On-line Energy Management for HEV based on Particle Swarm Optimization

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***Abstract*—. This study considers a Hybrid Electrical Vehicle supplied by a Fuel Cell stack and supercapacitances used as Storage Element. In such an application, real time energy management is of paramount importance in order to increase autonomy and be able to deal on-line with perturbed power demand. Many off-line power flow optimization principles are available but on-line algorithms are preferred and should be derived for optimal management of the instantaneous power splitting between the different available power sources. Based on particle swarm optimization algorithm, this study defines the parameters tuning of such algorithm in real time. The final power splitting allows not only recovering energy braking but also is robust to some disturbances occurring during the trip. The solution provides good-quality and high-robustness results in a certain class of mission profile and power disturbance.**

Key Words : **Particle Swarm Optimization, Hybrid Electric Vehicle, Multi-source System.**

I. INTRODUCTION

Replacing oil-based engines, and dealing with renewable sources is a challenge because the power distribution structure change drastically. In transport applications when zero emission is foreseen, Hybrid Electrical Vehicles are composed with a main sources of Energy (or Power) and storage elements to be able to store and to restitute an additional energy (or power) when requested [1]. In transport applications, it is obvious that energy braking recovery should be performed and the stored energy should be provided to the powertrain not only to respond to some high power requests but also to manage the global efficiency of the electrical system.

Maintaining the global efficiency at a maximum level with a dedicated energy management strategy allows autonomy to increase, minimizing the consumption on a given mission profile, and also allows increasing the durability of the different electrical and/or electrochemical components (Fuel Cell, Supercap or Batteries…). A certain level of knowledge of the power demand is requested to optimize the consumption. With this consideration two categories of optimization principles can be listed :

- off line global optimization
- on line 'partial' optimization

In off-line category, Dynamic Programming (D.P.) is one of the most used algorithms. Its principle is based on the Bellman's principle [2] and starts computation from the end of the profile to find an optimal path reaching the beginning and leaving the optimization criterion as low as possible. Then, the founded path should be re-played. Some considerations should be given to having an accurate solution but problems arise when constraints are added and when computer time computation is limited. Optimal control is also use to replay a sequence of control computed optimally off-line using Pontryagin principle [3]. This technique provides good results when the criterion can be expressed linearly and thus derived. Constraints are also not obvious to include and some parameters are hard to be tuned to obtain the solution.

Real time energy management strategies are mainly based on linguistic rules or artificial intelligence [4],[5],[6]. Commonly used in HEV, logical rules are quite easy to define, when considering the management of 2 or 3 sources. These rules impact directly on the consumption and should be optimized as well. Fuzzy-Logic supervisor, Neural Networks [4], System with Multi-Agent or adding Genetic Algorithm [10] are also used. All methods suffer from the same problems: complexity is increasing and all methods are based on learning patterns.

In this paper a stochastic on-line optimization principle is used. Particle Swarm is a method to explore a given space where an optimal solution is sought. In this case several iterations will ensure that the optimal solution is found. Therefore, a set of parameters can be tuned to reach the solution while keeping a low computation time. When the power splitting should be refreshed with a certain periodicity, this kind of algorithm can provide a sub-optimal solution or even reach the optimal one.

In part II, the HEV powertrain is described and all characteristics of the different onboard sources are given. In part III, the problem formulation is detailed to minimize the criterion and to respect all listed constraints. In part IV attention is focused on advantages of the proposed particle swarm algorithm. Part V presents the complete study of parameters tuning and results obtained using different actual profiles, with or without perturbations. Analysis, limitation and conclusion are given in Part VI.

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II. PROBLEM DESCRIPTION

A. Power flows and Energy Onboard

In this paper a classical Hybrid Electrical Vehicle is considered. Different power trains can be defined and sizing of all elements should be optimized as well. To not treat 'systemic' problem, a given hybridization is fixed here and only two electrical sources are linked to the same DC bus with their own choppers. Fig1 describes the considered serial electrical structure. It can be noticed that an electrical node appears between the different subsystems.

