# Power Split Strategy for a Plug-In Hybrid Electric Vehicle Using Driving Pattern Recognition and Genetic Algorithm


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## ABSTRACT

Hybrid and plug-in hybrid electric vehicles (HEV and PHEV) represent one of the best alternatives to conventional engine propelled vehicles since they are able to increase autonomy and reduce fuel consumption. Such vehicles require a high level control in order to establish the power split decision that minimizes fuel consumption while maintaining drivability. Since fuel consumption greatly depends on road type, this paper proposes a power split strategy which benefit from information on current and previous driving conditions. Based on the Dynamic Programming (DP) work, a chosen set of control parameters were optimized on specific driving cycles using Genetic Algorithm (GA). A driving pattern recognition module using a KNN classifier is then used to select the specific driving pattern, and consequently the relevant set of parameters, that fit the most with the current driving conditions. The efficiency of the proposed controller is demonstrated through simulations.



**Keywords:** Plug-in Hybrid Electric Vehicles, Energy Management Systems, Genetic Algorithm, Driving Pattern Recognition, Dynamic Programming

## 1. INTRODUCTION

Environmental concerns and fuel cost increase lead manufacturers and governments to develop alternative technologies to replace conventional internal combustion engine (ICE) vehicles. Vehicle electrification constitutes one possibility but HEV and PHEV architectures need a specific controller in order to take full advantage of them. Compared to a conventional engine powered vehicle, the additional power source in HEV or PHEV adds complexity and a high level controller, often called Energy Management System (EMS), has to be implemented in order to carefully choose the power distribution between the internal combustion engine and electric motor that reduces fuel consumption while maintaining battery state of charge (SOC) in a safe range and also assuring a good drivability. This is especially the case in a parallel hybrid configuration, where the internal combustion engine and electric motor are coupled together to a common mechanical shaft.

To cope with this challenge, many studies have been done and several solutions have been proposed. Global optimization techniques such as dynamic programming [1] [2] [3], particle swarm optimization [4] or genetic algorithm [5] are effective tools to find the optimal power split ratio in a parallel hybrid configuration in order to achieve the minimum fuel consumption over a known driving cycle. The major drawback is the computational complexity and the need to have a precise knowledge of the total future driving cycle. As a consequence, these techniques are almost never used in real time but are useful to compare actual controller performances with the optimal solution. Genetic algorithms [6] [7], DIRECT algorithm [8], machine learning [9] and gradient-based optimization [10] are also used as global optimization techniques to optimize a set of control parameters that defines the control logic. These optimization techniques manage to reach a quasi optimal solution and the obtained control parameters can be easily used in real time. In the process of globally optimizing the use of gasoline and battery energy, there is a need for information on the total driving cycle. Thus a unique set of optimized control parameters could be ineffective for certain driving conditions. This last point brings us to the importance of the driving pattern recognition. The driving profile greatly influences fuel consumption and the knowledge of near future driving conditions could reduce fuel consumption if the information is well used by the EMS [9] [11] [12].

In the proposed method, a chosen set of parameters was found to be relevant for the controller design according to DP results. A fast and simple Genetic Algorithm was developed to optimize this set of parameters on 10 specific driving cycles. Then an innovative driving pattern recognition module using KNN algorithm was added to select the suitable set of parameters based on the past driving conditions. This paper deals with the case of a discharged battery at the beginning of the trip. The presented controller has been designed to optimize fuel economy while maintaining the battery state of charge around a constant level of 30%. Section 2 will introduce the vehicle architecture, section 3 will expose the analysis made on the dynamic programming results, section 4 will present the design and choices of the controller itself and finally section 5 will present simulation results.

## 2. VEHICLE ARCHITECTURE

The vehicle configuration considered has a parallel hybrid 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 demand. The energy flow chart of the power train is described on Fig. 1. The engine output power $P_{ICE}$ and electrical motor output power $P_e$ are added thanks to a set of gears that composes the mechanical transmission in order to provide the required power to the wheel $P_w$. The motor output power can be negative for the battery to be recharged during the trip; wheel torque can be negative as well in case of braking the vehicle and negative engine output power is not allowed for efficiency consideration.

