HYBRIDIZATION EFFECT ON FUEL CONSUMPTION AND OPTIMAL SIZING OF COMPONENTS FOR HEV

Mauro G. Carignano[(a)], Norberto M. Nigro[(b)], Sergio Junco[(c)]

[(a)] EIM, Escuela de Ingeniería Mecánica, Facultad de Ciencias Exactas, Ingeniería y Agrimensura, Universidad Nacional de Rosario, Berutti 2109, Rosario, Argentina.
[(b)] CIMEC, Centro Internacional de Métodos Computacionales en Ingeniería, INTEC-CONICET-UNL, Güemes 3450, Santa Fe, Argentina.
[(c)] LAC, Laboratorio de Automatización y Control, Facultad de Ciencias Exactas, Ingeniería y Agrimensura, Universidad Nacional de Rosario, Riobamba 250bis, Rosario, Argentina.

[(a)]mauroc@fceia.unr.edu.ar, [(b)] norberto.nigro@cimec.santafe-conicet.gov.ar, [(c)]sjunco@fceia.unr.edu.ar

ABSTRACT
Reductions of fuel consumption and gas emissions count among the main advantages of hybrid electric vehicles (HEV). It is well known that the level of hybridization has a large influence on the fuel consumption. On the other hand, the cost of manufacturing HEV increases since at least two power sources are required. Therefore, a proper selection of the hybridization factor (HF) could be the result of a tradeoff between fuel consumption and cost. This paper shows how HF affects fuel consumption of a HEV. The work was realized using Series and Parallel architectures, with an internal combustion engine and electrochemical batteries as thermal machine and storage system respectively. Simulations with different HF are evaluated using urban and road driving profiles. In order to achieve optimal power split, dynamic programming was applied. The results show that there exists an optimal HF which generates the minimum fuel consumption for each architecture. According that, the optimal size of components are found for each case analyzed.

Keywords: hybrid electric vehicle, hybridization factor, fuel consumption, optimization

1. INTRODUCTION

Hybrid electric vehicles have had a great saving fuel compared with conventional internal combustion engine vehicles due to both, recovering braking energy and higher efficiency operation of the internal combustion engine (ICE). Accordingly, hybridization power-train of conventional vehicles makes them more efficient and cleaner. The hybridization factor (HF) is an important feature of the HEV, which points out the ratio between the installed power coming from electric source and total installed power. Commercial HEV have shown improved fuel consumption as HF is increased. Improving up to 45% efficiency can be achieved with full-HEV (Tie and Tan 2013). Contrasting to the advantages mentioned above, HEVs have higher costs than conventional vehicles because extra components such as electric machines and energy storage systems are required. Depending on the kind of HEV, the battery cost can reach one-third of the total vehicle cost (Tie and Tan 2013). Other issues like security, space, and life cycle are associated with some components of HEV. Therefore, proper election of the HF for a HEV has no trivial answer, but rather it will result from a complex tradeoff taken into account the fuel consumption, manufacturing costs and lifecycle, among others.

This work shows how HF affects the fuel consumption of the HEV. Energetic approach and backward models (Chan, Bouscayrol and Chen 2010) are used to perform the study. Specifically, Series and Parallel-HEV architectures with different HF are analyzed using urban and road driving cycle. Electrochemical batteries and internal combustion engine are used as energy storage system and thermal machine respectively.

Previous works from other authors addressed similar issues. Lukic et al. (Lukic and Emadi 2004) and Holder and James (Holder and Gover 2006) worked with Parallel-HEVs using ADVISOR. Capata and Coccia (Capata and Coccia 2010) tests Series-HEV with a gas turbine as thermal engine. Cuddy and Wipke (Cuddy and Wipke 1997) evaluate Series and Parallel-HEVs consumption through ADVISOR simulation. In all of them the power split was realized through suboptimal strategy of Supervisory Control (SC). It is known that SC has a large effect on fuel consumption (Sciarretta, Serrao, Dewangan, Tona, Bergshoeff, Bordons and Wu 2014). In this work, unlike the above, an optimal instead of suboptimal SC strategy is applied in order to achieve a better comparison. Specifically, dynamic programming is used to reach the minimal fuel consumption for each configuration.

The paper is organized as follows. First, models of the HEV components are described in Section II. Then, component sizing, backward approach and SC strategy are presented in Section III. Details and results of simulations are summarized in Section IV. Finally, some conclusions, comments and futures works are pointed out in Section V.

