Energy management strategies for HEVs: introduction and positioning

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Abstract: Hybrid Electric Vehicles are effective solutions to reduce energy consumption and pollution emission in the transport sector. They however present multiple energy sources and complex drivetrain structures involving numerous energy transformers. Their control is therefore complex and represents a key point to achieve the expected performance. The energy management is a part of this control and should be properly developed so that the efficiency of the HEV is enhanced. This topic has been of great concern in the two last decades and still mobilizes number of researchers. Energy management strategies (EMS) ensuring the power sharing between the different components, sources as well as transformers, adapted to different cases have been therefore developed and optimized. This chapter presents the definition and principle of the EMSs for HEV. Different families of EMSs are then introduced and illustrated by examples in order to provide a better understanding of the methods principles. Some of these methods are based on the expertise and the intuition of developer. Others use optimization theories in order to operate near the maximum expected efficiency. In most of the cases today, offline simulation using global vehicle models are used to develop and compare the performance of these different methods.

Keywords: Hybrid Electric Vehicle, Energy management strategies, optimization

1- Introduction

Hybrid Electric Vehicles (HEV) have two or more energy sources used for their motion. One of these sources has an electric energy type and is always bidirectional to allow energy recovery during vehicle deceleration and breaking. Although the hybridization concept is not limited to the use of thermal engines (diesel, gasoline or natural gas internal combustion engines), we will consider in this chapter only gasoline or diesel engines based HEVs. Other energy sources like Fuel cells based on Hydrogen supply or biofuel engines could apply to the methods presented here, but the characteristics of the considered generators should be studied to adapt to these methods.

Besides the multiple sources, the HEV generally uses several components to transmit the energy from the sources to the consumers which are usually the traction and the auxiliaries needs. This transmission may include electric machines but also mechanical components such as clutches and gears. The different arrangements of these components leads to multiple possible drivetrain architectures also called topologies. The most known are series, parallel and series-parallel (or power-split) architectures. Another classification of HEVs plays on the weight of the electric power installed compared to the overall maximum power of the vehicle. Called hybridization ratio or rate (H-rate), this parameter allows to give Hybridization hierarchy known as micro (lowest H-rate), mild (moderate H-rate) and full hybrid (highest H-rate). The last HEV categorization is related to the possibility of plugging them to the grid. In the case of possible recharge from the grid we talk about plug-in hybrid (PHEV). For the other case, we will consider the term conventional HEV instead of non plug-in HEV used by some authors.

Whatever the HEV H-rate, architectures or possible charging, the control of HEVs generally presents two main levels (figure 1). The first is a global level (called also supervisor) and is

responsible for relaying the driver's request in terms of vehicle movement and operation of auxiliaries. This level then distributes the demand to the different energy sources and provides the reference quantity to the various actuators of the vehicle. The second level is a local level and allows to communicate with the global supervision (generally through a data bus like CAN bus for example) to carry out the actions necessary to achieve the reference quantities and sends back information about possible limitation due to components limits (maximum voltage, maximum current, maximum temperature, …). The local control of the internal combustion engine (ICE) for example translates the torque request from the supervisor into a fuel injection set point according to the engine parameters. The local control of the EM (Electric Motor) makes it possible, from the torque (or speed) set point demand, to achieve the current control in the machine using the management of the inverter switches.
In this chapter, we will consider the global control level which allows the management of energy between the sources of the hybrid vehicle while respecting security coming from the dedicated CUs (Control Units).
After introducing the general principals and the state of the art of the methods used in energy management of HEVs, some families are detailed and examples are given.

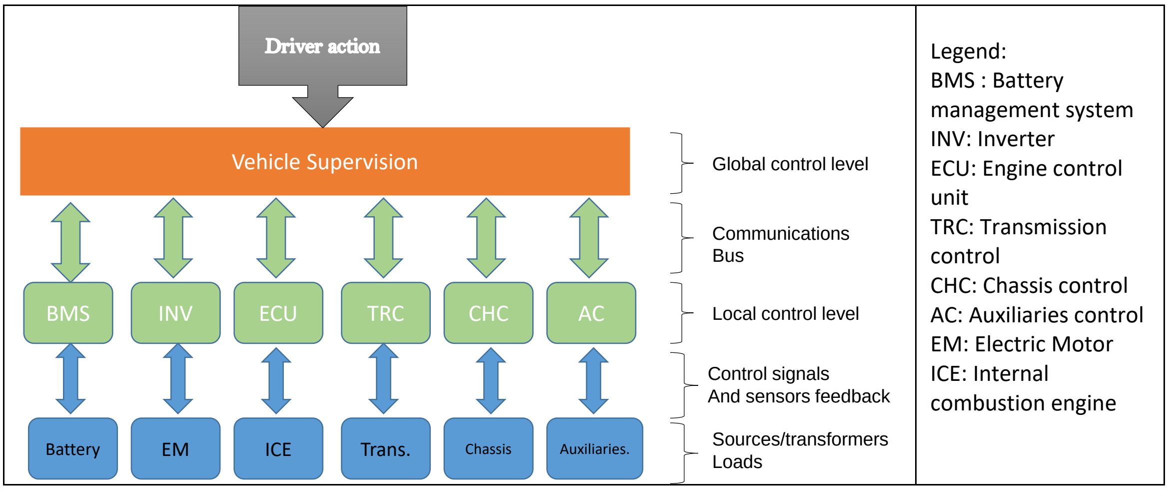


Figure 1: HEV control levels

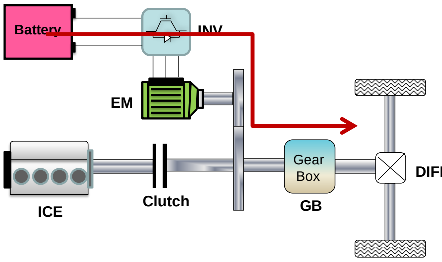
2- General considerations for HEVs energy management

2.1 Energy management Problem statement

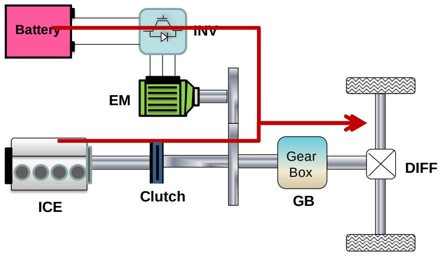
The existence of multiple sources and multiple energy converters makes it possible for the HEV to operate in different modes. The global level of the HEV control has to decide at each time in which mode the vehicle should operate and, for each mode, what are the quantities of power exchanged between the different elements of the vehicle. The main operating modes that are allowed by the association of two or more sources in a HEV, from its light version ("Micro-hybrid") to the most complete version ("Full-hybrid") could be simplified as follows:

- All-electric traction mode.
- Hybrid mode with Electric assistance during vehicle acceleration (called also “boost” function).
- Energy recovery during deceleration ("electric braking").
- Hybrid mode with charging the batteries on board by the IC engine.