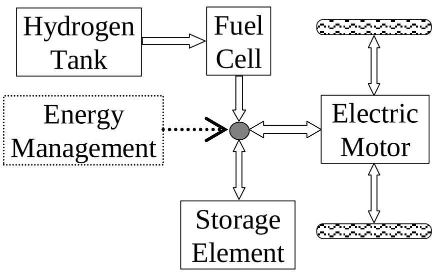

Fig 1: serial electrical structure for HEV with FC and SE

The Hydrogen Tank, the Fuel Cell and its ancillaries (Compressor, Valves and local control...) and the non reversible chopper are grouped constituting the Fuel Cell System and considered as the primary sources - FCS.

On the other hand, Supercaps Elements and its reversible chopper allow constituting a second electrical source - SSE – which can store or restitute energy.

The moto-propulsion group is here simplified because only the electrical power demand is considered. With this consideration if the powertrain architecture changes (boggy or wheels, synchronous or DC machine…) only the electrical power demand should be computed when leaving all the other elements in the optimization algorithm.

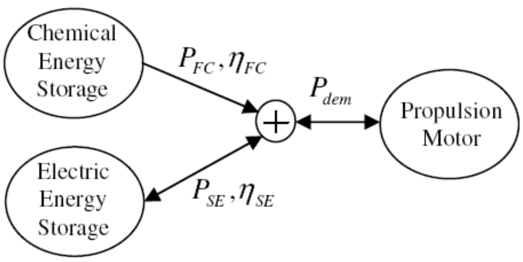

Fig 2 : Multi-source system problem formulation

Fig 2 presents the composition of the two main sources focusing on different efficiencies (losses) which should also be easily adapted if some element is changing (different FC size, different switching components in chopper etc.). Fig 2 also represents the electrical node and the power and efficiency data requested to be able to run an optimization algorithm in such an application.

B. Efficiency of the main elements

Algorithms, solving the optimal energy management problem are fed with data describing the efficiency of all elements. Each source has its own behavior meaning that it presents a different efficiency depending on the power delivered [7]. Local controls are considered effective. Fuel Cell Stack stay at a given temperature and pressure and hygrometry are supposed to be well-maintained [8],[9]. Homogenous current repartition in the FCS allows dealing with a global FCS efficiency behavior η_{FC}, described in Fig 3. In the same way, the storage element is made with several commercial supercaps in serial and parallel to obtain the System Storage Element (SSE). Balance between supercap elements is also considered effective and just one constant equivalent resistance *Rsc* and capacitance *Csc* are considered with losses only depending on losses in chopper, therefore the global efficiency η_{SE} is given in Fig 4.

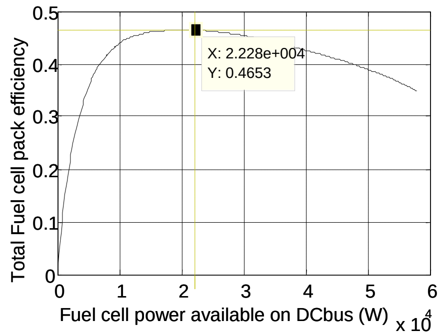

Fig 3: Fuel Cell system global efficiency curve

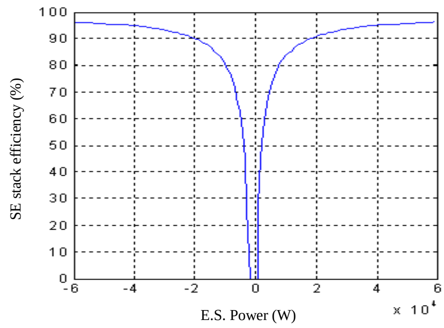

Fig 4 : Reversible Storage Element global efficiency curve

Note that the Maximum Efficiency Point for a Fuel Cell System is allocated at about 25% to 30% of the nominal power (22kW here for a 60kW FCS).

