Smart Charging of Plug-in Electric Vehicles (PEVs) in Residential Areas: Vehicle-to-Home (V2H) and Vehicle-to-Grid (V2G) concepts

Harun Turker*‡, Seddik Bacha*

*Grenoble Electrical Engineering Laboratory (G2Elab), Grenoble INP - Grenoble Institute of Technology (GIT), 11 rue des mathématiques, Saint Martin d'Hères, 38402, France

(harun.turker.1984@gmail.com, seddik.bacha@g2elab.inpg.fr)

‡Corresponding Author: Harun Turker; Tel: +33 6 99 64 31 71, E-mail: harun.turker.1984@gmail.com,

Received: 22.09.2014 Accepted: 04.10.2014

Abstract-The share of Plug-in Electric Vehicles (PEVs) will greatly increase in the coming years. This vast deployment will create challenges of integration in the power system. Especially in the residential areas where mostly charging will take place. It's imperative to propose solutions to minimize the future impacts caused by the PEVs. In this paper we use Dynamic Programming (DP) algorithm for optimal charged the PEV. The strategy works under constraints that the vehicle should reach the full State-of-Charge (SOC) at the departure time and the charge power should be constant during all time when the PEV is at home. The application of the DP algorithm on 10,000 real case studies shows that the approach proposed is a Vehicle-to-Home (V2H) concept because it allows cost savings at users. The financial gains obtained by a French PEV user can reach 22.9%. In addition, it is shown that the strategy proposed is also a Vehicle-to-Grid (V2G) concept because it allows at the distribution electric grid manager to preserve the grid elements such as the life duration of a low voltage transformer.

Keywords -Plug-in Electric Vehicle, Residential areas, Dynamic Programming, Vehicle-to-Home, Vehicle-to-Grid, Life duration, Low voltage transformer.

1. Introduction

The automotive sector is undergoing a major change. In the near future, an increase of the penetration of both Electric Vehicles (EVs) and Plug-in Hybrid Electric Vehicles (PHEVs), is expected. In the United States of America (USA), 2.4 billion dollars have been allocated for the development of PEVs with a hope to integrate 1 million of vehicles in 2020. The German government has fixed the same goal. In France, the government has launched an ambitious plan to integrate 2 millions of Plug-in Electric Vehicles (PEVs) in 2020. For all these reasons, several scientific challenges must be addressed.

The literature on PEVs' integration can be classified into two categories. The first one includes the study and analysis of the impacts induced by integrating these vehicles. The second category represents the investigations allowing PEVs integration with an objective to reduce these impacts. Regarding the first category, one can find papers that assess the PEVs impacts on national electric grids [1-2], on distribution power grids [3-5] and on residential electric grids [6-7]. Several papers have quantified the Loss-of-Life (LOL) of high voltage transformers [8-9] and low voltage transformers [10-12] caused by PEVs charging.

The scientific community considers that the impacts associated to the integration of PEVs are almost assessed. Research is now focused to mitigate these impacts. This second category of the literature can be separated into two parts: unidirectional and bidirectional smart charging algorithms. Only a state-of-the-art related to unidirectional charging algorithms is dressed. Papers [13-15] propose strategies to increase the penetration of PEVs without additional grid investments. Voltage profile control and losses minimization algorithms are proposed in [16-19]. Algorithms, which determine the available energy for charging PEVs connected to the electric grid while minimizing the transformer's aging, are proposed in [20-23]. The economic approach is not excluded because some algorithms integrate charging cost minimization [24-29].

In comparison with the literature, a different approach is presented in this paper to solve problems related to PEVs charging. Generally, the studies cited above require communication infrastructure. Unlike them, the methodology proposed in this paper is "local" and has a strong feature because it can be applied immediately with existing electric grids without any additional infrastructure. It's a significant idea and a major contribution because absent in literature. "Local" means that the algorithm is implemented locally for each residence without any communication with other houses or residences. In the context where each house is equipped with one PEV, a Dynamic Programming (DP) algorithm is used to determine the minimum constant (i.e. no variable) charging power of PEV by ensuring that the vehicle batteries reach full State-of-Charge (SOC) for the next use. For that, the entire time horizon when the vehicle is at home is exploited. The study is conducted with the assumption that PEV leaves and arrives at home once a day. The application of the DP algorithm on 10,000 real case studies shows that PEV user's can economize an important cost. In addition, these case studies have conceded the creation of databases used to illustrate that aging rate for a low voltage transformer that feeds a residential electric grid is minimized.

This paper is organized as follows: part II presents the input data used. Part III presents the DP algorithm and the results. Part IV is dedicated to transformer aging rate study results. This paper ends in part V with conclusion and future work.

2. Input Data

To conduct the study we have used our previous work [30]. First, we have exploited a generator to construct databases of houses Daily Load Profiles (DLPs). This generator is based on real electricity consumption of domestic's electrical devices provided by Electricité de France (EDF). In each iteration, it builds one profile. This algorithm is adapted to provide DLPs for different sizes of houses which vary from 3 to 6 rooms, with/without an electric heating system and for each season (summer and winter). For this study, for each season we have generated a database of 1,000 DLPs for each size of houses or 500 DLPs if these ones are equipped with an electric heating system. So, a total of 10,000 DLPs were generated.

Next, we have used a probabilistic algorithm of PEVs connections to integrate a single vehicle to each house [30]. It selects the arrival and departure times to/from home, the category and the State-of-Charge (SOC) of the PEV. The selections are random but based on predefined probabilities. The results from a survey related to the home-work travels in Ile-de-France (18.8% of the French population) are used for the home arrival and departure times selection [31]. We have fixed the probabilities for the selection of PEVs categories from the mixed of the French car fleet in 2015-2020 [2]. It was considered that this one is composed of 3 categories (Compact Car, Sedan Car and SUV). The sizes of batteries for each category are selected from prototypes or commercialized PEVs. For the selection of PEVs batteries SOCs at home arrival times, high probabilities for low SOCs portions are fixed arbitrarily. Table 1 summarizes this data. The probabilities of selection are uniform inside each part. The SOC selection accuracy is 1% and the time step is 10 minutes. We have performed 10,000 iterations of the probabilistic algorithm of PEVs connections to create distributions. These ones for arrival and departure times are illustrated on Figure 1.

Table 1. Input data for PEVs

Category	Probability	Brand
Compact Car	55%	Nissan Leaf
Sedan Car	43%	Coda
SUV	2%	Toyota RAV4

Size of batteries	Configuration (cells)
24.00kWh – 75.90Ah	95 series – 33 parallel
31.00kWh – 98.90Ah	95 series – 43 parallel
41.80kWh – 133.4Ah	95 series – 58 parallel
Probability of SOC selection	
30 < SOC (%) < 39 => 24%	40 < SOC (%) <49 => 24%
50 < SOC (%) <59 =>12%	60 < SOC (%) <69 =>12%
70 < SOC (%) <79 =>12%	80 < SOC (%) <99 =>16%

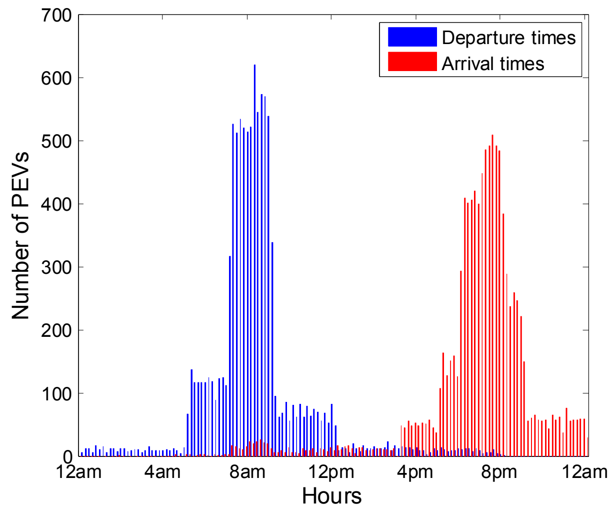


Figure 1. Home arrival and departure times

After that, we have used the Coulomb counting method for monitoring the battery SOC of PEV [32]. This one is adapted for Lithium battery technology because their capacities vary slightly following the charge/discharge rates. Equation (1) represents the model used during simulation.

$$SOC(t) = SOC(t-1) + \frac{\int \frac{I_{batt}(t)}{3600} \times dt}{Q_{nom}(t)} \times 100 \qquad (1)$$

$I_{batt} > 0 \rightarrow$ Charge of battery

$I_{batt} < 0 \rightarrow$ Discharge of battery

$Q_{nom} =$ Nominal battery capacity

At the end, we have used simultaneously the distributions from the probabilistic algorithm of PEVs connections, the size of batteries for each category of vehicles and the SOC monitoring model to construct databases of PEVs Daily Load Profiles (DLPs). So, three databases of PEVs DLPs charged at 3 standard charge power values (230V-8A, 230V-16A and 230V-32A) are constructed. Figure 2 shows some examples of these databases. We have considered an ideal PEV charger with unit cos φ. The apparent power is absorbed from the grid.