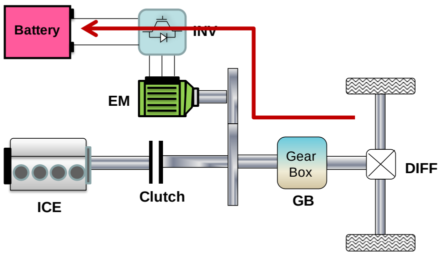
Figure 2 shows an example for a parallel HEV architecture including a clutch to allow ICE disconnection and thus a true electric mode.



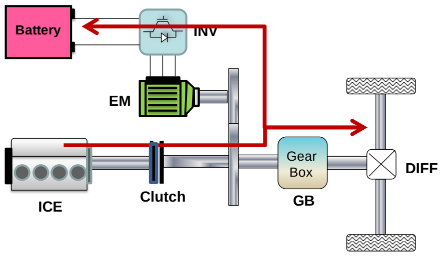
a) Electric Mode, traction



b) Hybrid Mode, electric assistance



c) Electric mode, regenerative braking



d) Hybrid Mode, battery recharging

Figure 2: Examples of operating modes encountered in a parallel HEV

Depending on the architectures and the hybridization rate, the functions listed above may or may not be possible and energetically efficient or not. This raises the problem of managing the instantaneous energy to activate one or the other of these functions. Viewed more generally, the existence of two or more energy sources introduces degrees of freedom in the control of the vehicle and therefore allows one or more strategies to be performed. This strategy, also called Energy Management Strategy (EMS) has to fulfill the following objectives:

- Provide the power distribution between the sources (fuel tank, battery, supercapacitors) at each time while ensuring the driver's demand,
- Manage the energy fluxes between the energy transformers (Electric machines, clutches, gears, …),
- Control the state of charge (*Soc*) of the energy storage systems (here we will limit to battery and supercapacitors).

2.2 Battery management

One of the goals of energy management is to control the state of charge of the energy storage systems (ESS). This objective must respond to a prior choice resulting from the vehicle concept and components sizing like the possibility of external recharging (plug-in hybrid) for instance. This choice then imposes the overall use of the ESS with floating charge (“charge sustaining”) or decreasing charge (“charge depleting”).

2.2.1 Control in floating state of charge ("charge sustaining")

When the hybrid vehicle is non-Plug-in (conventional HEV), the state of charge of the battery must be maintained by recharging phases on board the vehicle. These recharges come from the kinetic energy of the vehicle during deceleration phases or from the IC engine using the electric machine in generator mode. The charge sustaining window can be at most equal to the maximum battery capacity, but is generally much smaller for reasons of power availability and battery lifetime. Indeed, the maximum power of charge (respectively of discharge) of the battery depends on the *Soc* and falls drastically at the beginning (battery fully charged) respectively at the end (battery deeply discharged) (Belt et al. 2003). To maintain a charge and discharge power greater than a given value, it is imperative to reduce the useful interval of the battery *Soc* accordingly. With regard to lifetime, it is well known now that the depth of discharge magnitude *(ΔSoc)* accelerates the aging of the battery for a given vehicle use (Redondo et al. 2020). It was also observed, in correlation with these remarks, that the first hybrid vehicles put on the market in the late 1990s, all of them conventional, presented incursions of *ΔSoc* rarely greater than 10% of the total battery capacity (R. Trigui et al. 2003).

2.2.2 Control with decreasing state of charge ("charge depleting")

Decreasing *Soc* (or " charge depleting ") consists in letting the battery state of charge decrease during use until reaching a minimum value at the end of the Trip. This option is mainly used for battery management in plug-in HEVs. However, it is not excluded that a conventional HEV may pass through a ZEV ("Zero Emission Vehicle") zone and thereby achieve a temporary *Soc* decrease. This implies that the battery is sized in energy accordingly. In the literature, there are often three strategies in the management of the battery energy of a Plug-in hybrid vehicle (Figure 3).

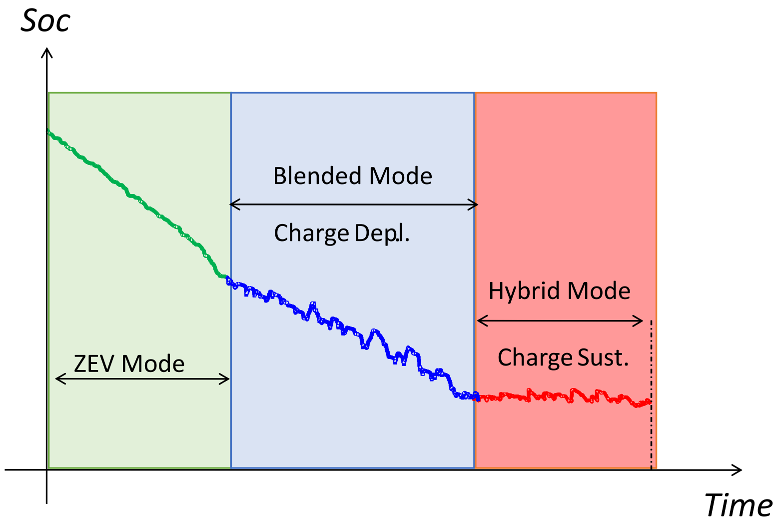


Figure 3: Soc battery control possibilities in an HEV

The first zone corresponds to an all-electric mode (known also as ZEV operation, for Zero Emission Vehicle). The decrease in state of charge is the fastest in this area. The second zone corresponds to a hybrid operation in decreasing state of charge, also known as the blended mode. This decrease is controlled by the alternate On/Off of the ICE. The last zone begins when the state of charge reaches its low limit and corresponds to a charge sustaining logic allowing the plug-in HEV to operate like a conventional HEV before the next possibility of recharging.

