# An Energy Management System Using Trip Information and Fuzzy Logic for a Plug-In Hybrid Electric Vehicle

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**ABSTRACT**

The growing interest in reducing fuel consumption and gas emissions provides an incentive for the automotive industry to innovate in the field of hybrid and plug-in hybrid electric vehicles. The two embedded power sources in these vehicles require an intelligent controller in order to make the best decision on the power distribution. Actually these controllers, often called energy management systems (EMS), are very important and greatly influence the achievable fuel economy. Many authors have studied the possibility of fuzzy based systems as they have proved to be robust, reliable and simple. However, they demonstrate a lack of optimality because their design is focused on the vehicle characteristics rather than the driving conditions. This paper proposes an approach that uses a fuzzy system fed with driving condition information in order to increase the controller effectiveness in every situation. The efficiency of the proposed controller is demonstrated through simulations.

**Keywords:** Plug-in Hybrid Electric Vehicles, Energy Management Systems, Fuzzy Logic, Driving Pattern Recognition

## 1. INTRODUCTION

In the last ten years, the automotive industry has developed the market of vehicle electrification, as it is seen as one solution to oil shortage and fuel inflation. Hybrid electric vehicles and plug-in hybrid electric vehicles are one of the most promising solutions to reduce environmental impact of individual transportation. The intrinsic architecture of HEV and PHEV requires the implementation of an Energy Management System (EMS) that can manage the power split distribution effectively. The main purpose of the EMS is to make sure that the battery state of charge is kept within range when exploiting the charge-sustaining mode while improving the fuel economy over a complete trip.

The state of the art in this field proposes many solutions that have their own advantages and drawbacks. The deterministic rule based methods use state machines to determine the vehicle operation in real-time using inputs from the driver and the vehicle [1] [2]. Fuzzy logic has also been used to build rule based strategies, which have proved an increase in the vehicle performance compared to the deterministic rule based methods [3] [4]. Both deterministic and fuzzy based strategies rely on the engineers' expertise and offer computational simplicity, robustness and reliability. Generally a set of rules using carefully selected thresholds are implemented in order to optimize power train efficiency and maintain SOC within suitable levels. Nevertheless, these methods will consider only current driving conditions and, as a consequence, exhibit a lack of optimality in terms of fuel economy and gas emissions when considered on a complete journey. Global optimization techniques such as dynamic programming algorithm are used to find the optimal control of the vehicle in order to get the minimum fuel consumption over a complete driving cycle [5] [6] [7]. However such techniques require high computation time and relatively high performance processors. Also the future driving cycle has to be accurately known in advance. Consequently they cannot be used directly in real time applications but they remain powerful tools to evaluate real time controller performances. Some authors point out the fact that the driving profile greatly influences fuel consumption and the knowledge of near future driving conditions could be used to decrease fuel consumption. As a consequence they propose some driving pattern recognition methods which are used to take relevant decision on the power distribution [8] [9] [10].

In this paper, the choice was made to use past and current driving information as an input to our fuzzy logic controller. The fuzzy logic keeps our controller simple and reliable. Moreover, the use of driving information allows an adaptive vehicle control relative to the different driving condition. The proposed controller will apply to a parallel hybrid configuration and will enable to maintain the battery SOC around a constant level of 30%. In a Plug-in Hybrid EV, the battery depletion will generally begin at 100% SOC, down to a level around 30% and then operate in charge-sustaining mode. However, a plug-in hybrid vehicle is likely to begin a route with an already discharged battery, where the fuel consumption will be more important and where energy management is critical for a reduced fuel usage. Hence, the paper will only cover the case of a parallel-hybrid operating in charge-sustaining mode. Section 2 will present the power train topology, section 3 will describe the developed DP algorithm and the conclusions based on the obtained results, section 4 will present the developed real time controller and finally section 5 will present simulation results.