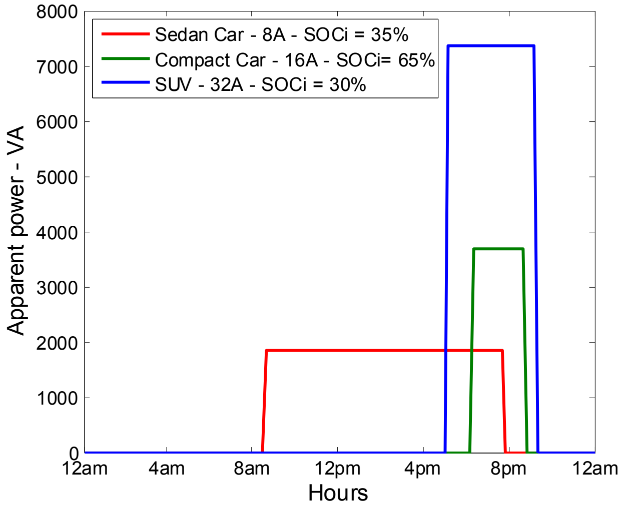


Figure 2. Some DLPs of PEVs

3. Dynamic Programming Algorithm

In this part, firstly a state-of-the-art of the optimization methods is presented. Secondly, the optimization problem formulation is exposed. Thirdly, Bellman's principle is explained and then, the simulations results are presented.

3.1. State-of-the-art of optimization methods

In this section, a state-of-the-art is presented through a classification of the Energy Management Strategies (EMS).

Most of widespread methods are likely classified following two categories. The first category includes Rule-Based strategies equivalent to sub-optimal algorithms whose operating modes are defined by heuristic rules. However, following the system studied, the optimality can be reached by determining an optimum threshold of the decision parameters of the algorithm. Rule-Based strategies are applied online when the system's time evolution is unknown. The second category includes optimization algorithms applicable online (real-time optimization) and offline (global optimization). Figure 3 shows a classification of the Energy Management Strategies (EMS). The literature on optimization methods is extensive and reader can refer to the work of [33-35].

For the dynamic resolution of the energy management system using global optimization such as considered in this paper, two methods, namely Pontryagin's minimum [36] and Bellman's principle [37] are adapted. The first method consists to minimize the Hamiltonian function of the system. Optimal control is an extension of static optimization which determines control parameters that extremize some criteria in a dynamic manner. Although it can, under special conditions, provide a state feedback control, this method gives a temporal control. By nature, the minimum principle presents necessary but not sufficient optimality conditions because a trajectory namely optimal which satisfies the conditions of optimality is not necessarily the optimal. To ensure that the solution is optimal, it must be showed that the admissible values of commands and the cost function are convex. The second method, known as Dynamic Programming, provides a control input depending of the system state. Dynamic Programming gives sufficient optimality conditions where discrete variables do not need to exhibit convex, continuous and differentiable evolutions. Following the system considered in this paper, Dynamic Programming has been selected and explained in the next paragraph.

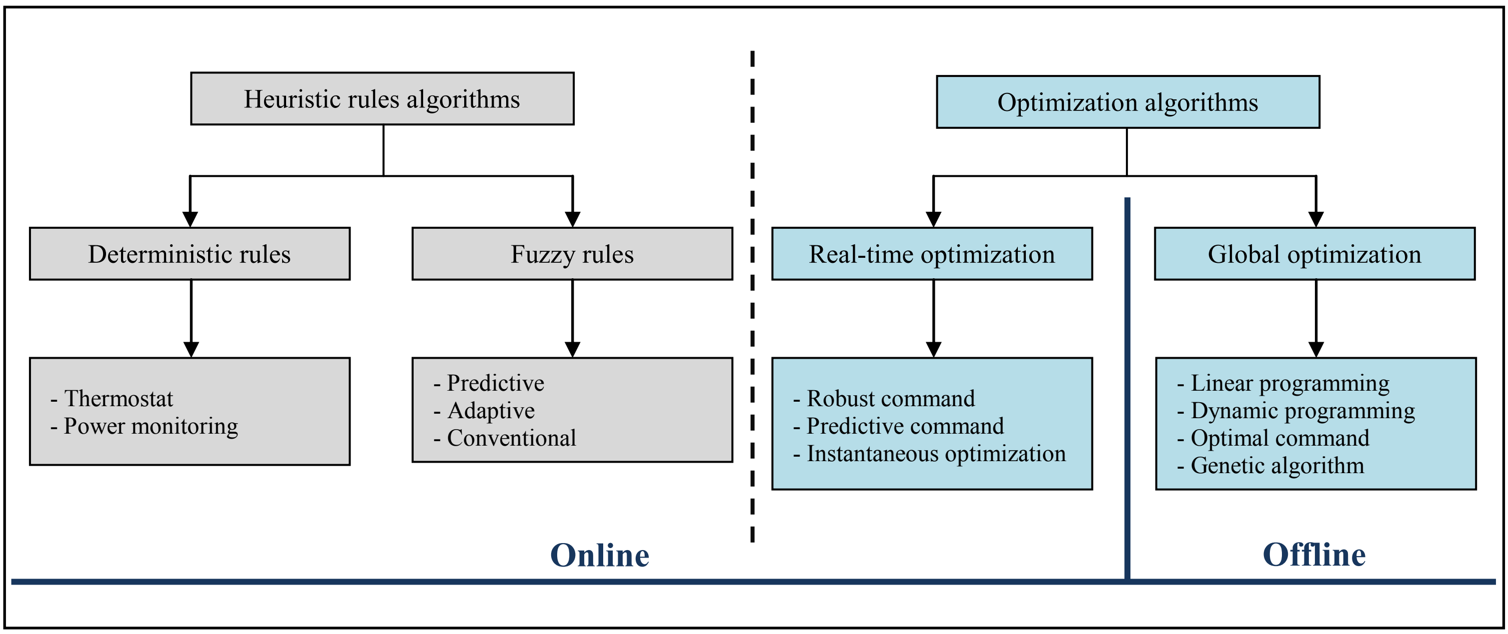


Figure 3. Classification of the EMS

3.2. Optimization problem formulation

Consistent with the intended application, the DP algorithm determines the optimal charge power that meets the constraints of the system. This one ensured that the PEV battery reaches the desired SOC by the user for the next use (home departure time). The need to know house Daily Load Profile (DLP) involves an offline character of DP algorithm.

