Preprints of the 2012 20th Mediterranean Conference on Control & Automation (MED), Barcelona, Spain, July 3-6, 2012

Optimal Electric Vehicles to Grid Power Control for Active Demand Services in Distribution Grids

Alessandro Di Giorgio, Francesco Liberati and Silvia Canale

Abstract— **In this paper we outline a novel approach for the design of an electric vehicle (EV) aggregator, a controller whose objective is to optimally manage the charging operations of an EV fleet. The control strategy we derive is based on model predictive control and allows to achieve costs minimization, also enabling the aggregator (hence, the EV fleet) to participate to the provisioning of active demand services to upper level market players. Explicative simulations are presented and discussed in order to show the effectiveness of the approach and also to investigate the role of vehicle to grid power.**

Index Terms— **Electrical vehicles, vehicle to grid power, active demand, demand side management.**

NOMENCLATURE

M	Set of EVs currently connected to the charging stations
M_k	Subset of M denoting the set of EVs connected to the charging stations during the k-th time interval (it does not include those EVs that leave the charging stations before the k-th time interval)
I	Start time of problem definition
E_m	Last allowed time instant for charging operations on the m-th EV (this value is set by the driver)
E	Last time instant of problem definition
ΔP_m	Charging power of the m-th EV
T	Discretization time step
$C_m[\cdot]$	Electricity tariff of the m-th EV
$U_m[\cdot]$	Control variable related to the charging operations on the m-th EV
$X_m[\cdot]$	State of the battery (charge level) of the m-th EV
X_m^{max}	Capacity of the battery of the m-th EV
X_m^{ref}	Desired final charge level of the m-th EV (set by the driver upon arrival at the charging station)
ξ_m	m-th EV's battery performance coefficient
$P^*[\cdot]$	Maximum power available for the EV fleet
C_m^0	Estimated cost for charging operation on the m-th EV (estimated upon arrival at the charging facility)

I. INTRODUCTION

The ongoing revolution introduced by the Smart Grid vision, prompted by the latest technological developments and a renewed attention to eco-sustainability, is quickly spreading also to the sector of mobility, traditionally dominated by fossil fuels. Although the scientific community has been discussing about electromobility for more than one decade, only today a breakthrough in this sector really appears at hand. Nevertheless, a number of issues have to be addressed in order to allow a large-scale deployment of Electric Vehicle (EV) technology. As a matter of fact, besides the very relevant challenges for electric utilities in terms of business models and infrastructure investments [1], EV technology raises a series of technical issues: studies like [2], [3] and [4] have clearly highlighted the impact that a large EV market penetration may have on the distribution network. A first, obvious consequence of the shift from fossil fuels to electricity in mobility will be a relevant change in load shape, with a significant increase of load on the distribution lines (e.g.: according to [5], the mechanical power of the US light vehicle fleet exceeds the electric power generation of the entire country by a factor of 24). Also, strengthening the couplings between the transportation and the electrical systems, without adding an adequate monitoring and control layer, will have the effect of further increasing uncertainty and intermittency of profiles (time of arrive of EVs to charging stations can be modeled by stochastic distributions), which are typical "side effects" associated with distributed energy resources (DER). As a result, grid management and network operation will become more complex in terms of load balancing, survivability of network elements and overall power quality [6].

But, in the broad picture of smart grids, EV technology also represents a valuable opportunity: since early works like [5] and [7], it was recognized that a proper management and control of EVs at fleet level can not only address the aforementioned issues, but also contribute to stabilizing the network, to integrating DER and balancing intermittent renewable energy sources (RES). Such results can be achieved by combining management of fleet charging process (as in [8]) with the control of reverse energy flows from the EVs to the grid. This second possibility was first suggested by Kempton and Letendre [9] (with pioneeristic contribution by Amori Lovins) and is today referred to as vehicle to grid (V2G) power control. Proper V2G power implementation appears as the effective way to exploiting the huge energy storage capabilities of EV fleets. Also, there are a number of works (e.g.: [10], [11]) remarking the potentialities of V2G for demand side management (DSM) and the provisioning of ancillary services to market actors.

In this paper, load management and V2G are both taken into account for the design of an EV aggregator aiming at optimizing fleet's charging operations. More specifically, we outline a model predictive control (MPC) strategy aimed at

This work is partially financed by the European Union FP7-2011-ICT-GC SMARTV2G project, grant agreement no. 284953.

