New Predictive Control Method for Optimal Minimization of Plug-in Electric Vehicle (PEV) Charging Cost with Vehicle-to-Home (V2H) capability

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***Abstract*—This paper presents a decentralized on-line strategy for optimal management of Electric Vehicles in the Smart Grids field. The aim of this Vehicle-to-Home (V2H) algorithm is to minimize the charging cost thanks to the bidirectional capability of the vehicle. The on-line V2H algorithm is based on the predictive control performed thanks to a parametric strategy which operates in off-line mode. At opposition to the sliding mode control mainly used in the predictive algorithms, the narrowing mode control is explored in this paper. The V2H algorithm proposed offers multiple degrees of adjustment and so, each user can exploit it according to the issues addressed; it is an exploratory tool facing smart charging of Plug-In Electric Vehicles (PEVs) challenges. The V2H algorithm has been validated with several cases studied. The results show that V2H algorithm has a great economic profitability potential.**

***Index Terms*-- electric vehicle, optimal management, predictive control, smart grid, Vehicle-to-Home.**

I. Introduction

The share of Plug-in Electric Vehicles (PEVs) will greatly increase in the coming years and will create challenges of integration in the electric grid. It's imperative to address these challenges, especially in the residential areas where charging will mostly take place. Indeed in recent years, developed countries promote the PEVs which are thriving. Many car manufacturers offer plug-in EVs and since some time, there is an emerging bidirectional EVs market. These are strategic because its allow to use the batteries for multiple purposes.

The research activities on the interaction EV/Grid field are spread since many years and evolve by steps. First, the impacts on the grid and their elements were assessed [1]. Secondly, significant research work were carried out to minimize impacts with centralized, decentralized, on-line and off-line strategies [2]. Research on the EV/Grid topic is now focused on Vehicle-to-Grid (V2G) and Vehicle-to-Home (V2H) concepts with various aims based mainly on economic aspect. In [3], EVs are used to support the grid frequency thanks to V2G. In this same theme aspect, EVs are also used to mitigate potential overloads in the distribution system and to minimize charging costs during the same operation [4]. Grid components are still at the heart of the research activities. As such, a centralized model to co-optimize the transformer loss-of-life with the benefits for EVs' owners on charging/discharging management was proposed [5]. Peak shaving with EVs is also implemented; [6] proves the possible profits in decrease of home peak load with customer costs together and [7] presented a two-stage mechanism for peak shaving coupled with renewable energies. An another theme in this field emerges, this one concerns the optimal sizing of batteries in an EVs charging facility with solar production [8]. Finally, include EVs management in the Smart Home with solar production, storage system and household appliances is a very emerging field [9]. In this paper, a new approach is attacked and in consequence, a V2H algorithm based on predictive control is proposed. The aim is to minimize the PEV charging cost during process at home in the residential area. In most countries the people subscript energy contract with Distribution System Operators (DSO) which have a maximum limit (more the maximum value is high and more the price of the contract is high). If the instantaneous call power exceed this limit, the supply energy is broken. The algorithm ensures that the house subscription contract is respected. The charging process of the vehicle will not cause an overrun of the maximum value. The V2H algorithm proposed is normalized and generic and so, it can be works with any energy billing system (all the energy pricing profiles are available). This work proposes an exploratory tool and it can be easily re-used in others EMS and fields issues. The paper is organized as follow: the V2H algorithm formulation is presented in part II. The third part exposed the simulation results. This paper end with conclusions in part IV.

II. Vehicle-to-Home (V2H) algorithm formulation

In this part, the formulation of the Vehicle-to-Home (V2H) algorithm based to the predictive control performed thanks to a parametric strategy is presented. The aim is to exploit the bidirectional capability of the vehicle (when he is at home) for reduce the charging price and to respect the subscription contract (i.e. not to exceed the maximum value of this one). The proposed methodology is appreciable because it offer many adjustable parameters which allows to study their influences on the results. Four sections composed this part: a/ proposed cost criterion formulation is presented, b/ constraints of the problem are introduced, c/ prediction horizon and sampling time selections are discussed, d/ developed strategy is exposed.

