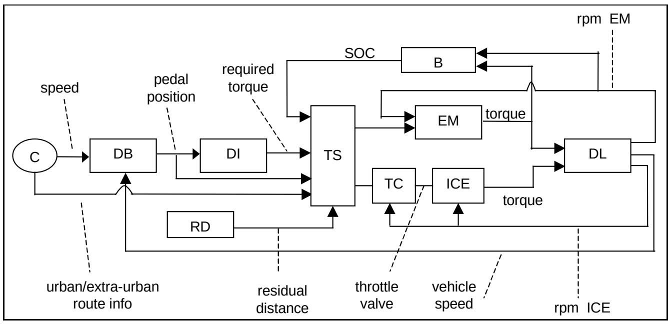
The pedal position and its derivative are used as input for the Driver Interpreter block (DI), which estimates the torque demand (traction or braking torque) to meet the driver intention. On a spark ignition engine, this system is known as torque based control and is implemented for drive-by-wire systems where the mechanical linkage between the gas pedal and the throttle valve is removed. The Driver Interpreter output is split into a torque demand for the ICE and the EM by the Torque Splitter controller (TS). This control action depends on the working modes (i.e. electric, hybrid, recharging and regenerative braking) as well as on the battery state of charge, the route condition (i.e. urban, extra-urban) and the residual mission profile.

According to the drive-by-wire system strategy, a throttle controller is implemented (TC) to provide the effective throttle opening position as function of the ICE torque demand, which is evaluated by the Torque Splitter. The throttle opening is assumed as input for the ICE model to simulate the engine behavior and to estimate the effective engine torque, the pre-catalyst emissions and the fuel consumption. For the current application, the throttle controller is a two-dimensional look-up table, derived from engine experimental data, where the throttle opening is estimated as function of the engine torque demand and the engine speed.

The effective torque delivered by the electric machine (EM) is estimated from the electric torque demand computed by the Torque Splitter, accounting for the EM efficiency stored into a look-up table.

The torque provided by both the EM and the ICE is used as input for the driveline model (DL) to compute the actual rotational speed of EM and ICE and the vehicle speed. For the DL model, a rigid body from the crankshaft to the tires is assumed and the effects of aerodynamic losses and rolling friction are considered.

During the battery recharging the mechanical torque to the generator is supplied by the ICE (recharging mode) or by the DL (regenerative braking mode). Then the battery state of charge (SOC) and the residual distance to destination are updated. In the following sections a description of each block is provided.




**Figue 2 - Block diagram of the parallel hybrid vehicle powertrain model with the driver sub-model (DB) interface. - C = Mission Profile; RD = Residual Distance; DI = Driver Interpreter; TS = Torque Splitter; TC = Throttle Controller; ICE = Internal Combustion Engine; EM = Electric Motor; DL = Driveline; B = Battery Package.**

## INTERNAL COMBUSTION ENGINE MODEL (ICE)

The Internal Combustion Engine (ICE) model is derived from the model O.D.E.C.S., which was developed by the authors for the optimal design of engine control strategies in spark ignition engines (Arsie et al., 2000) and is sketched in Figure 3. It is based on two different modelling approaches, depending on the goals and the phenomena to be studied. The first class of models is a set of black box (steady state neural networks) which provide the engine torque and the exhaust emissions as function of engine state (manifold pressure and engine speed) and control variables (injection time, spark advance). This approach is useful for the control strategy design and optimization, for which the recursive evaluation of a cost function is required. The optimization procedure can be based on either mathematical programming approach or genetic algorithms.

The second engine modelling approach is used to describe the dynamic effects of the air-fuel flow into the intake manifold and is based on a filling-emptying mean value model, neglecting the unsteady fluctuations due to periodic phenomena (Aquino, 1981; Heywood, 1988; Hendricks and Sorenson 1991).

An engine control unit module (ECU) is used to simulate the effects of different strategies for AFR and spark advance control.

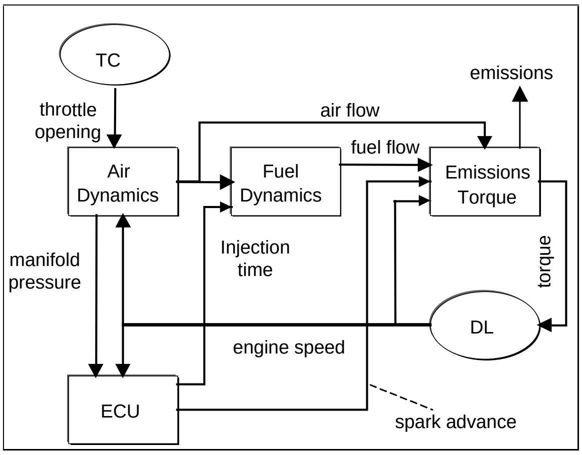



**Figure 3 - Internal Combustion Engine Model (ICE).**

## ELECTRIC MACHINE MODEL (EM)

In a parallel hybrid vehicle the electric machine can work as a motor or as a generator depending on the actual working mode (i.e. electric, hybrid or recharging) (Baumann et al., 1998; Burch et al., 1999; Arsie et al., 1999).