The charge of PEV is formulated as an optimization problem where the system is represented by a dynamic equation (2) and is controlled to minimize a cost function (3) respecting the inequality and equality constraints (4) and (5).

$$\dot{x}(t) = f(x(t), u(t), t) \tag{2}$$

$$\int_{ti}^{tf} \gamma(x(t), u(t), t)\, dt \tag{3}$$

$$\phi(x(t), u(t), t) \leq 0 \tag{4}$$

$$\psi(x(t), u(t), t) = 0 \tag{5}$$

Where *x(t)* represents the state variable of the system and *u(t)* the control variable. For this application, *x(t)* is the PEV battery State-of-Charge, *SOC(t)*. The power supplied by the electric grid, S_{Grid}, is selected as the control variable. So, the equation (2) which represents the dynamic of the system is defined by the equation (6).

$$S\dot{O}C(t) = -P_{Batt}(t) \tag{6}$$

The battery power, P_{Batt} (7), is calculated depending of the electric grid power, S_{Grid}, the house consumption, S_{House} and the efficiency of the PEV embedded charger, $\eta_{Charger}$. We have considered a unit efficiency of the battery because the maximum charge rate is low (for Lithium technology). So, it don't appear in equation (7).

$$P_{Batt}(t) = \underbrace{(S_{Grid}(t) - S_{House}(t))}_{S_{PEV}(t)} \times \eta_{Charger}(t) \tag{7}$$

The standard charge power values for electric vehicles impose minimum and maximum limits. The Energy Management Strategies (EMS) fix the minimum and maximum SOC that can be reached by the PEV battery. These ones form the inequality constraints (8) and (9). Table 2 lists these values.

$$P_{Batt-min} \leq P_{Batt}(t) \leq P_{Batt-max} \tag{8}$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{9}$$

Table 2. Values of inequality constraints

$P_{Batt-min}$	$P_{Batt-max}$	SOC_{min}	SOC_{max}
0W	7360W	30%	100%

The electric grid supplies the house consumption including PEV where physics laws require power balance (10). The final State-of-Charge, SOC_{Final}, desired by the user at the home departure time must be ensured (11). These ones form the equality constraints of the system.

$$S_{House}(t) + S_{PEV}(t) - S_{Grid}(t) = 0 \tag{10}$$

$$SOC(t_f) = SOC_{Final} \tag{11}$$

Two other constraints are introduced. First, the PEV charge power must not cause an overrun of the house subscription contract, S_C (12). Second, the charge of this one is prohibited if the theoretical house consumption exceeds the subscription contract (13).

$$S_{House}(t) + S_{PEV}(t) \leq S_C \tag{12}$$

$$\text{if } S_{House}(t) \geq S_C \rightarrow S_{PEV}(t) = 0 \tag{13}$$

The cost function is the house energy consumption including PEV supplied by the electric grid. However, home appliances are not controllable. So, DP algorithm finds the optimal (minimum) constant (i.e. no variable) PEV charge power during the interval [*ti*, *tf*] corresponding to the home arrival and departure times (14).

$$E_{PEV} = \int_{ti}^{tf} \frac{P_{Batt}(t)}{\eta_{Charger}(t)} dt \tag{14}$$

Following (3), the cost function is defined by the equation (15) for this system.

$$\gamma(x(t), u(t), t) = \frac{P_{Batt}(t)}{\eta_{Charger}(t)} \tag{15}$$

3.3. Bellman's principle

Bellman's principle of optimality is defined as follow [37]: "The principle that an optimal sequence of decisions in a multistage decision process problem has the property that whatever the initial state and decisions are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decisions". From this principle derives an additive cost function through time and a recursive operation of the algorithm. So, for an initial state *x0* and an admissible control strategy u composed of steps u_k from $k=0$ to $k=N$, the optimal total cost is defined by the equation (16).

$$C(x_0)=\min_{u}\left[\gamma_N(x_N)+\sum_{k=0}^{N-1}\gamma_k(x_k,u_k)\right] \tag{16}$$

k = Discrete time step

N = Number of decisions

The implementation of the algorithm requires to discretize the optimization space. First, the number of evaluation steps E depending of the time step Δt must be determined (17). Second, the number of points P is defined depending of the storage element discretized ΔSOC which varies between the minimum and maximum limits (18).

$$E=\frac{tf-ti}{\Delta t} \tag{17}$$

$$P=\frac{SOC_{max}-SOC_{min}}{\Delta SOC} \tag{18}$$

So, discretization of the optimization space changes the state, the constraints and the cost function of the system previously presented (6) to (15). As example, the cost function is described by equation (19).

$$C=\sum_{k}\frac{P_{Batt}(k)\cdot\Delta t}{\eta_{Charger}(k)} \tag{19}$$

For PEV battery, a domain of validity is defined by considering the minimum and maximum limits of divergence and convergence following the initial and final State-of-Charge (20). The validity domain is formed for minimized the time simulation of the DP algorithm. We define the area of optimal solution research. We prohibit the research in the areas with impossible solutions. For that, we charge (or discharge) the batteries at maximum powers. From SOC at arrival time of PEV, the domain is defined by the divergence limits. We exclude solutions outside of the limits defined by maximum charge *(SOCmax-div)* (21) and maximum discharge *(SOCmin-div)* (22) of PEV battery during all time where the vehicle is at home. Based on the same methodology, we defined the maximum (23) and minimum (24) convergence limits for SOC at departure time of PEV. The maximum charge and discharge powers are respectively 7360W and 0W. Figure 4 illustrates the domain of validity for the study system where are shown 1 example. The SOC evolutions are constant because the algorithm is implemented to define a charge power no variable.

$$\hat{SOC}_{min}(k)\le SOC(k)\le \hat{SOC}_{max}(k) \tag{20}$$

$$\hat{SOC}_{max}(k)=\max\left(SOC_{max},SOC_{max-div}(k),SOC_{max-conv}(k)\right)$$

$$\hat{SOC}_{min}(k)=\max\left(SOC_{min},SOC_{min-div}(k),SOC_{min-conv}(k)\right)$$

$$SOC_{max-div}(k)=SOC(0)+\sum_{i=1}^{k}P_{Batt-charge-max}(i)\,\Delta t \tag{21}$$

$$SOC_{min-div}(k)=SOC(0)+\sum_{i=1}^{k}P_{Batt-discharge-max}(i)\,\Delta t \tag{22}$$

$$SOC_{max-conv}(k)=SOC(N)-\sum_{i=1}^{k}P_{Batt-discharge-max}(i)\,\Delta t \tag{23}$$

$$SOC_{min-conv}(k)=SOC(N)-\sum_{i=1}^{k}P_{Batt-charge-max}(i)\,\Delta t \tag{24}$$

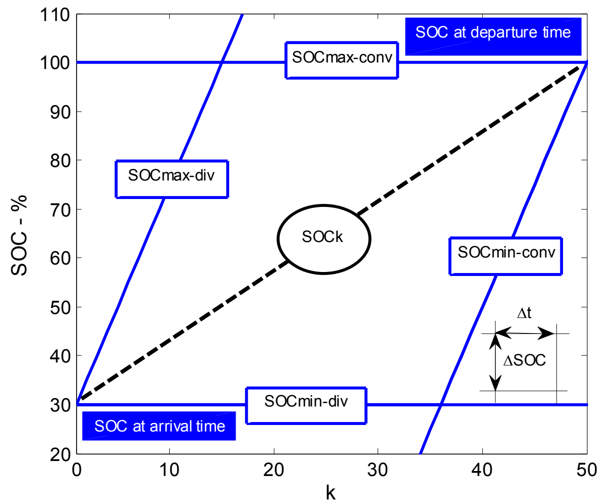


Figure 4. Validity domain of the PEV battery

Figure 5 shows the block diagram of the Dynamic Programming algorithm. The inputs correspond to the house consumption, $S_{House}(t)$, the PEV battery State-of-Charge, $SOC(t)$, and the system constraints. The algorithm provides the optimal power values from the electric grid, $S_{Grid-opt}(t)$, and for charging the vehicle, $S_{PEV-opt}(t)$. According to Bellman's principle and recursive operation of the algorithm, filling the matrices $S_{Grid-opt}(t)$, $S_{PEV-opt}(t)$, $SOC_{opt}(t)$ and $C(t)$ starts at $k=N$ returning back up to $k=1$. Each element k of these matrices contains the optimal values until the final step N. So, the cost matrix is equal to zero at $k=N$ and each element k contains the optimal cost until N. Therefore, the element $C(0)$ contains the value of the optimal total cost for the interval [ti, tf] corresponding the home arrival and departure times where the vehicle is available.

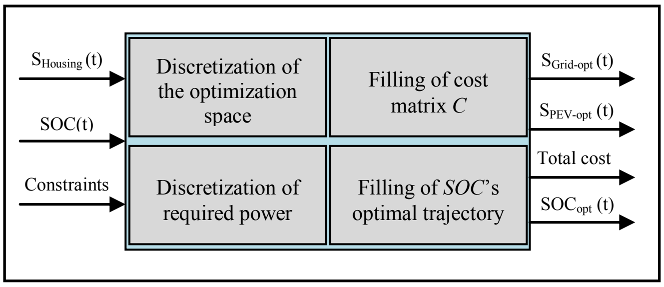


Figure 5. Block diagram of the DP algorithm

3.4. Results

In this section, the results obtained from the application of the DP algorithm on 10,000 real case studies are presented. First, an example (selected arbitrarily) is exposed (Figure 6). It shows the charge of a Sedan Car. The SOC of vehicle is equal to 40% at home arrival time (6:40pm). Departure time is planned to 8:00am. The domestic DLP represents the electricity consumption of a 3 room's house without electrical heating system in summer. The subscription contract value is 6KVA. The conclusion of these results confirms our expectations. That is, the entire time when the vehicle is at home is exploited to complete charging the batteries at a constant (i.e. no variable) charge power. Thereby, charging current is low (5.9A) with application of the DP algorithm. Without energy management strategy where charge of PEV is equal to 230V-32A, we see that the subscription contract value is exceeded. In practice, the protection device of house cuts the power.