2. HYBRID ELECTRIC VEHICLE MODEL

2.1. Architectures

HEVs are frequently classified regarding drive-train architecture. The most popular and widely used are Series, Parallel and Series/Parallel. The two first are discussed in this work. Although there exist different possibilities inside each drivetrain architecture, only those shown in Figure 1 will be utilized.

As shown, most of the typical HEV components are present in both architectures. The generator is only present in the Series architecture, whereas in the Parallel two gear boxes are required. Main difference is in the way of interconnection. Each component is related to the rest through a power flow. As mentioned in introduction, this approach leads to an energetic and power analysis.

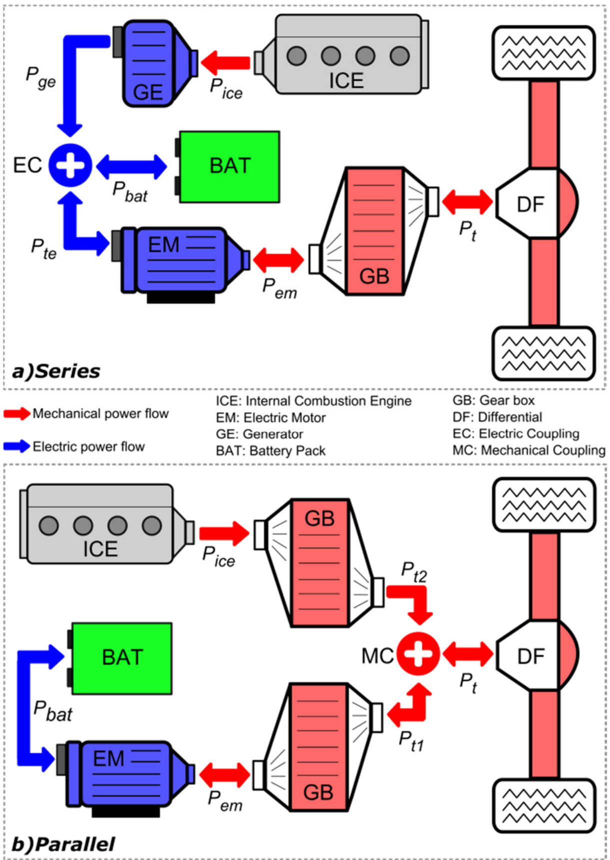

Figure 1: Architectures a) Series b) Parallel

Some components shown in Fig. 1 are considered to be ideal, i.e. power lossless. This group includes differential, mechanical and electric coupling. The ideal Electrical and mechanical coupling are represented by the following power balance equations:

$$Electrical\ Coupling: \quad P_{te} = P_{bat} + P_{ge} \tag{1}$$

$$Mechanical\ Coupling: \quad P_t = P_{t1} + P_{t2} \tag{2}$$

On the other hand, for electric motor, internal combustion engine, generator, battery and gear box, efficiency values are considered as simplified models. This will be explained in detail in Section III.

2.2. Hybridization Factor (HF)

In order to evaluate the influence of HF on the fuel consumption, this concept would be defined explicitly for both architectures. For Parallel and Series/Parallel-HEV, HF is the relation between the maximum power of the electric motor and the total installed power (Lukic, Cao, Bansal, Rodríguez and Emadi, 2008). This is:

$$HF \triangleq \frac{P_{em\_max}}{P_{em\_max} + P_{ice\_max}} \tag{3}$$

Where $P_{"x"\_max}$ is the maximum power that component "x" is able to deliver and/or receive. This definition is not suitable for Series-HEV. For example, if maximum power from battery tend to zero, $P_{em\_max} \cong P_{ice\_max}$ and HF tend to 0.5 (see Fig.1a). HF should tend to zero 0 when maximum power from electric source tends to zero (like conventions vehicles or vehicles with electric drive-train without electric storage). Inversely, HF should tend to 1 when maximum power of fuel source tends to 0 (like purely electric vehicle).

In this work a slight modification to HF for Series-HEV is proposed. It is deduced following the idea that HF expresses the relation between maximum mechanical power coming from electric source and the maximum mechanical power coming from fuel + electric source. Accordingly, in case of Parallel-HEV (considering equal efficiency for both GBs), HF is correctly defined by Eq. 3. However, in case of Series-HEV, HF results:

$$HF \triangleq \frac{P_{bat\_max} \cdot \eta_{em} \cdot \eta_{gb}}{P_{bat\_max} \cdot \eta_{em} \cdot \eta_{gb} + P_{ice\_max} \cdot \eta_{ge} \cdot \eta_{em} \cdot \eta_{gb}}$$

Assuming $P_{ice\_max} \cdot \eta_{ge} = P_{ge\_max}$ and simplifying leads to:

$$HF \triangleq \frac{P_{bat\_max}}{P_{bat\_max} + P_{ge\_max}} \tag{4}$$

Eq. (3) and Eq. (4) could be seen as a relation between the maximum powers involved in coupling component (see Fig.1). These expressions will be used in Section III to define the size of the components.