In what follows we assume that the battery management strategy is known and therefore the desired state of charge of the end of use is fixed.

2.2.3 Supercapacitors management :

HEV could also use supercapacitors as second or third energy source. In the two cases, as supercapacitors are used for their high power density, their low energy density does not allow to use them intensively during a long period. Besides, the power delivered and the efficiency of the supercapacitors are related to their *Soc* and thus their voltage level. That is why the supercapacitors are generally used with no more than 50% of depth of discharge. The management of supercapacitors in HEV application is then of charge sustaining type, based mainly on the voltage instantaneous level control.

2.3 The different energy management methods

To achieve instantaneous power sharing between the energy sources and transformers in the HEV, while controlling the storage elements *Soc*, several methods have been developed over the past two decades. In the literature there are several classifications of these methods. The best structured in our opinion is that proposed by Salmasi in (Salmasi 2007) also taken up by many authors, among them recently Qicheng Xue (Qicheng Xue et al 2020), and represented in a simple way in Figure 4. It allows energy management methods to be split into two large families: those which are based on modal logic using expert knowledge of the system (called also rule based), and those which use optimization principles.

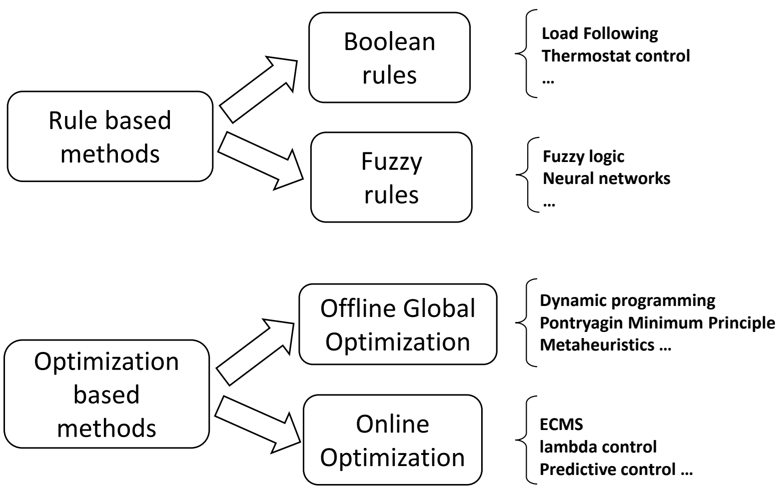


Figure 4: Energy Management Strategies classification

2.4 Model based EMS development

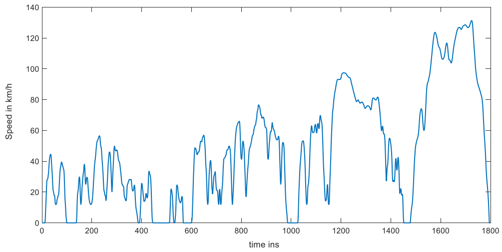
As will be detailed further, some of the EMS methods could be intuitive and directly implemented in the ECU of the HEVs. Nevertheless, it is widely admitted today that using model based EMS development brings many advantages, among them:

- Methods testing (debugging) is much easier offline using high capacity computers
- Benchmark of methods could be done in a first step only by simulation
- Some platforms offer easy transfer from simulation to Hardware In the Loop prototyping (HIL) and then to vehicle onboard tests

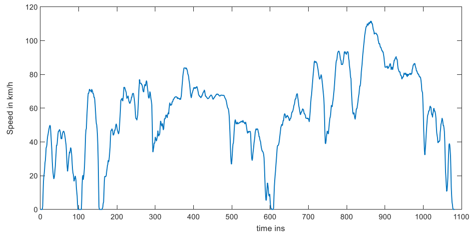
Many models or representations based on a systemic approach for the HEVs simulation provide sufficiently accurate results in terms of energy consumption so that EMS performance could be compared before their real implementation. This comparison uses generally as input predefined speed profiles also called driving cycles (see frame 1), in order to take into account the diversity of HEVs' uses (urban, extra urban, highway, standards, …). However, in order to obtain acceptable accuracy, the modeling techniques need to be validated with appropriate data for each subsystem of the vehicle.

Frame 1: driving cycles concept

Speed profiles called also driving cycles are now common required knowledge in the domain of vehicles energy simulation and evaluation. HEVs EMS development and comparison use also these profiles. We can distinguish different types of profiles or driving cycles, namely standard profiles or database-origin profiles. Standard profiles (like WLTC for Europe) depend on countries and are used to compare new vehicles in terms of consumption and pollutant emissions (figure 6a). Profiles from databases are previously registered and stored, sometimes even statistically treated to define typical trips of vehicles in real use (example: Artemis database in Europe (André 2004)) (figure 6b).



a) WLTC standard cycle



b) Exra-Urban Artemis cycle

Figure 6: different types of speed profiles (driving cycle).

In real life operation, speed profiles could be stored in the vehicle memory, and/or predicted on a given future time horizon as required in some kinds of controls presented in this chapter. Energy consumption is directly linked to the instantaneous variation of speed. Vehicle energetic global models try to estimate precisely this energy using driving cycles as input.

3- Rule based EMS methods

Thanks to multiple energy sources and multiple energy converters, HEVs could operate in different possible modes for the different movement phases. The most important modes are summarized in Table 1.

HEV Use phase	Mode name	Description
Traction phase	Electric mode	Only battery and electric machines ensure the vehicle movement. The ICE is off.
	ICE only mode	Only the ICE ensures the vehicle movement. No electric flux to or from the battery.
	Hybrid mode with electric assistance	The ICE is on and gives a part of the required traction power, the battery and the electric motor give the complement of power.
	Hybrid mode with Battery charging	The ICE is on and provides the required traction power while charging the battery with an extra power.
Braking phase	Electric mode, regenerative braking	The electric motor operates as generator to slow the vehicle using electric braking and regenerate energy to batteries
	Mechanical braking	Total or a share of the mechanical brakes is used to decelerate or to stop the vehicle
Stand still	Engine stop	This function makes it possible to switch off the ICE engine when the vehicle is stationary. Idling consumption will thus be avoided.