## 2. VEHICLE TOPOLOGY

The described vehicle has a parallel topology in the sense that power of both electrical motor and engine are added in order to provide the required power to the wheel. The battery pack can be regenerated by electrically braking the vehicle or by overpowering the engine. In all cases, power contributions of the two power sources have to satisfy the driver's demand. The energy flow chart is described in Fig. 1 and torque and speed equations can be written as

$$N_w = \frac{N_{ICE}}{i_{pr}.i_{gb}.i_{sec}.i_{fin}} = \frac{N_e}{i_{mg}.i_{fin}} \;, \tag{1}$$

$$\begin{aligned} T_{ICE}.i_{pr}.i_{gb}.i_{sec}.\eta_{pr}.\eta_{gb}.\eta_{sec} + T_e.i_{mg}\left(\frac{1-sg(P_e)}{2}\frac{1}{\eta_{mg}} + \frac{1+sg(P_e)}{2}\eta_{mg}\right) \\ = \frac{T_w}{i_{fin}}\left(\frac{1-sg(P_w)}{2}\eta_{fin} + \frac{1+sg(P_w)}{2}\frac{1}{\eta_{fin}}\right) \;, \end{aligned} \tag{2}$$

where $N_w$, $N_{ICE}$ and $N_e$ are respectively wheel, engine and motor speeds, $T_w$, $T_{ICE}$ and $T_e$ are respectively wheel, engine and motor torques, $i_{pr}$, $i_{sec}$, $i_{mg}$ and $i_{fin}$ are respectively primary, secondary, motor and final drive ratio, $i_{gb}$ is the selected gearbox ratio, $\eta_{pr}$, $\eta_{sec}$, $\eta_{mg}$, $\eta_{gb}$ and $\eta_{fin}$ are the drive efficiencies, $P_w$ and $P_e$ are wheel and motor mechanical power, $sg$ is the sign function.

The electric power train is composed of a Li-Ion technology battery pack that provides power to a voltage source inverter using IGBTs, the latter being able to drive a permanent magnet synchronous motor. The electrical power train configuration can be seen on Fig. 2. For a matter of space in our vehicle two major choices were made. The electrical power train does not contain any DC/DC converter in order to stabilize the bus voltage, thus the inverter will see a variable bus voltage depending on the required battery current. This will affect the whole power train efficiency. Moreover there is no clutch on the electrical motor shaft which

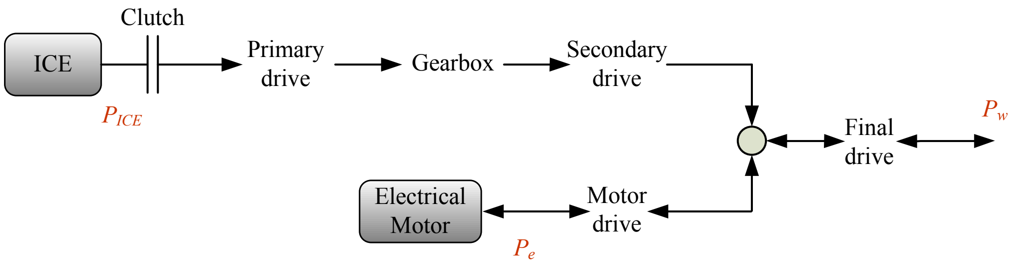


**Figure 1. Energy flow chart**

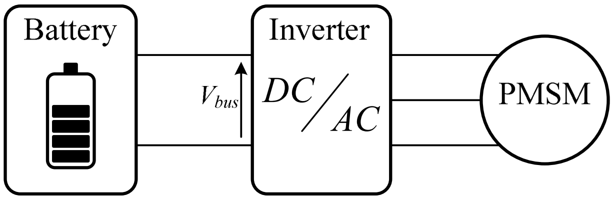


**Figure 2. Electrical power train configuration**

means that the electrical motor will always be coupled to the wheel and could work in inefficient area.

The complete vehicle model was established in a previous work [11], the mechanical model provides an estimation of the required torque based on the information of the vehicle speed, the engine is simulated using a map that gives instantaneous consumption for every speed and torque and finally the electrical power train was characterized by its mathematical equations.