A. Di Giorgio, F. Liberati and S. Canale are with the Department of Computer, Control, and Management Engineering Antonio Ruberti, "Sapienza" University of Rome, ITALY {digiorgio,liberati,canale}@dis.uniroma1.it

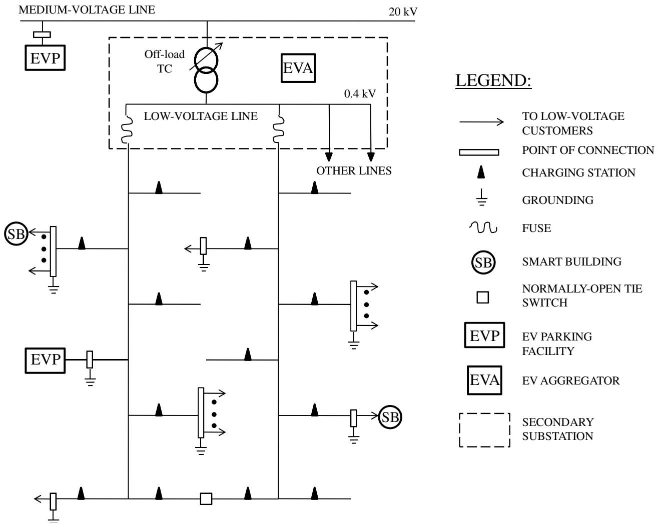

Fig. 1. Proposed reference scenario.

minimizing charging costs and able to support the provisioning of ancillary services. The proposed algorithm minimizes the cost paid by the entire fleet. Moreover, proper constraints are designed in order to keep under control the cost for the single user and guarantee that technical limitations (both of the EVs and the grid) are always respected. The algorithm supports time varying prices and time varying power thresholds, thus enabling the fleet controller to react to price and volume signals, which are at the base of most of the innovative DSM schemes [12]. A survey on the concept of EV aggregators can be found in [13]. Here we deal with a low-level aggregator, which manages a portfolio of dozens/hundreds of EVs.

The remainder of the paper is organized as follows. Section II details the reference scenario we focus on, highlighting the most relevant system modeling aspects. In Section III we introduce the proposed MPC problem formulation, by describing the overall control scheme and detailing the optimization algorithm. Section IV briefly discusses some possible model refinements. Finally, Section V presents some preliminary simulation results, while Section VI draws the conclusions of this work and indicates possible future works.

II. REFERENCE SCENARIO

The controller we propose is flexible enough to adapt to a number of different scenarios, such as:

- Control of EV parking (EVP) facilities (blocks EVP in Fig. (1)). In this case the aggregator is logically placed at the connection point of the EV parking with the grid;
- Control of EVs charging operations in a household (blocks SB in Fig. (1)). In this case, the controller is physically placed in the Smart Building. It can be an home gateway, responsible for the optimization of local energy management [14] and operation of the EVs;
- Control of a fleet of EVs connected to public charging stations located on the same low-voltage network.

In this paper we focus on the third scenario, which is depicted in Fig. (1): the proposed aggregator is logically placed in the secondary substation and is responsible for the management of all the EVs connected to the charging stations along the low-voltage lines. Note that, as in most of the cases, the low voltage network is operated radially. This scenario is quickly materializing today, and will be very common in the next years. In such a scenario, the objective of the aggregator is to optimize fleet charging operations (minimizing costs while respecting drivers preferences) and respond to active demand requests coming from upper-level actors.

In the following subsections we briefly discuss the main actors belonging to the reference scenario.

A. EVs

For ease of discussion, we consider here only fully EVs. From the technical point of view, they are characterized by the following parameters: the capacity of the electric batteries, the input/output battery performance coefficients, the maximum and minimum allowed charge level and the charge/discharge rates. An exhaustive technical discussion can be found in [15]. Finally, the interaction between the EV/driver and the charging infrastructure can be modeled by assuming that, upon arrival at the charging station, the driver specifies the desired charge level and the maximum allowed duration of the charging process.

B. Charging stations

Charging stations are already available on the market, and standardization is proceeding quickly. Depending on the circuit (single phase or three phase) and on the current and voltage levels, different *fixed* charging levels are today available. There are two very common charging levels: 1) *normal charging* (around 3.3 kW) and 2) *fast charging* (60-150 kW). For this reason, charging stations are often equipped with at least two different plugs and recharging interfaces (e.g. the Scame plug, single phase, 16 A - $3,5$ kW, and the Mennekes plug, single phase or three phase 42 kW). The number of charging stations per substation reflects the market penetration of EV technology. Different scenarios can be simulated (low, medium and high market penetration).

