Analysis of a Rule-Based Control Strategy for On-Board Energy Management of Hybrid Solar Vehicles

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Abstract: In the paper, the performances of a rule-based (RB) control strategy for a series Hybrid Solar Vehicle (HSV) are assessed via comparison with a batch genetic algorithm-based (GA) optimization. The RB strategy relies on heuristic rules defined by optimizing ICE start&stop strategy as function of average traction power and current solar irradiation. The comparison with the reference GA benchmark confirms the suitability of the proposed RB strategy for HSV on-board energy management. Extensive simulations were performed to test the influence of driving cycle features, power-prediction time-horizon and solar irradiation on HSV fuel economy. Such simulation analysis, beyond providing useful indications about correct implementation of the RB strategy, also demonstrates the potentialities offered by HSV powertrains in both urban and highway driving conditions.

Keywords: Engine Modeling, Engine Control, Optimization, Hybrid Vehicles, Solar Energy.

1. INTRODUCTION

In the last years, there is an increasing awareness about the need to achieve a more sustainable mobility, allowing to meet actual mobility demand without compromising development expectations of future generations (Kyoto protocol, 1997). The most pressing arguments towards new solutions for personal mobility mainly relate to: fossil fuels depletion; CO2-related greenhouse effects, with dangerous and maybe dramatic effects on global warming and climatic changes; increasing worldwide demand for personal mobility.

One of the most realistic short term solutions to the reduction of gaseous pollution in urban drive, as well as to the energy saving requirements, is represented by Hybrid Electric Vehicles (HEV). These vehicles, which have already evolved to industrial maturity, allow achieving significant benefits in terms of fuel economy, but still using fossil fuels. On the other hand, in recent years increasing attention is being spent towards the application of solar energy to both electric and hybrid cars. But, while pure solar vehicles do not represent a practical alternative to cars for normal use, the concept of integrating hybrid electric car with solar panels appears more realistic. The reasons for studying and developing a Hybrid Solar Vehicle (HSV) can be therefore summarized as follows:

- solar energy is renewable, free and largely diffused. Photovoltaic panels (PV) are subject to continuous technological advances in terms of cell efficiency, their diffusion is rapidly growing, while their cost, after a continuous decrease and an inversion of the trend occurred in 2004, appears quite stable in last years (Solarbuzz, 2009);
- solar cars, in spite of some spectacular outcomes in competitions such as the World Solar Challenge, do not represent a practical alternative to conventional cars, due to limitations on maximum power, range, dimensions and costs;
- despite maximum power collected by solar panels is significantly lower than typical traction power demands, PV daily energy may represent a significant fraction of the energy required for traction (Arsie et al., 2008-I);
- possibility of fruitfully combining HEV- and solar power-related energetic benefits.

In principle, Hybrid Solar Vehicles (HSV) could sum up the advantages of HEV and solar power, by the integration of Photovoltaic Panels with a Hybrid Electric Vehicle. But it would be simplistic to consider the development of an HSV as the simple addition of photovoltaic panels to an existing Hybrid Electric Vehicle. In fact, the development of HEVs, despite it was based on well-established technologies, showed how considerable research efforts were required for both optimizing the powertrain design and defining the most suitable control and energy-management strategies. Analogously, to maximize the benefits associated with the integration of photovoltaic with HEV technology, it is required performing optimal re-design of the whole vehicle-powertrain system, on one hand, and, on the other, to define on-board energy management strategies that are well suited to maximize PV energy contribution, especially during parking phases (Arsie et al., 2007).

Another difference between HEV and HSV regards with their structure. In fact, the prevailing architectures for HEV are parallel and parallel-series (Musardo et al., 2005; Sciarretta and Guzzella, 2007; Pisu and Rizzoni, 2007), while in case of HSV the series structure seems preferable (Letendre et al., 2003). Despite some known disadvantages (higher efficiency losses due to more energy conversion stages), series structure is simpler and may offer significant advantages, which now are pushing relevant car manufacturers to adopt series configuration in new HEV vehicles (Bullis, 2007). Among them, the most attractive series features are: i) suitability for plug-in and vehicle to grid (V2G) applications (the generator can be used as co-generator when the vehicle is parked at home, Letendre et al., 2003); ii) the absence of mechanical links between generator and wheels enhances effective vibration insulation; iii) the opportunity of operating the internal combustion engine (ICE) at fixed conditions encourages the introduction of advanced techniques for noise reduction (i.e. active noise reduction); iv) Engines specifically optimized for steady operation can be used (i.e. D.I. stratified charge engines, micro gas turbine and so on); v) compatibility with the use of in-wheel motors with built-in traction control and anti-skid and, finally vi) potentiality of acting as a bridge towards the introduction of hybrid fuel cell powertrains (Konev et al., 2006; Bullis, 2007).