## 3. ANALYSIS OF THE OPTIMAL BEHAVIOUR

### 3.1 The Dynamic Programming Algorithm

The dynamic programming algorithm is an efficient and ideal optimal control algorithm for non linear and complex systems [12], it was used to find the optimal power split ratio over a complete driving cycle that minimizes the global fuel consumption. The chosen control variables were the engine torque $T_{ICE}$ and the gear ratio $k$. Control variables values are optimally determined by the DP algorithm over a driving cycle to minimize the fuel consumption, with an initial battery SOC of 30%. The dynamic system is the core of the algorithm and relates the battery charge/discharge rate with the control variables. This complex relation is established using the numerical model of the vehicle [11]. The cost function to be minimized is the global consumption $J_{tot}$ given by

$$J_{tot} = \sum_{t=0}^{N-1} D\big(k(t), T_{ICE}(t)\big).\Delta \ , \tag{3}$$

where $D\big(k(t), T_{ICE}(t)\big)$ is the engine instantaneous consumption based on control variables values and $\Delta$ is the sample time of the DP algorithm.

Architectural constraints written in (1) and (2) and physical constraints such as maximum and minimum torque of the electric motor and combustion engine allow writing constraints on engine torque for every wheel torque and speed. In that way, maximum and minimum engine torque are computed at each time step. From eq. (2), we derive:

$$T_{ICEmin} = \frac{\frac{T_W}{i_{fin}}\left(\frac{1-sg(P_W)}{2}\eta_{fin}+\frac{1+sg(P_W)}{2}\frac{1}{\eta_{fin}}\right)-T_{emax}.i_{mg}\left(\frac{1-sg(P_e)}{2}\frac{1}{\eta_{mg}}+\frac{1+sg(P_e)}{2}\eta_{mg}\right)}{i_{pr}.i_{gb}.i_{sec}.\eta_{pr}.\eta_{gb}.\eta_{sec}} \quad , \tag{4}$$

$$T_{ICEmax} = \frac{\frac{T_W}{i_{fin}}\left(\frac{1-sg(P_W)}{2}\eta_{fin}+\frac{1+sg(P_W)}{2}\frac{1}{\eta_{fin}}\right)-T_{emin}.i_{mg}\left(\frac{1-sg(P_e)}{2}\frac{1}{\eta_{mg}}+\frac{1+sg(P_e)}{2}\eta_{mg}\right)}{i_{pr}.i_{gb}.i_{sec}.\eta_{pr}.\eta_{gb}.\eta_{sec}} \quad , \tag{5}$$

where $T_{emin}$ and $T_{emax}$ are respectively the minimum and maximum torque of the electric motor.

Furthermore physical constraints on engine speed set the constraints on gear ratio $k$. Consequently the admissible set of gear ratio is updated at every time step based on the information on vehicle speed

$$k(t) \in K(t) \qquad K(t) \subset \{0; 1; 2; 3; 4; 5; 6\} \quad , \tag{6}$$

where $K(t)$ is the admissible set of gear ratios at time $t$.

Finally, as the vehicle works in charge sustaining mode, the state of charge is constrained to be equal at the beginning and the end of the driving cycle. Equations (3), (4), (5), (6) and constraint on state of charge set the constrained minimization problem that can be solved using the Bellman principle of the DP algorithm [12]. As a constraint, a battery SOC below 20% is not tolerated at any time. A DP solution which would provide only one event in time with a SOC < 20% would be discarded.

The DP algorithm was run the 11 Facility-Specific Drive Cycles developed by Sierra Research Inc. [10] which describe vehicle operation over different types of roadway (arterial, local and freeway) with several congestion levels.

**3.2 Dynamic Programming Results Analysis**

The first step of the controller design was to observe the optimal behavior coming from the DP results. Since there is no clutch on the electrical power train, the vehicle can be run in only two main modes which are pure electric or hybrid. Also the purpose of DP results observation is to try to find two laws; one that rules the optimal power split decision during hybrid mode and one that rules the optimal decision for transition between pure electric and hybrid mode.