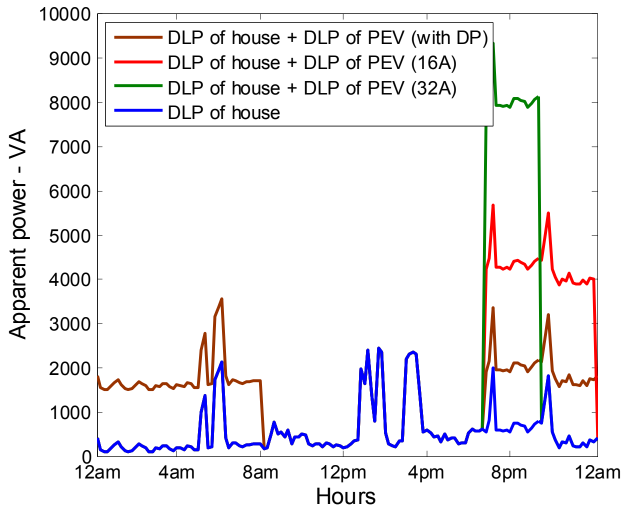
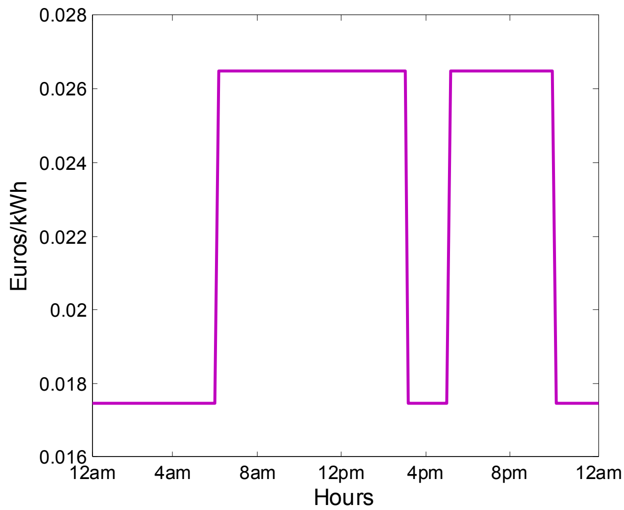
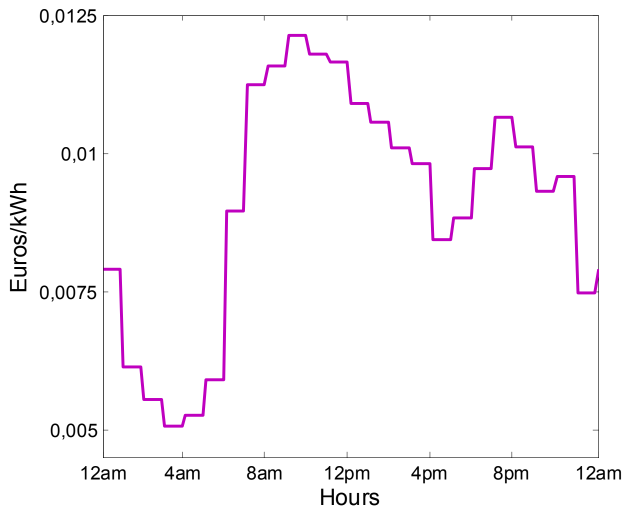


Figure 6. Application of the DP algorithm

The economic benefits for users are assessed without and with application of the DP algorithm. For this, we have used two daily energy pricing profiles (Figure 7). The first represents the electricity pricing system for residential sector in France (i.e. Peak Hours - PH/ Off-Peak Hours - OPH). The second describes a pricing system with a variable energy tariffs similar to that in USA. For the second curve, the values are used as a guideline but with a realistic form [38]. For the previous example shown above (Figure 6), table 3 lists the daily energy cost. The evaluation is performed first without vehicle and then when the PEV is integrated with two standard charge power values (230V-16A and 230V-32A). Finally, the daily energy price is assessed when the PEV is charged with the implementation of the DP algorithm. We observe that the price without PEV is very low (same compared when the charge of PEV is performed with DP algorithm) because the daily consumption of house is extremely minor. We can see through this example that the application of the DP algorithm allows for the user to realize economic gains in comparison with PEV charging without any energy management strategy.



(a) For France



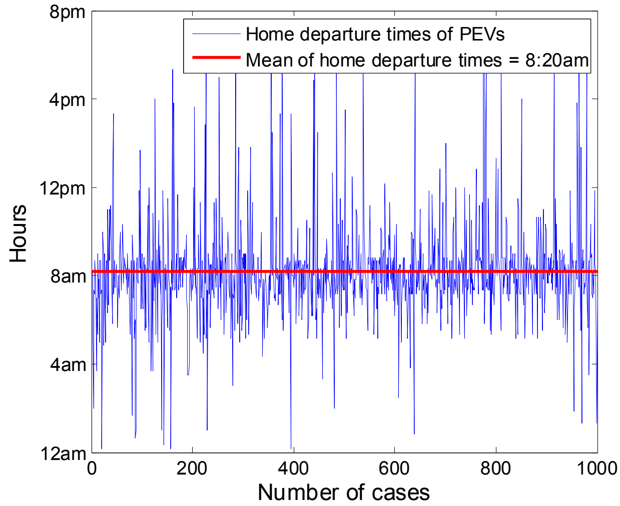
(b) "Spot"

Figure 7. Daily energy pricing profiles

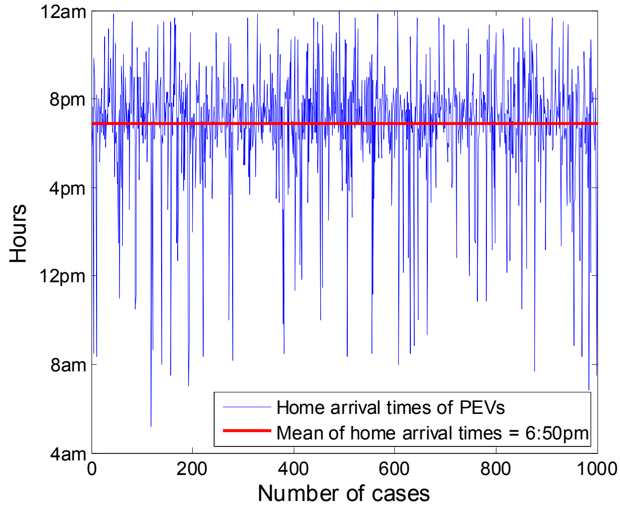
Table 3. Assessment of the daily energy price

Cost (€)	France	"Spot"
House DLP without PEV	1.89	1.53
House DLP + PEV16A DLP	4.61	3.76
House DLP + PEV32A DLP	5.00	3.92
House DLP + PEV DLP (with DP)	4.26	3.34

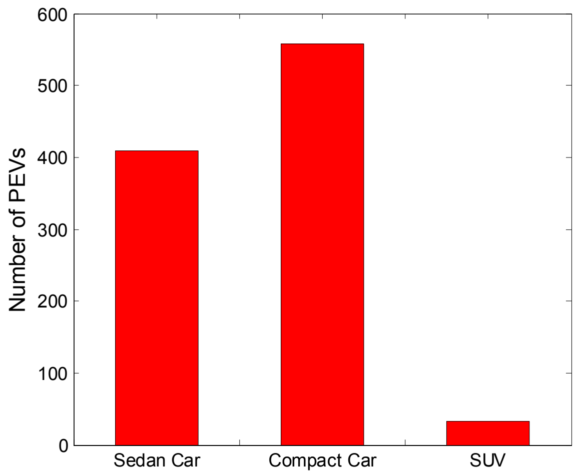
For the database which represent 1,000 DLPs of 6 room's houses without electrical heating system in summer season (selected arbitrarily), the results obtained from the application of the DP algorithm are exposed. Figures 8 and 9 show respectively the distributions issued from the application of the probabilistic algorithm of PEVs connections and the 1,000 PEVs charging currents acquired. We can observe that the average charge power obtained is low (equal to about 1kW).