Fig 3 and 4 provide the efficiency maps to be considered by the algorithm to compute the efficiency of the powertrain through a criterion to be minimized.

The two power demands used are presented in fig 5 - INRETS is an urban profile for a personal vehicle and fig 6 - ESKISEHIR is the name of a power profile measured on a tramway line in Turkey [9],[10].

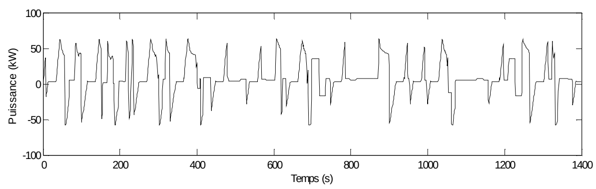

Fig. 5. INRETS : Power profile of a hybrid vehicle in urban area

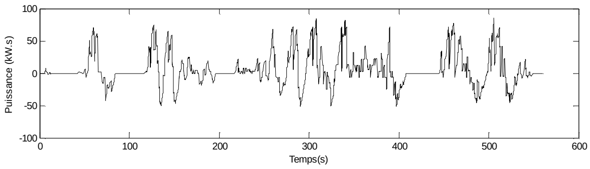

Fig. 6. ESKISEHIR : Power profile of a tram on the line of Eskisehir (Turkey)

The element sizing is made to let the power splitting explore all possible solutions and let emerge if possible solutions using only FCS or only SSE, or all combination to supply the power demand. No 'systemic' hybridization linked to size or weight is considered in this approach to provide efficient algorithms whatever the HEV characteristic is (parameters used are given in Table I).

TABLE I
SYSTEM POWER AND ENERGY CONSTRAINTS

Symbol	Quantity Value
PSEmin	-60kW
PSEmax	60 kW
PFCmin	0 kW
PFCmax	70 kW
SOEmin	400 kW.s
SOEmax	1600 kW.s

Considering a given requested power profile (cf. figures 5 and 6), this paper proposes to respond to the following question : what is the optimal power splitting in order to obtain a maximal efficiency of the vehicle (and thus the lowest fuel consumption) on the driving cycle under Table I constraints ?

III. ALGORITHMS AND ENERGY MANAGEMENT

The energy management problem is formulated here as a global dynamic optimization problem under constraints. The hydrogen consumption is quantified as a cost function to be minimized. The cost function is evaluated over a defined period of time. The system's dynamic equation is:

$$\dot{E} = -P_{FC}(t)$$

Where the energy level stored E is the state variable and the power P_{FC} the control variable.

The cost function to minimize is the "total consumed energy" of hydrogen E_{H_2} over a period of time [t_f-t_i].

$$E_{H_2} = \int_{t_i}^{t_t} \frac{P_{FC}(t)}{\eta_{FC}(P_{FC}(t))} dt \qquad (1)$$

Using the previously defined efficiency, the cost criterion is therefore:

$$\gamma = \frac{P_{FC}(t)}{\eta_{FC}(P_{FC}(t))} \qquad (2)$$

The system is subject to non linear constraints of inequality related to the constraints linked to the design of the stack, the storage element power and state of charge resumed in (3):

$$P_{SE\_\min} \le P_{SE}(t) \le P_{SE\_\max} \ ; \ P_{FC\_\min} \le P_{FC}(t) \le P_{FC\_\max}$$
$$E_{\min} \le E(t) \le E_{\max} \qquad (3)$$

Satisfying the power demand imposes an equality constraint (4):

$$P_{SE} + P_{FC} - P_{dem} = 0 \qquad (4)$$

The Storage Element efficiency must be used at this step to add its behaviour as the Fuel Cell. An additional condition (5) is imposed artificially in order to ensure that the state of charge is maintained at the end of the cycle and to facilitate cycling the power demand without any more consideration from an energy management point of view.

$$E(t_f) = E(t_i) \qquad (5)$$

A. *On-line principles : Rules-Fuzzy-AI*

Based on expert knowledge, logical rules are easy to establish. In fact it is easy to say the system should use the FC when SE is empty or should use both FC and SE when power is high and SE in its average State Of Charge etc. A lot of research deal with such 'natural' approach only listed here to show advantages of the following proposed solution.