In order to reduce the computational effort, the behavior of the electric machine is modeled through a 2-D look-up table of the efficiency, which is expressed as function of the required torque and the motor/generator rotational speed (Guzzella and Amstutz, 1999). The efficiency map has been derived from literature data and refers to an asynchronous motor with a rated power of 30 [kW] at 9000 rpm. The same efficiency has been assumed, for both motor and generator working modes. Depending on the working mode, the electrical power $P_{EM}$ is given by the following equations (Guzzella and Amstutz, 1999):

$$P_{EM} = T_{EM}\omega_{EM}\eta(\omega_{EM}, T_{EM}) \tag{1}$$

$$P_{EM} = \frac{T_{EM}\omega_{EM}}{\eta(\omega_{EM}, T_{EM})} \tag{2}$$

Equation (1) holds in case of recharging mode when the EM works as generator and charges the battery pack by an electric power $P_{EM}$, while equation (2) is applied for electric and hybrid working modes. In these latter conditions, the EM works as electric motor and is powered by the battery pack which is depleted with an electric power $P_{EM}$. $T_{EM}$ is the torque provided by the EM as required by the Torque Splitter controller and can be either negative or positive depending on the EM working mode.

## DRIVELINE (DL)

The driveline model describes the rotational dynamics of ICE, electric motor, transmission, final drive and wheels. It is composed by a one state dynamic system, neglecting the clutch dynamics during gearshift, the torsional shaft deformation and the tire elasticity. This approach is suitable for simulating long transients where a global analysis on the dynamic behavior is required. However, a multi state dynamic model (Ercole et al., 1999) has been implemented for studies (Arsie et al., 1999, 2000) on comfort, gear shifting, vehicle-driver interface or clutch dynamics.

The driveline is modelled making use of the Newton's law, reducing all the load torque and the momentum inertia to the crankshaft; the aerodynamic losses and the tire rolling friction have been considered as resistant torque. Thus, the driveline dynamics is described by the following differential equation:

$$I\frac{d\omega}{dt} = T_{ICE} + T_{EM} - T_{Res} \qquad (3)$$

where $I$ is the equivalent inertia of the powertrain-vehicle system, $T_{ICE}$, $T_{EM}$ and $T_{Res}$ are the ICE torque, the EM torque and the resistant torque, respectively. In case of electric or hybrid working mode, the EM works as a motor and powers the driveline ($T_{EM}>0$). On the other hand, in case of recharging mode, the EM works as generator and $T_{EM}$ is considered as a load torque ($T_{EM}<0$).

## BATTERY'S MODEL (B)

The Battery package (B) (see Figure 2) has been simulated using the ESS block (Energy Storage System) derived from the ADVISOR simulator (Burck et al., 1999). This block models the batteries taking into account the basic electrochemical processes including heat exchange phenomena as well. The computational block provides the battery state of charge (SOC), the actual current and other variables such as the current thermal state as function of the actual electrical power (i.e. positive or negative). The actual current is computed starting from the electrical power, making use of the Kirchhoff's voltage law. For a complete description of the battery model the reader is addressed to the original work of Burch et al. (1999). For the current application the battery pack is composed by a set of 30 modules of valve-regulated lead-acid (VRLA) 12 V batteries.

## DRIVER MODEL (DB)

The driver model simulates the human driving behavior in following a vehicle mission profile. The driver operation on the engine actuators (accelerator and brake pedals) is indeed dependent upon physical and psychological factors as well as on the actual driving situation. Though the behavior of the driver is theoretically known, mathematical algorithms are not sufficiently realistic yet. Several approaches are available in the literature, addressing to classical control, fuzzy logic or a combination of them (Kiencke and Nielsen, 2000; Allen et al., 1996). In the proposed vehicle model, the control of the longitudinal dynamics is performed adopting a fuzzy logic controller. In order to reproduce both acceleration and deceleration transients the controller operates alternatively on the gas pedal or on the brake. The Fuzzy Logic controller, whose control map is shown in Figure 4, has two inputs corresponding to the actual vehicle acceleration and the error between target and actual vehicle speed, and outputs the gas pedal position (>0; 0÷100%) or the braking pedal position (<0; -100÷0 %). The controller has been designed with seven triangular membership functions for the first input and the output and five triangular membership functions for the second input. 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 (Babuška, 1998).

