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Smart Management of Electric Vehicles Charging Operations: the Vehicle-to-Charging Station Assignment Problem ⋆

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Abstract: The widespread diffusion of Electric Vehicles (EVs) gives a concrete answer to the growing environmental problems linked to the mobility in urban areas. This paper deals with a particular management problem related to the EVs charging operations: the integration of the EVs with the power distribution system. Possible electrical grid disruptions due to uncoordinated charging operations and the need of guaranteeing to drivers a certain level of confidence while travelling with an EV explain the efforts in the identification of a smart approach for the *EVs charging management problem*. In this work, a hierarchical mathematical programming approach is considered and a system made up of two interdependent optimization models is introduced in order to identify the optimum spatial and temporal scheduling of EVs charging operations in an urban area served by several charging stations. Moreover, a Mixed Integer Linear Programming (MILP) formulation for the *Vehicle-to-Charging Station Assignment Problem* is proposed and a preliminary example of application is presented.

1. INTRODUCTION

In recent years, the pressing needs of reducing pollutant emissions in urban areas and of alleviating the reliance of mobility on fossil fuels have increased the interest on new transport solutions and, in particular, Electric Vehicles (EVs) are reaching great popularity. However, many drawbacks hinder a complete diffusion of such a new technology and, in particular, limited driving range and the correlated *range anxiety* represent serious concerns that limit the ability of the EVs to compete with conventional Internal Combustion Engine (ICE) vehicles. In this context, the deployment of a widespread public charging infrastructure is essential and the *charging infrastructure planning problem* is largely analyzed in the literature (Hess et al. [2012], Xu et al. [2013], Chen et al. [2013]). At the same time, the integration of the charging operations with the electric power grid represents a central topic, since uncoordinated charging (the so-called *dumb charging*) would lead to severe grid disruptions, with extra power losses and voltage deviations. Different approaches to the smart control of the charging operations have been investigated so far, and all of them are based on the concept of *Smart Grid* (SG). This new paradigm implies, among other things, bidirectional communications between power providers and consumers and therefore an optimized real-time control of the grid operations is possible (Andreotti et al. [2012]).

Literature contributions to the *EVs charging management problem* can be categorized on the basis of the considered *optimization strategy*, the *timing of the control* and the *paradigm of the control*.

Different optimization strategies are considered to determine the optimal charging profile for the EVs: *grid requirements*, *drivers' utility* or both. When grid requirements are taken into account, the most common objective function is represented by the minimization of power losses and voltage deviations and the flattening of the overall load profile during the day is sought (Andreotti et al. [2012], Clement-Nyns et al. [2010], Li et al. [2012]). At the same time, the ability of the EVs to provide a number of ancillary services and, so, contribute to the integration of the Distributed Generation (DG) into the grid is widely analyzed (Clement-Nyns et al. [2011], Vandael et al. [2011]).

On the other hand, the maximization of the users' utility turns into a spatial assignment and a temporal scheduling of the charging operations able to minimize a given cost function, e.g., the total waiting time or the total charging cost (Gharbaoui et al. [2012], Qin and Zhang [2011], Xu and Pan [2012]).

The timing of the control could be based on forecasts of energy and travel demand and in this case a *day-ahead planning* is possible,(Gan et al. [2012]); on the other side, when *real-time control* is considered, a continuous monitoring of the system conditions is required.(Han Peng et al. [2012], Li et al. [2012]).