A. Criterion

In literature, the cost functions proposed in the predictive control are often quadratic. They allow the individual or simultaneous minimization (according to a weighting) of the follow-up errors of the reference, of the command or the increment of the command. However, the cost is generally proportional to the energy tariff (in the absence of its square) for the technical-economic optimization problems such as treated in this paper. Therefore, a linear formalization of the EMS is proposed and the cost function formulation is presented by (1). This one evaluates the energy supplied from the grid during all time where the vehicle is at home. The sum of electricity consumption from the grid at each sampling time is performed by incrementing or subtracting an amount of power at the domestic load curve according that the vehicle is respectively charged or discharged in accordance with the optimal command *u* emerging of the strategy (covered next).

$$J(k) = min \sum_{k=N_1}^{N_2} \left[(1-j) \times \left(S_{ES} - S_H(k)\right) \times E_{Buy}(k) \times u(k)\right] - \left[j \times S_H(k) \times E_{Sell}(k) \times u(k)\right] \quad (1)$$

N_1 and N_2 = Length of the output prediction horizon
S_H = The house energy consumption
S_{ES} = The value of the electricity subscription
u = The charge/discharge command of the PEV
k = The sampling time
$j = 0$ when $u > 0$ and $j = 1$ when $u < 0$
E_{Buy} = Cost of purchased energy
E_{Sell} = Feed-in tariff
$\left(S_{ES} - S_H(k)\right)$ = Maximum EV charge power
$S_H(k)$ = Maximum EV discharge power

B. Constraints

The inequalities constraints of the problem are described by (2), (3) and (4). Equation 2 ensures that the PEV charging don't caused an overrun of the maximum value of the house contract subscripted. Equations 3 and 4 delimit, respectively, the maximum charge/discharge powers of the vehicle and the minimum/maximum State-of-Charge (SOC) of the batteries. Two equalities constraints are available. The grid ensures the requested power of the housing including the PEV where the physics laws impose the balance of the powers at each time step (5). A relaxed constraint is introduced (6). This one represents the desired SOC at the next use and she comes from a strict constraint available in the strategy (covered next). A last constraint is used which consists to ban the charging process of the vehicle if the electricity consumption of the house exceeds the maximum value of the contract subscripted (7).

$$S_{House}(k) + S_{PEV}(k) \leq S_{Subscription} \quad (2)$$

$$\underbrace{S_{House}(k) \times u}_{PEV\ discharge} \leq S_{PEV}(k) \leq \underbrace{\left[S_{Subscription} - S_{House}(k)\right] \times u}_{PEV\ charge} \quad (3)$$

$$SOC_{Min} \leq SOC(k) \leq SOC_{Max} \quad (4)$$

$$S_{House}(k) + S_{PEV}(k) - S_{Grid}(k) = 0 \quad (5)$$

$$SOC(k) =^{*} SOC_{Final} \quad (6)$$

$$if\ S_{House}(k) \geq S_{Subscription} \rightarrow S_{PEV}(k) = 0 \quad (7)$$

Excepted the limits of charge/discharge powers of the PEV, the numerical values of the constraints are not mentioned. This is because the algorithm is developed from a point of view of automatic field where all the parameters are normalized. For the exception, criterion formulation shows that the maximum PEV charging command is the energy available by subtracting the house electricity consumption at current sampling time from the maximum value of the contract subscripted. So, this constraint is dynamic and evolutionary since it requires an update during the operation of the algorithm. She is maximum when the house electricity consumption is zero. In this case, its value is equals to the maximum value of the contract subscripted. In the same way, the dynamic and evolutionary constraint related to the PEV discharging command is directly linked to the house electricity consumption. Its maximum value is equals to the house consumption at the corresponding sampling time.