In the next chapters, the main issues associated to proper management of energy flows on series HSV are addressed and discussed. Then, a new implementable rule-based approach, proposed by the authors for energy flow management, is presented. Simulation-based assessment of RB strategies is performed, by comparison with Genetic-Algorithm-based optimization of ICE start&stop scheduling. Finally, further simulation-based analyses are carried out to quantify the influence of driving cycle characteristics, power prediction strategies and solar irradiation level on HSV fuel consumption.

2. CONTROL ISSUES FOR HYBRID SOLAR VEHICLES

Although HSV share many common features with HEV, for which several remarkable studies on energy management and control have been presented in the last decade (Sciarretta and Guzzella, 2007; Pisu and Rizzoni, 2007; Arsie et al., 2005; Powell et al., 1998), there are some significant differences between the two vehicle typologies. Particularly, the presence of solar panels, along with the adoption of a series structure (see Figure 1), entail studying and developing specific solutions for HSV optimal management and control.

As it is well known, in most HEV a charge sustaining strategy is adopted: at the end of a driving path, the battery state of charge should remain unchanged. With an HSV, a different strategy should be adopted as battery is charged during parking hours as well. Therefore, for HSV the objective is to restore the initial state of charge within the end of the day rather than after a single driving path (Arsie et al., 2007).

Moreover, the series configuration suggests quite an efficient solution, namely to operate the engine in an intermittent way at constant operating conditions. Of course, the maximum gain in terms of fuel consumption occurs when the EG power corresponds to the most efficient value. In such case, the ICE-EG system may be designed and optimized to maximize its efficiency, emissions and noise at design point, while in current automotive engines the maximum efficiency is usually sacrificed to the need of assuring stable operation and good performance in the whole operating range. In case of ICE intermittent operation, the effects exerted on fuel consumption and emissions by the occurrence of thermal transients in engine and catalyst should be considered (Arsie et al., 2008-II; Ohn et al., 2008). These effects are neglected in most studies on HEV (Guzzella and Amstutz, 1999) and on HSV (Preitl et al., 2007), where a steady-state approach is usually preferred to evaluate fuel consumption and emissions.

In order to address the afore-mentioned control issues, in the last years the authors have performed several off-line analyses aimed at individuating optimal energy management strategies for series HSV (Arsie et al., 2007, 2008-II and Sorrentino et al., 2009). Specifically in this work, the research interests and aims turned towards the development of an RB control strategy to perform quasi-optimal on-board energy management for a series HSV powertrain.

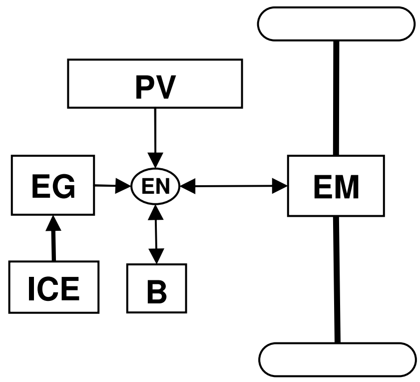

Fig. 1. Scheme of a series hybrid solar vehicle. Acronyms are intended as follows: EM (electric motor); PV (photovoltaic panels); EG (electric generator); EN (electric node); ICE (internal combustion engine); B (battery).

3. RULE-BASED CONTROL STRATEGY FOR A SERIES HYBRID SOLAR VEHICLE

The RB control architecture consists of two tasks, external and internal respectively:

- external task: defines the desired final state of charge SOC_f (see Figure 3), to be reached at the end of the driving cycle to enable full storage of solar energy capted during the following parking phase (i.e., $E_{sun,p}$).
- internal task: estimates the average power delivered by ICE-EG and SOC deviation (dSOC) from SOC_f as function of average traction power and $E_{sun,p}$.