Finally, the paradigm of the control can be centralized or

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distributed. In particular, in the centralized approach a central controller determines the optimal charging profile for a population of EVs on the basis of the grid conditions. However, this solution is computationally efficient only for a limited number of EVs, since a large amount of information and a remarkable communication effort are required (Clement-Nyns et al. [2010], Xu and Pan [2012]). Alternatively, in a distributed control scheme EVs themselves calculate their charging schedules, for example responding to a price signal broadcast by the grid operators in order to influence users' behavior (Gan et al. [2013], Karfopoulos and Hatziargyriou [2013], Jin et al. [2013]), or each charging station determines which EVs recharge and when operate the charging activities by negotiating with a set of neighbor stations (Qin and Zhang [2011]).
This paper is part of this framework and its aim is to propose a smart management strategy for the coordination of the EVs charging operations. In particular, charging operations involving the public charging infrastructure are considered.
The approach traditionally followed in literature in order to take into account simultaneously drivers' and grid requirements is to determine the minimum cost charging profile for each EV on the basis of a control signal broadcast by the grid operators. However, the assignment of the vehicles to the best available charging station is a problem handled separately from grid concerns.
Our attempt is to solve such a resources allocation problem considering not only the traditional assignment and capacity constraints, but also grid requirements. In our idea, this turns into a time-varying configuration of the considered public charging infrastructure. In particular, maximum charging power and energy price at the different available stations throughout the day are settled in order to influence drivers' behavior and so minimize power losses and voltage deviations on the grid. Then, on the basis of such time varying parameters, EVs are assigned to the charging stations while maximizing drivers'utility. For this purpose, a hierarchical bilevel decision structure is introduced: the upper-level optimization problem deals with the optimal charging infrastructure configuration, while the lower-level problem handles the allocation of the charging stations to the EVs.
Hence, the contribution of the paper is twofold: first we introduce the general architecture of a *leader-follower* management approach for the *EVs charging management problem*; second, we propose a Mixed Integer Linear Programming (MILP) formulation for the lower-level problem, i.e., the *Vehicle-to-Charging Station Assignment Problem* (VCSA).
The remainder of the paper is structured as follows. In Section 2 the structure and the assumptions of the *EVs Charging Smart Management System* (ECSMS) are presented. Moreover, in Section 3 the VCSA is formalized. In Section 4 a preliminary example of application of the realized model is introduced and, finally, Section 5 summarizes conclusions and future works.

2. THE EVS CHARGING SMART MANAGEMENT SYSTEM

The problem of the management of the electric vehicles recharges involves two classes of actors, EVs drivers and electric grid operators, that have different requirements and, often, conflicting objectives. Indeed, from the electric grid point of view it is essential to minimize the impacts

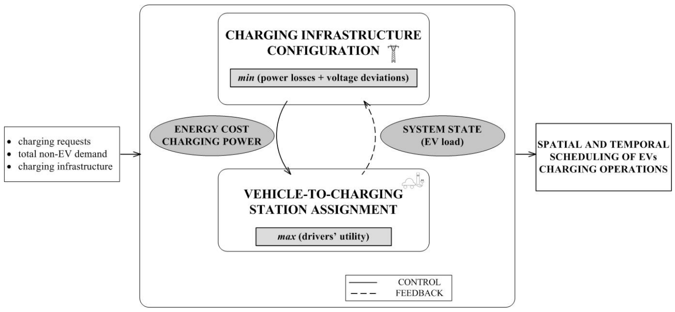

Fig. 1. The EVs Charging Smart Management System

of EVs charging on the power system. To this aim, it would be suitable to defer such operations to *off-peak* hours and to shift them to areas characterized by low electricity demand in order to avoid transformer overloads and minimize power losses and voltage deviations.
On the other side, in order to overcome the general diffidence of customers towards the electric mobility and, so, overtake the undeniable competitive advantage of conventional ICE vehicles, a certain level of flexibility has to be guaranteed. More precisely, drivers should have the possibility to choose when and where recharge their vehicles according to their needs, as actually happens for the refuelling of traditional vehicles. Therefore, in order to obtain a strategic and effective coordination of the EVs charging operations, a management system able to guarantee the fulfilment of both grid operators' and drivers' requirements is necessary.
In this context we consider an urban area served by several charging stations: the aim is to assign a population of EVs that need to be recharged to the best available station, taking into account not only drivers' needs but also electric grid requirements. In our approach, the considered problem is outlined as the interplay of two different decision makers who act sequentially and whose choices are mutually dependent.
Accordingly, a bilevel optimization structure is introduced (Fig. 1):

(1) the *upper-level optimization* determines optimal charging power and energy price at the different charging stations in order to temporally and spatially reshape electricity demand for EVs recharges. Hereafter, we refer to such a level as *Charging Infrastructure Optimal Configuration* (CIOC);
(2) the *lower-level optimization* assigns optimally EVs to the charging stations maximizing a given users' utility function (the aforementioned *Vehicle-to-Charging Station Assignment Problem* (VCSA)).

More in detail, VCSA is a parametric optimization problem whose parameters are determined by CIOC. Once VCSA has been solved, the resulting system state is communicated to CIOC, which updates accordingly its strategy. Therefore, from the interaction between the two levels a dynamic configuration of the charging infrastructure and a spatial and temporal scheduling of the charging operations results. Furthermore, Algorithm 1 describes the procedure characterizing ECSMS.