C. Aggregator

The aggregator we describe is what results from the research we are currently undertaking in the FP7 SmartV2G project [16]. It is a control entity which logically acts at substation level (but it could be physically placed elsewhere, e.g. in a SCADA control room). Fig. 2 details input and output signals to the aggregator. Input signals are from the EV fleet (authentication, transmission of EVs' data: battery capacity, power rate, etc.) and from the distribution system operator (DSO) and upper level market actors (DSM signals, market offers and notification of the electricity tariff). Also, based on the algorithm presented here, the aggregator is able to compute offers and biddings to respond to requests from upper-level market actors. Finally, based on the level of EV penetration, the aggregator sets an upper threshold to the power available for EV operations.

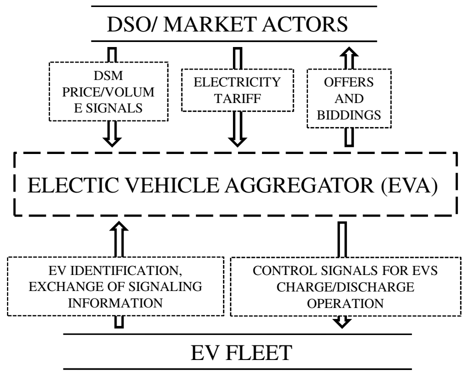

Fig. 2. Logical interaction between the aggregator and the other actors in the reference scenario.

D. DSO and market actors

The DSO may send DSM signals to the aggregator. It also provides technical validation of the aggregator's operations (this aspect is not analyzed here). Furthermore, other regulated or deregulated players may search for active demand services [12] (e.g.: rescheduling, reprofiling, etc.) which the aggregator may be able to fulfill by aggregating flexibility from the EV fleet.

III. PROBLEM FORMULATION

Bearing in mind the reference scenario description, in this section we outline a basic formulation for the problem of optimal charging management of an EV fleet. Some simplifying assumptions are made:

- EVs can absorb/supply energy at a unique, fixed rate. This is quite a realistic assumption, since charging station prototypes currently allow fixed power flows between the grid and the EVs. However, as we will show in Section IV, taking into account multiple rates or even continuous rates does not conceptually complicate the formulation;
- For ease of exposition, we consider a unique electrical tariff $C[\cdot]$ for all the EVs;
- The cost of energy absorbed by the EVs and the price of V2G energy are equal. To remove this assumption we would need to develop a model of the local energy market, something which is out of the scope of this paper. However, once buy/sell prices are known, the present formulation allows to take into account different and time-variant prices;
- V2G behavior: we assume the EV fleet globally behaves always as a load;
- Input and output battery efficiency coefficients are assumed to be coincident (equal to ξ_m for the *m*-th EV).

These assumptions are made in order to obtain a simple, yet meaningful problem formulation. In Section IV we will explain how they can be removed/relaxed.

The idea behind our approach is quite simple: if we imagine to take a snapshot of the EV fleet at a given time, we have that each EV is characterized by three fundamental variables: 1) the current state (charge level); 2) the final desired charge level (set by the driver upon arrival); 3) the departure time (also set by the driver). Hence, if we assume that no other EV will join the fleet, by solving an optimization problem it is possible to find, for each EV, an optimal charging strategy that satisfies driver's preferences (of course, only if they are satisfiable) while minimizing costs. As we shall see next, the main inputs to the optimization problem are: the models of the EVs, the electricity tariff and power thresholds for overload management. However, the resulting solution is intrinsically open-loop: it looses optimality every time an event changes the initial data set (arrival of an EV, change of the electricity tariff, change of the power thresholds, DSM events, etc.). Like in MPC, this problem is solved by iterating optimization every time a "relevant" event happens; after each iteration, the new calculated control strategy replaces the portion of the previous control strategy that has not been implemented yet.

In the following subsections we describe the discrete-time optimization problem that the aggregator solves at the generic iteration time.