2.3. Electric motor, Generator, Internal combustion engine and Gear box

Fuel consumption and global efficiency of a HEV depend on the efficiency of each drive-train component. EM, GE, ICE and GB are the main components that contribute to overall efficiency. Due to the high complex phenomena present in each of these components, detailed analytical model should be employed to obtain its efficiency. A common practice is testing each of them and obtaining an efficiency surface as a function of port variables (voltage, current, speed and torque) (Sciarretta, Serrao, Dewangan, Tona, Bergshoeff, Bordons and Wu 2014). Processing this surface it is possible to extract a curve of best efficiency as function of output power. It

ISBN 978-88-97999-63-8; Bruzzone, Dauphin-Tanguy, Junco and Longo Eds.

other words, each value on the curve represents the best possible efficiency for each power value. It is assumed that GB is automatic and able to position the ICE and EM on a speed that generates the best efficiency. Here, data from EM, GE, ICE and GB similar to those used on the Toyota Prius are considered as reference (Wipke, Cuddy and Burch 1999; Olszewski 2005). Because GB shows low efficiency variations, a constant $\eta_{GB} = 0.95$ is considered in all power range.

The maximum power of each component changes according to the architecture and HF selected. So it is useful in these cases to work with normalized efficiency curves. Once defined the maximum power of the components, final efficiency tables are generated scaling linearly these curves. Figure 2 shows normalized curves of efficiency for EM, GE and ICE respectively.

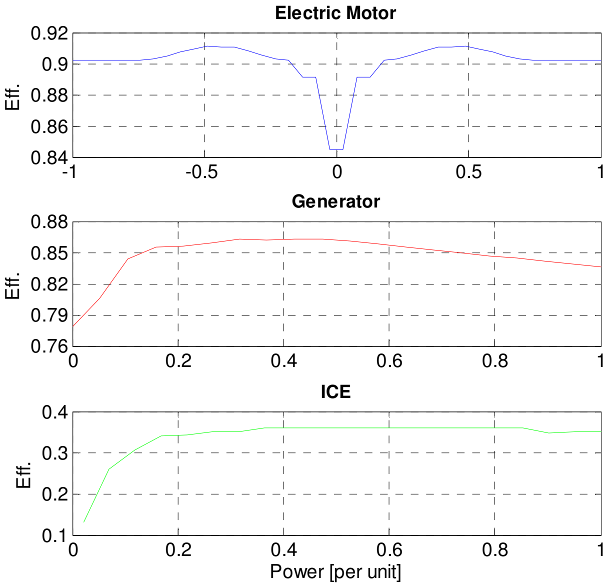

Figure 2: Efficiency of components

Notice that the EM can work both as motor and generator, whereas GE and ICE only work as power suppliers. Efficiency of power electronics converters as rectifiers or inverters are included in these curves.

2.4. Battery model

In this subsection, in contrast with previous ones, an explicit expression of battery efficiency and energy storage will be deducted.

Generally a battery is composed by a number of electrochemical cells (N_cell). However, it can be idealized as a system composed of a single component. Accordingly, a model of battery used to get its efficiency is presented in Fig. 3. It consists on an ideal voltage source and an internal resistance connected in series, so only ohmic losses are considered. Variations of voltage and resistance in function of state of charge of battery are neglected.

$P_{0bat} \triangleq I_{bat} U_{0bat}$ is the power flow from the ideal electric source, and $P_{bat} \triangleq U_{bat}\, I_{bat}$ is the power flow as seen from battery terminals. The power balance leads to:

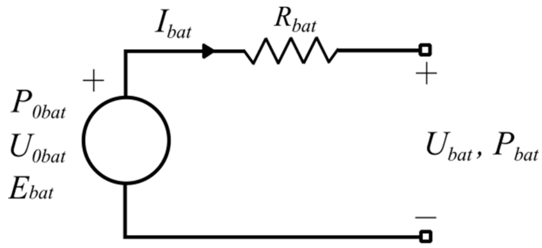

Fig. 3: Battery circuit model

$$P_{0bat} - I_{bat}^2\, R_{bat} - P_{bat} = 0 \tag{5}$$

The battery energy storage and state of charge can be expressed as:

$$E_{bat}(t) = E_{t0bat} - \int_0^t P_{0bat}(\tau)d\tau \tag{6}$$

$$SoC(t) = \frac{E_{bat\_max} - E_{bat}(t)}{E_{bat\_max}} \tag{7}$$

Where E_{bat_max} and E_{t0bat} are full energy capacity and initial energy of battery respectively.