As it can be seen, both the optimization problems are alternately iterated. Moreover, the length δ of the time interval between two consecutive iterations has to be strategically set, solving the trade-off between the ability of the ECSMS to fulfil accurately both drivers' and grid

Algorithm 1 EVs Charging Smart Management Procedure

1: **Consider** total current non-EV energy demand
2: **Solve** CIOC and determine the charging infrastructure current configuration
3: **Communicate** current charging power and energy price at the different charging stations to VCSA
4: **Solve** VCSA and determine current total EV energy demand
5: **Let** the system evolve for δ time units (t.u.)
6: **if** the entire planning horizon has been considered **then**
7: **End** the procedure
8: **else**
9: **Communicate** current total EV energy demand to CIOC
10: **Go** to 1
11: **end if**

needs along the entire planning horizon and the required computation and communications efforts.
Finally, note that every time VCSA is solved, not only EVs that have just made a charging request are considered, but also EVs assigned in the previous interation of the problem but whose charging operations have not already started or who have not accepted the decision are re-assigned.

3. THE VEHICLE-TO-CHARGING STATION ASSIGNMENT PROBLEM

In this section, the considered scenario and the mathematical formulation of the lower-level optimization problem (VCSA) are described and discussed.

3.1 The Model

We consider an urban area served by several charging stations and a population of EVs: the objective is to coordinate the charging operations during the day by optimally assigning each vehicle to a charging station and identifying the optimal charging period for each driver.
In particular, the following assumptions are introduced:

- *electric grid*: a smart grid is considered and bidirectional communication capabilities between the single EV and a system operator are supposed;
- *no home-charging*: only charging requests involving public charging stations are taken into account, while home-recharges are not considered in this context;
- *charging stations*: each charging station is equipped with one or more charging outlets and its charging power and energy cost are time-varying;
- *EVs*: when it needs to be recharged, each vehicle communicates its position, its battery residual state of charge, when it desires to start the recharge (i.e., *EV release time*) and the time within which it wants to leave the charging infrastructure (i.e., *EV deadline*);
- *charging operations*: incomplete recharges are admitted, but charging operations of a vehicle cannot be interrupted and restarted later (i.e., no *preemption* is allowed). Moreover, the charging cannot start before the stated release time and it must be interrupted within the specified deadline. Finally, we consider that the total charging monetary cost paid by each driver depends on the unit energy price characterizing the assigned charging station at the time interval during which the charging starts;
- *users' level of acceptance*: when an EV is assigned to a charging station, an outlet is reserved for it. If the driver does not accept the system indication, his request will be re-assigned in the following iteration of the VCSA.

The objective pursued in solving the assignment problem is the maximization of the EVs drivers' utility: to this aim, an *users' cost function* made up of 4 different entries is considered:

(1) the *waiting time* for the charging;
(2) the *charging monetary cost*, meant as the unit energy price that each driver has to pay for the charge;
(3) the *distance* that the driver has to go through to reach the assigned charging station;
(4) the *penalty for incomplete charging*, i.e., a quantification of the users' annoyance resulting from leaving the charging station with a not fully charged vehicle.

Moreover, in our model a linear combination of such functions is considered: therefore, a single-objective optimization problem is proposed.

3.2 Mathematical Formulation

As described in the previous section, VCSA is solved several time throughout the considered planning horizon on the basis of the evolution of the parameters determined by CIOC. At each iteration k of the optimization problem, the objective is to determine the minimum cost vehicle-to-charging station assignment while respecting several operating constraints.
A Time Indexed Formulation (TIF) is considered: the planning horizon is discretized into T time intervals, each lasting Δ time units. Each time interval t starts at time $t-1$ and ends at time t, i.e., we consider the time periods $1, 2, \ldots, T$.
In order to describe the Mixed Integer Linear Programming (MILP) formulation, the following notation is introduced.

Numerical Sets

- $\mathbb{R}^+$: set of all positive real numbers
- $\mathbb{R}_0^+$: set of all real numbers including 0
- $\mathbb{N}^+$: set of all positive natural numbers

Sets

- $\mathcal{V} = \{1, 2, \ldots, N\}$: set of *charging stations*
- $\mathcal{U}_k = \{1, 2, \ldots, M\}$: set of *EVs* that make a charging request during the iteration k of the optimization problem
- $\mathcal{T} = \{1, 2, \ldots, T\}$: set of *time periods.*

Parameters

(1) *Charging Stations Parameters*
Each charging station $n \in \mathcal{V}$ is characterized by:
  - $cost_n^t \in \mathbb{R}^+$: unit charging cost at charging station n during time interval t
  - $p_n^t \in \mathbb{R}_0^+$: charging power at charging station n during time interval t
  - $r_n \in \mathbb{R}_0^+$: maximum number of charging outlets available at charging station n.