A. Target Function

At each iteration of the algorithm, the target function is given by the cumulative cost the EV fleet has to sustain:

$$F = \sum_{m \in M} \sum_{k=I}^{E_m - 1} \Delta P_m T C[k] U_m[k], \tag{1}$$

where M is the set of EVs currently present on the low-voltage network, I is the initial time, E_m is the departure time of the *m*-th EV, ΔP_m is the absorption/supply rate of the *m*-th EV, T is the sampling time, $C[k]$ is the electricity tariff and $U_m[k] = \{1, 0, -1\}$ is a control variable which is one if the EV is in charge mode, minus one if the EV is in discharge mode and zero otherwise.

B. Prediction Model

In MPC problems, the prediction model is used to evaluate the future state of the system, allowing optimization and constraints satisfaction over all the defined control horizon.

In our case, the prediction model is simply given by the dynamics of the EV batteries. We take a simple first-order model:

$$X_m[k+1] = X_m[k] + \Delta P_m T (U_m[k] - \xi_m |U_m[k]|), \tag{2}$$

where $m \in M$, $k \in [I, E_m)$, $X_m[\cdot]$ is the state of the battery (its charge) and ξ_m is the charge/discharge efficiency.

C. Control Constraints

With control constraints we assure that control variables remain within tolerable ranges and the system well behaves. In case of fixed absorption/supply rates, the following control constraints can be individuated:

- Constraint on the control variables: $U_m[k] \in \{0, 1, -1\}$ $\forall\, m \in M,\ k \in [I, E_m)$;
- Upper threshold on the maximum available power for the EV fleet, established in order to assure safe and reliable

operation of the network. It must hold:

$$\sum_{m \in M_k} \Delta P_m U_m[k] \le P^*[k] \quad \forall k \in [I, E), \tag{3}$$

where $M_k = \{m \in M : I \le k < E_m\}$ is the set of EVs possibly involved in the charging/discharging operation during the *k*-th time interval, $E = max\{E_m : m \in M\}$ is the last time instant of problem definition and $P^*[\cdot]$ is the power threshold assigned to the EV fleet insisting on the low-voltage network;

- Constraint on the cost of charging/discharging operation for the single EV. Up to this point, we have addressed costs minimization and technical constraints satisfaction related to the entire EV fleet. However, it may happen that a cost-efficient and technically feasible solution for the entire fleet does not equally distribute the cost (or the saving) among the EVs, thus penalizing some EVs and excessively rewarding some others. To take this into account, we add a constraint on the cost of charging/discharging operation for the single EVs:

$$\sum_{k=I}^{E_m-1} \Delta P_m T C[k] U_m[k] \le (1+\epsilon) C^0 \quad \forall m \in M, \tag{4}$$

where C_m^0 is the cost "budgeted" to the user upon arrival to the charging station (after the first iteration of the algorithm). Parameter $\epsilon \ge 0$ is a small tolerance factor. This constraint makes sure that the cost for the single users does not grow unpredictably iteration after iteration;

- V2G constraint. In order to gradually analyze the effect of V2G, in this paper we limit the analysis to the case in which it is allowed only the exchange of energy "within" the EV fleet. Then, the following constraint holds:

$$\sum_{m \in M_k} \Delta P_m U_m[k] \ge 0 \quad \forall k \in [I, E). \tag{5}$$

This means that the EV fleet does not contribute to possible reverse power flows. In other words, the fleet globally behaves as a load, never as a generator.

D. State Constraints

It is straightforward to individuate the following state constraints:

$$0 \le X_m[k] \le X^{max} \quad \forall m \in M, \ \forall k \in [I, E_m). \tag{6}$$

In practice, for efficiency reasons, the battery pack is never allowed to fully charge or deplete. Equation (6) thus becomes:

$$X_m^{min} \le X_m[k] \le \alpha X_m^{max} \quad \forall m \in M, \ \forall k \in [I, E_m), \tag{7}$$

where $\alpha \in (0, 1]$ is a proper coefficient.

E. Termination Constraints

Termination constraints are related to the desired state of charge X_m^{ref} of the *m*-th EV at the end of the stop at the charging station:

$$X_m[E_m] \ge X_m^{ref} \quad \forall m \in M. \tag{8}$$

We end this section by summarizing the discrete-time optimization problem at the base of our MPC approach. We also show that this problem is Combinatorial Optimization (CO) problem.