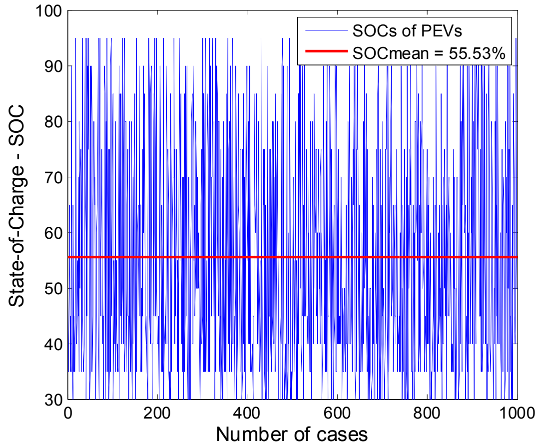
(a) Home departure times



(b) Home arrival times



(c) Categories of PEVs



(d) SOCs of PEVs

Figure 8. Application of the probabilistic algorithm of PEVs connections

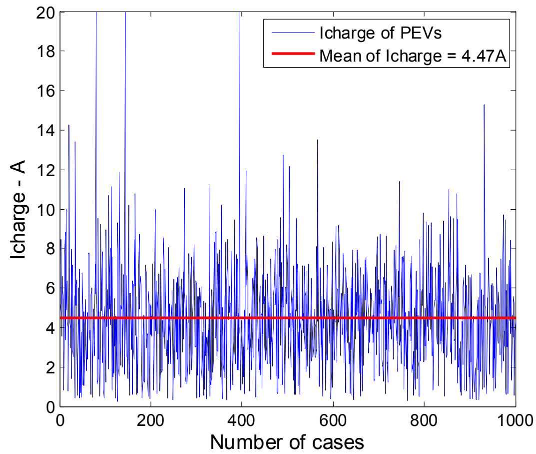


Figure 9. Database of the PEVs charging currents

The DP algorithm is applied on 10,000 real case studies. Figure 10 illustrates the PEVs charging currents. Basic statistics are performed on these data (Table 4). We observed as previously that the average charge power obtained is low against the case without EMS. We also find that the dispersion is reasonable because 67% of the results are placed in the symetric interval around the average current bounded by the standard deviation.

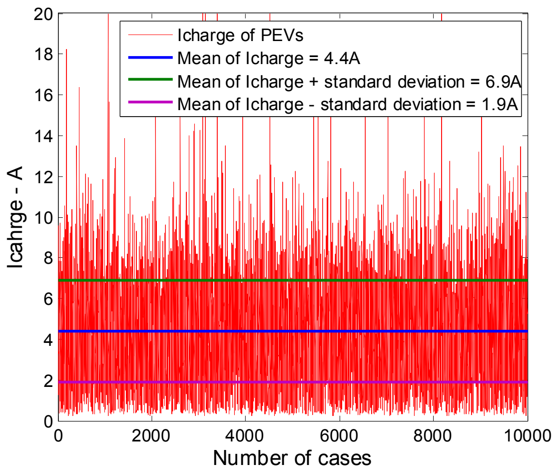


Figure 10. PEVs charging currents – Application of the DP algorithm on 10,000 cases

Table 4. Statistics in the results of DP algorithm application on 10,000 cases

Min.	Mean	Max.	σ	Mode	Median
0.22A	4.4A	37.25A	2.5A	6.74A	4.38A
PEVs ϵ [mean – σ ; mean + σ]					
67%					

Using 10,000 real case studies, we have employed the daily energy pricing profiles previously presented for assessing the economic benefits for users provided by the application of the DP algorithm. So, based on all the cases, Table 5 lists the average cost of one day on one hand without vehicle and on the other hand with PEV charged at 230V-16A and 230V-32A and charged with the application of the DP algorithm. For France where real electricity prices are used, the mean cost saving reaches 12.9% and 22.9% thanks to DP algorithm in comparison with PEV charging without energy management strategy.

Table 5. Assessment of the energy price and cost saving based on 10,000 cases

Cost (€)	House DLP without PEV	House DLP + PEV16A DLP
France	4.56	6.42
“Spot”	1.81	2.56
Cost (€)	**House DLP + PEV32A DLP**	**House DLP + PEV DLP (with DP)**
France	6.66	6.18
“Spot”	2.63	2.43
Cost saving		
France	DP => PEV 16A : 12.9%	
France	DP => PEV 32A : 22.9%	
“Spot”	DP => PEV 16A : 17.3%	
“Spot”	DP => PEV 32A : 24.4%	

The application of the DP algorithm on 10,000 real case studies gives significant observation. We obtain an average charge power about 1kW with a reasonable dispersion. We find that a French PEV user reached an average cost saving equal to 12.9% and 22.9% if charging the vehicle respectively at 230V-16A and 230V-32A. The DP algorithm is a energy management strategy which allows to user obtain financial gains. It’s a Vehicle-to-Home (V2H) concept. This work has conceded the creation of databases which are composed of houses DLPs incremented by the consumption of PEVs charged with the application of the DP algorithm. Theses databases have enabled the analysis covered by the remainder of this paper. That is the assessment of the impacts in the aging rate of a low voltage transformer which supplies a residential electric grid.

4. Impacts on the transformer

The low voltage transformers are first elements of residential electric grid to be impacted by the PEVs integration. Thereby, these ones will suffer a premature aging. So, this part evaluates this phenomenon and allows to observe the benefits of applying the Dynamic Programming for PEVs charging. For that, first the laws for life duration calculation are exposed. These ones require the dynamic monitoring during operation of the hot-spot temperature in the transformer windings. Second the most of widespread thermal model in the literature is presented. Third, a modelisation is performed for a distribution transformer of 160kVA and then, a quantification of the impact on the transformer life duration is presented.

4.1. Life duration

It’s commonly accepted that the life duration of a transformer is reduced to the life duration of the insulations. Equation (25) from the Arrhenius law represents the life duration of a transformer [39].

$$\text{Per unit Life} = A \times \exp\left(\frac{B}{\theta_h + 273}\right) \tag{25}$$

$\theta_h =$ Hot-spot temperature of the windings
A and B = Constants

Equations (26) and (27) describe respectively the laws to calculate the aging rate *V* for thermally upgraded paper (reference temperature is equal to 110°C) and non-thermally upgraded paper (reference temperature is equal to 98°C) [40].

$$V = \exp\left(\frac{15000}{110+273} - \frac{15000}{\theta_h + 273}\right) \tag{26}$$

$$V = 2^{\frac{(\theta_h - 98)}{6}} \tag{27}$$

Given that the aging rate is a cumulative process, a equivalent aging factor F_{EQA} for the total time period is introduced (equation (28)) [39].

$$F_{EQA} = \frac{\sum_{n=1}^{N} F_{AAn} \times \Delta t_n}{\sum_{n=1}^{N} \Delta t_n} \tag{28}$$

F_{EQA} = Equivalent aging factor for the total time period
F_{AAn} = Aging acceleration factor for the temperature during the time interval Δt_n
Δt_n = Time interval in hours
N = Total number of time intervals

Equation (29) represents the percentage of transformer Loss-of-Life *(LOL)* for a variable hot-spot temperature during a time interval [39][41].

$$\mathrm{LOL}(\%) = \frac{F_{EQA} \times t \times 100}{\mathrm{NIL}\ (\text{Normal Insulation Life})} \tag{29}$$

LOL = Percentage of transformer Loss-of-Life
t = Time interval in hours
NIL = 20.55 years and 30 years respectively for transformers with insulations which are thermally upgraded paper and not

Equation (30) presents a second method which assesses the lifetime consumption *L* during a time interval [40].

$$L = \int_{t1}^{t2} V \times dt \quad \text{or} \quad L \approx \sum_{n=1}^{N} V_n \times t_n \tag{30}$$

4.2. Thermal model

Obviously, the hottest element of the transformer will suffer the most damage. Therefore, the life duration of transformer is directly related to the hot-spot temperature. This one is usually placed at the top of the low voltage windings because the flux density is largest. For hot-spot temperature calculation, we have used the thermal model proposed by CEI 60076-7 [40]. This one is adapted for dynamic monitoring during operation.