C. Prediction horizon and sampling time

One of the strong features of the predictive control is its capacity to taking into account a criterion and/or dynamic constraints. However, lot of parameters, which vary in continuously, increases the on-line computational load and so, resolution of the optimization problem can be compromised (for example if the resolution time is higher than the sampling time). The time required to solve the optimization problem evolves with the size of the prediction horizon and the number of constraints. These last represent usually the restrictions emerging from the physical limitations of the system and they undergo no modification during operation of the algorithm. In fact, it is usually recurrent to reduce the prediction horizon for curtail the calculation time but in this case, a loss of precision occurs. The studied system have only two dynamic and evolutionary constraints (related to the PEV charging /discharging commands). The prediction horizon have been selected in accordance with the availability of the PEV (when he is at home). The narrowing mode control is so explored in this paper. The sampling time chosen is 10 minutes and it is the same of the house daily load profile used in the test part.

D. Strategy

The predictive control proposed in this paper is based on a parametric strategy which uses a databases of real housing Daily Load Profiles (DLPs) (Figure 7) [10-11]. These ones represent the prediction model of the algorithm. The methodology consists to call an off-line parametric strategy to calculate an optimal control sequence using the house DLPs database and then applied the results to the on-line case (where the house Daily Load profile is unknown). Given the use of the DLPs database, it is an on-line predictive control algorithm that contains an off-line strategy. The residential sector is studied here and so, it's considered that the algorithm knows the energy pricing profiles. Figure 1 shows the main synoptic of the V2H algorithm. Figure 2 presents the synoptic of the off-line parametric strategy which is applied at each sampling time and where the house DLPs database is used.

According to the Figure 1, the first step consists to execute the off-line parametric strategy at each sampling time during all the time where the vehicle is plugged. So, the narrowing mode control is used. The principle of the parametric optimization is as follows: at first, is generated a $P_{INITIAL}$ vector that contains five variables (8). According to the Figure 3, this vector is bounded by two variable parameters (*A* and *Z*) offering degrees of adjustment. The next step consists to build the command graph (Figure 4) linking linearly the command to the electricity price. The *u* command, to be apply to a desired number of house DLPs (index *i* in Figure 1), is obtained thanks to (9) and the following trivial strategy. If *G* is less than or equal to $THRESHOLD_{LOW}$, the command is maximum. Conversely, if *G* is greater than or equal to $THRESHOLD_{HIGH}$, the command is minimal. Equation 10 represents the command *u* calculation where appropriate. The adjustment parameter μ in *G* allows to increase the electricity price according to the house electricity consumption at the current sampling time. This process is attractive because it's able to influence (increase or decrease) the application of the PEV. For example, it will interesting to study the PEV batteries State-of-Health (SOH) during different scenarios. Equations 11 and 12 presents the thresholds, respectively low and high, that allow to build the command graph. The command *u* is applied to a desired number of house DLPs (in off-line mode) during all the prediction horizon by knowing the variation of the energy price. Thus, the J_{TOTAL} cost corresponding to this command *u* is obtained at PEVs homes departure times.