As will be seen later, P_{bat} will be a control variable and E_{bat} a state variable. So it is necessary to obtain an expression to evaluate $E_{bat}(t)$ using P_{bat} as input. The battery efficiency is defined as:

$$\eta_{bat}(P_{bat}) \triangleq \frac{P_{bat}}{P_{0bat}} \tag{8}$$

Using eq. (5) and $I_{bat} = \frac{P_{0bat}}{U_{0bat}}$, P_{bat} can be written as:

$$P_{bat} = P_{0b} - \left(\frac{P_{0bat}}{U_{0bat}}\right)^2 R \tag{9}$$

Then, P_{0bat} can be written as function of P_{bat} as follows:

$$P_{0bat} = \frac{U_{0bat}^2}{2\,R}\left(1 + \sqrt{1 - \left(\frac{4\,R_{bat}\,P_{bat}}{U_{0bat}^2}\right)}\right) \tag{10}$$

Using eq. (9) and eq. (10) in (8), the efficiency results:

$$\eta_{bat}(P_{bat}) = \frac{1}{2}\left(1 + \sqrt{1 - \left(\frac{4\,R\,P_{bat}}{U_{0bat}^2}\right)}\right) \tag{11}$$

This is an expression of battery efficiency, with R_{bat} and U_{0bat} as parameters. It will be useful to further analysis to use the maximum battery power (P_{bat_max}) as parameter instead of the previous two.

P_{bat_max} could be calculated from the maximum allowed voltage variation ΔU_{bat_max}. It can see that using $\Delta U_{bat\_max} \triangleq 0.2\, U_{0bat}$, the maximum battery power results:

ISBN 978-88-97999-63-8; Bruzzone, Dauphin-Tanguy, Junco and Longo Eds.

$$P_{bat\_max} = 0.16\ \frac{U_{0bat}^2}{R} \tag{12}$$

Using eq. (12) in eq. (11) the battery efficiency results:

$$\eta_{bat}(P_{bat}) = \frac{1}{2}\left(1 + \sqrt{1 - \left(\frac{0.64\ P_{bat}}{P_{bat\_max}}\right)}\right) \tag{13}$$

This is the final expression desired. It is worth noticing that this efficiency expression only depends on the maximum battery power. Figure 4 shows battery efficiency as function of P_{bat} per unit.

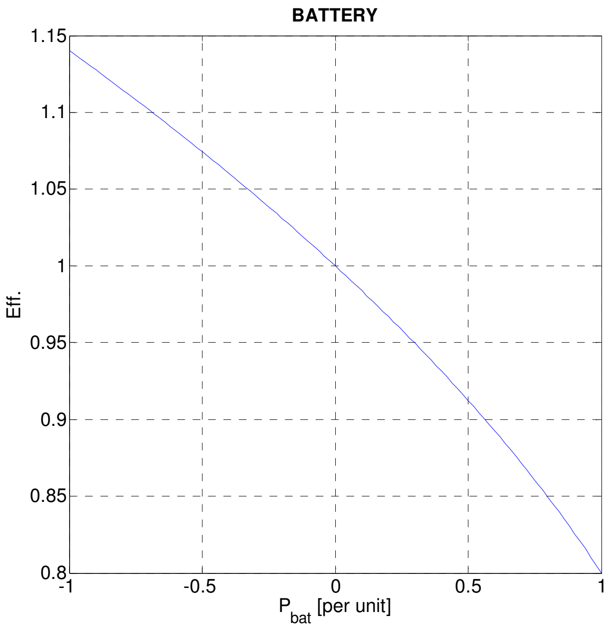

Fig. 4: Battery efficiency

Finally, from eq. (6), E_{bat} can expressed as follows:

$$E_{bat}(t) = E_{t0bat} - \int_0^t \frac{P_{bat}(\tau)}{\eta_{bat}(P_{bat}(\tau))} d\tau \tag{14}$$

Returning to the idea of a battery as a set of cells, for a given electrochemical cell, the relation between P_{bat_max} and N_{cell} can be calculated as:

$$N_{cell} = \frac{P_{bat\_max}}{P_{cell\_max}} \tag{15}$$

Where, similar to eq. (12):

$$P_{cell\_max} = \frac{0.16\ U_{0cell}^2}{R_{cell}} \tag{16}$$

Then, N_{cell} can be evaluated from these two equations at each configuration proposed.