In order to deal with the first point, the engine load points coming from DP results were plotted for every speed cycle. In each speed cycle it was observed that the engine always works around its maximum efficiency during the hybrid mode.

For the second point, required power to the wheel and electrical motor power were compared. In the case where the power of the electric motor matches the required power, this means that the vehicle is in pure electric mode and engine is off. On the contrary, the vehicle is in hybrid mode when the power from the electric motor does not follow the vehicle required power. For each driving cycles, it can be observed that the vehicle works in hybrid mode as soon as relatively high power is required. More precisely, the optimal behavior shows that the vehicle works in hybrid mode as soon as required power is above an approximately constant power threshold $P_{th}$. This is one of the findings in this research. When the vehicle required power is under this threshold $P_{th}$ the vehicle works in pure electric mode. An example for "Arterial LOS A-B", which is one of the 11 Facility-Specific Drive Cycles, can be seen on Fig. 3.

The absence of a DC/DC converter between the battery and the inverter and the need for a flux weakening current at higher rotational speeds will increase the power losses in the whole electrical power train when high mechanical power is required. Examining the results from the DP optimization of Fig. 3, this can explain why the electric motor operates in a relatively low range of power. More interesting, the different results showed that the above mentioned power threshold can be observed for every speed cycles but varies with the type of driving pattern in order to sustain the battery SOC. In a general manner, $P_{th}$ increases for high speed cycles and decreases for low speed cycles. The aim of the controller will be to compute $P_{th}$ online in order to intelligently manage the transition decision based on the past driving condition and SOC.

## 4. CONTROLLER DESIGN

The hybrid mode of the controller is quite simple. A map is used to compute $T_{ICE}$ and $k$ for every vehicle speed and required torque in order to maximize engine efficiency. The imposed

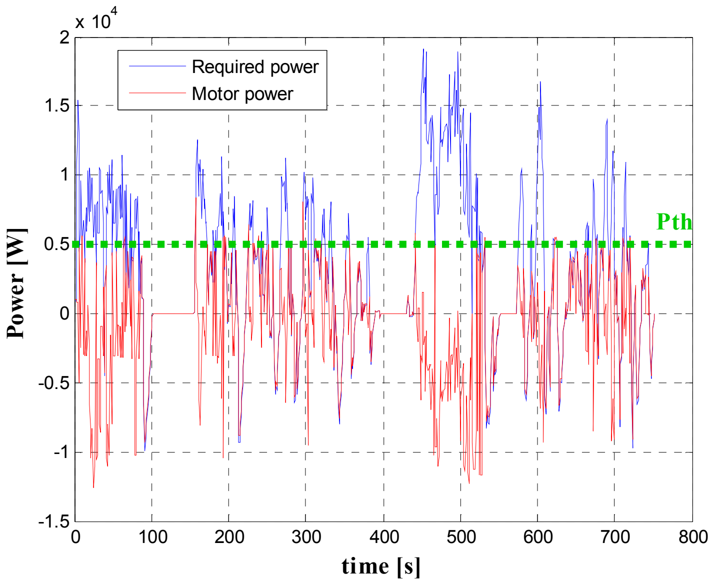


**Figure 3. Power comparison on "Arterial LOS A-B"**

motor torque compensates the engine torque in order to provide the required power to the wheel.

The electric/hybrid transition management is made using the power threshold $P_{th}$ which is computed using a fuzzy logic controller. The vehicle works on hybrid or electric mode when required power is respectively above or under $P_{th}$. The first step to design the fuzzy logic controller was to select 3 speed cycles out of the 11 which were used for DP. These 3 speed cycles are “Arterial LOS A-B”, “Freeway LOS A-C” and “Freeway LOS G”. They cover a wide speed range and have very different speed distribution profiles. A histogram of vehicle velocity for the 3 speed cycles was plotted and approximated using Gaussian distributions. The fuzzy logic controller has two inputs and one output, the first input is a moving average of the past speed and the second input is the battery SOC. The output is $P_{th}$. The membership functions for the speed are defined by the previous Gaussian distributions. In this way the fuzzy logic controller can locate current speed among the three speed distribution, and thus, benefit from the past driving information to adapt the control logic. The SOC input allows a feedback that helps maintaining SOC in its admissible range. The membership functions of both inputs are described on Fig. 4.