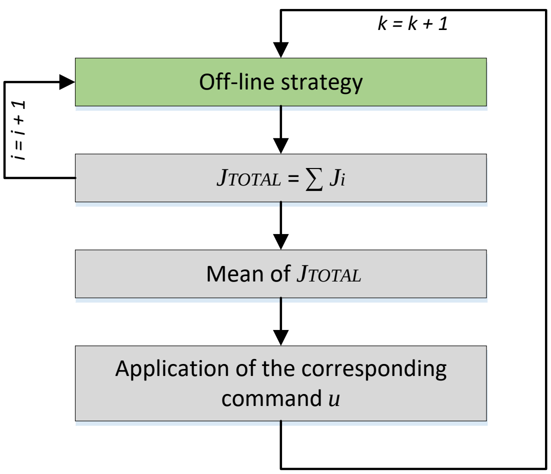


Figure 1. Main synoptic of the Vehicle-to-Home algorithm

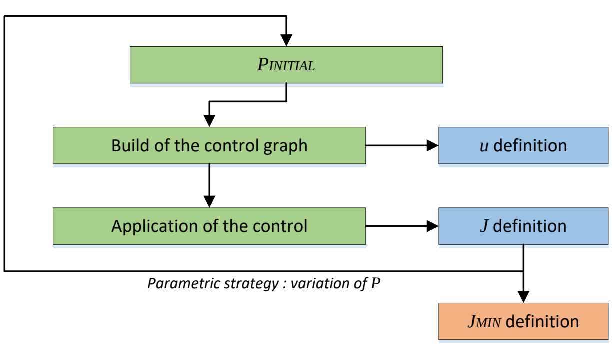


Figure 2. Synoptic of the off-line parametric strategy

The following step is the parametric optimization. These consists to find the optimal combination of the vector *P* and ipso facto, of the command *u* minimizing the total cost related all the number of house DLPs selected (in off-line mode) by ensuring the compliance with the hard equality constraint introduced; which is of the statistical type. This hard constraint concerns the PEVs SOCs at the departure times. This strict limit is met when a desired percentage of PHEVs, among the number of cases handled by the off-line strategy, has reached a previously set threshold. An exhaustive research is carried out in the region of *P* vector to determine the optimal combination. A first incrementation makes it possible to refine the search in the region "+" or "-" to decrease the convergence time of the algorithm (Figure 3). Equations 13 and 14 allow the variation of the *P* vector and so, to determine the command *u* minimizing the cost criterion thanks to the following process: If the J_{TOTAL} cost decreases and the hard equality constraint is respected, α is updated according (13). Otherwise, (14) is used to update α. Therefore *P* vector is updated by adding it with α. This process is repeated until the absolute value of α becomes less than a fixed value which attested the convergence of the algorithm. α is an adjustment parameter that can be modified by the user of the algorithm. After have determined the optimal combination of the vector *P*, are obtained the optimal command *u* profiles over the all prediction horizon thanks to apply of the off-line parametric strategy on the desired number of house DLPs. So, a single value of the total cost function is obtained and these one is used as reference for the on-line case. Indeed, the command *u* corresponding to the mean value of J_{TOTAL} is applied to the on-line case for the current sampling time. At the next sampling time and until the home departure time of the vehicle, the entire process is repeated and constitutes the V2H algorithm proposed in this paper.

$$P = [G_{MIN}, G_{MAX}, U_{MAX}, U_{MIN}, \mu] \tag{8}$$

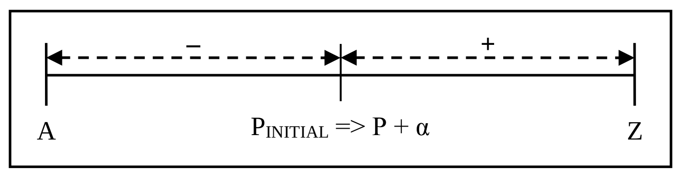


Figure 3. Region of *P* vector

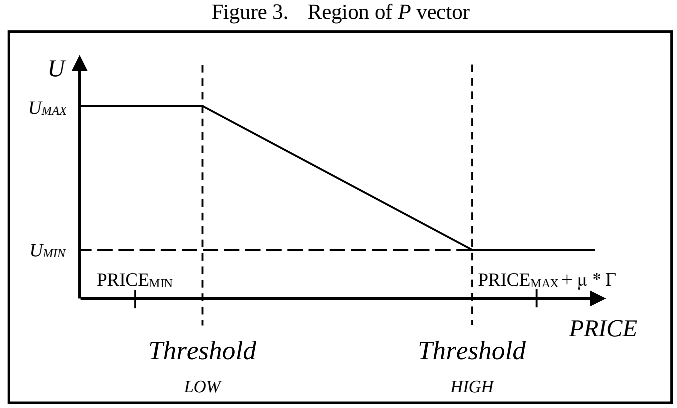


Figure 4. Graph of the command *u*

$$G(kk) = PRICE(kk) \times \left(1 + \mu \times S_{HOUSE}(kk)\right) \tag{9}$$

$$u(kk) = \frac{U_{MAX} + (U_{MIN} - U_{MAX})}{(T^*_{HIGH} - T^*_{LOW}) \times (G(kk) - T^*_{LOW})} \tag{10}$$