Figure 2 provides a qualitative description of the start&stop strategy enabled by the above-described control tasks. For sake of simplicity, in Figure 2 it is assumed that initial state of charge SOC_0 equals SOC_f and does not vary with time. The battery is initially depleted until SOC becomes lower than $SOC_{lo} = SOC_f$ - dSOC. At this point ICE-EG is turned on at the assigned power level and switches off when the maximum threshold $SOC_{up} = SOC_f$ + dSOC is reached. The procedure is repeated until the end of the driving cycle. It is worth mentioning here that effective final state of charge may differ from the desired SOC_f due to the difficulty of precisely predicting the end of the driving phase. This consideration entails satisfying the following energetic constraint:

$$SOC_{up} + \Delta SOC_p < 1 \quad (1)$$

where ΔSOC_p represents the state of charge increase subsequent to battery recharging performed by PV panels during parking phases.

The described control strategy relies, on one hand, on the online estimation of current SOC level and, on the other, on predicting or properly estimating traction power demand over an assigned driving route. The following equations express the rules on which the external and internal task rely.

$$SOC_f = f\left(E_{sun,day}\right) \tag{2}$$

$$P_{EG} = f\left(\overline{P}_{tr},\ E_{sun,day}\right) \tag{3}$$

$$dSOC = f\left(\overline{P}_{tr},\ E_{sun,day}\right) \tag{4}$$

where $E_{sun,day}$ and $\overline{P}_{tr}$ are, respectively, the daily solar energy (evaluated on a year base, see Table 3) and average traction power. The latter variable can be updated every t_h time horizon by means of the following a-priori method:

$$\overline{P}_{tr}(t)|_{t_i<t<t_i+t_h} = \frac{1}{t_h}\int_{t_i}^{t_i+t_h} P_{tr}(t) \tag{5}$$

Figure 3 gives a schematic description of the rule-based control strategy implementation. Eq. (2) provides the desired SOC_f. Then, in the internal task the average power at which the ICE-EG works is evaluated by Eq. (3). The ON-OFF rules for the ICE-EG will depend on the SOC excursion (i.e. dSOC) addressed by Eq. (4). The logic described in Figure 3 results in the control actions qualitatively shown on Figure 2. It is worth remarking here that the a-priori strategy expressed by Eqs. (2-5) becomes suitable for online application once coupled either to GPS information or model-based forecasting of traction power demand. Nevertheless, some preliminary analyses were conducted implementing an a-posteriori version of the RB strategy (Rizzo et al., 2009), showing highly promising performance as compared to the a-priori strategy herein discussed.

Further details on the development of rule-based control rules (i.e. Eqs. 2-4) can be found in (Rizzo et al., 2009).

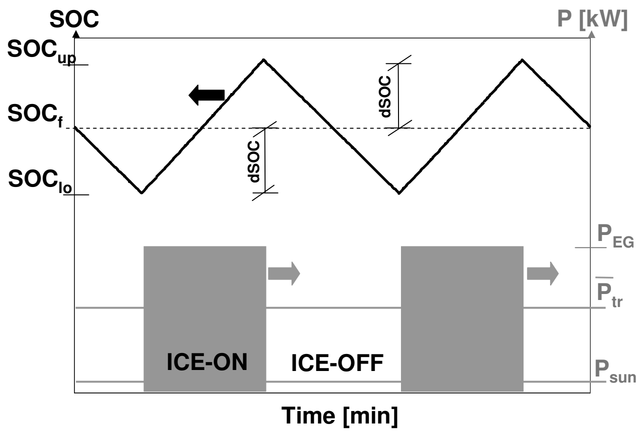

Fig. 2. Schematic representation of the rule-based control strategy for quasi-optimal energy management of a series HSV powertrain.

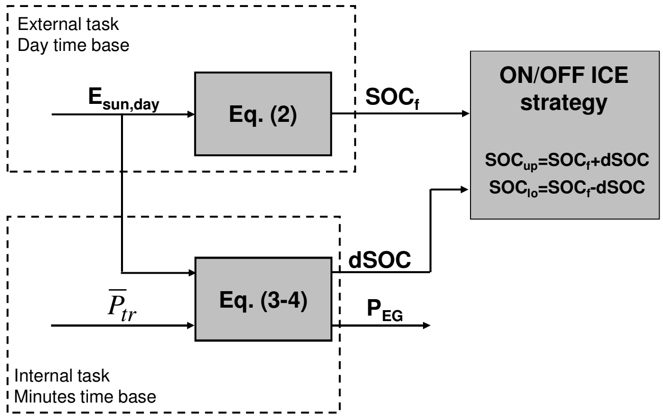

Fig. 3. Schematic description of external and internal task actions within the RB control strategy.