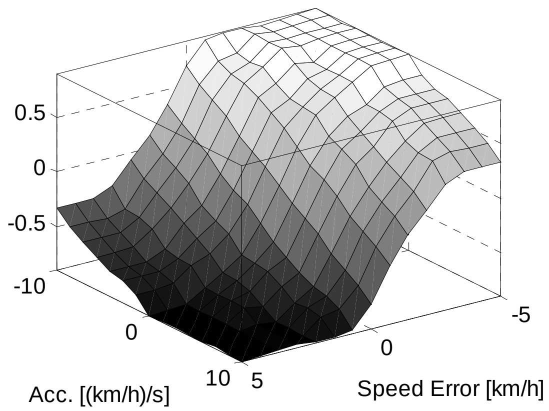



**Figure 4 – Fuzzy control map of the driver model.**

## TORQUE SPLITTER (TS)

The Torque Splitter (TS) manages the on-board energy flow and is the main component of the HEV control system. It computes the torque to be delivered by the ICE and by the EM and evaluates the most suitable working mode (i.e. hybrid, recharging, regenerative braking) for the actual system status, which is defined by the pedal position, the urban/extra urban route, the battery state of charge, the required torque and the residual distance (Figure 5).

Two different strategies are adopted depending on urban or extra-urban drive course by means of a logical switch operated by the driver. They are based on the fuzzy-logic technique and have been designed considering the following main goals: *i)* increase the energy efficiency of the system, *ii)* limit pollution in the urban area, *iii)* guarantee an adequate battery state of charge.

Urban Cycle: the fuzzy logic controller developed for the urban driving cycle receives as inputs the torque demand and the battery state of charge and outputs the torque supplied by the EM, and is composed by 12 membership functions (4 for each input/output variable).

During the urban cycle the electric working mode is assumed as default and the ICE is switched off; the hybrid mode is activated when the vehicle speed exceeds the threshold of 40 [km/h] and the engine load reaches 30 [Nm]. In this condition the ICE supplies most of the required torque. As the battery state of charge decreases, the amount of torque supplied by the ICE increases in order to save the residual battery charge. This control strategy is shown in the fuzzy control map in Figure 6, which illustrates the torque supplied by the electric motor as function of the torque demand and the battery SOC during the urban driving cycle in case of hybrid working mode. The behavior of the fuzzy logic controller is also summarized by the rules reported in Table I, from which it emerges that, as an example, for a great torque demand (High), the torque delivered by the EM is reduced from High to Medium Low as the battery SOC decreases from High to Low.

In order to limit pollution, the recourse to the ICE in urban area is only allowed to power the vehicle, without supplying any extra power for recharging the battery, unless the state of charge is below 25 %. In such a case the recharging mode is enabled and the engine powers the electric generator until a state of charge of 50 % is reached.

Extra-Urban Cycle: in case of extra-urban driving cycle the fuzzy controller estimates the ICE torque as function of the torque demand, the battery SOC and the residual distance, and is composed by 14 membership functions (3 for the battery SOC and the residual distance, 4 for the torque demand and the output).

During the extra-urban cycle the vehicle works in recharging mode, the engine supplies the required traction torque and powers the electric generator for recharging the battery. As the required torque approaches the maximum engine torque, the power supplied to the generator is reduced in order to satisfy the torque demand. Moreover, when the torque demand exceeds the maximum engine torque, the hybrid mode is activated and the electric machine commutes from generator to motor, supplying the extra torque demand. Figure 7 shows the fuzzy control map of the torque delivered by the ICE as function of the battery state of charge and the traction torque demand. The recharging torque is the difference between the torque delivered by the engine (*z*-axes) and the torque required for the traction (Torque Demand). The figure exhibits an increase of the recharging torque when the state of charge approaches the minimum, unless the traction torque demand is close to the maximum engine torque. In such a condition the recharging torque is strongly reduced regardless to the battery SOC and the EM may assist the ICE in providing the extra torque demand. The behavior of the fuzzy logic controller is also evidenced by the rules set showed in Table II.

The influence of the residual distance, which has not been considered in Figure 7 neither in Table II for sake of simplicity, has a minor influence on the whole strategy. A short residual distance weakly affect the controller output by a slight increase of the recharging torque, due to the need to recharge the battery in a shorter time.