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

The complete vehicle model (mechanical and electrical) was established in a previous work by the authors [13]. The latter model will therefore enable predicting the mechanical torque profile to be supplied to the wheel for a given vehicle speed profile to be driven. For the internal combustion engine, its torque will be determined by considering a map that gives

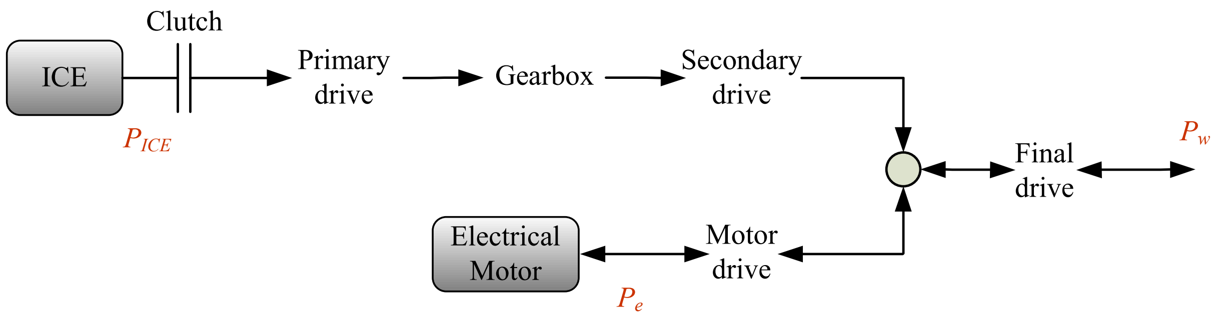


**Figure 1. Energy flow chart**

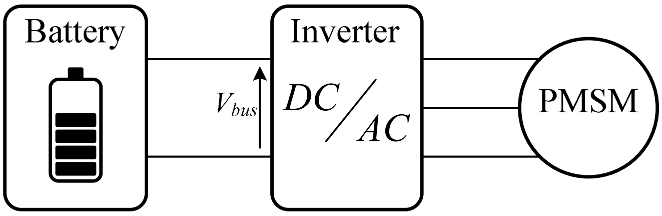


**Figure 2. Electrical power train**

instantaneous consumption for every speed and torque. Finally the electrical power train was characterized by its mathematical equations.

## 3. DESIGN DECISIONS BASED ON THE OPTIMAL RESULTS

### 3.1 The Dynamic Programming Algorithm

The dynamic programming algorithm is a well-known and efficient optimal control algorithm for non linear and complex systems [14]. It was used to find the optimal power split ratio that minimizes the global fuel consumption over a complete driving cycle. The chosen control variables were the engine torque $T_{ICE}$ and the gear ratio $k$. The values of these two control variables are optimally determined by the DP algorithm over a driving cycle to minimize the fuel consumption. The dynamic system is the core of the algorithm and relates the battery charge/discharge rate with the control variables thanks to the numerical model [13]. The cost function to be minimized is the total fuel consumption $J_{tot}$ over the chosen driving cycle, given by

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

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 and physical constraints such as maximum and minimum torque of both motors 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. The optimized ICE torque value must be found somewhere between the computed limitation, which will minimize the overall fuel consumption.

Furthermore physical constraints on engine speed set the constraints on gear ratio $k$. Since the vehicle has a six speed transmission the admissible set of gear ratio is a subset of {0; 1; 2; 3; 4; 5; 6} which is updated at every time step based on the information on vehicle speed. In this paper, the focus is made on optimizing the charge sustaining mode. Hence, the initial and final

SOC were imposed to be 30%. Equations (1) and the above constraints set the constrained minimization problem that can be solved using the Bellman principle of the DP algorithm [14]. The DP algorithm was run on the 11 Facility-Specific Drive Cycles developed by Sierra Research Inc. [12]. They describe vehicle operation over different types of roadway (arterial, local and freeway) with several congestion levels.