4. REFERENCE BENCHMARK

In order to assess the performance of the rule-based control strategy presented in section 3, a reference benchmark must be individuated.

In most cases, Dynamic Programming (DP) is adopted for off-line optimal energy management in hybrid vehicles, with steady state hypothesis for thermal engine. Nevertheless, in this paper DP was not adopted, mainly because: i) ICE thermal transients are accounted for, thus the dimensionality of the DP problem would be increased and ii) the asymptotic behavior of engine temperature would represent a significant problem for backward computation involved in DP. Therefore, the genetic-algorithm-based optimization of ICE intermittent scheduling proposed by the authors in (Sorrentino et al., 2009) was selected. Such a choice is particularly suited for this specific problem, as it allows treating Mixed Integer Programming (MIP) problems (Sakawa et al., 2001).

4.1 Optimization of Electric Generator Scheduling by Means of Genetic Algorithm

In case of intermittent ICE scheduling, the optimal EG power trajectory can be found by solving the following constrained optimization problem:

$$\min_X \int \dot{m}_{f,HSV}(X)dt \tag{6}$$

subject to the constraints:

$$SOC \geq SOC_{\min} \tag{7}$$

$$SOC \leq SOC_{\max} \tag{8}$$

where $\dot{m}_{f,HSV}$ is the HSV fuel consumption [kg/s].

The decision variables X include number of EG-on events N_{EG}, along with corresponding starting time $t_{0,EG,i}$ and duration $\Delta t_{EG,i}$, where i is the i-th EG-on event. This way, since N_{EG} is an integer variable, the optimization procedure expressed by Eqs. (6-8) falls in the field of MIP problems, thus confirming the suitability of GA search methods (Sakawa et al., 2001). Regarding EG power levels, in this work a modification was introduced with respect to the previous approach (Sorrentino et al., 2009). Particularly, aiming at increasing the number of degrees of freedom in the GA optimization, it was assumed that four different P_{EG} power level can be imposed for each EG-on phase. Therefore, the power-related decision variables are $P_{EG,i,j}$, where j varies in the integers interval [1-4].

The constraints expressed by Eqs. (7-8) were defined accounting for internal resistance dependence on battery state of charge. For lead-acid batteries, in the SOC range [0.5 0.9] both charging and discharging resistances exhibit limited variability while being close to their minimum values (Burch et al., 1999). Therefore in this analysis SOC_{min} and SOC_{max} were set to 0.5 and 0.9, respectively.

For the current application, the following operating parameters were assumed for the GA search procedure (Chipperfield et al., 2009):

Table 1. GA operating parameters.

Population size	35
Number of generations	250
Crossover probability	0.8
Mutation probability	0.003
Elitism percentage [%]	3

A binary representation of the decision variables was selected, as reported in Table 2.

Table 2. Binary representation of the optimization problem.

Decision variable	Definition range	Precision	Number of bits
N_{EG}	[1 8]	1	3
t_{EG} (min)	[0 78/ N_{EG}]	0.073/ N_{EG}	10
Δt_{EG} (min)	[0 78/ N_{EG}]	0.073/ N_{EG}	10
P_{EG} (kW)	[0 43]	0.040	10

The GA optimization was applied to minimize the fuel consumption for a 1.3 hours long driving cycle composed of a series of ECE-EUDC modules. HSV fuel consumption was simulated by means of the backward longitudinal vehicle model presented in (Sorrentino et al., 2009). In the analysis the effect of thermal transients on ICE performance and HC emissions were also taken into account following the approach proposed in (Arsie et al., 2008-II). Table 3 lists the specifications of the reference HSV. The simulated fuel economy yielded by the GA optimization algorithm on the ECE-EUDC cycle was as high as 22.49 km/l. Figure 4 through Figure 6 show the EG power, engine temperature and SOC trajectory associated to the GA optimal solution. Regarding SOC simulations, it is worth pointing out that the HSV model (Sorrentino et al., 2009) also accounts for the dependence of battery internal resistance on SOC.

5. SIMULATION BASED ANALYSIS OF RB STRATEGY PERFORMANCE

The comparison of simulated GA and RB performance indicates how the latter gets significantly close to the former, resulting in fuel economy decrease of about 0.1 % on the ECE-EUDC cycle.