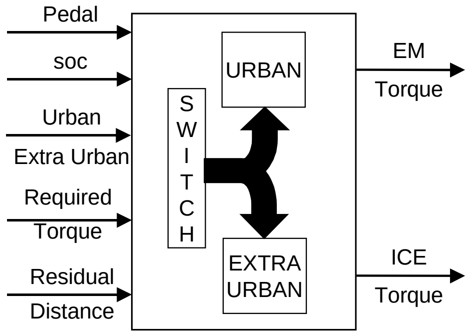



**Figure 5 - Flowchart of the Torque Splitter (TS) controller.**

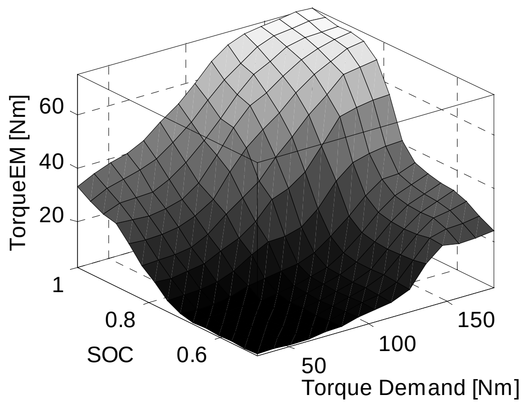



**Figure 6 – Fuzzy control map of the EM torque during urban cycle – Hybrid mode.**

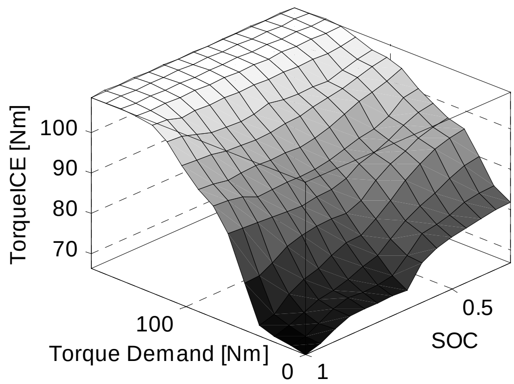



**Figure 7 - Fuzzy control map of the ICE torque during extra-urban cycle – Recharging mode.**

**Table I – Rules set for the fuzzy logic controller during urban cycle – Hybrid mode**

| Torque Demand | SOC: Low | M Low | M High | High |
|---|---|---|---|---|
| High | M Low | M High | High | High |
| M High | Low | M Low | M High | High |
| M Low | Low | Low | M Low | M High |
| Low | Low | Low | Low | M Low |

**Table II – Rules set for the fuzzy logic controller during extra-urban cycle – Recharging mode**

| Torque Demand | SOC: Low | Medium | High |
|---|---|---|---|
| High | High | High | High |
| M High | High | M High | M High |
| M Low | M High | M Low | Low |
| Low | M Low | Low | Low |

## CONTROL STRATEGY OPTIMIZATION

The design of the membership functions and the assignment of an adequate set of rules is one of the most critical task in using fuzzy logic for non-linear control systems (Baumann et al., 1998).

As described in the previous sections, in the present study fuzzy logic controllers have been developed for both the driver behavior and the energy flow management. Nevertheless, in the former case the membership functions have been designed heuristically, while an optimization methodology has been implemented for the latter case, which is directly connected with the key task of improving the energy efficiency of system. Moreover, the fuzzy logic controller for the energy flow management is composed by 26 membership functions (12 for the urban driving cycle and 14 for the extra-urban one), which is difficult to design heuristically with a satisfactory accuracy.

The implemented optimization methodology is based on the genetic algorithms theory, which has been widely adopted for the optimal tuning of fuzzy controllers (Gurocak, 1999; Goldberg, 1989; Herrera et al., 1995) and is detailed in the appendix. In order to reduce the computational burden, Gaussian membership functions have been selected instead of the more common triangular functions, with a significant reduction of the parameters to be identified. Gaussian functions are indeed univocally defined by a mean value ($c$) and a distribution width ($\sigma$), whereas triangular functions require three parameters for their definition. The genetic algorithm realizes then a tuning procedure operating on the membership function peaks ($c$) within a fixed range (Figure 8) and on the distribution widths ($\sigma$) for a total of 52 parameters.

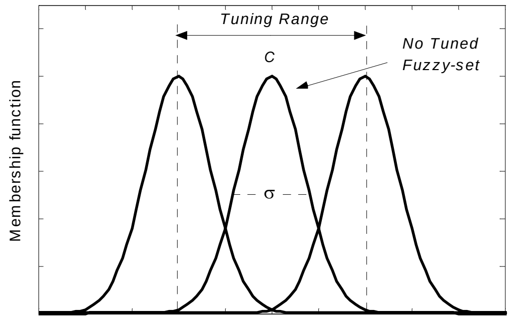



**Figure 8 – Membership functions and tuning range.**

The control strategy optimization has been performed with respect to the specific fuel consumption along the whole driving test cycle. Moreover, a constrain has been introduced to force the battery SOC to recover its initial value at the end of the test cycle. The optimization procedure addresses then to a non linear equality-constrained problem (NEP) (Gill et al., 1989) which has been solved introducing a quadratic penalty function. Thus the objective function to be minimized is:

$$P_Q(c_i,\sigma_i,\rho)=C_s(c_i,\sigma_i)+\rho\,\Delta SOC^2 \qquad (3)$$

where $C_s$ is the specific fuel consumption computed for the whole transient, $\rho$ is a penalty parameter and $\Delta SOC$ is the difference between initial and final battery state of charge. The results of the control strategy optimization and the improvements with respect to an heuristic design of the fuzzy controller are discussed in the next section.

## RESULTS

The proposed model has been used to simulate the behavior of a HEV along a standard ECE-EUDC driving cycle, which accounts for a 4.45 km urban route and a 6.86 km extra-urban route for a total of 11.31 km.

According to the main purpose of HEVs to improve fuel economy, the main task of the proposed methodologies is to design the optimal strategy for the energy flow, reaching the maximum energetic efficiency of the whole powertrain.