	Engine on, recharging the battery	If needed (and if possible), the battery is charged during the vehicle stops using the ICE and an electric motor used as generator

Table 1: Operating modes of an HEV

Based on an approach using mode selection the rule-based EMS methods are themselves divided into two categories: Boolean rules and fuzzy rules methods. In both cases, these rules must meet the objectives of energy management mentioned above. Given the modal and intuitive nature of this type of method, no guarantee can be given as to their optimality with respect to a criterion. On the other hand, their implementation in real time is relatively easy. For the two categories, Boolean and fuzzy, some strategies will be presented as examples.

3.1. Strategies based on Boolean rules

3.1.1 Principle

Boolean rules, often having the logic "If a condition (threshold) is reached, then an action is undertaken", allow to activate in a simple and intuitive way the different operating modes. They can be developed with or without the use of HEV simulation model. To implement these rules one can use combinations of logical operations or state machines (Weimin Li et al. 2007) for example.

3.1.2 Example1: the "thermostat" strategy

Based on Boolean rules, this strategy uses a simple and effective control of the state of charge of the battery based on a hysteresis between two values of this variable. Therefore, when the state of charge reaches a high threshold, the ICE engine is turned off and the vehicle operates in Electric mode. When it reaches a low threshold, the ICE engine is started and one of the hybrid modes is selected. The strategy also uses the notion of energy efficiency of the ICE engine by taking into account the specific fuel consumption in the whole working area (usually known as engine map). It aims generally to track the operating points of the best efficiency so that when the ICE engine is on, its targeted operating point is fixed on the optimal power curve. Depending on the traction power required, the optimum power of the ICE engine may be greater than the demand and the difference will be used to recharge the battery. In the other case (power demand higher than optimal power), the battery provides energy to assist the ICE engine.

Advantages - One of the main advantages of this method is its simplicity of implementation. The hysteresis control of the state of charge of the battery ensures the localization of this state in a precise band. In certain hybrid configurations and certain components' sizes, the operation of the ICE engine on the best points of specific consumption is really advantageous as in the case of a series hybrid with a hybridization rate close to 0.5 (ie the power of the battery is of the same order as the power of the IC engine).

Disadvantages - The disadvantages of this method are multiple.

- The number of stops / starts of the ICE is set by the width of the hysteresis band of the state of charge control and is completely disconnected from the power demand.
- Depending on the hybrid architecture and the sizing of the components, especially for parallel HEV and for low hybridization rates, it is impossible to constantly operate the ICE at its best operating points.
- If the architecture and the components sizing allow it, the operation of the ICE at its best operating points leads to an intensive use of the battery recharging mode. In addition to the limited energy efficiency of this mode (due to the efficiency cascade of the subsystems), the high demand on the battery leads to the risk of premature ageing.

3.1.3 Example2: the Load following strategy (LFS)

Unlike the thermostat strategy, the power following strategy (or load following) (Kimura et al. 1999), favors the traction request to activate one or other of the operating modes. Its principle is based on a set of rules such as the following.

1) Switching from electric mode (IC engine off) to hybrid mode (IC engine running) depends on crossing a vehicle speed threshold or a power threshold or a combination of the two with a hysteresis between the activation of both modes to avoid oscillations.

2) Electric assistance mode (boost) is activated when the power required for traction exceeds the maximum available power of the ICE engine.

3) The battery recharging mode by the ICE engine is activated when the state of charge of the battery reaches a low threshold.

4) Braking energy recovery via the electric motor is promoted as soon as the vehicle power is negative (braking phase).

Usually, these rules are supplemented by limitations and protections to insure the safe use of the different components.

Advantages - The main advantage of this method is its universal aspect since it can be applied to different architectures and different H-rates of HEVs. It also provides a soft use of the battery as the ICE contribution is related to (and not disconnected from) the required power.

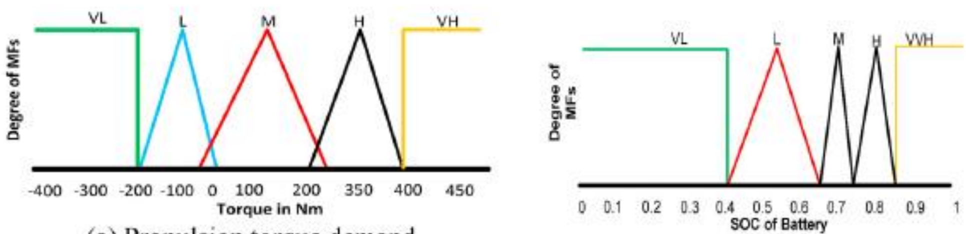
Disadvantages - Among the disadvantages of this method we can cite the control of the implicit and non-explicit state of charge and the difficulty of setting the various thresholds. Like all rule-based strategies, this strategy does not guarantee near optimal consumption or emission of pollutants.

3.1. Strategies based on Fuzzy rules

Given the high number of parameters involved in the energy management of HEVs as well as the uncertainties and possible non-linearities, a fuzzy logic approach could be effective (J. S. Won & R. Langari 2002). Usually a fuzzy logic controller has four components:

- "fuzzification": it allows the transformation of an input variable into a fuzzy variable.
- Knowledge base: it contains the definitions of the membership functions of the variables. These functions can be of different forms: triangle, bell, etc.
- Fuzzy logical inference: reasoning of the fuzzy system according to the established rules, generally performed in one or several tables.
- "Defuzzification": transformation of the fuzzy calculation result into a quantized output for decision making.

These operations allow, through the notion of relative membership of input variables to an output class, to replace the Boolean logic applied to expert rules by a more flexible logic. As an example (Krishna et al 2021) proposed the following fuzzification of two key variables used in energy management of power-split HEV (figure 5).



(a) Propulsion torque demand (b) Battery SoC

Figure 5: Fuzzification and degree of membership for two variables a) propulsion torque demand and b) Battery Soc. (Krishna et al 2021)

In this way, Instead of having precise thresholds that initiate an action (Engine start for example), fuzzy levels (Very Low, Low, Medium, High and Very High in this example) are used. Generally, tables of correspondence are set to determine actions on control variables according to the different fuzzy levels of the state variable (Soc) and the driver request (torque demand). As an example, one fuzzy rule could be: If the level of torque demand is Medium and Soc is Low then ICE is On and battery is recharged with recharge level corresponding to medium. The defuzzification phase allows then to translate "medium" value of recharge into a numerical value corresponding to the required battery recharging power.