Table 3. HSV specifications.

Nominal ICE power [kW]	46
Fuel	gasoline
Nominal EG power [kW]	43
Nominal EM power [kW]	90
Number of Lead-acid battery modules	27
Battery capacity C_B [kWh]	8
PV horizontal surface [m^2]	3
PV efficiency	0.13
Coefficient of drag (Cd)	0.33
Frontal area [m^2]	2.3
Rolling resistance coefficient [/]	0.01
Weight [kg]	1500
Driving hours h_{car} [h]	1.3
Average $E_{sun,day}$ at 30° Latitude [kWh/m^2]	4.31
Daily irradiation hours h_{sun} [h]	10

Figure 4 through Figure 6 compare the EG, engine temperature and SOC trajectory, simulated by means of the RB strategy, with those referring to the reference GA benchmark. It is worth noting that, in order to account for the different SOC that will be reached at the end of the day, HSV equivalent fuel consumption was computed as follows:

$$m_{f,eq} = m_f - \frac{\Delta SOC_{ext} \cdot C_B}{\overline{\eta}_{ICE-EG} \cdot H_i} \tag{9}$$

where $\overline{\eta}_{ICE-EG}$ is the average ICE-EG efficiency over the entire driving cycle and ΔSOC_{ext} is the extra SOC increase at the end of the day, i.e., after the parking phase (Rizzo et al., 2009). Regarding the prediction time-horizon adopted in the RB simulations, it was found minimizing fuel consumption over the entire ECE-EUDC cycle. In order to analyze the dependence of t_h value on driving cycle characteristics, the procedure was repeated on the other driving cycles listed in Table 4. Figure 7 shows the variation of t_h as function of average traction power. Interestingly, t_h exhibits a linear trend with respect to $\overline{P_{tr}}$. The latter observation can be explained considering that higher $\overline{P_{tr}}$ values are usually associated to constant-speed highway driving, where P_{tr} standard deviation is very small. In such conditions, limited variation in future power demands is expected, thus allowing to extend prediction time horizon, as it emerges from Figure 7. It is worth mentioning here that h_{car} was set to 1.3 h for all the driving cycles listed in Table 1. Therefore, the simulated driving routes consist of a sequence of corresponding standard cycles.

Finally, Figure 8 illustrates the impact of solar irradiation on HSV fuel economies for all the analyzed driving cycles. The reference value (i.e. corresponding to 100 % in Figure 8) relates to the $E_{sun,day}$ value given in Table 3. As expected, increased irradiation level mainly improves urban-related fuel economies.

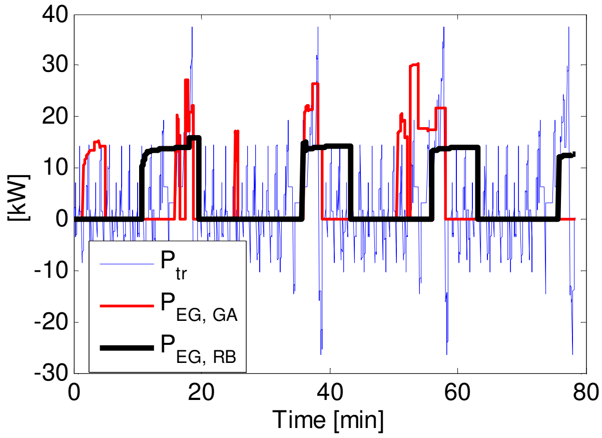

Fig. 4. Simulated power trajectories.

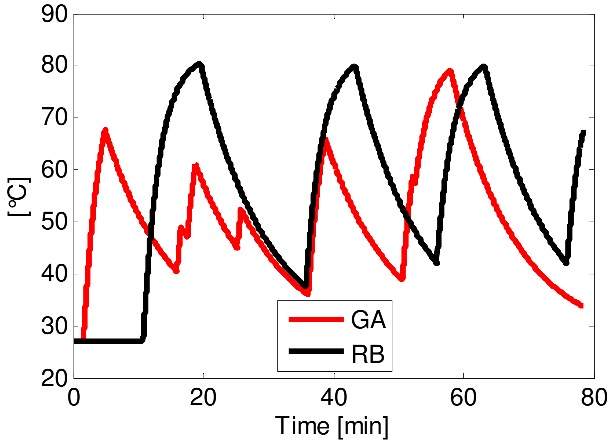

Fig. 5. Simulated engine temperature trajectories.