Figure 9 illustrates the simulated mission profile: the ECE-EUDC driving cycle is characterized by fast acceleration/deceleration transients in both urban and extraurban areas, thus being indicated to evaluate the overall vehicle behavior. On the same figure the actual vehicle speed profile is superimposed; it exhibits an excellent agreement with the target speed evidencing the satisfactory features of the driver behavior model (DB).

The Figure 10 and Figure 11 focus on the energy control strategy actuated by the torque splitter controller (TS), which is the most critical component to be designed in order to ensure the expected improvement in fuel economy. The figures show the torque demand estimated by the driver interpreter (DI) and the torque supplied by the EM and ICE along the transient, in the urban and extra-urban route respectively.

In the urban route (Figure 10) the control strategy enables the electric working mode; the EM powers the vehicle while the ICE is switched off, in order to avoid low efficiency working conditions. As the engine load increases, the hybrid working mode is enabled and the ICE assists the EM in powering the vehicle in order to preserve the battery state of charge (see Figure 10, around 140 s).

In the extra-urban route (Figure 11), the recharging working mode is enabled; the ICE works at high load around the operating condition with minimum specific fuel consumption and powers both the vehicle and the EM for recharging the battery pack. During the vehicle deceleration (see Figure 11, after 1128 s) the ICE is switched off and the generator is powered by the vehicle kinetic energy (i.e. regenerative breaking working mode)

The behavior of the battery state of charge (SOC) along the transient is shown in Figure 12. It exhibits a reduction during the urban cycle up to 805 s when the EM works as a motor depleting the battery pack, with a partial energy recovery due to the regenerative braking. During the extra-urban route (from 805 to 1200 s), the SOC increases due to the recharging operation and it reaches a final value which is about 10 % more than the initial condition.

The improvement of fuel economy in HEVs due to the recourse to several energy sources (chemical, electrical and mechanical) and the advantages concerned with their optimal control strategy of the energy flow are shown in the next figures.

Figure 13 and Figure 14 show the ICE working conditions during the ECE-EUDC driving cycle vs. the ICE global efficiency map, in case of non-optimized and optimized energy control strategy, respectively. The comparison of the two figures evidences that in case of optimal control strategy, the operating conditions are moved toward the high efficiency area (over 30 %), corresponding to the minimum specific fuel consumption.

The specific fuel consumption for the whole driving cycle is shown in Figure 15. The results are referred to the HEV in case of optimized and non optimized energy control strategy and to an equivalent standard ICE vehicle, with a mass reduced by 400 kg, due to the absence of the battery pack and the EM. The comparison evidences the progressive reduction of specific fuel consumption, moving from the standard ICE powertrain to the optimised HEV, through the non optimised HEV.