Problem 1 (Optimal control of dispersed EV fleet charging operations)**.** *Given a set M of EVs insisting on a same low-voltage network at a given time, an electricity energy price time sequence $C[\cdot]$ and a threshold $P^*[\cdot]$ on power available for the fleet, find an optimal charging strategy for the vehicles in order to minimize costs, by respecting EVs and grid technical constraints and satisfying users preferences in terms of duration of the charging process and final desired charge level.*

The solution to this problem (under the assumptions made in Section III) can be found by solving the following CO problem, which directly derives from manipulation of equations (1) to (8):

$$\min \sum_{m \in M} \sum_{k=I}^{E_m-1} \Delta P_m T C[k] \left(u_m[k] - v_m[k]\right), \tag{9}$$

subject to constraints:

$$\begin{cases} \sum_{m \in M_k} \Delta P_m (u_m[k] - v_m[k]) \le P^*[k] \quad \forall k \in [I, E) \\ \sum_{k=I}^{E_m-1} \Delta P_m T C[k] (u_m[k] - v_m[k]) \le (1+\epsilon) C_m^0 \quad \forall m \in M \\ \sum_{m \in M_k} \Delta P_m (u_m[k] - v_m[k]) \ge 0 \quad \forall k \in [I, E) \\ X_m^{min} \le X_m[I] + \sum_{h=I}^{k} \Delta P_m T \big\{(1-\xi_m) u_m[h] + \\ \qquad -(1+\xi_m) v_m[h]\big\} \le \alpha X_m^{max} \quad \forall m \in M, \ \forall k \in [I, E_m) \\ X_m[E_m] \ge X^{ref} \quad \forall m \in M \\ u_m[k] + v_m[k] \le 1 \quad \forall m \in M, \ \forall k \in [I, E_m), \\ u_m[k] \in \{0, 1\} \quad \forall m \in M, \ \forall k \in [I, E_m) \\ v_m[k] \in \{0, 1\} \quad \forall m \in M, \ \forall k \in [I, E_m) \end{cases} \tag{10}$$

where the set of integer variables $U_m[k]$ has been simply split into two sets of boolean variables $u_m[k]$ and $v_m[k]$. The former set is related to the charging process, the latter to the discharge process. As a matter of fact, we have that $U_m[k] = u_m[k] - v_m[k]$, under constraint $u_m[k] + v_m[k] \le 1$.

Typically, CO problems require suitable, sometimes ad hoc solution strategies exploiting the combinatorial nature of the decision variables (charge and discharge variables in this case) and their relation with the optimal continuous solution when a set (or a subset) of integer variables is fixed, as usually happens in standard Branch-and-Bound setting. On the other side, efficient and effective heuristics providing good quality solutions can dramatically improve Branch-and-Bound based solution strategies. The quality of solutions provided by specific heuristic algorithms is usually validated by means of a bound approximating the distance from the optimal solution. As far as we know, no heuristic has been proposed for finding good solutions for Problem (1).

Problem (1) only defines a general iteration of the whole MPC strategy. Every time a new EV reach the charging facilities, and every time the tariff or the power threshold change, the algorithm must be iterated in order to preserve optimality (after having updated all the needed information). Re-optimization, seen as an implicit control feedback realization, is one of the key concepts of MPC.

IV. MODEL REFINEMENTS

The model can be further refined in order to relax the assumptions made in Section III:

- If variable charge/supply rates are allowed then, in the previous formulas, the product $\Delta P_m U_m[k]$ should be replaced by a continuous variable $P_m^{min} \leq P_m[k] \leq P_m^{max}$ with upper and lower bounds. Constraints from Section III-B to III-E can be easily modified accordingly;
- For ease of formulation, we have considered a unique electricity tariff $C[\cdot]$ for all the EVs. Differentiation of energy contracts can be taken into account by introducing different price time sequences $C_m[\cdot]$, $\forall\ m \in M$;
- V2G behavior. V2G possibility is something which involves both pricing issues (how energy from EVs to grid should be priced) and power flow issues. The approach outlined here enables to take into account both aspects. In particular, we assumed that the cost of the energy adsorbed by the EVs and the price of the energy supplied by the EVs are equal. This assumption can be removed only once an energy pricing model is chosen. At that point, instead of having only one control variable, there will be two control variables (with the associated energy cost/price), one for the charge phase and the other one for the supply phase. Then it will be also possible to remove the assumption inherent in constraint (5): the power exchanged by the EV fleet with the distribution network at the point of connection will be properly regulated by the DSO. As a consequence, constraints (5) and (3) will be merged into a new constraint that will allow to regulate power exchange.