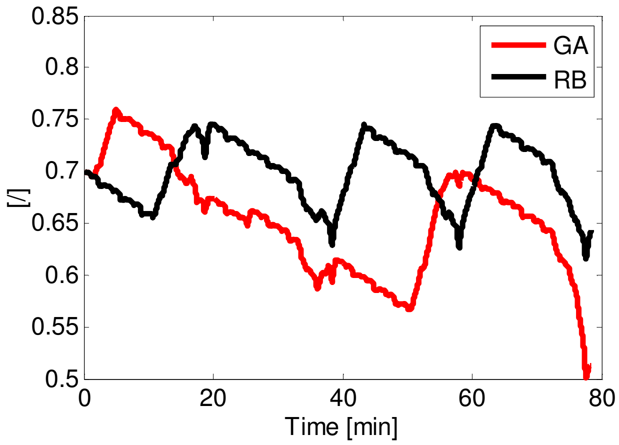

Fig. 6. Simulated battery SOC trajectories.

Table 4. Selected driving cycles in the prediction time horizon analysis.

Driving cycle	$\overline{P}_{tr}$ [kW]	RB fuel economy [km/l]
CYC_1015_6PRIUS	1.51	26.32
FUDS	2.33	23.25
ECE-EUDC	2.99	22.45
FHDS	8.31	20.97
US06HWY	16.60	13.54

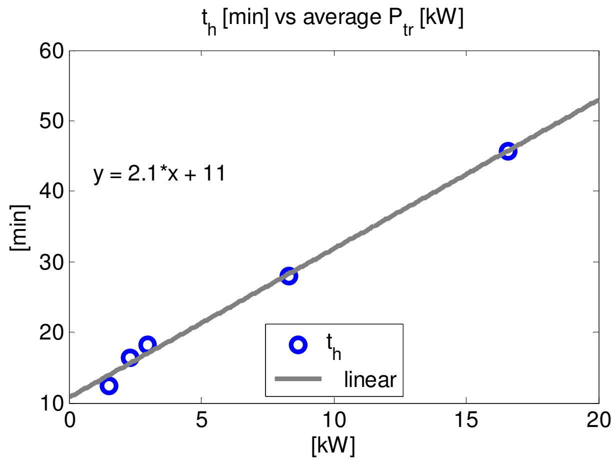

Fig. 7. Variation of prediction time horizon (t_h) as function of average traction power $\overline{P}_{tr}$.

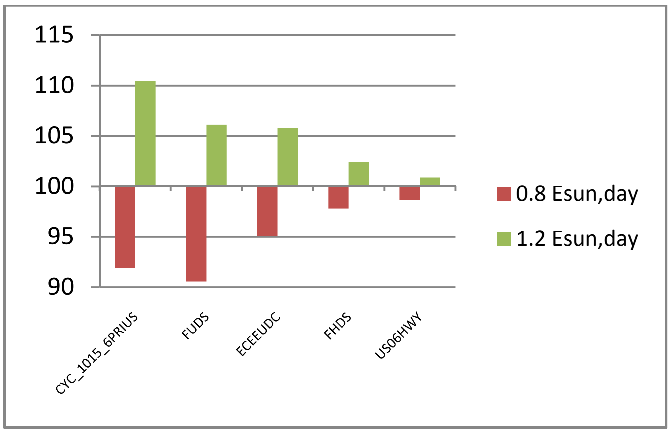

Fig. 8. Impact of daily PV energy contribution on HSV fuel economies. 100% corresponds with the average $E_{sun, day}$ value given in Table 3.

6. CONCLUSIONS

In the paper, a simulation based analysis was carried out to assess the performance of a rule-based control strategy for real time energy management of HSV powertrains. An optimal ICE scheduling addressed by genetic-algorithm-based batch optimization was assumed as reference benchmark. The comparison between the two fuel economies demonstrated the suitability of the proposed RB methodology.

Further simulations were conducted to investigate the dependence of power prediction time horizon, on which the

RB strategy is based, from driving cycle features. An interesting linear trend of such time horizon with respect to average power demand at wheels emerged. Some simulations also were conducted to assess the impact of irradiation level variation on HSV fuel economies, highlighting the higher contribution guaranteed by solar energy in urban driving.