3. METHODOLOGY

3.1. Sizing components

The size of a component in a HEV is generally expressed by the maximum power the component is able to deliver or receive. In this subsection power requirements and constraints will be defined and used to size the components of the HEV. This allows to perform reasonable comparisons between different configurations and architectures.

In the batteries, the size could be defined by either the maximum power flow allowed or the storage capacity (Carignano, Cabello and Junco 2014). Results obtained in current paper have shown that, in all cases of HEV simulated, the battery size is conditioned by the maximum flow power. This means that the minimum charge level is never reached if the battery has been sized according to the maximum power flow.

Main requirement to take into account for sizing is the maximum total power of HEV, i.e. the maximum power available at wheels (P_{t_max}). For this work the value $P_{t\_max} = 75\ kW$ was considered.

Moreover, some power constraints must be fulfilled for each architecture. These can be easily derived from Figure 1. In case of Series-HEV:

$$P_{em\_max} = \frac{P_{t\_max}}{\eta_{gb}} \tag{17}$$

$$P_{ge\_max} + P_{bat\_max} = \frac{P_{em\_max}}{\eta_{em}(P_{em\_max})} \tag{18}$$

$$P_{ice\_max} = \frac{P_{ge\_max}}{\eta_{ge}(P_{ge\_max})} \tag{19}$$

For the Parallel-HEV the power constraints are:

$$P_{em\_max} + P_{ice\_max} = \frac{P_{t\_max}}{\eta_{gb}} \tag{20}$$

$$P_{bat\_max} = \frac{P_{em\_max}}{\eta_{em}(P_{em\_max})} \tag{21}$$

Notice that for Series-HEV there are 3 equations and 4 unknowns (P_{em_max} ; P_{ge_max} ; P_{bat_max}; P_{ice_max}), while for parallel-HEV there are 2 equations and 3 unknowns (P_{em_max}; P_{bat_max}; P_{ice_max}). The remaining equation in both cases is provided by the HF definitions presented in subsection 2.2.

Finally, a constraint from minimum road speed imposes that the HEV must be able to maintain a constant speed of 120Km/h without using electric source, i.e. working only with ICE. This restriction will limit the minimum size of the ICE.

3.2. Backward approach and Supervisory control

As mentioned in the introduction, backward models (Chan, Bouscayrol and Chen 2010) are used in this work. This approach avoids using low level controllers (typically PID) in order to follow speed references. This means that dynamic and control from power components are not modeled and they was assumed fast enough to be neglected. Figure 5 shows schematic block diagrams for both architectures.

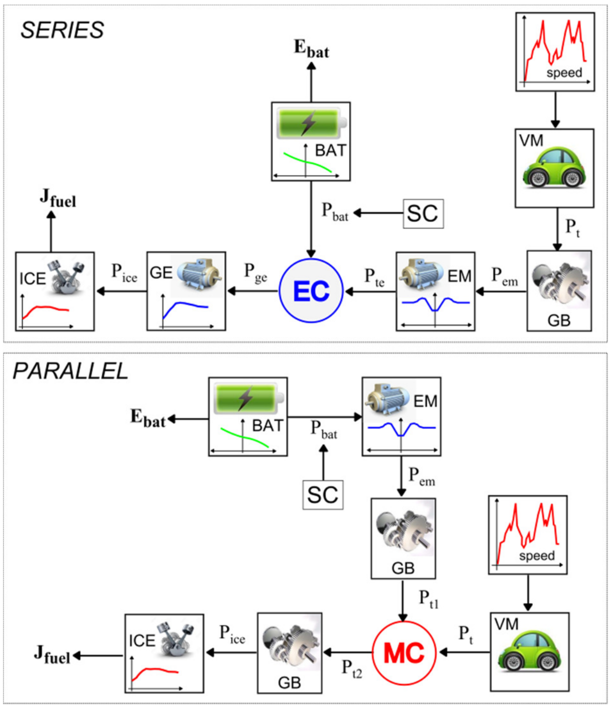

Figure 5: Backward models

VM is a first order non linear vehicle model that considers inertial forces, rolling and aerodynamic resistances (Carignano, Cabello and Junco 2014). SC stands for Supervisory Control. As mentioned in the introduction, in order to achieve the minimum fuel consumption for each configuration simulated, optimal control through dynamic programming (DP) was applied.
There exists different ways to implement DP in order to achieve a minimum fuel consumptions in a HEV (Vinot, Trigui, Cheng, Espanet, Bouscayrol and Reinbold 2014; Pérez, Bossio, Moitre and García 2006).
Discretized time domain is used for these approaches. Total cycle time T is divided in N equal intervals of length $t_s = T/N$. The objective function to be minimized in this work is the accumulated fuel consumption, which can be calculated as follows:

$$J_{fuel} = \sum_{i=1}^{N} \dot{m}_f \, . t_s \qquad (22)$$

where $\dot{m}_f$ represents instantaneous fuel rate consumption. This is considered to be constant during one interval of time. $\dot{m}_f$ depends on instant power delivered by ICE ($P_{ice(i)}$). According to the models described, $P_{ice(i)}$ can be calculated as function of P_t and P_{bat}:

$$P_{ice\,(i)} = g(P_{t(i)}, P_{bat(i)}) \qquad (23)$$

where $g(\cdot)$ represent an static relations between $P_{ice\,(i)}$, $P_{t\,(i)}$ and $P_{bat(i)}$. Notice that $g(\cdot)$ is different for each architecture. Then, P_t only depends on the driving cycle for a given VM model. Furthermore, P_{bat} is a free variable that is controlled by SC. Using eq. (23) in (22) the objective function can be written as:

$$J_{fuel} = T. \sum_{i=1}^{N} \dot{m}_f(i, P_{bat(i)}) \qquad (24)$$

Notice that J_{fuel} only depends on the power flows from the battery (control variable).
The energy in the battery is the state variable and its dynamics can expressed as:

$$E_{bat(i+1)} = E_{bat(i)} - \frac{P_{bat(i)}}{\eta_{bat}(P_{bat(i)})} \qquad (25)$$

Both control and state variables are constrained as follows:

$$-P_{bat\_max} \leq P_{bat(i)} \leq P_{bat\_max} \qquad (26)$$

$$0 \leq E_{bat(i)} \leq E_{bat\_max} \qquad (27)$$

Furthermore, power limits of the other components also must be respected:

$$-P_{em\_max} \leq P_{em(i)} \leq P_{em\_max} \qquad (28)$$

$$0 \leq P_{ge(i)} \leq P_{ge\_max} \qquad (29)$$

$$0 \leq P_{ice(i)} \leq P_{ice\_max} \qquad (30)$$

Finally, charge-sustaining operation is assumed, i.e. no variations of the battery SoC is allowed between the beginning and the end of the cycle. This boundary conditions can be written as:

$$E_{bat(1)} = E_{bat(N)} \qquad (31)$$

Implementation of optimal control strategies aims to find the optimal sequence $\{P^*_{bat(1)}, P^*_{bat(2)}, \ldots, P^*_{bat(N)}\}$, that minimize J_{fuel}, subjects to constraints and boundary conditions. The optimal fuel consumption can only be achieved using off-line techniques, which the driving cycle is known in advance. DP is an off-line iterative procedure relying on Bellman's Optimality Principle (Kirk 2012) that allows find the optimal solution.
Summarizing, DP provides the sequence of the control variable $P_{bat(i)}$ that generate minimum fuel consumptions. Then, this information is used as SC in the backward model shown in Fig. 5 and the minimum fuel consumptions associated to each configuration is

obtained. This procedure was repeated for each architecture and for each HF proposed. The results obtained are shown in the following section.

4. SIMULATION RESULTS

Two different driving cycles, an urban and a road cycle were selected to perform simulations (André 2004). Each of the described architectures was tested with different HF using these cycles. Table 1 summarizes the parameters common to all HEV configurations.

Table 1: Parameters of HEV

Vehicle Model	Total mass, m	1400 Kg
	Frontal area, A_f	2 m^2
	Drag coefficient, D_c	0.3
	Rolling resistance, r_0 ; r_1	0.015; 7 . 10^{-6} m^2/s^2
Battery's cells	Nominal voltage, U_{0cell}	1.25 V
	Internal resistance, R_{cell}	0.002 Ω
	Nominal energy, E_{0cell}	8.12 Wh
Gear box	Efficiency, η_{gb}	0.95
Fuel	Lower heating value, Q_{LHV}	42.6 kJ/g

For each configurations tested, the following sequence was employed: setting HF and sizing component according to Section 3; updating efficiency of component according to the model presented in Section 2; running the DP algorithm; running simulation using backward model.