These rules are impacting directly on the consumption and the expert should come up with a way to pass from one rule to the other. So the fuzzy approach is a solution to define each rule, the membership functions and the universe of discourse [5],[6]. Moreover position of all membership functions can be optimized on a given profile. In fact, Genetic Algorithm [10] or Neural Network [6] can 'learn' the profile and the optimization is still made off-line on a given profile but the supervisor build in this way is able to propose an optimal or near-optimal solution even if the profile is not exactly the one known. Artificial intelligence and expert analyzes should be mixed to have not only an accurate optimal solution, respecting constraints but also an algorithm keeping under control the complexity and the computer time requested to reach the solution in real time.

B. *On-line stochastic : Particle Swarm*

Considering that computing all solutions is not possible on-line and in real time (with actual processor). Considering that rule-based algorithm should still be optimized off-line and using them on-line can sometimes not respect important constraints, the idea is here to use both advantages using particle swarm optimization principle. Particle Swarm Optimization (PSO) principle is based on (6) and (7):

$$\vec{v}_{k+1} = \vec{a} \otimes \vec{v}_k + \vec{b}_1 \otimes \vec{r}_1 \otimes (\vec{p}_1 - \vec{x}_k) + \vec{b}_2 \otimes \vec{r}_2 \otimes (\vec{p}_2 - \vec{x}_k) \qquad (6)$$

$$\vec{x}_{k+1} = \vec{c} \otimes \vec{x}_k + \vec{d} \otimes \vec{v}_{k+1} \qquad (7)$$

Where $\vec{v}$ is a vector of particles speed, $\vec{x}$ their positions and $\otimes$ represents terms by terms vector multiplication [11],[12].

This stochastic algorithm explores randomly the space of solution and depending on the number of particles and the number of iterations made; engineer can fix accuracy and limit the requested computation time.

This evolution (6) is based on bee behavior (random flights of bee swarm) and to the optimal solution after some iteration *k-> infinity*, the swarm conserves the better value seen in the previous iteration p_1 and the best value ever seen p_2 to update velocities and thus particle positions. Attracting coefficients *a*, *b*, *c*, *d* ensure exploration and convergence form (zigzagging, oscillating, exponentially converging…). In this considered classical case (no abrupt optimal or sub-optimal minima) values found in literature are used: a=0.729, b=1.494 and without loss of generally c=1, d=1 and *r1* and *r2* are randomly chosen in [0 1], [11]. Details should be added in the final paper.

IV. PARTICLE SWARM AND ON-LINE HEV ENERGY MANAGEMENT

In the HEV on-line energy management problem, the number of particles *nb_part*, the number of iteration *nb_it*, and the number of swarm *nb_swarm* should be fixed. Moreover to limit the number of calculus and the computing time, the problem should be reduced to an optimization in a given window size, so, the whole power profile demand should be divided (Fig 7).

The optimization purchased is always the lower consumption cost but made in a window where beginning and ending power is known as the best one. The windows bound are computed off–line by the dynamic programming optimization and available in a lookup table for example. The solution is still the Fuel Cell power to deliver P_{FC} and in consequence the power delivered by the storage Element $P_{SE,}$ this computation is made in real time in the windows and if there is no power demand disturbances the optimal solution must be found as quick as possible.

A certain number of particle *nb_part*, is fixed randomly at different energy level at each time in a window [*tk tk*+1]. The sampling time Δt and window's size increase the computation time. All particles are free to explore all energy level from [0 100%] with a step of about 1%, this ΔE is chosen to be as accurate as possible taking into account the possible chopper and source capacity to maintain E_k and also to preserve a realistic computation time.