(2) *EVs Parameters*
Each EV $m \in \mathcal{U}_k$ is characterized by:
  - $t_m^{min} \in \{1, \ldots, T\}$: release time of vehicle m
  - $t_m^{max} \in \{1, \ldots, T\}$: deadline of vehicle m
  - $cap_m \in \mathbb{R}^+$: battery capacity of vehicle m
  - $res_m^0 \in \mathbb{R}^+$: residual battery state of charge (SoC) of vehicle m when it makes its charging request

- $f_m \in \mathbb{R}^+$: energy consumption per unit distance of vehicle m
- $v_m \in \mathbb{R}^+$: average speed of vehicle m
- $\eta_m \in [0,1]$: charging efficiency of vehicle m
- $d_{n,m} \in \mathbb{R}_0^+$: distance between charging station $n \in \mathcal{V}$ and vehicle m, when the vehicle makes its charging request.

(3) *Model Parameters*
- $B \in \mathbb{N}^+$: a sufficiently large integer.

Decision Variables

For each charging station $n \in \mathcal{V}$ and EV $m \in \mathcal{U}_k$ we define the following decision variables:

$$y_{n,m} = \begin{cases} 1, & \text{if } m \text{ is assigned to } n \\ 0, & \text{otherwise} \end{cases}$$

$$h_{n,m}^t = \begin{cases} 1, & \text{if the charging of } m \text{ at } n \text{ starts during time interval } t \\ 0, & \text{otherwise} \end{cases}$$

$$w_{n,m}^t = \begin{cases} 1, & \text{if } m \text{ is being charged at } n \text{ during time interval } t \\ 0, & \text{otherwise} \end{cases}$$

$s_{n,m} \in \mathbb{N}^+$ = time interval during which the charging of m at n starts.

Moreover, we define the following time indexed variables describing the state of each EV $m \in \mathcal{U}_k$ at time interval t:

$e_m^t \in \mathbb{R}_0^+$ = amount of energy received by vehicle m during time interval t;

$res_m^t \in \mathbb{R}_0^+$ = residual battery SoC of vehicle m at the beginning of time interval t;

$o_m^t \in \mathbb{R}_0^+$ = maximum amount of energy that vehicle m could receive during time interval t;

$q_m^t \in \mathbb{R}_0^+$ = amount of energy requested by vehicle m at the beginning of time interval t.

Finally, we introduce the following auxiliary decision variable for each $m \in \mathcal{U}_k, t \in \mathcal{T}$:

$$x_m^t = \begin{cases} 1, & \text{if } q_m(t) \le o_m(t); \\ 0, & \text{otherwise.} \end{cases}$$

The problem can be formulated as follows:

$$\text{minimize } z = \sum_{i=1}^{4} (\alpha_i \cdot z_i) \tag{1}$$

where

$$\alpha_i \in [0,1]; \tag{2}$$

$$z_1 = \sum_{m=1}^{M} \left(\sum_{n=1}^{N} \left(s_{n,m} - t_m^{min} \cdot y_{n,m} \right) \right); \tag{3}$$

$$z_2 = \sum_{m=1}^{M} \left(\sum_{n=1}^{N} \sum_{t=1}^{T} \left(cost_n^t \cdot h_{n,m}^t \right) \right); \tag{4}$$

$$z_3 = \sum_{n=1}^{N} \sum_{m=1}^{M} \left(d_{n,m} \cdot y_{n,m} \right); \tag{5}$$

$$z_4 = \sum_{m=1}^{M} \left(cap_m - \left(res_m^T + e_m^T \right) \right); \tag{6}$$

s.t.