4- Optimization based EMS

The rule based EMSs have the advantage of being simple to implement and robust in use, but do not fully address the problem of energy optimization, necessary for the viability of hybrid vehicles. Therefore, Energy management could also use optimization methods to improve the efficiency potential of HEV. This involves using the degrees of freedom of hybridization to optimize a criterion, often minimizing fuel consumption (equivalent in a first approximation to minimizing CO2 emissions). This criterion could be more complex by integrating pollutant emissions and / or the intensity of use of the battery. The optimization methods can be classified into two categories depending on whether they are used offline with a priori knowledge of the instantaneous mission of the vehicle (speed versus time profile), or online without prior knowledge of this mission.

4.1 Global offline optimization

Offline global optimization methods are based on a priori knowledge of the speed profile (known also as driving cycle, (see frame 1) and usually use a model based approach. They are therefore intended only for simulation, but are the only ones to guarantee a global optimality of the control when accepting deviations introduced by the modeling errors. On the other hand, their principles and / or their results, as will be seen below, can be used to develop online methods.

4.1.1 formalization of the optimization problem.

The formalization of the optimization problem is based on the following approach:

- identification of state variables, control variables and degrees of freedom,
- the establishment of a criterion to be optimized,
- identification of the constraints to be respected.

In the case of the HEV, if we limit ourselves to overall control (supervision), there is a degree of freedom in the instantaneous choice of the power required from each source as we saw previously. It is therefore possible, based on a demand for power at the wheels and the requested power for auxiliaries, to distribute this demand between the sources by optimizing a criterion. The generated control will directly condition the state of charge of the battery usually considered as the state variable of the optimization problem. Apart from a few applications aimed at maximizing dynamic performance, the hybrid vehicle is often developed to reduce fuel consumption and pollutant emissions. The criterion to be minimized in this case is the following:

$$\mathrm{J} = \sum_{i=1}^{N}(\alpha_{fuel}\dot{m_{fuel}}(i) + \alpha_{NOx}\dot{m_{NOx}}(i) + \alpha_{HC}\dot{m_{HC}}(i) + \alpha_{CO}\dot{m_{CO}}(i))T_e \quad (1)$$

Where *N* is the number of samples over a period of use of the vehicle, $\dot{m}$ is the instantaneous fuel flow or the instantaneous emission of the pollutant considered (in g / s) and α the weight given to each of the flows. *Te* is the time sample.
In what follows, for simplicity of understanding, we will consider a single criterion minimizing fuel consumption over the entire use horizon considered.

$J = \sum_{i=1}^{N} \dot{m_{fuel}}(i)\, T_e$ (2)

The constraints to be respected are of two levels. The first deals with the last objective of the global control which is the control of the state of charge of the battery with the prior choice of the two possible options ("charge sustaining" or "charge depleting"). Indeed, an obvious solution to minimize criterion J is never to use the ICE engine (the control variable $T_{ICE} = 0$). However, this solution requires a permanent use of the battery leading to a continuous discharge without control of the Soc. The first constraint to respect is therefore:

$Soc(N-1) - Soc(0) = \Delta Soc$ (3)

ΔSoc represents the variation in the state of charge over the fixed horizon, the value of which is consistent with the battery management option chosen. The other constraints are of the equality type, specific to each hybrid architecture, or of the inequality type representing the limitations of the various subsystems of the drivetrain (see table 2).

Battery	Electric Motors	ICE
$I_{bat\_min} < I_{bat} < I_{bat\_max}$	$T_{EM\_min} < T_{EM} < T_{EM\_max}$	$T_{ICE\_min} < T_{ICE} < T_{ICE\_max}$
$U_{bat\_min} < U_{bat} < U_{bat\_max}$	$\omega_{EM\_min} < \omega_{EM} < \omega_{EM\_max}$	$\omega_{ICE\_min} < \omega_{ICE} < \omega_{ICE\_max}$
$TMP_{Batt\_min} < TMP_{Batt} < TMP_{batt\_max}$	$TMP_{EM} < TMP_{EM\_max}$	$TMP_{ICE} < TMP_{ICE\_max}$

Table2: Example of components limits to be taken as constraints for the optimization problem
I refers to current, *U* to voltage, *T* to torque, ω to rotating speed, *TMP* to temperature. Suffixes are *ICE* for engine, *EM* for electric motor, and *bat* for battery.

The 2nd step after formalizing the optimization problem is to choose a method to solve it. There are generally two families of methods: metaheuristic methods and exact methods. In the following we will introduce these two types of methods.

4.1.2 Metaheuristics EMS methods

Metaheuristics are optimization methods intended to explore in a random or organized manner a domain of a complex nature for the search for extremum. They are often iterative and stochastic in nature, and can be based on algorithms inspired by physical or natural processes and from biology. Among these methods applied to the overall optimization of energy management in HEVs we can cite the followings:

- The simulated annealing method: inspired by a process used in metallurgy (cooling / heating cycle process), this method was used for the energy management of a parallel hybrid vehicle (Paganelli et al. 2000). The authors noted, however, that the minimum found was a local minimum, although close to the global minimum.
- Genetic (or Evolutionary) Algorithms: use the notion of population and its genetic evolution. A selection process (inspired by natural selection) makes it possible to converge

on the optimal solution (the species). In (Poursamad & Montazeri 2008) the authors use genetic algorithms for parameter tuning of a fuzzy logic-based hybrid vehicle control.