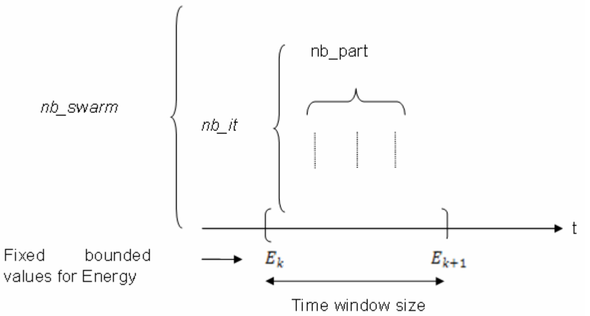

Fig 7 : set of parameters of the particle swarm algorithm

The criterion is minimized on the window size and consumption is minimized optimally using energy levels E_k and E_{k+1}. These levels used as references should have been computed off-line by Dynamic Programming algorithm. It can be noticed that this approach mixes the off-line optimization and the on-line minimization which can be seen as an adaptation capacity. In fact, if no disturbance occurs, particle swarm optimization should converge to the same path as Dynamic Programming. In case of disturbance, the rejection is ensured by particle swarm to locally change the path and return, if possible, to the optimal energy level E_{k+1} that ensure an optimal ending (with no other disturbance).

All set of parameters can be tested on a profile in a first step to be roughly defined. The correct set should ensure almost 50% of swarm funding the optimal path and delivering a result in a time lower than the refreshing reference period t_{k+1}-t_k.

A. *Simulation based tuning*

Running some simulations with different sets of parameters allows establishing the values shown in Table III. Obviously, the higher are the *nb_swarm* or *nb_it* or *nb_part* higher the computation time. If 3 on 5 swarms have found the optimal path means the path is found with 60% of chance, so the path can be considered always found. It can also be seen that using 5 swarms and 20 particles is correct because this set provides the optimal path with 60% of chance in a low and feasible actual computing time. Lower values provide less than 50% path found and are considered too risky to be used in the real time optimization problem.

NB: program executed in Matlab® R2008a on a Windows XPpro environment dedicated to calculus (processor: PowerEdge 6850, Quadri Xeon, 3.2GHz, 32Go Ram, 2x150 Go Scsi UTRA 320)

TABLE III

Set of parameters and solution found

nb_swarm	*nb_part*	*nb_it*	Average computation time (s)	Optimal path found
5	50	100	4.28s	5
5	50	50	1.78s	5
5	40	100	3.42s	5
5	40	50	1.38s	4
5	30	100	2.46s	4
5	30	50	1.06s	4
5	20	100	1.56s	3
5	20	50	0.76s	3

Of course, depending on the processor used, the higher is the number of swarm or number of iteration, the higher is the probability to found the best path in a given time. Even if the program and communication data are not implemented on the final processing system, such data can put in evidence relatively the cost and advantages of the different parameters. Thus, the code should be also optimized so values given in Table III should be used only in a relative way.

B. *Validation on actual profiles*

Using sampling time of Δt=2s, ΔE=1kWs, the power demand is satisfied and state of charge of the storage element is shown in Fig 8.

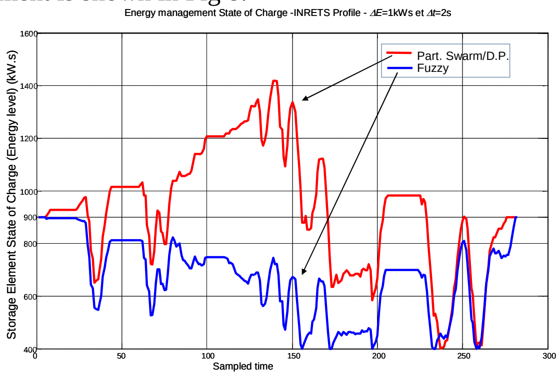

Fig 8 : Energy management State of Charge -INRETS Profile - ΔE=1kWs et Δt=2s

In this figure with no perturbation on the profile, it can be noticed that D.P. path is the same as the one find in each Particular Swarm window, the curves obtained with fuzzy logic is only provided to see the possible different energy managements and details are in [10].