$$T^*_{LOW} = P^*_{MIN} + G_{MIN} \times [(P^*_{MAX} + \mu \times \Gamma) - P^*_{MIN}] \tag{11}$$

$$T^*_{HIGH} = P^*_{MIN} + G_{MAX} \times [(P^*_{MAX} + \mu \times \Gamma) - P^*_{MIN}] \tag{12}$$

$$\alpha = min\ (Z, \beta^+ \times \alpha) \tag{13}$$

$$\alpha = sign\ (-\beta^- \times \alpha) \times max\ (A, |\alpha|) \tag{14}$$

$$T^* = THRESHOLD; P^* = PRICE$$

III. RESULTS

The predictive control proposed is this paper is normalized and generic. It can be easily re-used in others algorithms and fields (also into algorithms in the same field, grids/PEVs/residential, attacked in this paper). However, the values of the parameters are specific to each studied system. As it is impossible to scan all possible scenarios of PEVs charging, here the aim is to assess the influence of the adjustment parameters on the performances and also to prove the efficiency of the proposed V2H algorithm. For that, three performances indices are introduced (this makes it possible to compare this algorithm with others strategies): first is the simulation time, second is the cost function evaluation (Equation 1) and last is the batteries SOH impact. Three tests have been realized. It is recalled that the results (in terms of numerical) is not the most important (reference scenario is not existing). Here the major aim is to show a new concept of algorithm and operational availability of the capabilities of this one. Table I presents the values of the adjustment parameters and the simulations times. Tests 1 and 2 used the same daily energy pricing profiles (Figure 5). In contrast, value of the $\beta+$ is lower for the second test and so, computational time is more short (the results are the same). In the thirdly test, the values of the adjustment parameters is the same as the test two but the daily energy pricing profile used is different (Figure 5). For all the tests, the number of house DLPs treated by the off-line parametric strategy is 500 and the hard equality constraint is respected when 99% of PEVs reached (among the 500) a SOC greater than 95% at the house departure time. These high conditions explain the fairly high convergence time. The presence time of the vehicle, equals to 6h, and the houses DLPs used (in off-line and on-line cases) are the same in the three tests (Figures 6 and 7). Figure 7 shows only three house DLPs among the 500 cases treated in off-line. All the DLPs used in this paper are real house electricity consumption. They emerge from previous scientific works. Electricity consumption surveys were carried out on 100 houses dispatched in France over a period of two years. The data were recorded with a time step of 10 minutes. More information are available in [10]. Finally, for all tests, Figures 8, 9, 10, 11 and 12 shows the simulations results of the algorithm, respectively, the evolutions of the PEVs SOCs related to the 500 cases treated by the off-line parametric strategy, the evolutions of PEV SOC in on-line case, the optimal profiles of the PEV command u applied in the real time (on-line) case, the evolutions of PEV SOH in on-line case and the evolutions of the cost function for the real time case. A model of battery State-of-Health (SOH) presented in [10] is used for the dynamic monitoring of the aging. Its principle consists to assess the quantity of the energy loss at each discharge of the battery by taking into account two parameters: the Deep-of-Discharge (DoD) and the discharge rate (C-rate).

TABLE I. TESTS DATA

Parameters	Test 1	Test 2	Test 3
$\alpha_{INITIAL}$ and $\alpha_{CONVERGENCE}$	0.1 – 0.01		
μ	0		
A and Z	0.005 – 1.2		
Γ	1		
β^+ and β^-	1.5 – 0.35	1.1 – 0.1	
$SOC_{INITIAL}$	10%		
Simulation Time	11mins	8mins	8mins