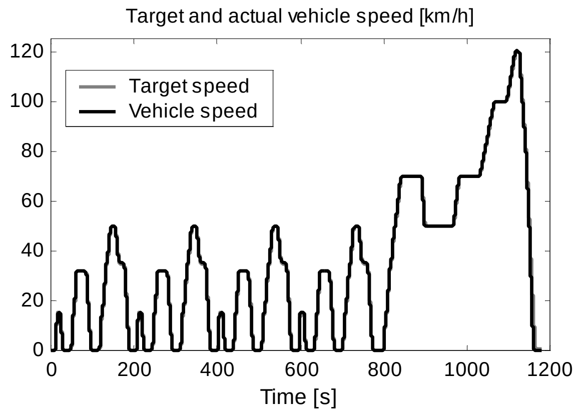



**Figure 9 – Target and actual vehicle speed.**

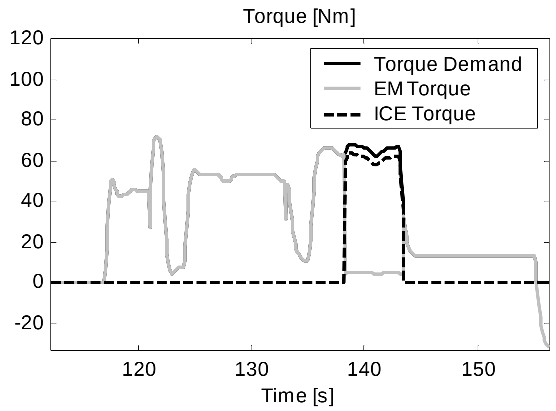



**Figure 10 - Torque management in the urban route.**

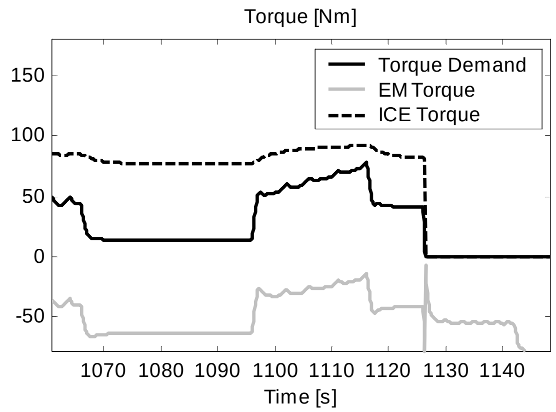



**Figure 11 - Torque management in the extra-urban route.**

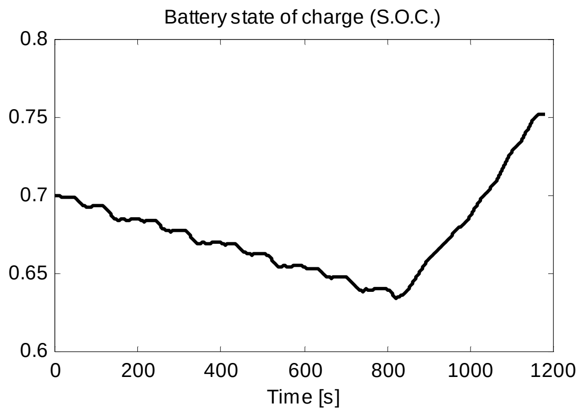



**Figure 12 - Battery state of charge along the transient.**

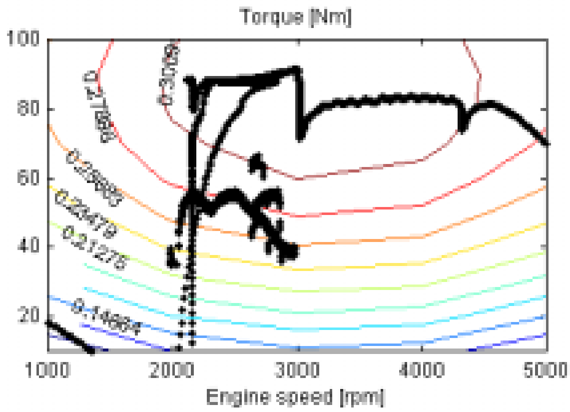



**Figure 13 – Map of the ICE global efficiency, showing the effective working conditions.**

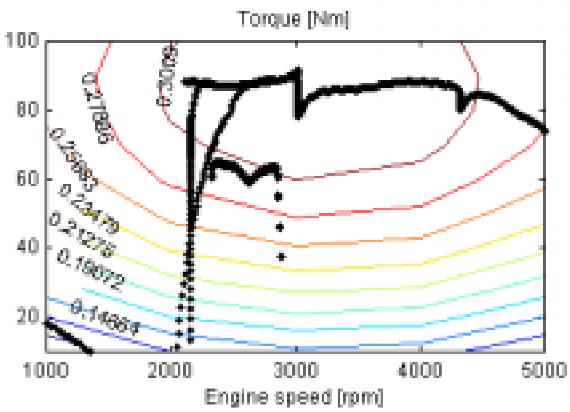



**Figure 14 - Map of the ICE global efficiency, showing the effective working conditions for the optimized control strategies.**

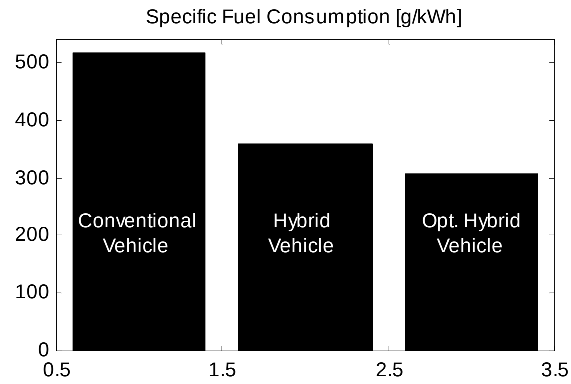



**Figure 15 - Specific fuel consumption for the overall driving cycle.**

## CONCLUSIONS

The paper has dealt with the simulation of a parallel Hybrid Electric Vehicle (HEV) and the design of the optimal control strategies for the on board energy flow. A powertrain model has been used to simulate the dynamic behavior of all the HEV components, making use of different modeling approaches ranging from mean value models (MVM) to fuzzy logic, through neural networks. MVMs have been used to simulate the air-fuel dynamics in the intake manifold and the driveline-vehicle dynamics. Neural Networks have been used to model the in-cylinder processes for estimating engine performances. Fuzzy logic controllers have been designed for the most critical task, which is the management of the energy flow between ICE, EM and battery pack.

The proposed model structure allows to simulate the HEV behavior for a given driving cycle and to design optimal energy control strategies for improving fuel economy. This objective has been pursued making use of genetic algorithms, which have been implemented to identify the parameters of the fuzzy logic controllers.

The proposed simulation and optimisation methodologies have been tested for a standard ECE-EUDC driving cycle, evidencing a reduction of about 20 % in the specific fuel consumption with respect to a standard ICE vehicle. Moreover, the energy control strategy optimization, performed via genetic algorithms, has given a further improvement of the global efficiency by 10 %. Future works will be devoted to meet the conflicting goals to improve fuel economy and reduce environmental impact, by the optimization of the fuzzy logic controller with respect to both fuel consumption and exhaust emissions.