Fig. 6 shows the effect of HF on fuel consumption, which is expressed in liters per 100km. $HF = 0$ correspond to conventional ICE-vehicles, whereas $HF = 0.83$ corresponds to the minimum possible size of ICE that assures sustained charge of battery at the end of the cycle. Vertical dotted red line denotes HF_{max}, which expresses maximum HF according to the road speed constraint mentioned in Subsection 2-1.

In all cases it can be seen that the fuel consumption curve is concave, which ensures the existence of a minimum. Specifically there exists an optimum HF for which the fuel consumption reaches a minimum value (HF_{opt}). it is worth noticing that in all cases $0 < HF_{opt} < HF_{max}$.

Furthermore, Fig. 6 shows that effect of reductions in fuel consumption decreases as HF increases until reaching HF_{opt}, then the fuel consumptions is kept approximately constant or slightly increased as HF increases.

Comparing optimal HEV with conventional vehicles (i.e. $HF = 0$) it can be seen that reduction of the fuel consumption reaches 43% for urban profile and 20% for road profile, approximately.

Finally, comparing both architectures, it can be seen that the parallel configuration has the lowest fuel consumption. Table 2 summarizes optimal size of components for each of the simulated cases.

It is worth noticing that in Series architecture HF_{opt} is the same for both driving profiles. This is different to the Parallel architecture although their values are close to each other.

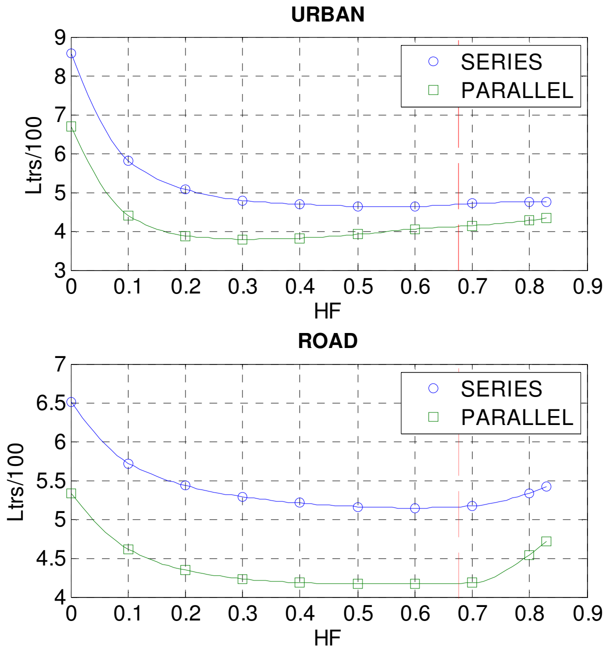

Fig. 6: Hybridization effect on fuel consumption

Table III: Optimal HEV configuration

		SERIES	**PARALLEL**
URBAN	HF_{opt}	**0.6**	**0.3**
	$Lts/100\ km$	**4.636**	**3.790**
	P_{bat_max}	52.6 kW	26.3 kW
	N_{cell}	421	210
	P_{ice_max}	42.3 kW	55.3 kW
ROAD	HF_{opt}	**0.6**	**0.5**
	$Lts/100km$	**5.145**	**4.164**
	P_{bat_max}	52.6 kW	43.9 kW
	N_{cell}	421	350
	P_{ice_max}	42.3 kW	39.5 kW

5. CONCLUSION

In this paper, hybridization effect on the fuel consumption of HEVs has been analyzed through simulations. Series and Parallel architectures were tested using urban and road driving profile. Architectures, models and sizing procedure were described along the work.

The results show similar behavior in all cases simulated. A great reduction in fuel consumption is achieved with low hybridization levels. Then, as HF increases, the fuel consumptions changes slightly until reaching a minimum. Beyond this value the consumption increases again. In all cases the optimum HF is placed in a region of the curve with a reduced slope. Besides these results, which are valid only for the particular cases simulated, it

is worth mentioning that the methodology presented in this paper is general enough to cover a wide range of problems concerning the optimization of HEVs.
Following this line, we are working on improving current strategies of high level supervisory control applicable to HEVs in real-time.

REFERENCES

André, M., 2004. The ARTEMIS European driving cycles for measuring car pollutant emissions. Science of the total Environment, 334, 73-84.

Capata, R., & Coccia, A., 2010. Procedure for the design of a hybrid-series vehicle and the hybridization degree choice. Energies, 3(3), 450-461.

Carignano, M. G., Cabello, J. M., & Junco, S., 2014. Sizing and performance analysis of battery pack in electric vehicles. In Biennial Congress of Argentina (ARGENCON), 2014 IEEE (pp. 240-244). IEEE.