V. SIMULATIONS

We present two preliminary simulations for proof of concept. With the former simulation we give some insight into the V2G behavior of the fleet and we show that the controller achieves costs minimization, always respecting drivers preferences. With the latter we test the capability of the controller to optimally react to DSM events. As far as concerns the choice of parameters, for simplicity, all the EVs are assumed equal (therefore, in the following, we omit subscripts). We take the following realistic values [15]: $X^{max} = 16\ kWh$, $\Delta P = 3.3\ kW$ (normal charge level). A value of $\xi = 0.02$ is chosen. Furthermore, we assume the charge level must always be between 20% and 80% of the maximum value. In reality, upon arrival at the charging facility, each EV is identified and the real (possibly different) technical parameters are communicated to the aggregator. $P^*[k]$ is set to $0.1\ MW\ \forall k$. As far as concerns the electricity tariff, in order to easily evaluate the effectiveness of the controller, we use a simple two-valued, three-zone tariff: the cost is 16.75 €*cent* in the time intervals [00:00 - 08:00] $\cup$ [19:00 - 24:00] and 21.22 €*cent* in the interval [08:00 - 19:00]. As it will be highlighted by the simulations, the choice of proper tariffs and power threshold values will be a key point to evaluate, in order to avoid overloads (EVs plug in all at the same time).

Simulations have been performed with the IBM® ILOG® CPLEX® V12.2 optimization library, installed on a 2.39 GHz, 1.98 GB RAM computer.

A. Costs minimization and V2G behavior

We simulate the sequential arrival at the charging stations of 25 EVs (one every 10 minutes, starting at 15:00). For the sake of simplicity, initial conditions and user preferences are the same for all the EVs. We have (omitting subscripts): $X[I_{arr}] = 4\ kWh$, where I_{arr} is the arrival time, $X^{ref} = 8\ kWh$, dwell time at the charging station set to 2 hours. In addition, we simulate the presence of five "stationing" EVs (plugged from 15:00 to 24:00). This simple scenario will allow to evaluate both the shifting capabilities of the controller and V2G power implementation.

Re-optimization is performed each time an EV arrives at a charging station. Fig. 3 presents the final evolution of power flow between the fleet and the grid. This is after the last iteration, at 19:10. Each color refers to a different EV. Positive values indicate flows from the grid to the EVs (charging power), negative values indicate V2G power. We observe that, starting from about 18:20 and compatibly with dwelling times set by the drivers, the aggregator delays part of the charging operations after 19:00, when electricity is cheaper. This reduces overall costs (a total cost of 18.54 €, compared to 20.35 € in the non-automated case), but has a very relevant side-effect: peaks appear in the power profile (most of the EVs are charged simultaneously). This phenomenon can be further highlighted (see Fig. 5) if a small term linear in time is added to the cost function, in order to choose those optimal solutions (Problem (1) has in general many solutions) characterized by fast (early) charging operations and minimal number of battery activations (which is desirable):

$$F = \sum_{m \in M} \sum_{k=I}^{E_m - 1} \Delta P_m T C[k] \left(1 + \frac{1}{\alpha} k\right) (u_m[k] - v_m[k]), \tag{11}$$

with α a big coefficient ($\alpha = 10^5$ in the simulation). How to assure overload avoiding when controlling EV fleets is a relevant problem. In our scheme, this issue can be addressed at least in two ways: 1) by diversifying the electricity tariff; 2) by properly designing the threshold on the power available for the EVs. In the latter case, if the optimal control problem becomes infeasible, then user preferences may be relaxed and adequate incentives provided to those users who accept a delay in their charging operations. This will be evaluated in future works. Coming back to Figs. 3 and 5, also V2G implementation is evident (negative power in the figures): it is mostly caused by stationing EVs, which provide power to charging EVs during peak period, and recover energy

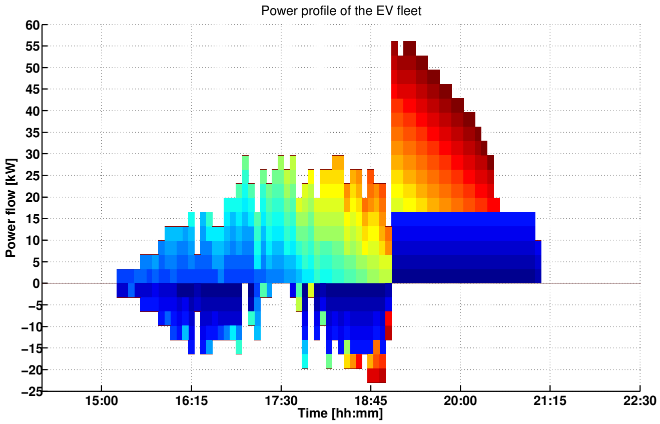

Fig. 3. Final power flow between the EV fleet and the grid.