The hot-spot temperature calculation is performed from the top-oil temperature and the increase of hot-spot temperature in comparison with the top-oil (equation (31)).

$$\theta_h = \theta_0 + \Delta\theta_h \tag{31}$$

θ_h = Hot-spot temperature at the load considered

$\Delta\theta_h$ = Hot-spot-to-top-oil (in tank) gradient at the load considered

Equation (32) allows the top-oil temperature calculation.

$$\left[\frac{1+K^2 R}{1+R}\right]^x \times \Delta\theta_{or} = k_{11} \times \tau_0 \times \frac{d\theta_0}{dt} + [\theta_0 - \theta_a] \tag{32}$$

K = Load factor (ratio of the load current to the rated current)
R = Ratio of load losses at rated current to no load losses
$\Delta\theta_{or}$ = Top-oil (in tank) temperature rise in steady state at rated losses
k_{11} = Thermal model constant
τ_0 = Average oil time constant
θ_0 = Top-oil temperature (in the tank) at the load considered
θ_a = Ambient temperature
x = Exponential power of total losses versus top-oil (in tank) temperature rise (oil exponent)

The increase of the hot-spot temperature in comparison with the top-oil is calculated by the equation (33).

$$\Delta\theta_h = \Delta\theta_{h1} - \Delta\theta_{h2} \tag{33}$$

$$k_{21} \times K^y \times \Delta\theta_{hr} = k_{22} \times \tau_w \times \frac{d\Delta\theta_{h1}}{dt} + \Delta\theta_{h1}$$

$$(k_{21} - 1) \times K^y \times \Delta\theta_{hr} = \frac{\tau_0}{k_{22}} \times \frac{d\Delta\theta_{h2}}{dt} + \Delta\theta_{h2}$$

$\Delta\theta_{hr}$ = Hot-spot-to-top-oil (in tank) gradient at rated current

k_{21} and k_{22} = Thermal model constant

τ_w = Winding time constant

y = Exponential power of current versus winding temperature rise (winding exponent)

4.3. Modeling of a low voltage distribution transformer

A low voltage distribution transformer of 160kVA which supplies a residential electric grid area is chosen. This one is installed in a distribution station type “PSS” (insulated cabin). We have selected a low voltage transformer for several reasons. On one hand, these ones are widely used in France (about 700,000). On the other hand, they will the first elements of the grid to be impacted by the integration of PEVs. The ambient temperature affects the hot-spot temperature and in consequence, impacts the life duration of transformer [42]. So, we have used a daily average ambient temperature profile from real data provided by EDF for the Nimes city in 2006. This allows assess the average aging rate of the transformer. Given the transformer position (inside the cabin), we have increment 10°C at the daily average ambient temperature profile (Figure 11).

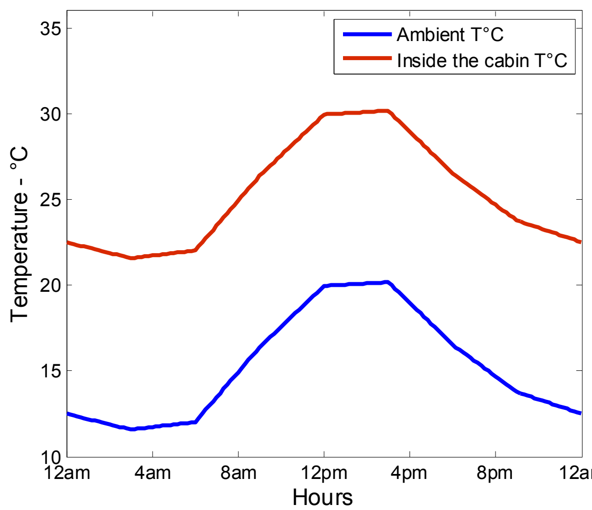


Figure 11. Daily ambient temperature profiles

In order to minimize errors caused by the assumption made to exclude harmonics induced in the power grid from domestic electrical appliances and PEVs, a transformer made with aluminum foil of the secondary is selected. This type of transformer is less sensitive to harmonics because the increase of losses is only due to the increase of the RMS value of the charging current [43]. Table 6 describes its electrics and geometrics characteristics [43].

Table 6. Electrics and geometrics characteristics of transformer [43]

Apparent power	160kVA
Cooling mode	ONAN
Prim. voltage	20kV
Sec. voltage	410V
Prim. current	4.6A
Sec. current	225.3A
No-load loss	381W
LV Pj (75°C)	1230W
MV load loss (75°C)	1615W
P_{OSL}	60W
Prim. conductors	ø1mm
Prim. layers number	16
Rac1	75Ω
Sec. conductors	Alum. foil (= 0.35mm)
Sec. layers number	46
Rac2	7.7mΩ

The life duration of the selected transformer is 30 years [41] and its insulations are non-thermally upgraded paper (reference temperature is equal to 98°C). So, the aging rate *V* calculation is performed by the equation (27). Matlab Simulink software is used for developed thermal model proposed by CEI 60076-7. Table 7 lists the values of parameters [43].

Table 7. Values of parameters from the thermal models [43]

$\Delta\theta_{or}$	50.4°C
$\Delta\theta_{hr}$	19°C
x	0.8
y	1.6
τ_0	120mns
τ_w	4mns
k_{21}	1
k_{22}	2
k_{11}	1

Figure 12 illustrates the hot-spot temperature profile obtained from the thermal model. The rated current (225.3A) has been applied at the secondary of the transformer. The hot-spot temperature fluctuation observed is due to the variation of the ambient temperature (day/night).

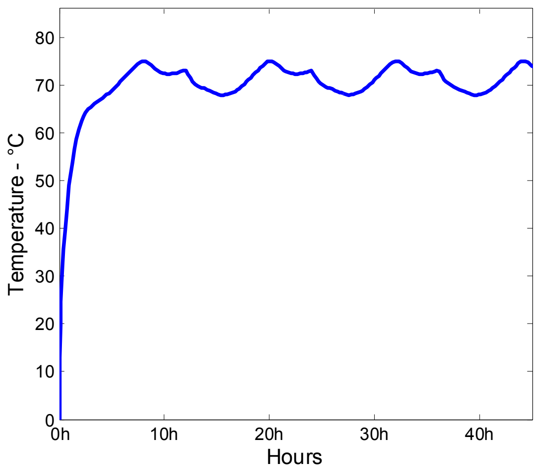


Figure 12. Hot-spot temperature profile

4.4. Quantification of the impact in the life duration

We have assessed the aging rate of a 160kVA low voltage transformer that feeds a residential electric grid. Thus, we have used the databases created previously which are composed of houses DLPs incremented by the consumption of PEVs charged with the application of the DP algorithm. The goal is to analyze the benefit in the life duration of transformer obtained by the application of a energy management strategy. We recall that the study is conducted with the following assumption: each home is equipped with only one PEV.

The life span of a transformer is related to its Load Rate (LR) and the ambient temperature [44]. Even if the electric grid is composed of an equal number of houses, the LR varies due to the expansion of the electricity consumption of all the houses which constitute the electric grid. While forecasting the habits of people provides an approximation of the transformer DLP, the random factor is decisive. By creating databases of transformer DLPs, one can minimize this factor. Given that, the study is realized by varying the LR from 0 (no houses) to 120 houses (with 5 houses step). For each analysis point, 2,000 transformer DLPs are generated without, then, with the presence of one PEV per house charged with two standard charge powers on one hand, and on the other, with the application of the DP algorithm. These created databases of transformer DLPs take into account the disparity of the houses size and the percentage of house with an electric heating system in France [30]. For the 2,000 transformer DLPs generated at each analysis point, all the houses and PEVs selected randomly are different but the data (home arrival and departure times, category, SOC and batteries size) of the PEV first charged with the two power levels (230V-16A and 230V-32A) without management and then charged with the application of the DP algorithm are identical.

Nevertheless, because of the disparity among 2,000 LRs is too high, we define the average DLPs for each of the cases assessed for each analysis point. Indeed, the differences related to LRs are decisive for considering the averages DLPs and thus studying the average aging rate of the transformer. So, first we define the life duration of the transformer for each case. Figure 13 shows the results.