It has to be noticed that both optimization provides quite the same consumption of energy on the whole profile (Part. Swarm/D.P.= 10362kW.s and Fuzzy= 10358kW.s) but fuzzy leaves some power demands not furnished (due to saturation at low SOC) and is only shown for comparison purposes. Storage element is considered to be charged at 900kWs and respect its min and max S.O.C. during the trip and allows managing optimally the energy on board.

V. VALIDATION AND COMPARISON

Previous sections demonstrate that particular swarm algorithm is able to found the optimal path, windows by windows, using the off-line energy level computed for example with D.P. on a given profile as a reference. This section tests the proposed algorithm on different profiles and with an unknown perturbation added artificially to characterize the robustness of such an approach.

A. *First comparison*

In fact, depending on the power profile, parameter adjustment should be made. Of course, *nb_part* and *nb_it* are linked to the convergence velocity and thus the possibility to adapt the particle speed quickly to the profile variation. Therefore, using ESKISEHIR profile instead of INRETS with the set of parameter *nb_part*=50, *nb_it*=50, *nb_swarm*=5 is not sufficient. Analyzing where are the problems, it has been noticed that no solution where found in some specific windows (the others are computed without any problem). For these windows the power variation is greater as in INRETS profile and difference is shown in Fig9. This profile presents some section with a higher power variation so the *nb_part* or *nb_it* should be increased to be able to found the optimal path. Thus, as for many other methods, analyzing the power demand in terms of max power, mean power and power variation demand, not only provides sizing information but also information to tune accurately optimization parameters in the algorithm.

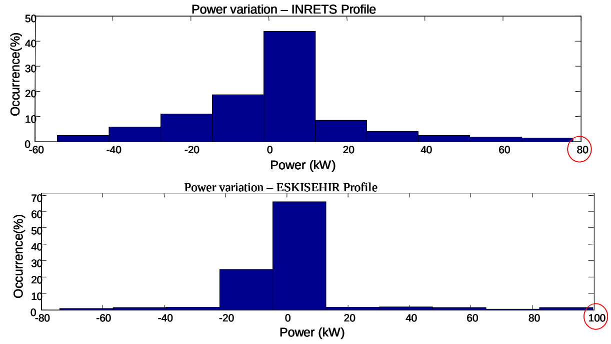

Fig 9 : Power variation occurrence in different ranges of magnitude

Using *nb_part*=20, *nb_it*=50, nb_swarm=7 is convenient for both profiles. The same study should be made on other profiles to be sure to be able to optimize the criterion. Even if the optimization is not optimal, the particle swarm algorithm provides a solution better than optimization following off-line references. Adding a perturbation on a given profile may justify the adaptation ability of particle swarm algorithm.

B. *Performance and robustness comparison*

To verify the possible adaptation of the proposed algorithm, a perturbation is added to the known power demand INRETS limited to the 50th first point (50s) Fig11. In Fig 11, a non expected positive power demand is added during 5s (acceleration required for example due to the road traffic). In Fig 11bis the disturbance is proposed to be negative to simulate a non expected braking… The perturbation occurs during 5s which is the size of the optimization window; tests could be made for longer disturbances but are out of scope of this paper.