Figure 5. Daily energy pricing profiles

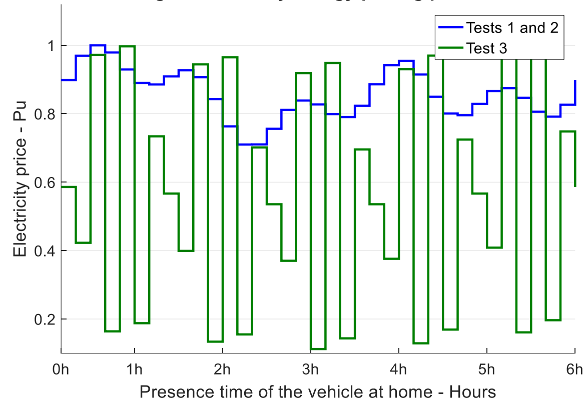


Figure 6. Daily Load Profile of house – On-line case

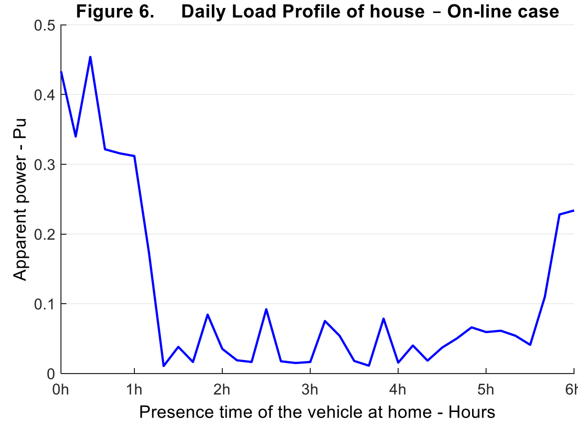


Figure 7. Three house DLPs among the 500 off-line cases

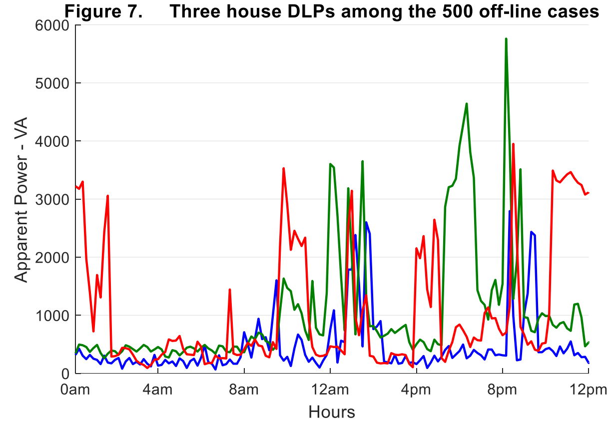


Figure 8. Evolutions of PEVs SOCs - 500 off-line cases

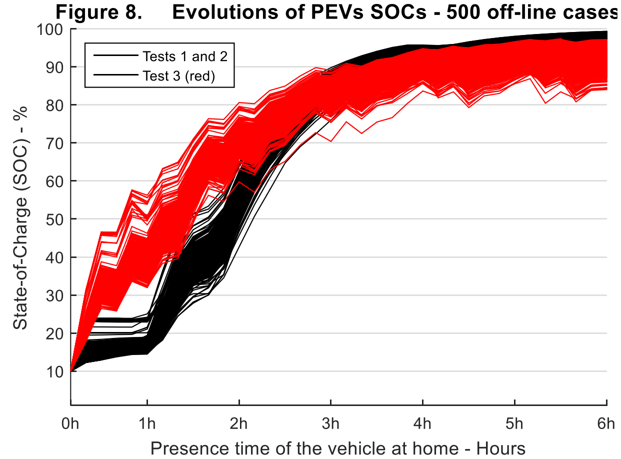


Figure 9. Evolutions of PEV SOC – On-line case

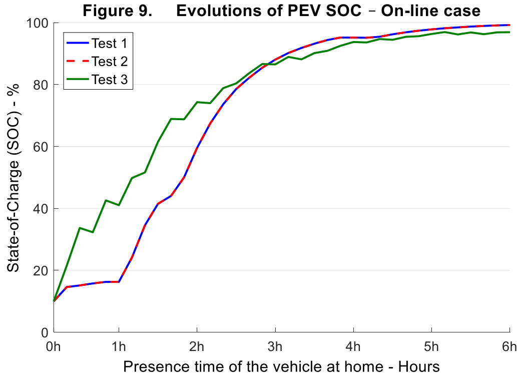


Figure 10. Optimal profiles of the PEV command u – On-line case

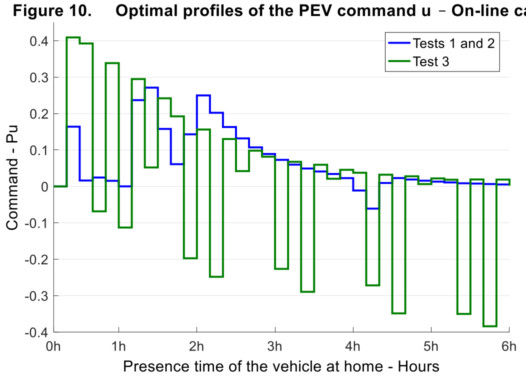


Figure 11. Evolutions of PEV SOH – On-line case

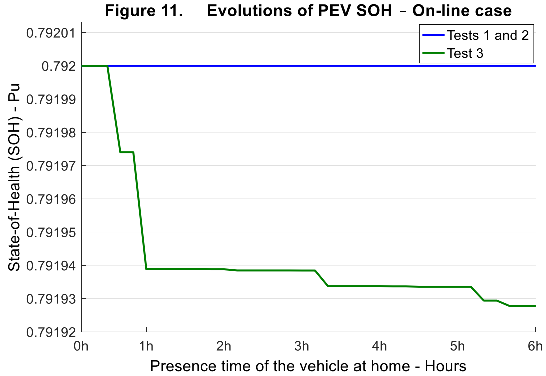
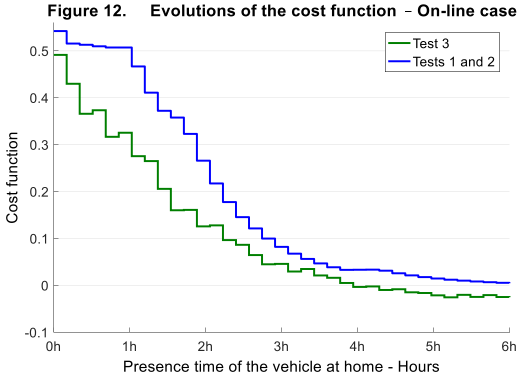


Figure 12. Evolutions of the cost function – On-line case



The final PEV SOC at departure time is very highly (close to 100% but not). It's one of the strong features of the algorithm proposed. It's thanks to the relaxed constraint introduced where a high final SOC is ensured from the hard equality constraint (placed very high here). The optimum is find between a high final SOC of the batteries and minimization of the charging cost. Test 3 shows a cost function less than zero and so, the charging cost is negative; that is to say, the algorithm allows win money in addition to charge the EV. In the two others test, the cost function is slightly greater than zero (=cheap charging).

IV. Conclusions

An on-line V2H algorithm is proposed in this paper. This one is based to the predictive control performed thanks to a parametric strategy which operates in off-line mode. At opposition to the sliding mode control used in the predictive algorithms, in this paper the narrowing mode control is explored. The V2H algorithm proposed offers multiple degrees of adjustment and so, each user can be find the optimum values of the parameters in facing theirs data. This work provides an exploratory tool where lot of tests can be performed as: sensitivity on the results of the number of house DLPs used in the parametric optimization, modification of the linear relation between the command and the electricity price in the command graph, test of different values related the hard equality constraint, soften (or harden) the convergence of the algorithm thanks to the variation of the α, etc. The tests carried out make it possible to argue that the algorithm has a high potential to reduce the charging cost by ensuring a final PEV SOC very close to the desired one by the user at the departure time. In parallel the algorithm ensures that the house subscription contract is respected. The charging process of the vehicle will not cause an overrun of the maximum value. In addition, the predictive control proposed in this paper is normalized and generic. It can be easily re-used in others algorithms and fields.

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