### 3.2 Analysis and design decisions

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 1) pure electric 2) hybrid. Also the purpose of observing the DP results 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 each of the 11 speed cycles. In each speed cycle, it was observed that the engine always works around its maximum efficiency during the hybrid mode. For the second point, the electrical motor load points obtained with DP were plotted for every speed cycle (star points on Fig. 3) and compared with the case where the entire speed cycle would have been performed in pure electric mode (circles on Fig. 3). Pure EV is identified by the DP algorithm as an optimal mode of operation when DP load points (star) match with pure electric load points (circles). On the contrary, the DP algorithm will identify the hybrid mode as optimal in other cases, where the compared load points are separated (star and circles do not coincide). For each driving cycles, it was observed that the vehicle works in hybrid mode as soon as

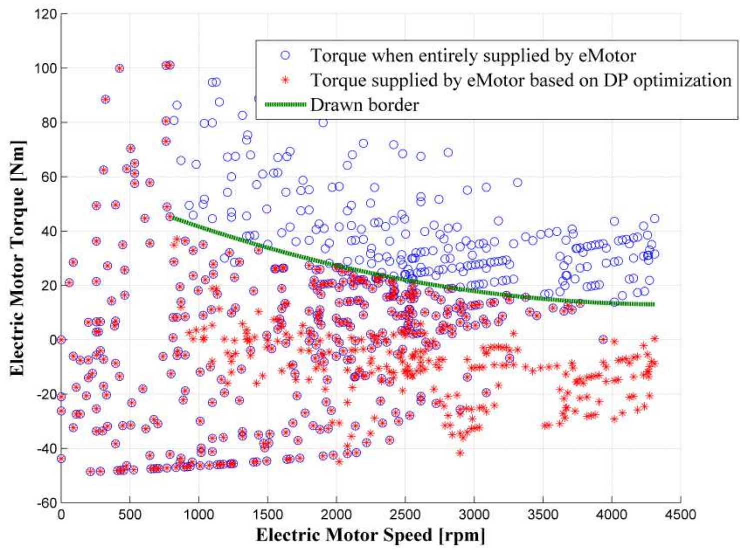


**Figure 3. Motor load points on “arterial LOS A-B”**

relatively high power is required. The resulting idea is that a border line can be drawn above which the electric motor should not operate alone in pure EV, in order to stay close to optimality. However, at low speed, it is observed that the vehicle always runs in pure electric mode, especially where the ICE speed is below the idle speed.

The absence of DC/DC converter and the need for flux weakening current increase the power losses in the whole electrical power train, especially when high mechanical power is required. This can explain why the electric motor operates in a relatively low range of power in DP results. The different results showed that the drawn borders are different for every considered speed cycle. The key originality of the work lays in the fact that the controller will try to recreate and adapt this border based on the current driving pattern.

## 4. DESIGN OF THE REAL TIME CONTROLLER

The DP algorithm cannot be used in a real-time control of the power split estimation. The assessment of the optimized power split ratio based on a DP calculation may take several hours on a powerful computer. However, the border line of Fig. 3, which results from the DP calculation, may easily be implemented in a real-time controller. In this section, the electric/hybrid transition management is made using GA and driving pattern recognition

### 4.1 Parameters Optimization Using Genetic Algorithm

The drawn border in Fig.3 can be interpreted as a torque threshold, which depends on the motor speed $N_e$, above which the electrical motor should not operate. From the work presented in section 3, the DP analysis has shown that the optimal threshold, called $T_{th}$, can be described by a function with the following form

$$T_{th} = a\, N_e^2 + b\, N_e + c\,. \tag{2}$$

The three parameters $a$, $b$ and $c$ will be dependent on the speed cycle considered. As the DP does not provide the $a$, $b$, $c$ coefficients of function (2), these parameters were optimized on each speed cycle using a GA that minimizes both SOC deviation and fuel consumption based on the fitness function $f_{fit}$,

$$f_{fit}(a,b,c) = fuel_{cost} + \gamma\, \Delta SOC\,, \tag{3}$$

where $fuel_{cost}$ is the fuel consumption in L/100km, $\Delta SOC$ is the difference between initial and final SOC and $\gamma$ is a scale factor depending on the considered driving cycle. The fitness function can give SOC evolution and fuel consumption based on the vehicle model, speed, desired torque and transition decision ruled by the previous parameters. The constructed GA uses remainder selection, heuristic crossover and uniform mutation. At each step, the GA works on improving two subpopulations of 50 individuals based on their scores (fitness values) and 60 % of the individuals in the new generation are created by crossover. It should be noted that the vehicle cannot run in hybrid mode less than 5 seconds or in electric mode less than 3 seconds in order to prevent multiple start stops. The GA optimization takes this last constraint into account.