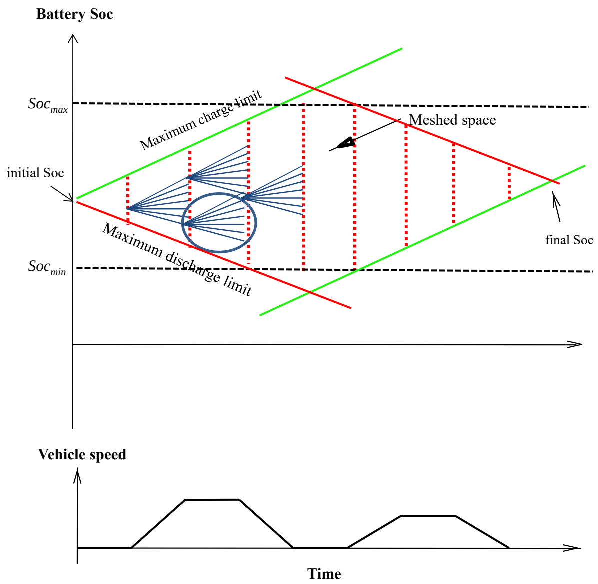
- Other methods inspired by animal biology such as the ant colony algorithm or particle swarms POS can also be applied (Chen 2018). These methods can be more useful in the case of complex systems (also called difficult) whose parameters and behavior are relatively unknown (which is seldom the case in HEV design). On the other hand, they have several drawbacks such as a significant mobilization of computing resources and the need for tedious and intuitive adjustment of the parameters. Achievement of the global minimum in this type of approach is also not guaranteed.

4.1.3 The exact methods

Exact methods make it possible to find explicit, analytical or numerical solutions to the optimization problem. For this a mathematical or numerical representation is necessary for their uses. Among the best known and most widely used methods in the field of HEV energy management is dynamic programming (DP) (Vinot 2016) and variational calculus using the Pontryagin Minimum Principle (PMP) (Lino Guzzella & Antonio Sciarretta 2008).

4.1.3.1 Dynamic programming

Dynamic programming is defined as a numerical resolution method allowing to explore in a sampled and systematic way the space of admissible solutions and to select the global solution meeting the chosen optimization criterion. Graph theory is often used to formalize this method. One or more state variables are chosen then their meshed temporal space with a given sampling step is performed. Dedicated algorithms are then used to find the path of the graph that ensures the optimization of the selected criterion. In the case of HEVs, the state variable chosen to be represented by the graph is usually the state of charge of the battery. The mesh of the space (Soc vs time) leads to a two-dimensional graph. The initial and final Soc points may be equal (generally for charge sustaining strategies) or different (mainly for PHEV). When considering the whole meshed space with sufficiently tight step sample, the algorithm of building the graph and finding the optimal path needs high computing resources. In order to reduce the search space, and therefore the calculation time and the size of the memory the meshed space is firstly limited between a minimum and a maximum Soc. Then the charge and discharge limits corresponding to the maximum and minimum currents of the battery are also introduced leading to a more restricted area to explore (figure 7) (Vinot 2016).



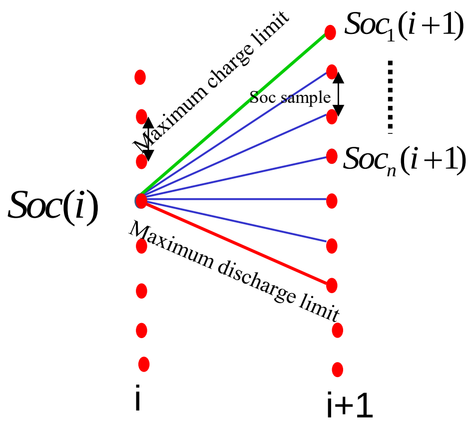


Figure 7: Mesh of the battery state of charge domain for the dynamic programming method

Figure 8: Example of a range of arcs between two instants of the graph

At each instant i of the cycle, and from a point on the graph representing a state of charge *Soc (i)*, different possibilities of achieving the state of charge for the following instant Soc_j *(i + 1)* are possible (figure 8). Each point *Soc (i)* can therefore be connected by an arc to a next point in space leading to explore an exponential number of possibilities. As the *Soc* is an integral function of the current, the slope of an arc connecting two points on the graph represents the battery current between time *i* and time *i + 1*. Therefore, for each arc, and assuming known the instantaneous speed profile, it is possible to calculate all the relevant variables including the fuel consumption considered here as the cost function by using a system modeling of the hybrid vehicle (Vinot 2016). The best Soc trajectory on the whole cycle, minimizing the total consumption is deduced using specific algorithms based on Bellman equation (Bellman 1957). Control variables corresponding to the arcs of the best path are then identified and considered as instantaneous best control.

4.1.3.2 Pontryagin minimum principle (PMP)

Criterion J (cf. equ. 2) can be also minimized under its associated constraints, on the cycle known in advance, by using the Pontryagin minimum principle (Pontryagin 1962). This principle makes it possible to transform the global optimization problem into an instantaneous minimization of a function called Hamiltonian. If we apply this method to the problem of overall optimization of the energy management of HEVs, we can express the problem as follows.

$$H(x(t),u(t),\lambda(t),t) = m_{f\dot{u}el}(u(t),t) + \lambda(t).P_{bat}(t) \qquad (4)$$

$$\dot{x}(t) = \frac{\partial H(x(t),u^*(t),\lambda(t),t)}{\partial \lambda} \qquad (5)$$

$$\dot{\boldsymbol{\lambda}}(\boldsymbol{t}) = \frac{\boldsymbol{\partial H(x(t),u^*(t),\lambda(t),t)}}{\boldsymbol{\partial x}} \qquad (6)$$

$$H(x(t),u^*(t),\lambda(t),t) \leq H(x(t),u(t),\lambda(t),t) \qquad (7)$$

Where x is the state variable, u is the control variable (T_{ICE} and Gear number are generally considered in the case of HEV), λ is the Lagrange multiplier representing the weight given to the battery use and u^* the optimal control that minimizes the Hamiltonian function.
The state variable considered here is the state of energy *Soe*, with P_{bat} the power delivered by the battery. In other formulation, Soc could be taken as state variable if we replace the battery power by the battery current in equation 5. In the Hamiltonian expression, the fuel flow is independent of the state variable. If we assume that at any time, the power (or current) of the batteries is independent of the state of energy (or of the *Soc*), the second optimality condition (equation 7) would lead to a derivative of λ equal to zero and therefore to a constant Lagrange multiplier λ for the entire horizon considered. This hypothesis is plausible as long as the battery power limit is not reached and the *Soc* is in a limited window. This is not the case, however, for supercapacitors (Vinot et al. 2013). In the case of a HEV using batteries in charge sustaining mode, this property makes it possible to reduce the problem of optimal control into a search of a single parameter (λ) on the considered horizon.
The third optimality condition ($H(x(t),u^*(t),\lambda(t),t) \leq H(x(t),u(t),\lambda(t),t)$) allows the search for the optimal control vector u^* (generally T_{ICE_opt})which minimizes the Hamiltonian at each time. To solve this minimization problem different methods are possible, we can cite:

- Calculating numerically H vs u at each time and use a minimum search algorithm,
- Approximating the models of the components by piecewise polynomial functions resulting in a differentiable Hamiltonian function that allows a one shot algebraic calculation of the minimum expression.