Chan, C. C., Bouscayrol, A., & Chen, K., 2010. Electric, hybrid, and fuel-cell vehicles: Architectures and modeling. Vehicular Technology, IEEE Transactions on, 59(2), 589-598.

Cuddy, M. R., & Wipke, K. B., 1997. Analysis of the fuel economy benefit of drivetrain hybridization (No. 970289). SAE Technical Paper.

Holder, C., & Gover, J., 2006. Optimizing the hybridization factor for a parallel hybrid electric small car. In Vehicle Power and Propulsion Conference, 2006. VPPC'06. IEEE (pp. 1-5). IEEE.

Kirk, D. E., 2012. Optimal control theory: an introduction. Courier Corporation.

Lukic, S. M., & Emadi, A, 2004. Effects of drivetrain hybridization on fuel economy and dynamic performance of parallel hybrid electric vehicles. Vehicular Technology, IEEE Transactions on, 53(2), 385-389.

Lukic, S. M., Cao, J., Bansal, R. C., Rodríguez, F., & Emadi, A., 2008. Energy storage systems for automotive applications. Industrial electronics, IEEE Transactions on, 55(6), 2258-2267.

Olszewski, M., 2005. Evaluation of 2004 TOYOTA PRIUS Hybrid electric drive system. Energy Efficiency and Renewable Energy, FreedomCAR and Vehicle Technologies, Vehicle Systems Team, Oak Ridge.

Pérez, L. V., Bossio, G. R., Moitre, D., & García, G. O., 2006. Optimization of power management in an hybrid electric vehicle using dynamic programming. Mathematics and Computers in Simulation, 73(1), 244-254.

Sciarretta, A., Serrao, L., Dewangan, P. C., Tona, P., Bergshoeff, E. N. D., Bordons, C., ... & Wu, M. 2014. A control benchmark on the energy management of a plug-in hybrid electric vehicle. Control Engineering Practice, 29, 287-298.

Tie, S. F., & Tan, C. W, 2013. A review of energy sources and energy management system in electric vehicles. Renewable and Sustainable Energy Reviews, 20, 82-102.

Vinot, E., Trigui, R., Cheng, Y., Espanet, C., Bouscayrol, A., & Reinbold, V., 2014. Improvement of an EVT-based HEV using dynamic programming. Vehicular Technology, IEEE Transactions on, 63(1), 40-50.

Wipke, K. B., Cuddy, M. R., & Burch, S. D., 1999. ADVISOR 2.1: a user-friendly advanced powertrain simulation using a combined backward/forward approach. Vehicular Technology, IEEE Transactions on, 48(6), 1751-1761.

AUTHORS BIOGRAPHY

Mauro G. Carignano received the Mechanical Engineering degree from Facultad de Ciencias Exáctas Ingeniería y Agrimensura de la Universidad Nacional de Rosario, Rosario, Argentina, in 2011. He is currently working toward the Ph.D. degree.
His research interests include optimal sizing of components and strategies of high level supervisory control for hybrid electric vehicles.

Norbeto M. Nigro received the Mechanical Engineer at Universidad Tecnologica Nacional de Buenos Aires in 1985, Got his doctorate in Engineering Sciences in Universidad Nacional de Cordoba during 1993 under the direction of Sergio Idelsohn in topics related to FEM solutions to CFD problems, especially stabilization. In 1994-1995 a postDoc in Minnesota Supercomputer Institute under the advisory of Tayfun Tezduyar. Since 1996 Researcher at CONICET (National Council of Science and Technology in Argentina). At present Principal Researcher of CONICET and Associate Professor of Universidad Nacional del Litoral at Santa Fe, Argentina in topics related with multiphase reactive flow problems by CFD with applications in energy management, in particular internal combustion engines, oil & gas and nuclear industries. Also his interest lies on external aerodynamics of vehicles.

Sergio Junco received the Electrical Engineer degree from the Universidad Nacional de Rosario in 1976. He joined the National University of Rosario in 1982, where he currently is a Full-time Professor of System Dynamics and Control and Head of the Automation and Control Systems Laboratory. His current research interests are in modeling, simulation, control and diagnosis of dynamic systems, with applications in the fields of motion control systems with electrical drives, power electronics, mechatronics, vehicle dynamics and smart grids. He has developed, and currently teaches, several courses at both undergraduate and graduate level on System Dynamics, Bond Graph Modeling and Simulation, Advanced Nonlinear Dynamics and Control of Electrical Drives, as well as Linear and Nonlinear Control with Geometric Tools.