The GA was found to be efficient. For example, on the “arterial LOS A-B”, GA gives 4.46 L/100km while DP gives 4.35 L/100km. The consumption increase is mainly due to the delay for engine start/stop. The SOC evolutions for both techniques were compared on Fig. 4.

### 4.2 Driving Pattern Recognition

The introduced parameters were optimized on the 11 Facility-Specific Drive Cycles. If we assumed that the driving cycle is not known in advance, the real-time controller needs to have a driving pattern recognition module in order to select the suitable set of parameters. This module analyses past information on which it extracts some features which are then associated to a specific driving pattern thanks to a k-nearest neighbors (KNN) classifier.

The first step is to extract features from the known driving cycles. The feature selection was based on the work in [15]. Based on the statistical distribution of the features for every speed cycles, some of them were found irrelevant or noisy for KNN classification. Some other relevant features were also added. The 11 selected features are maximum, minimum and average speed, speed standard deviation, maximum and average acceleration, acceleration standard deviation, average deceleration, deceleration standard deviation, percentage of time between 0 and 15 km/h and between 15 and 30 km/h. For each driving cycles, features were extracted on 200 windows of 60 seconds uniformly selected in the global cycle.

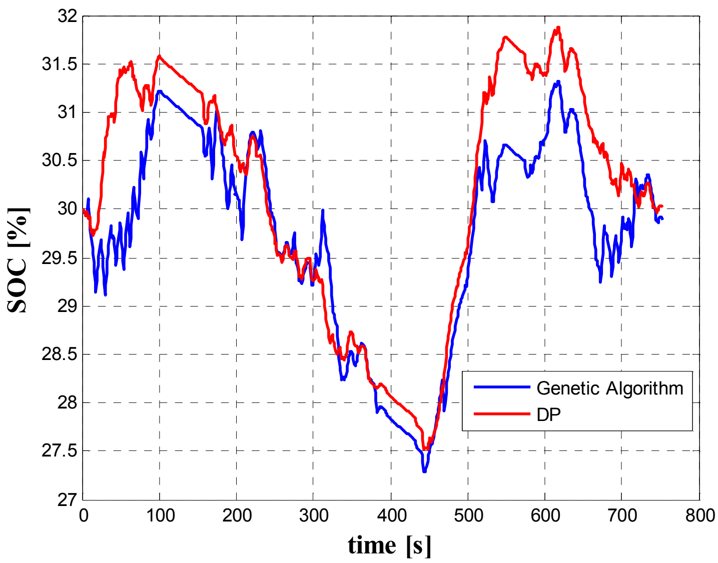


**Figure 4. SOC evolution on “arterial LOS A-B”**

It is known that classification becomes more difficult with the increasing number of classes (the driving cycles in this case). However, keeping as many cycles as possible allow the controller to deal with many situations. After some iteration, it was decided to keep 10 driving cycles among the 11. This choice offers better results even if the fraction of misclassification increases. The selected driving cycles are High-speed freeway, Freeway under LOS A-C, D, E, F and G, Arterial under LOS A-B, C-D and E-F, and Local Roadway.

Using the cross validation technique, it was found that the cross validation loss increases with the number of neighbor $k$. Nevertheless, choosing a too small $k$ could lead to unsteadiness in the prediction and $k$ = 20 was found to be a good tradeoff. The "Mahalanobis" distance exhibited the smallest fraction of misclassification and was chosen in the KNN algorithm. Finally the supervised classification was made on the basis of 2000 observations separated with 10 labels. The fraction of misclassification over all the observations is 14.5 %.

In the real-time controller, features are extracted every 5 seconds from the last 60 seconds of trip and are used to predict the driving pattern in which the vehicle currently is.