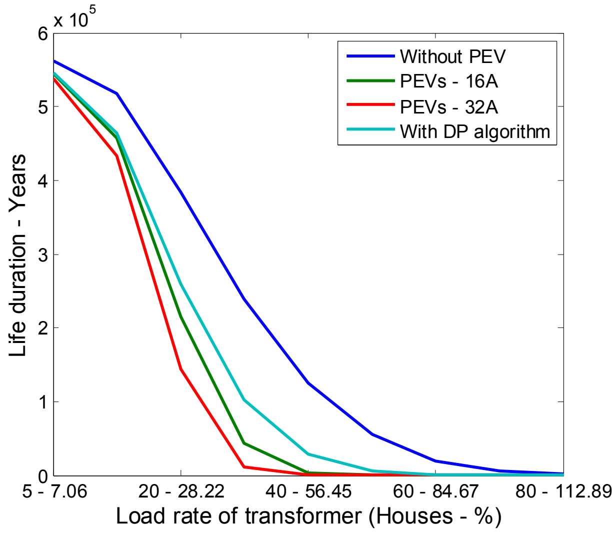


Figure 13. Life duration of the transformer

Taking as reference the life duration of the transformer without PEV, we defined the aging rate of the transformer for each case. Figure 14 illustrates the results. We observe that the aging rate is strongly reduced when the PEVs are charged with the application of the DP algorithm. This one is a Energy Management Strategy (EMS) which allows at the distribution electric grid manager to preserve the grid elements. It's a Vehicle-to-Grid (V2G) concept.

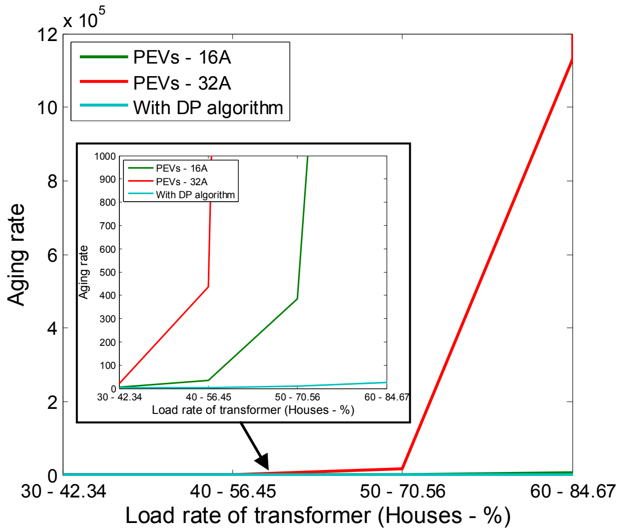


Figure 14. Aging rate of the transformer

5. Conclusion and Future Work

In this paper, we have proposed a smart charging algorithm of Plug-in Electric Vehicles (PEVs) in residential areas. This Energy Management Strategy (EMS) is based on a Dynamic Programming algorithm with offline configuration because it know house Daily Load Profile (DLP). A future work is proposed related to the offline character of the strategy.

In this study, the aim has been to find the minimum constant (i.e. no variable) charge power of PEV by ensuring that the vehicle batteries reached the full State-of-Charge (SOC) for the next use. The entire time when the vehicle is at home is exploited. The study has been conducted with several assumptions: first, the home is equipped with only one PEV and second, this one leaves and arrives once a day. Perspectives are proposed referred to these assumptions.

Another approach is used in this paper to solve the problems dealing with PEVs charging. Unlike the studies of the literature, the proposed methodology is "local" and it's applicable immediately with existing electric grids without any additional infrastructure. It's a major contribution because absent in literature. "Local" means that the algorithm is implemented locally for each residence without any communication with other houses or residences.

Following the results from the application of the DP algorithm on 10,000 real case studies, we have proved that the EMS proposed is a Vehicle-to-Home (V2H) and Vehicle-to-Grid (V2G) concepts. This one allows cost savings for the users and to preserve the grid elements which greatly benefits to the distribution electric grid manager. For a French PEV user, the financial gains obtained can reach 22.9% and we have observed that the life duration of a low voltage transformer is extended.

Many study perspectives can emerge. Under the assumption of one PEV per house, a first future investigation issue can be proposed. Several departures and arrivals of vehicles per day will affect the results. Therefore, the first approach is to take into account the details of behaviors of users from experimental tests. The adaptation of the developed DP algorithm to integrate up to three PEVs/house could be a second issue. This will require a similar study, as in this paper, wherein we will assume that the entire French fleet consists of PEVs and takes the probabilities of the number of vehicles/home into account. Finally, a last investigation issue can be proposed. This one consists to propose an online real-time optimal algorithm for PEVs charging in residential areas with the assumptions considered in this paper.

References

[1] Karsten Hedegaard, Hans Ravn, Nina Juul, Peter Meibom, "Effects of electric vehicles on power systems in Northern Europe," Elsevier Energy, Vol.48, no.1, pp.356-368, December 2012.

[2] Turker, H.; Bacha, S.; Chatroux, D., "Impact of Plug-in Hybrid Electric Vehicles (PHEVs) on the French electric grid," Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES, pp.1-8, 11-13 October 2010.

[3] H. Turker, A. Florescu, S. Bacha, D. Chatroux, "Load Rates of Low Voltage Transformers and Medium Voltage Profile Assessments on a Real Distribution Electric Grid based on Average Daily Load Profile (DLP) of a Housing for a High Penetration of Plug-in Hybrid Electric Vehicles (PHEVs)," Vehicle Power Propulsion Conference (VPPC), 2011 IEEE PES, pp. 1-8., 6-9 September 2011.

[4] L. P. Fernandez, T. G. S. Roman, R. Cossent, C. M. Domingo, P. Frias, "Assessment of the Impact of Plug-in Electric Vehicles on Distribution Networks," Power Systems, IEEE Transactions on, Vol.26, No.1, pp. 1-8, February 2011.

[5] Robert C. Green II, Lingfeng Wang, Mansoor Alam, "The impact of plug-in hybrid electric vehicles on distribution networks: A review and outlook," Elsevier Renewable and Sustainable Energy Reviews, Vol.15, no.1, pp.544-553, January 2011.

[6] S. Deilami, A.S. Masoum, P.S. Moses, M.A.S. Masoum, "Voltage Profile and THD Distortion of Residential Network with High Penetration of Plug-in Electrical Vehicle," Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES, pp.1-6, 11-13 October 2010.

[7] H. Turker, A. Florescu, S. Bacha, D. Chatroux, "Voltage profile and excess subscription assessments indexes based on random selection of real Daily Loads Profiles (DLPs) on residential electric grid areas for a high penetration of Plug-in Hybrid Electric Vehicles (PHEVs)," Vehicle Power Propulsion Conference (VPPC), 2011 IEEE PES, pp. 1-5., 6-9 September 2011.

[8] Staats, P. T.; Grady, W.M.; Arapostathis, A.; Thallam, R. S., "A procedure for derating a substation transformer in the presence of widespread electric vehicle battery charging," Power Delivery, IEEE Transactions on, vol.12, no.4, pp.1562-1568, October 1997.

[9] Agah, S.M.M.; Abyaneh, H.A., "Distribution Transformer Loss-of-Life Reduction by Increasing Penetration of Distributed Generation," Power Delivery, IEEE Transactions on, vol.26, no.2, pp.1128-1136, April 2011.

[10] Turker, H.; Bacha, S.; Chatroux, D.; Hably, A., "Low-Voltage Transformer Loss-of-Life Assessments for a High Penetration of Plug-In Hybrid Electric Vehicles (PHEVs)," Power Delivery, IEEE Transactions on, vol.27, no.3, pp.1323-1331, July 2012.

[11] Rutherford, M.J.; Yousefzadeh, V., "The impact of Electric Vehicle battery charging on distribution transformers," Applied Power Electronics Conference and Exposition (APEC), 2011 Twenty-Sixth Annual IEEE, pp.396-400, 6-11 March 2011.

[12] Argade, S.; Aravinthan, V.; Jewell, W., "Probabilistic modeling of EV charging and its impact on distribution transformer loss of life," Electric Vehicle Conference (IEVC), 2012 IEEE International, pp.1-8, 4-8 March 2012.