Future work will focus on coupling the RB control architecture with suited power predictors, either based on GPS derived information or model-based forecasting. Moreover, the performance achievable with a-posteriori traction power estimation will be analyzed, thus enhancing real time implementation of the proposed RB control strategy.

REFERENCES

Arsie, I., Graziosi, M., Pianese, C., Rizzo, G., Sorrentino, M. (2005). Control Strategy Optimization for Hybrid Electric Vehicles via Provisional Load Estimate. *Review of Automotive Engineering,* Vol. 26, pp. 341-348.

Arsie, I., Rizzo, G., Sorrentino, M. (2007). Optimal Design and Dynamic Simulation of a Hybrid Solar Vehicle. *SAE Transactions - Journal of Engines*, Vol. 115-3, pp. 805-811.

Arsie, I., Rizzo, G., Sorrentino, M. (2008-I). A Model for the Optimal Design of a Hybrid Solar Vehicle. *Review of Automotive Engineering,* Vol. 29:3, pp. 439-447.

Arsie, I., Di Martino, R., Rizzo, G., Sorrentino, M. (2008-II). Energy Management for a Hybrid Solar Vehicle with Series Structure. Proc. of 17th IFAC World Congress, July 6-11, 2008, Seoul, Korea.

Bullis, K. (2007). GM's New Electric Vehicle. Available at http://www.technologyreview.com/energy/18042/?a=f.

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

Chipperfield, Chipperfield, A.J., Fleming, P.J., Polheim, H., Fonseca, C.M. (2009). Genetic Algorithm Toolbox – Matlab Tutorial. Available at www.shef.ac.uk/acse/research/ecrg/getgat.html.

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, pp. 1762-1769.

Konev, A., Lezhnev, L., Kolmanovsky, I. (2006). Control Strategy Optimization for a Series Hybrid Vehicle. SAE paper 2006-01-0663.

Kyoto Protocol (1997). http://unfccc.int/kyoto_protocol/items/2830.php

Letendre, S., Perez, R., Herig, C. (2003). Vehicle Integrated PV: A Clean and Secure Fuel for Hybrid Electric Vehicles. Proc. of the American Solar Energy Society Solar 2003 Conference, June 21-23, 2003, Austin, TX-USA.

Musardo, C., Rizzoni, G., Guezennec, Y., and Staccia, B., (2005). A-ECMS: An adaptive algorithm for hybrid electric vehicle energy management. Eur. J. Control, vol. 11, no. 4–5, pp. 509–524.

Ohn, H., Yu, S., Min, K.D. (2008). Effects of Spark Ignition Timing and Fuel Injection Strategy for Combustion Stability on HEV Powertrain During Engine Restart and Deceleration Driving. Proc .of IFAC World Congress 2008, July 6-11, 2008, Seoul, Korea.

Pisu, P., Rizzoni, G., (2007). A Comparative Study Of Supervisory Control Strategies for Hybrid Electric Vehicles. IEEE Transactions on Control Systems Technology, vol. 15, no. 3, pp. 506-518.

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, 1998.

Preitl, Z., Bauer, P., Kulcsar, B., Rizzo, G., Bokor, J. (2007). Control Solutions for Hybrid Solar Vehicle Fuel Consumption Minimization. Proc. of the 2007 IEEE Intelligent Vehicles Symposium, Istanbul, Turkey, June 13-15, 2007.

Rizzo, G., Sorrentino, M., Arsie, I. (2009). Rule-Based Optimization of Intermittent ICE Scheduling on a Hybrid Solar Vehicle. SAE paper 2009-24-0067.

Sakawa, M., Kato, K., Ushiro, S., Inaoka, M. (2001). Operation planning of district heating and cooling plants using genetic algorithms for mixed integer programming. Applied Soft Computing Vol.1, pp. 139–150.

Sciarretta, A., Guzzella, L., (2007). Control of hybrid electric vehicles. IEEE Control Systems Magazine 27 (2), pp. 60-70.

Solarbuzz (2009). www.solarbuzz.com/Moduleprices.htm.

Sorrentino, M., Arsie, I., Di Martino, R., Rizzo, G., (2009). On the Use of Genetic Algorithm to Optimize the On-Board Energy Management of a Hybrid Solar Vehicle. Oil & Gas Science and Technology - Revue de l'IFP. DOI: 10.2516/ogst/2009035.