## 5. SIMULATION RESULTS

The entire controller can be seen in Fig. 5. The driving pattern recognition allows selecting the relevant set of parameters previously computed by GA. Then the torque threshold is calculated using speed information and selected parameters. In order to deal with the problem of stability, a correction factor $\alpha_{SOC}$ is multiplied to the computed $T_{th}$. When the state of charge is under 23% this correction factor decreases $T_{th}$ and the hybrid mode become preponderant in order to charge the battery. On the contrary when the state of charge is above 38%, $\alpha_{SOC}$ increases $T_{th}$ to favor electric mode. In other cases, the correction factor does not influence $T_{th}$.

The proposed "GA based EMS" controller was tested on the normalized urban Federal Test Procedure (FTP) cycle and performances were compared to dynamic programming results. The fuel consumption obtained with "GA based EMS" was 4.54 L/100km compared to 4.32

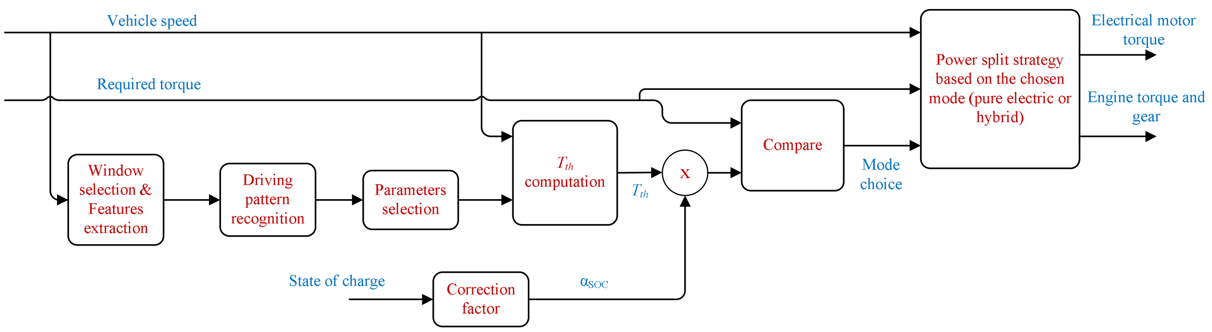


**Figure 5. Proposed real-time controller**

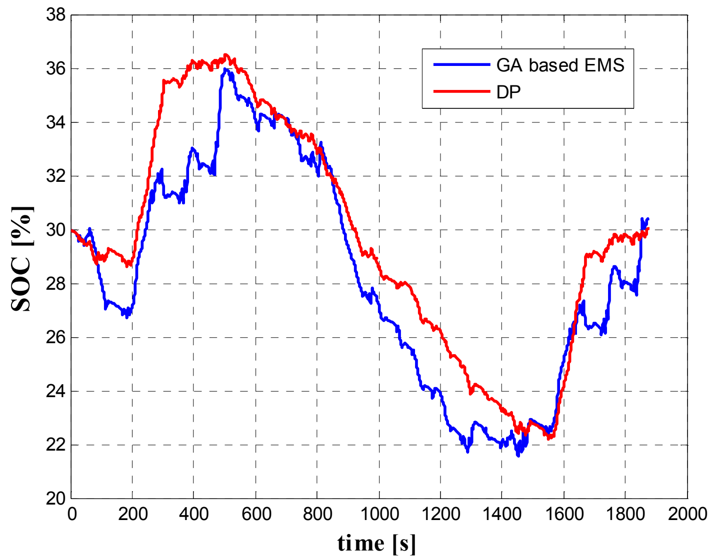


**Figure 6. SOC evolution for the GA based EMS**

L/100km for DP, which represents an increase of 5.3 %. As it can be seen on Fig. 6 the SOC evolution obtained with the "GA based EMS" is close to optimality even without future knowledge of the trip and SOC appears to be well sustained by the EMS over the cycle.

## 7. CONCLUSION

The paper proposed a new energy management system adapted to a PHEV. Based on the dynamic programming algorithm results, a set of optimized parameters were computed on 10 defined driving cycles using Genetic Algorithms. Then a driving pattern recognition system using KNN algorithm was constructed to choose the relevant set of parameters based on the past information of the speed. The "GA based EMS" does not need any future knowledge of the driving cycle and however, offers performances close to the optimal behavior.

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