[13] Richardson, P.; Flynn, D.; Keane, A., "Optimal Charging of Electric Vehicles in Low-Voltage Distribution Systems," Power Systems, IEEE Transactions on, vol.27, no.1, pp.268-279, February 2012.

[14] Hajimiragha, A.H.; Canizares, C.A.; Fowler, M.W.; Moazeni, S.; Elkamel, A., "A Robust Optimization Approach for Planning the Transition to Plug-in Hybrid Electric Vehicles," Power Systems, IEEE Transactions on, vol.26, no.4, pp.2264-2274, November 2011.

[15] Karnama, A.; Resende, F.O.; Lopes, J.A.P., "Optimal management of battery charging of electric vehicles: A new microgrid feature," PowerTech, 2011 IEEE Trondheim, pp.1-8, 19-23 June 2011.

[16] Karfopoulos, E. L.; Hatziargyriou, N. D., "A Multi-Agent System for Controlled Charging of a Large Population of Electric Vehicles," Power Systems, IEEE Transactions on, vol.28, no.2, pp.1196-1204, May 2013.

[17] Sortomme, E.; Hindi, M.M.; MacPherson, S.D.J.; Venkata, S.S., "Coordinated Charging of Plug-In Hybrid Electric Vehicles to Minimize Distribution System Losses," Smart Grid, IEEE Transactions on, vol.2, no.1, pp.198-205, March 2011.

[18] C.H. Dharmakeerthi, N. Mithulananthan, T.K. Saha, "Impact of electric vehicle fast charging on power system voltage stability," Elsevier International Journal of Electrical Power and Energy Systems, Vol.57, pp.241-249, May 2014.

[19] D.Q. Oliveira, A.C. Zambroni de Souza, L.F.N. Delboni, "Optimal plug-in hybrid electric vehicles recharge in distribution power systems," Elsevier Electric Power Systems Research, Vol.98, pp.77-85, May 2013.

[20] Q. Gong, S. Midlam-Mohler, V. Marano, G. Rizzoni, "Study of PEV Charging on Residential Distribution Transformer Life," Smart Grid, IEEE Transactions on, Vol.3, No.1, pp. 404-412, March 2012.

[21] A. D. Hilshey, P. D. H. Hines, P. Rezaei, J. R. Dowds, "Estimating the Impact of Electric Vehicle Smart Charging on Distribution Transformer Aging," Smart Grid, IEEE Transactions on, Vol.4, No.2, pp. 905-913, June 2013.

[22] J. M. Sexauer, K. D. McBee, K. A. Bloch, "Application of Probability Model to Analyze the Effects of Electric Vehicle Chargers on Distribution Transformers," Power Systems, IEEE Transactions on, Vol.28, No.2, pp. 847-854, May 2013.

[23] Ghazal Razeghi, Li Zhang, Tim Brown, Scott Samuelsen, "Impacts of plug-in hybrid electric vehicles on a residential transformer using stochastic and empirical analysis," Elsevier Journal of Power Sources, Vol.252, pp.277-285, April 2014.

[24] Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang, J. Li, "An Optimized EV Charging Model Considering TOU Price and SOC Curve," Smart Grid, IEEE Transactions on, Vol.3, No.1, pp. 388-393, March 2012.

[25] Alessandro Di Giorgio, Francesco Liberati, Silvia Canale, "Electric vehicles charging control in a smart grid: A model predictive control approach," Elsevier Control Engineering Practice, Vol.22, pp.147-162, January 2014.

[26] Wencong Su, Jianhui Wang, Kuilin Zhang, Alex Q. Huang, "Model predictive control based power dispatch for distribution system considering plug-in electric

vehicle uncertainty," Elsevier Electric Power Systems Research, Vol.106, pp.29-35, January 2014.

[27] A. Sheikhi, Sh. Bahrami, A.M. Ranjbar, H. Oraee, "Strategic charging method for plugged in hybrid electric vehicles in smart grids; a game theoretic approach," Elsevier International Journal of Electrical Power and Energy Systems, Vol.53, pp.499-506, December 2013.

[28] Alireza Zakariazadeh, Shahram Jadid, Pierluigi Siano, "Multi-objective scheduling of electric vehicles in smart distribution system," Elsevier Energy Conversion and Management, Vol.79, pp.43-53, March 2014.

[29] F.J. Soares, P.M. Rocha Almeida, J.A. Pecas Lopes, "Quasi-real-time management of Electric Vehicles charging," Elsevier Electric Power Systems Research, Volume 108, pp.293-303, March 2014.

[30] Turker, H.; Bacha, S.; Chatroux, D.; Hably, A., "Modelling of system components for Vehicle-to-Grid (V2G) and Vehicle-to-Home (V2H) applications with Plug-in Hybrid Electric Vehicles (PHEVs)," Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES, pp.1-8, 16-20 January 2012.

[31] Observatoire Social de Lyon, "Enquête auprès des salariés d'Île-de-France sur les transports en commun domicile-travail," February 2010.

[32] Kong Soon Ng, Chin-Sien Moo, Yi-Ping Chen, Yao-Ching Hsieh, "Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries," Elsevier Applied Energy, Vol. 86, pp.1506-1511, September 2009.

[33] F.R. Salmasi, "Control strategies for hybrid electric vehicles: Evolution, classification, comparison, and future trends," Vehicular Technology, IEEE Transactions on, pages 2393-2404, 2007.

[34] H. Abou-Kandil. "La commande optimale des systèmes dynamiques."Book Lavoisier, 2004.

[35] E. Laroche. "Commande optimale."Technical report, Technical report of École Nationale Supérieure de Physique de Strasbourg, 2009-2010.

[36] I. Michael Ross. "A Primer on Pontryagin's Principle in Optimal Control." Book, 2009.

[37] Moshe Sniedovich. "Dynamic Programming: Foundations and Principles," Second Edition. Book CRC Press, 2010.

[38] www.epexspot.com/fr/ (October 9, 2013)

[39] IEEE Guide for loading mineral oil immersed transformers. C57-91, 1995.

[40] CEI Loading guide for oil immersed power transformers. 60076-7, 2005.

[41] K. Najdenkoski, G. Rafajlovski, and V. Dimcev, "Thermal aging of distribution transformers according to ieee and iec standards," Power Engineering Society General Meeting, 2007 IEEE, pp.1-5, 24-28 June 2007.

[42] J. W. Stahlhut, G. T. Heydt, and N. J. Selover, "A preliminary assessment of the impact of ambient temperature rise on distribution transformer loss-of-life," Power Delivery, IEEE Transactions on, vol.23, no.4, pp.2000-2007, October 2008.

[43] Wilfried Frelin, "Impact de la pollution harmonique sur les matériels de réseau."PhD thesis, Ecole Supérieure d'Électricité - Université Paris 11, 2009.

[44] J. A. Jardini, H. P. Schmidt, C. M. V. Tahan, C. C. B. Oliveira, S. U. Ahn, "Distribution Transformer Loss of Life Evaluation: A Novel Approach Based on Daily Load Profiles," Power Delivery, IEEE Transactions on, Vol.15, No.1, pp. 361-366, January 2000.

Biographies

Harun Turker was born in Grenoble, France, on June 2, 1984. He received the Master's degree in Électronique, Électrotechnique, Automatique and Traitement du Signal (EEATS) from the University of Joseph Fourier, Grenoble, France, in 2009 and the PhD. Degree in Electrical Engineering from the Grenoble Institute of Technology (Grenoble INP) in 2012. It has been Postdoctoral Researcher and Teacher Scholar at the Grenoble Electrical Engineering Laboratory (G2ELab) and Grenoble INP in 2013 and 2014. He created the company Turker Smart Grid Expertise & Consulting in 2015. His main research field is Smart Grid including Electric Vehicles/Plug-in Hybrid Electric Vehicles. Recently, he extended these research areas. New interest fields are: optimal design of machines, methods hybridization of vehicles and integrated battery chargers in electric vehicle applications.

Seddik Bacha (M'08) received the Engineer and Magister degrees from École Nationale Polytechnique de Algiers, Algeria, in 1982 and 1990 respectively, and the Ph.D. degree from Institut National Polytechnique de Grenoble, France in 1993. He joined the Laboratoire d'Electrotechnique de Grenoble (LEG) in 1990 and in 1998 he was habilitated to conduct research. He is currently Manager of the Power Systems Group with Grenoble Electrical Engineering Laboratory.