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## REFERENCES

Allen R.W., Rosenthal T.J., Hogue J.R. (1996), *Modeling and Simulation of Driver/Vehicle Interaction*, SAE Paper 960177.

Aquino C.F. (1981), *Transient A/F Control Characteristics of the 5 Liter Central Fuel Injection Engine*, SAE Paper 810494.

Arsie I., Caraceni A., Pianese C., Rizzo G., Toro C. (1999), *Modello Dinamico del Sistema Propulsore–Trasmissione di una Vettura Ibrida per Applicazioni Controllistiche*, Proc. of 54° Congresso ATI, L'Aquila, sept. 14-17 1999, pp. 1281-1292, (in Italian).

Arsie I., Pianese C., Rizzo G., Flora R., Serra G. (2000), *A Computer Code for S.I. Engine Control and Powertrain Simulation*, SAE Paper 2000-01-0938, in SAE 2000 Transactions - Journal of Engines, Vol. 109-3.

Babuška R. (1998), Fuzzy Modeling for Control, Kluwer Academic.

Baumann B., Rizzoni G. and Washington G. (1998), *Intelligent Control of Hybrid Vehicles using Neural Networks and Fuzzy Logic*, SAE paper 981061, in SP-1356, pp. 125-133.

Burch S., Cuddy M., Johnson V., Markel T., Rausen D., Sprik S., Wipke K. (1999), *ADVISOR: Advanced Vehicle Simulator*, available at: http://www.ctts.nrel.gov/.

Ercole G., Mattiazzo G., Mauro S., Velardocchia M. (1999), *Co-operating Clutch and Engine Control for Servoactuated Shifting through Fuzzy Supervisor*, SAE Paper 1999-01-0746.

Gill P. E., Murray W., Wright M. (1989), Practical Optimization, Academic Press.

Goldberg D. (1989), Genetic Algorithms in Search, Optimization, and Machine Learning, Addison Wesley.

Gurocak H.B. (1999), *A Genetic-Algorithm-Based Method for Tuning Fuzzy Logic Controllers*, Fuzzy Sets and Systems, vol. 108, pp. 39-47, Elsevier Science Ltd..

Guzzella L. and Amstutz A. (1999), *CAE Tools for Quasi-Static Modeling and Optimization of Hybrid Poweretrains*, IEEE Transactions on Vehicular Technology, vol. 48, no. 6, November 1999.

Hendricks E. and Sorenson S.C. (1991), *SI Engine Controls and Mean Value Engine Modelling*, SAE Paper 910258.

Herrera F., Lozano M., Verdegay J. (1995), Tuning fuzzy controllers by genetic algorithms, Internat. J. Approx. Reasoning.

Heywood J.B. (1988), Internal Combustion Engine Fundamental, MC Graw Hill.

Hochgraf C.G., Ryan M.J., Wiegman H. (1996), *Engine Control Strategy for a Series Hybrid Electric Vehicle Incorporating Load-Leveling and Computer Controlled Energy Management*, SAE Paper 960230, in SP-1156, pp.11-24.

Kiencke U., Nielsen L. (2000), Automotive Control Systems, Springer.

Nagasaka A., Nada M., Hamada H., Hiramatsu S., Kikuchi Y., Kato H. (1998), *Development of the Hybrid/Battery ECU for the Toyota Hybrid Systrem*, SAE Paper 981122, in SP-1331, pp. 19-27.

Powell B.K., Bailey K.E., Cikanek S.R. (1998), *Dynamic modeling and Control of Hybrid Vehicle Powertrain Systems*, IEEE Transactions on Control Systems, vol. 18, no. 5, October 1998.

Riley Q. R. (1994), Alternative Cars in the 21st Century: A New Personal Transportation Paradigm, SAE Publication.


## APPENDIX A

The fuzzy logic theory has found wide applications in the field of modeling and control of dynamic systems, due to its capability to integrate information from several sources, such as physical laws, empirical models and measurements data (Babuška, 1998).

Fuzzy models can be seen as logical models based on the use of rules as:

*"**if** the battery SOC is **low then** the recharging torque is **high**"*

which establish logical relation between the system variables (i.e. battery SOC and recharging torque) and relate their qualitative values (***low***, ***high***). The interface between the linguistic qualitative values in the rules and the numerical input/output variables is given by the membership functions (or fuzzy sets).

The membership function $\mu_A(x)$ of a numerical variable ($x$) can be seen as a transfer function from the space $X$ to a new ordered space, which expresses the degree of fulfillment of the input $x$ to the fuzzy set $\mu_A(x)$:

$$\mu_A(x) : X \Rightarrow [0,1] \qquad \text{(A.1)}$$

The fuzzy logic modeling is performed through three different process: fuzzification, inference, defuzzification (Babuška, 1998).