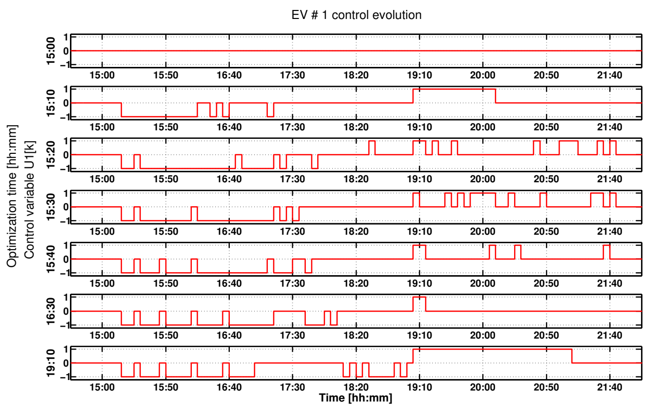

Fig. 4. Evolution of EV 1 control sequence.

during the off-peak period. As we said before, V2G power is only allowed here to balance other EVs. Then, the equivalent effect at the point of connection of the secondary substation with the medium voltage feeder is a load shift. This can be very relevant if the tariff is designed so as to reflect the congestion state of the network. Fig. 4 presents the evolution of the control sequence of a stationing EV (in case (1) is the target function). The control sequence is updated iteration after iteration (only seven iteration are displayed). Final control (the last subplot) results from the concatenation of the control sequences implemented between one iteration and the following one. Finally, Fig. 6 displays final control and state evolution of two peculiar EVs: the first one is a stationing EV, the second one a charging EV. It is seen that the controller manages to guarantee the final desired charge level. For what concerns computational time-complexity, the optimal control sequence is always found in less than 4 seconds, with a mean value of 1.43 seconds.

B. Reaction to DSM events

In the same scenario as above, we simulate the notification to the aggregator of a power-reduction volume signal. The volume signal is notified at 16:00 and limits the power available for the EV fleet to 27 kW, in the time interval [18:30-20:00]. From the "snapshot" of the final power exchange

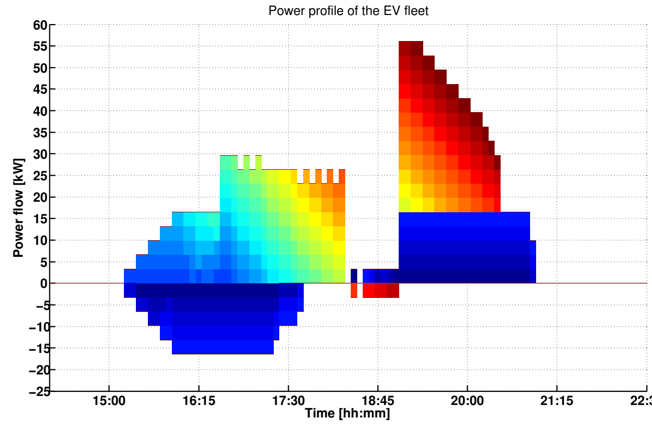

Fig. 5. Final power flow between the EV fleet and the grid in case (11) is the target function.

between the fleet and the grid (Fig. 7) we see that the aggregator manages to fulfill the volume-reduction request. The role of V2G power is fundamental in this case: otherwise the problem would be infeasible, and the only way to satisfy the active demand request would be a relaxation of user preferences. Of course, the total cost may increase (the cost is 18.62 €, compared with 18.54 € found previously). Hence, the aggregator will participate to the provisioning of the active demand service only if the market actor requiring the service will offer more than the difference between the two costs. Incidentally, we notice that the power peak after 19:00 has been reduced with only a little increase in the cost. This simulation is characterized by a high computational time-complexity. The slowest iteration takes about 155 seconds, a value which is incompatible with a real implementation.