Globally the defined rules increase $P_{th}$ for high speed and high SOC in order to make pure electric mode preponderant. On the contrary, $P_{th}$ is decreased for low speed and low SOC. The rules are listed in Table 1. The membership functions of the output $P_{th}$ were constructed using DP results on the different driving cycles.

The fuzzy logic controller uses classical Mamdani defuzzification. In order to improve drivability, the controller imposes a time delay between mode transition to avoid too many

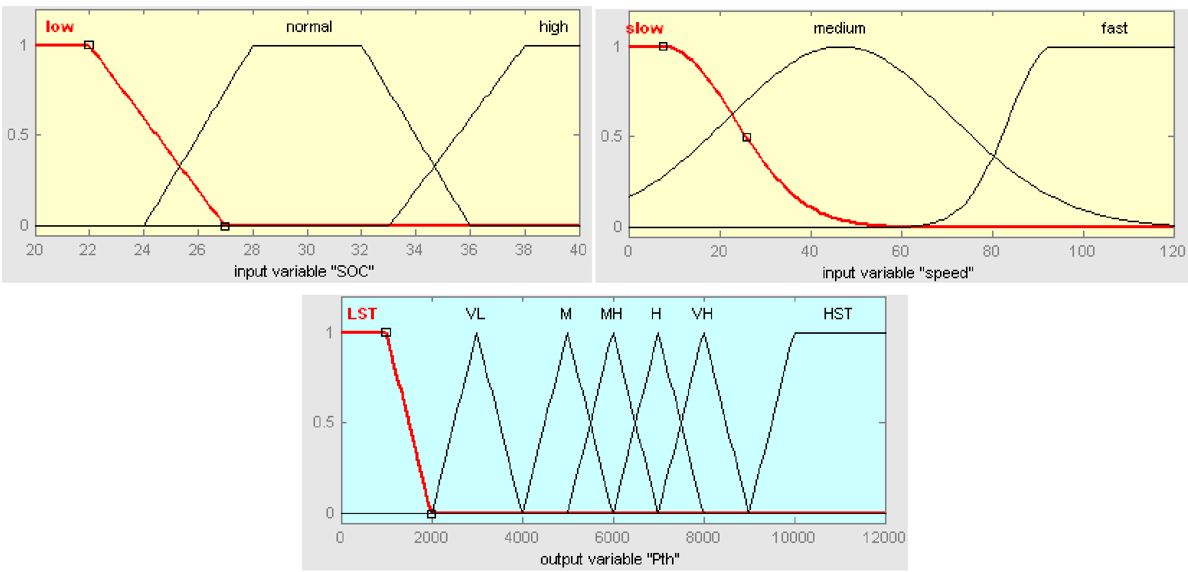


**Figure 4. Membership functions for SOC [%], speed [km/h] and $P_{th}$ [W]**

| | |
|---|---|
| Rule 1 | **If** speed is "fast" **and** SOC is "high" **then** $P_{th}$ is "HST" |
| Rule 2 | **If** speed is "fast" **and** SOC is "normal" **then** $P_{th}$ is "VH" |
| Rule 3 | **If** speed is "fast" **and** SOC is "low" **then** $P_{th}$ is "MH" |
| Rule 4 | **If** speed is "medium" **and** SOC is "high" **then** $P_{th}$ is "H" |
| Rule 5 | **If** speed is "medium" **and** SOC is "normal" **then** $P_{th}$ is "M" |
| Rule 6 | **If** speed is "medium" **and** SOC is "low" **then** $P_{th}$ is "VL" |
| Rule 7 | **If** speed is "slow" **and** SOC is "high" **then** $P_{th}$ is "M" |
| Rule 8 | **If** speed is "slow" **and** SOC is "normal" **then** $P_{th}$ is "VL" |
| Rule 9 | **If** speed is "slow" **and** SOC is "low" **then** $P_{th}$ is "LST" |

**Table 1. Fuzzy Logic Rules**

starts and stops of the engine. This additional constraint necessarily increases fuel consumption. The final controller can be summed up on the Fig. 5. The time frame for speed moving average is 60 seconds.