**Fuzzification**: it is the process of evaluating the degree of membership $\mu_A(x)$ of the input $x$ to the fuzzy set $A$. In case of different input variables, the logical *i-th* rule $R_i$ is:

***if*** $x_1$ is $A_{i1}$ ***and*** $x_2$ is $A_{i2}$ ***and*** . . . ***and*** $x_n$ is $A_{in}$ ***then*** $y$ is $B_i$ (A.2)

and the fuzzification process creates a multivariate *fuzzy-set,* whose degree of fullfillment is estimated with the intersectrion ($\cap$) of the $n$ degrees of fullfillments of the antecedents:

$$\beta_i = \mu_{Ai1}(x_1) \cap \mu_{Ai2}(x_2) \cap .. \cap \mu_{Ain}(x_n) = \min(\mu_{Ai1},..,\mu_{Ain}) \qquad \text{(A.3)}$$

**Inference**: is the process of deriving an output fuzzy set given the rules and the inputs. The most commonly used method is the Mamdami inference process, which is based on three steps:

***1)*** estimation, for each rule $i$, of the degree of fulfillment $\beta_i$ of the antecedent:

$$\beta_i = \mu_{Ai1}(x_1) \cap \mu_{Ai2}(x_2) \cap \ldots \cap \mu_{Ain}(x_n) \qquad \text{(A.4)}$$

***2)*** evaluation, for each rule, of the output fuzzy set $B'_i$:

$$\mu_{B'i}(y) = \beta_i \cap \mu_{Bi}(y), \;\; \forall y \in Y' \qquad \text{(A.5)}$$

***3)*** evaluation of the aggregated output fuzzy set by taking the maximum union of the individual conclusions:

$$\mu_{B'}(y) = \max_{i=1\ldots n} \mu_{B'i}(y),\ \forall y \in Y' \quad \text{(A.6)}$$

**Defuzzification**: is a transformation that replaces a fuzzy set by a single numerical value representative of that set. The most commonly used defuzzification method is the centre of gravity:

$$Z = \frac{\sum_{q=1}^{N_q} \mu_{B'}(y_q) \cdot y_q}{\sum_{q=1}^{N_q} \mu_{B'}(y_q)} \quad \text{(A.7)}$$

where $N_q$ is the number of discretized values $y_q$ in $Y'$.

## APPENDIX B – GENETIC ALGORITHMS

Genetic algorithms are adaptive optimization methods, which according to the Darwin theory, emulate the genetic processes of the biological species. The algorithms are based on the manipulation of numerical strings representing the system variables in binary code. The computational process describes the reproduction, the mutation and the decay of a population of individuals, each represented by a finite-length numerical string (Goldberg, 1989). The structure of a genetic algorithm is composed by an iterative procedure through the following four main steps:

1. Creation of an initial population $P_o$.
1. Evaluation of the performance of each individual *p* of the population $P_o$ by means of a fitness function.
2. Application of the genetic operators: Reproduction, Crossover and Mutation.
3. Iteration on the steps 2) and 3) for a preset number of generations.

**Initial population:** to start the algorithm an initial population of individuals (or chromosomes) is needed; for the current application an individual is a fuzzy logic controller characterized by a set of membership functions and a population is a collection of fuzzy logic controllers among which the method is searching for the best. The individuals are formed by encoding the initial membership functions which are heuristically generated by the designer.

**Fitness setting:** a fitness value is associated to each individual, expressing the performance of the related solution with respect to a fixed objective function to be minimized or maximized.

**Reproduction:** is the process in which the most fit individuals (chromosomes) in the population receive correspondingly large number of copies in the next generation.

This procedure increases the quality of the chromosomes in finding the optimal solution to the tuning problem. Every solution (individual) is reproduced in a number of copies *q* proportionally to its fitness ($f_i$), by means of a methodology which is known as biased roulette wheel:

$$q = \cdot \frac{f_i}{\sum_{=1}^{n} f_i} \quad \text{(B.1)}$$

where *n* is number of individuals of the population.

**Crossover**: when a collection of good individuals has been selected, they exchange information by the crossover operator. Two chromosomes (parents) randomly swaps part of them in the range [1, $\ell$-1] ($\ell$ is the string length), thus generating two new chromosomes (offsprings) (Figure A.1). This mechanism makes the best performing individuals to mix and match each other in order to evidence their qualities.

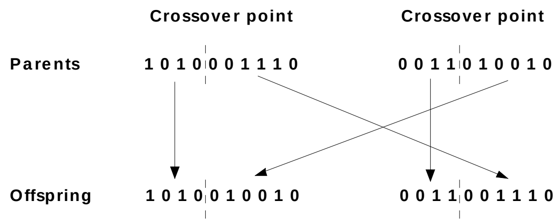


**Figure A.1 – Crossover operator.**

**Mutation:** is a small perturbation of a chromosome by randomly flipping one of its bits. It allows investigating new chromosomes which are not directly derived from the previous generation.

The next generation is then formed by some individuals from the previos generation, some offsprings and some perturbations. After a preset number of generations, the algorithm outputs the individual with the best fitness, which corresponds to the optimal solution of the problem.