4.2 Online optimized EMSs

Offline global optimization EMS can not be implemented online without modification as they need the exact instantaneous speed profile on the optimization time horizon. On the other hand, rule based EMS gives no guaranties to be near the optimal result. To implement suboptimal but effective EMS able to perform the energy management in a real use of an HEV while approaching an optimal efficiency of the system, online optimized EMS could be designed in different ways.

4.2.1 Optimizing rule based parameters

As stated before, rule based strategies suffer from heuristic tuning of their parameters that could lead to an uncontrolled efficiency performance. One possible way to improve this issue is to use simulation, like in optimization EMS development, to find the best parameters leading to a global best behavior (considering a representative set of driving cycles).
To achieve this, one can use brute force method that explores a wide range of rule based parameters values and simulate them (Horrein 2015). Optimization method like simplex method (fmincon in Matlab for example) or heuristics (particle swarm, genetic algorithms (Wei Du 2020),…) may also be used but results should be checked as the possibility of finding a local minimum is not excluded due to multiple non-linearities in the HEV system.

4.2.2 Minimization of equivalent consumption (ECMS)

The method of minimizing equivalent consumption has been used for about 20 years. More recent publications use adaptive variants of this strategy, (Hofman et al. 2007). The basic method is applicable to a hybrid vehicle with charge sustaining management of the battery and at all times considers an equivalent fuel consumption made up of:

- the actual fuel consumption of the current point,

- virtual or future additional consumption. The latter can be positive or negative and corresponds to a fictitious quantity of fuel necessary to recharge or discharge the battery so that overall this "auxiliary fuel tank" has a constant mean state.

The principle of the method is based on an instantaneous minimization of the equivalent consumption. It can be used as a real time realization of PMP like the λ-Control technique (Serrao et al., 2009) (see 5.4 section). However, because of an average estimate of the performance of the various components required to estimate the virtual consumption, an undesired deviation in the state of charge of the battery is possible.

4.2.3 Neural networks or machine learning from offline optimization

The offline exact optimization requires knowledge of the speed profile to find the optimal solution for the EMS. In order to replicate online the results of optimization based on dynamic programming or PMP methods, neural network approach or more recently machine learning based methods could be used. The principle is to consider one or several networks that have as input measured and/or estimated parameters necessary to the HEV control (Vehicle and machines speed, traction and auxiliaries power demand, actual Soc, targeted Soc, …). The output of these networks are the control variables of the HEV, namely the torque request of the ICE and the electric motors, as well as the gear number and the clutches states if exist. Using learning database generated offline by applying DP or PMP on a HEV model and a driving cycle set, the networks can learn decisions on control variables to be used at each time. The idea is to interpolate the current state of the HEV with the nearest encountered states in the database so that the control variable selected would be near the optimal ones calculated by DP or PMP. In general, a SOC controller is added to these kind of networks as a deviation with time is possible as reported in (Scordia 2009)

4.2.4 ⍰-Control

Another possibility of using offline global optimization to develop an online suboptimal strategy is to implement the Pontryagin minimum principle (PMP) by estimating the value of the Lagrange multiplier λ online. Indeed, as explained in the 4.3.2 section, for a battery used in charge sustaining mode, one can assume that a constant value of λ on a given driving horizon would insure the optimality of the EMS based on this method. However, this will be possible only if the instantaneous value or at least a detailed distribution of the battery power is known on the whole considered horizon (often calculated using the speed profile and a HEV model).

To adapt the offline method to online constraints, a constant or periodically estimated value of λ has to be supplied to the control. In practice, the estimated value of λ could be calculated online using a speed prediction and a HEV model. This calculation could need important processing resources that are not always available on board the HEV. A priori mapped values of λ or an algebraic estimation when a simple mathematic model of the vehicle is available are often used to tackle this issue (Nguyen 2019).

For PHEV or for HEV that uses supercapacitors instead of batteries, constant λ value becomes quite a strong approximation. An iterative calculation of an instantaneous value of λ could be achieved using the second equation of Pontryagin optimality (equation 7) assuming a time dependent λ value (Vinot 2013).

The λ control method could be extrapolated to HEVs with 3 sources (fuel tank, Battery and supercapacitors for example). In this case, two multipliers (λ_1 and λ_2) values are needed and have to be estimated at each time (see section 5)

4.2.5 Stochastic DP

Dynamic programming (DP) is used as offline global optimization method as it requires the precise knowledge of the speed profile on the whole considered horizon (see section 4.3.1). A derived method, called stochastic DP allows to introduce uncertainties about the encountered drive conditions and thus to facilitate real life online implementation of the optimization method. The principle is to use bellman equation (Bellman 1957) as in the case of offline DP but applied to a reduced time horizon and considering possible future variation in the predicted speed profile. In (Vagg 2016) the speed profile prediction is based on Markov chain where the probability of moving from a speed to another in the near future is explicitly determined using a database of typical driving cycles. The probability of different instantaneous future cost (the cost function is generally the fuel consumption) as well as the *Soc* matrix of probability can be calculated using the HEV model. To select the best solution, the optimization of the total future cost uses a waited infinite sum of all the future instantaneous costs where the weighting factor is constant to be determined or has an exponential decreasing value (equal to one for the present instant and converging to zero in the infinite horizon) (Vagg 2016).

4.2.6 Model Predictive Control

Model Predictive Control is a well known control method developed in the late 70s and is more recently used to implement online optimized EMS for HEV.
The principle of the method is based on three steps:

- Generate optimized set points of the state variables of the system on a considered time horizon
- Calculate, using a model of the system, a succession of future control sequences on a reduced horizon (known also as receding horizon) to be applied to the system in order to obtain the desired setpoints
- Apply at the current time only the first value of the control sequence

These steps are then repeated each time and result in adapting the control when output deviation from the predicted values occurs using instantaneous measurements.
When applied to HEVs EMS, this method could use one of the exact methods (DP or PMP for example) to generate the optimized states and controls on the defined receding Horizon by predicting the speed profile in this time window and by using the HEV model (step one and two) (Xiaosong 2020). Then the optimal control is applied and adapted at each time using different methods for optimizing trajectory tracking (quadratic programming associated to linearization process for example).