## 5. SIMULATION RESULTS

The vehicle used in simulation has a 35 kW peak electrical motor, a 35 kW engine, a 2.5 kWh battery pack and a mass of 565 kg without the driver.

The proposed real-time controller is illustrated on Fig. 5 and was tested on the normalized urban Federal Test Procedure (FTP) cycle. Performances were compared to dynamic programming results. A fuel consumption of 4.80 L/100km was obtained for the fuzzy based EMS while the DP algorithm showed a minimal consumption of 4.32 L/100km. The evolution of $P_{th}$ and SOC during the cycle can be observed on Fig. 6. It can be seen that the fuzzy logic controller adapt the threshold $P_{th}$ based on the current speed profile. For example, after around 230 s of trip, a faster speed profile is detected and $P_{th}$ is increased. The fuzzy based EMS appears to well maintain SOC into its allowable range and we can note that further fuel saving improvement could have been done if the fuzzy based EMS was able to impose the final SOC at a lower level.

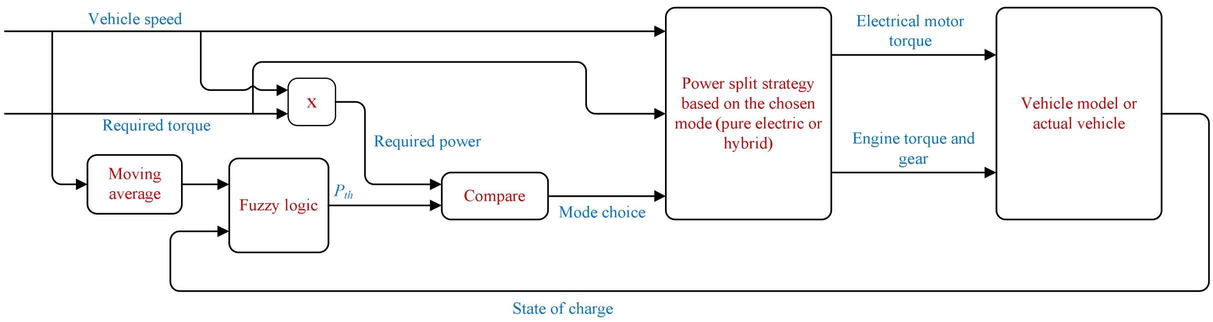


**Figure 5. Proposed real-time controller**

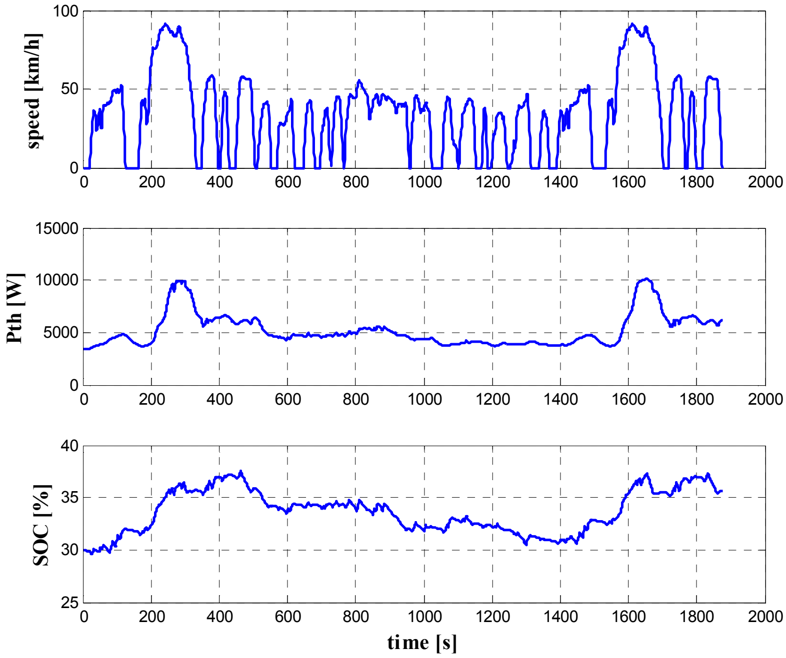


**Figure 6. Fuzzy based EMS performance on the FTP urban cycle**

## 6. CONCLUSION

The proposed EMS is able to perform charge sustaining mode in a plug-in hybrid electric vehicle. The controller design has been made on the basis of the DP algorithm results and the vehicle control is achieved by using a fuzzy system that benefits from previous trip information. The proposed controller has proved to offer good fuel economy performance, well maintain SOC and is able to adapt itself to the current driving condition.

## 8. REFERENCES

[1] Banvait, H and Anwar, S, "A Rule-Based Energy Management Strategy for Plug-in Hybrid Electric Vehicle (PHEV)", in *2009 American Control Conference* (St. Louis, MO, USA, June 10-12, 2009)

[2] Sun, L, Liang, R and Wang, Q, "The Control Strategy and System Preferences of Plug-in HEV", in *IEEE Vehicle Power and Propulsion Conference* (Harbin, China, September 3-5, 2008)