VI. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

In this paper we have outlined a possible approach for the design of an EV aggregator able to optimally manage charging operations of an EV fleet. We have adopted a MPC approach, which allows to update the control strategy

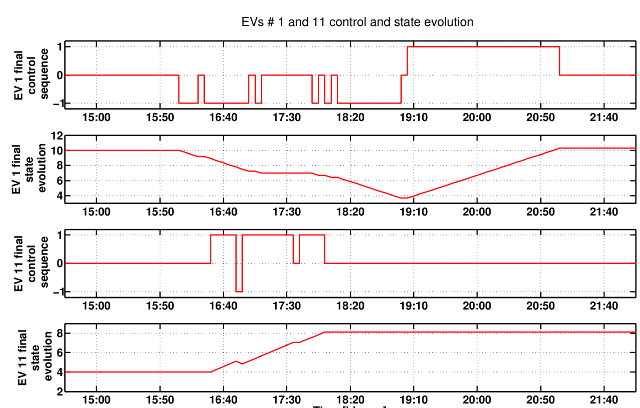

Fig. 6. Final control sequence and state evolution of a stationing EV (EV 1) and a charging EV (EV 11).

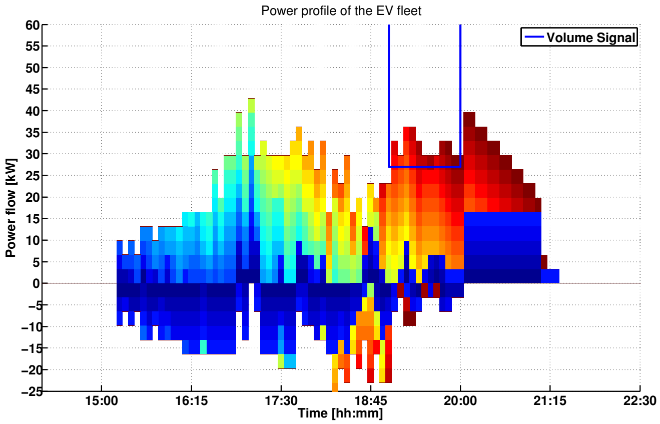

Fig. 7. Final power flow between the EV fleet and the grid: the aggregator effectively reacts to the volume signal.

according to the evolution of EVs arrivals, of the electrical tariff and power thresholds. Our approach is based on formulating the original problem as a CO problem. In this case, we define a set of integer solutions (namely, the feasible set) where each integer solution represents a feasible solution of our original problem. On the other side, each feasible solution of the original problem is represented by an integer solution in the defined feasible set. Since we adopt an exact solution method (a commercial implementation of the branch-and-cut method), the optimal solution is always found by the proposed method. Hence, the controller achieves costs minimization, always satisfying drivers preferences (desired charge level and dwelling time at the charging station). It is also able to cooperate in the provisioning of active demand services, by aggregating the flexibility of the EV fleet. Early simulations have shown the role that V2G power can play both in cost minimization and in adding the flexibility required to provide active demand services.

B. Future Works

A number of improvements will be suggested in future works: 1) Development of a more adequate formulation of the problem (see Section IV); 2) More accurate investigation of the impact on the grid of simultaneous plug-in of EVs (considering the design of proper electric tariffs and power thresholds, and the inclusion of more specific constraints into the problem); 3) It should be evaluated the convenience of "equally distributing" the savings among the EVs. As a matter of fact, with the current approach the saving is entirely retained by those EVs that are responsible for V2G power; 4) As we expected, solving Problem (1) for increasing dimension (i.e. larger set M and interval E) shows that standard exact approach based on general Branch-and-Bound schema is impractical for real world instances considered so far. Therefore, there is the need for more efficient solution strategies concerning two main aspects: a) finding good upper bounds (i.e. heuristic solutions) for Problem (1) in order to reduce the gap significantly in shorter time; b) developing ad hoc branching strategies for speeding up the Branch-and-Bound tree search.

We have not considered heuristic methods so far (an exact approach to the problem has been considered). Of course, this kind of algorithms will be very considered in the future, as they are definitely useful for improving the exact approach's performances.

VII. ACKNOWLEDGMENTS

The authors gratefully acknowledge the suggestions of Francesco Delli Priscoli and Francisco Facchinei, full professors at the University of Rome "Sapienza", Carlo Mannino, associate professor at the University of Rome "Sapienza" and Andrea Mercurio.

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