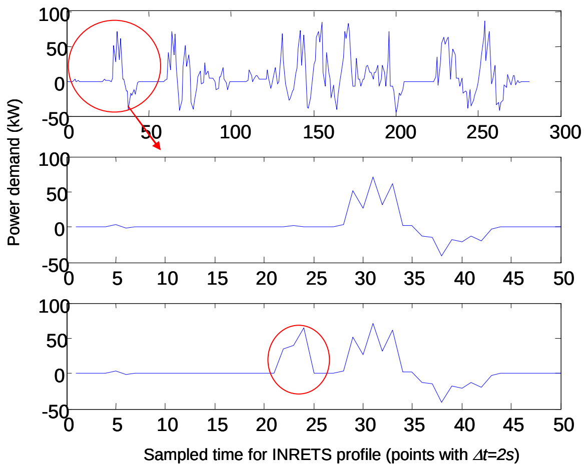

Fig 11 : Initial profile, sequence selected and first disturbance injected Dist=50kW (case dist>0).

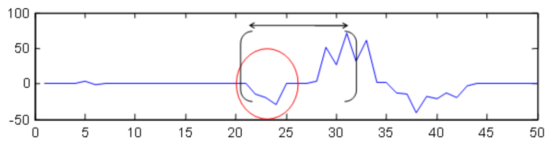

Fig 11b : second disturbance type : Dist=-40kW (Case dist<0)

From the start point 0 to point 50, with no disturbance, the optimal energy consumption is 790kWs, with positive disturbance used, the consumption is 1404kWs and when a braking energy not expected is used (negative disturbance) the consumption is 592kWs.

Depending on the position and here mainly on the perturbation magnitude, it is possible or not to optimize the criterion in a given window size. In the case under study, the profile does not present high power demands after the disturbance point [25-28] and the energy recovered can not be delivered in the foreseen windows. Moreover, if the energy stored is quickly used in this phase, the Fuel Cell power may decrease, decreasing its efficiency, thus a bad criterion is obtained. Using a window twice larger (Fig 11b), the algorithm can find a solution to return to the energy state imposed respecting constraints of the system. Increasing the optimization window size means increasing the computation time and the necessity to verify real time constraints. *nb_swarm*=1 solves partially this issue but 4 tests on 10 provides no optimal path (only with an increase of fuel consumption limited to 1%).

TABLE IV

Set of parameters and robustness

	Ideal	Dist >0	Dist<0
Window size (nb points)	5	5	12
nb_swarm	7	1	7
nb_part	20	20	100
nb_it	50	50	50

This last study means that an adaptation is requested on line when a disturbance is detected to be able to switch the strategy (different set of parameters for the particular swarm – resumed in Table IV) to obtain a good result. Of course, a prediction or a statistical data-base can be used to classify the different possible disturbances as well as the requested analysis to classify the profile.

VI. Conclusions

Particle swarm optimization is an efficient solution for on-line energy management for Hybrid Electrical Vehicle. It did not pass over common problems in such application: the profile should be studied and classified to found accurate set of tuning parameters. Performances are better when references are provided with off-line global optimization. Disturbances should be predicted or a degree of freedom should be used to cancel their influences.

This approach is not really an Artificial Intelligence approach using learning phase, but using optimal references, the particular swarm optimization algorithm is able to compute, in a limited computation time, the optimal path in terms of fuel consumption. The proposed solution combined on-line and off-line optimization scheme in their classical form. There is no need at this level to track new evolution and new programming of these approaches but focusing our attention on real time implementation and tracking accuracy of the solution with modifications of the mission profile is of paramount importance.

The proposed solution strategy one of the goods solution to split the energy supplies references to be followed to provide the power demand of the HEV composed here with a Fuel Cell stack and Storage with supercapacitance elements.

Particles are able to compute in real time the optimal path with some capacity to reject disturbances and in each case to adapt the optimal path to a sub-optimal path respecting real time computing constraints. Implementation on an actual vehicle should be made in a next step in order to validate the approach.

Aknowlegment

INRETS: to provide actual measurements obtained in actual vehicle and trip, and interests given in energy management in transport application.

FEMTO-ST / FCLAB: to provide actual data obtained on fuel cell test bench developed in Belfort (France) and collaboration in this study.

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