[3] Lu, D, Li, W, Xu, G and Zhou, M, "Fuzzy Logic Control Approach to the Energy Management of Parallel Hybrid Electric Vehicles", in *Proceedings of International Conference on Information and Automation* (Shengyang, China, June 2012)

[4] Li, S.G, Sharkh, S.M, Walsh, F.C and Zhang, C.N, "Energy and Battery Management of a Plug-In Series Hybrid Electric Vehicle Using Fuzzy Logic", *IEEE Transactions on Vehicular Technology*, vol. 60, no. 8, October 2011, pp. 3571-3585

[5] Ngo, V. N, Hofman T., Steinbuch M. and Serrarens, A. F. A, "An Optimal Control-Based Algorithm for Hybrid Electric Vehicle using Preview Route Information", *American Control Conference* (Baltimore, MD, USA, June 30-July 02, 2010)
[6] Karbowski, D, Rousseau, A, Pagerit, S and Sharer, P, "Plug-in Vehicle Control Strategy: From Global Optimization to Real-Time Application" in *Proceedings 22nd Int. Battery, Hybrid Fuel Cell Electric Vehicle Symposium Exhibition* (Yokohama, Japan, 2006)
[7] Gong, Q, Li, Y and Peng, Z-R, "Trip-Based Optimal Power Management of Plug-in Hybrid Electric Vehicles", *IEEE Transactions on Vehicular Technology*, vol. 57, no. 6, November 2008, pp. 3393-3401
[8] Wang, R and Lukic, S.M, "Review of Driving Conditions Prediction and Driving Style Recognition Based Control Algorithms for Hybrid Electric Vehicles" in *Vehicle Power and Propulsion Conference* (Chicago, USA, September 6-9, 2011)
[9] Murphey, Y.L, Chen, Z.H, Kiliaris, L, Park, J, Kuang, M, Masrur, A and Phillips, A "Neural Learning of Driving Environment Prediction for Vehicle Power Management" in *IEEE World Congress on Computational Intelligence* (Hong Kong, June 1-6, 2008)
[10] Langari, R, Won, J-S, "Intelligent Energy Management Agent for a Parallel Hybrid Vehicle – Part I: System Architecture and Design of the Driving Situation Identification Process", *IEEE Transactions on Vehicular Technology*, vol. 54, no. 3, May 2005, pp. 925-934
[11] Denis, N, Dubois, M.R, Gil, K.A, Driant, T and Desrochers, A, "Range Prediction for a Three-Wheel Plug-In Hybrid Electric Vehicle" in *Transportation Electrification Conference and Expo* (Dearborn, Michigan, USA, June 17-20, 2012)
[12] Lewis, F.L and Syrmos, V.L, "Dynamic Programming", *Optimal Control*, New York, John Wiley & Sons, 1995