5- Case of using supercapacitors

Supercapacitors (SCs) could be used as the main ESS instead of batteries mainly for micro and mild hybrid configurations (figure 9). In this case, as they have high power density and low energy density, they are generally used to recover energy during braking and to provide electric assistance during acceleration. On the other hand, and in order to improve the power density of battery based ESSs, supercapacitors could be used as a third energy source (figure 10). In both cases, energy management strategies previously detailed can be applied while taking into account the low amount of energy stored in the SCs compared to batteries. Some examples of strategies are given in the following.

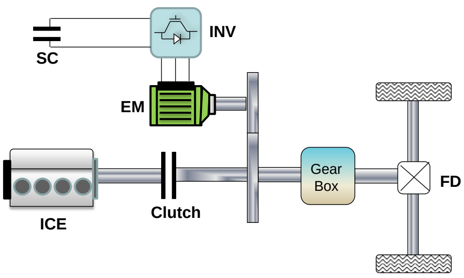


Figure 9: Example of parallel HEV with SC as ESS

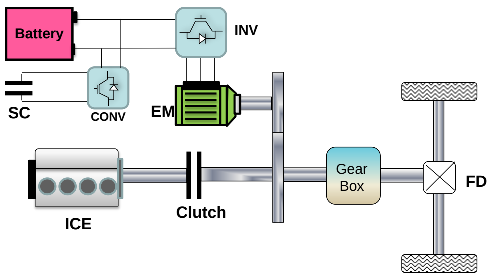


Figure 10: Example of parallel HEV with hybrid ESS (battery and SC)

5.1 Rule based strategies

Rule based EMS strategies are the most flexible ones and could be adapted easily to different kind of energy storage. For configurations with a supercapcitors based ESS (figure9), load following strategy is the most convenient to be used compared to thermostat strategy. For example, adapting thresholds of ICE on/off and removing full electric mode due to the few electric energy available in the SCs could be easily done. The thermostat strategy would lead to a very frequent switching of the ICE state as the SCs have low energy capacity.

For the configuration where the SCs are associated to batteries as a third source (figure 10), it is more complicated to apply directly the previous strategies. One method could be to consider the battery and SCs as a unique equivalent source and apply one of the rule based strategies. The energy share between battery and SCs is then done locally (vinot 2013). One obvious rule of sharing could be: when the required electric power from the equivalent source (positive for traction and negative for braking) is higher than a threshold, the supercapacitors are used, otherwise the batteries supply (or receive) the whole electric power.

Another strategy that could also be classified as a rule based is what is called the filtering strategy. This kind of EMS is well adapted to multiple sources' HEVs (more than two) as it is based on frequency domain identification of each source. The principle is to split the required power of the HEV into three components, one for each source, using low pass filters with an adapted cutting frequency for each source. If we consider a HEV with an ICE and a hybrid storage system (battery and supercapacitors), the power of higher frequency will be requested to the supercapacitors, the intermediate to the battery and the low frequencies to the ICE. This strategy is also valid when a Fuel Cell is used instead of the ICE (Snoussi 2018).

5.2 Optimization based strategies

Offline optimization strategies as well as online ones could be applied to the case of HEVs with supercapacitors. When Supercapacitors are the sole electric source, only the equations of the system change, the optimization problem formulation remains the same. The constraint of the battery Soc is replaced by the constraint of minimum and maximum voltage of the supercapacitors. For the HEVs with a hybrid ESS (battery and supercapacitors) the application of the PMP (Pontryagin Minimum Principle) is the easiest way to tackle the optimization problem. The Hamiltonian equation is then adapted to handle a third term with a second Lagrange multiplier corresponding to the penalty attributed to the SCs use.

$$H(x(t), u(t), \lambda(t), t) = \dot{m_{fuel}}(u(t), t) + \lambda_1(t). P_{bat}(t) + \lambda_2(t). P_{SC}(t) \qquad (8)$$

Online, this method leads to the use of two lambda-control components; each one is dedicated to one electric source state (Castaings 2020). Dynamic programming can also be used but it needs to consider a two dimensional graph, each dimension corresponds to the state of one electric source. This causes a high computing burden and is very difficult to handle for driving cycles of hundreds of seconds.

6- Conclusion

The management of energy in hybrid vehicles is a key element in the success of the objective for which this type of vehicle has been designed. Indeed, the distribution of instantaneous power between the sources and the transformers directly impacts the energy consumption and the efficient use of the storage elements. For more than two decades this topic has mobilized a large number of researchers. Various methods have been developed and implemented. Some of them rely on the different modes allowed by the hybridization with an intuitive setting of parameters. Called rule based methods these EMSs are generally simple to develop and could be easily adapted to different HEV types. However the main disadvantage is the unknown relative position from the optimal efficiency of the HEV due to the heuristic parameters setting. The other kind of EMSs use optimization principles and strive to approach the optimum solution by simulation using model based optimization methods. These methods could provide the exact solution when the speed profile on the whole use horizon is known. The use of this kind of methods is thus restricted to simulation and usually provides an ultimate reference for the other EMSs. In order to develop efficient methods useful offline, the formers could serve as sources of inspiration either to develop learning database or to approximate some of their parameters like the use of speed profile prediction instead of the real speed for example.

For now, most of online optimization methods give satisfactory results when applied to real HEV control. However, if we try to get closer to very optimal behavior, the remaining challenges could be:

- Improve velocity profile prediction capabilities. This could use vehicle connectivity to include current and future traffic conditions as well as weather and road profile.
- Take into account the thermal control of the subsystems, in particular for the batteries
- Improve the optimization criterion to also minimize battery aging

Finally, we have also to remind that development and comparison of EMSs for HEVs is usually based on HEV global modeling. The accuracy expected from the EMSs are then directly related to the validity of the model used for their development. Another challenge is then to improve the accuracy of the components models while taking into account temperature influence.

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