$$\sum_{n=1}^{N} y_{n,m} = 1 \quad \forall m \in \mathcal{U}_k \tag{7}$$

$$d_{n,m} \cdot f_m \cdot y_{n,m} \le res_m^0 \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k \tag{8}$$

$$s_{n,m} = \sum_{t=1}^{T} t \cdot h_{n,m}^t \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k \tag{9}$$

$$\sum_{n=1}^{N} \sum_{t=1}^{T} h_{n,m}^t = 1 \quad \forall m \in \mathcal{U}_k \tag{10}$$

$$s_{n,m} \ge t_m^{min} \cdot y_{n,m} \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k \tag{11}$$

$$s_{n,m} \le T \cdot y_{n,m} \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k \tag{12}$$

$$s_{n,m} \ge \left\lceil \frac{d_{n,m}}{v_m \cdot \Delta} \right\rceil \cdot y_{n,m} \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k \tag{13}$$

$$\sum_{m=1}^{M} w_{n,m}^t \le r_n \quad \forall n \in \mathcal{V}, t \in \mathcal{T} \tag{14}$$

$$t \cdot w_{n,m}^t \le t_m^{max} \cdot y_{n,m} \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k, t \in \mathcal{T} \tag{15}$$

$$\sum_{t=1}^{T} w_{n,m}^t \ge y_{n,m} \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k \tag{16}$$

$$w_{n,m}^t \le q_m^t \cdot B \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k, t \in \mathcal{T} \tag{17}$$

$$cap_m \ge res_m^t \quad \forall m \in \mathcal{U}_k, t \in \mathcal{T} \tag{18}$$

$$res_m^t = \begin{cases} res_m^0 - \sum_{n=1}^{N} \left(d_{n,m} \cdot f_m \cdot y_{n,m} \right) & \forall m \in \mathcal{U}_k, t = 1 \\ res_m^{t-1} + e_m^{t-1} & \forall m \in \mathcal{U}_k, t \ne 1 \end{cases} \tag{19}$$

$$o_m(t) = \sum_{n=1}^{N} \left(p_n^t \cdot \Delta \cdot \eta_m \cdot w_{n,m}^t \right) \quad \forall m \in \mathcal{U}_k, t \in \mathcal{T} \tag{20}$$

$$q_m(t) = cap_m - res_m^t \quad \forall m \in \mathcal{U}_k, t \in \mathcal{T} \tag{21}$$

$$T + s_{n,m} \ge t \cdot w_{n,m}^t + T \cdot w_{n,m}^t \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k, t = 1 \tag{22}$$

$$s_{n,m} - T \le t \cdot w_{n,m}^t - T \cdot w_{n,m}^t \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k, t = 1 \tag{23}$$

$$T + s_{n,m} \ge t \cdot w_{n,m}^t - T \cdot w_{n,m}^{t-1} + T \cdot w_{n,m}^t \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k, t \ne 1 \tag{24}$$

$$s_{n,m} - T \le t \cdot w_{n,m}^t + T \cdot w_{n,m}^{t-1} - T \cdot w_{n,m}^t \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k, t \ne 1 \tag{25}$$

$$e_m^t \le q_m^t \quad \forall m \in \mathcal{U}_k, t \in \mathcal{T} \tag{26}$$

$$e_m^t \le o_m^t \quad \forall m \in \mathcal{U}_k, t \in \mathcal{T} \tag{27}$$

$$cap_m + e_m^t \ge q_m^t + cap_m \cdot x_m^t \quad \forall m \in \mathcal{U}_k, t \in \mathcal{T} \tag{28}$$

$$cap_m + e_m^t \ge o_m^t + cap_m \cdot (1 - x_m^t) \quad \forall m \in \mathcal{U}_k, t \in \mathcal{T} \tag{29}$$

$$y_{n,m}, h_{n,m}^t, w_{n,m}^t, x_m^t \in \{0,1\} \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k, t \in \mathcal{T} \tag{30}$$

$$s_{n,m} \quad integer \quad \forall n \in \mathcal{V}, m \in \mathcal{U}_k \tag{31}$$

$$e_m^t, res_m^t, o_m^t, q_m^t \ge 0 \quad \forall m \in \mathcal{U}_k, t \in \mathcal{T}. \tag{32}$$

The objective function (1) represents the total assignment cost and, as mentioned in the previous section, is a linear combination of 4 different functions: (3) is the *total waiting time*, expressed as the difference between the *release time* specified by each driver and the effective starting time of the charging operations; (4) is the *monetary cost* associated to the recharges, formulated as the sum of the unit energy prices that each driver has to pay for the charging; (5) expresses the *distance* between the EVs and the assigned charging station; finally, (6) is the *penalty for incomplete charging*. The weights (2) are used to combine such functions and vary between 0 and 1 according to the drivers' awareness to the different cost entries.

Contraints (7) ensure that each EV is assigned to one and only one charging station, while constraints (8) impose that a vehicle can be assigned to a certain facility only if its initial residual battery SoC is sufficient to reach it. Constraints (9) describe the relationship between the decision variable expressing the time interval during which the charging operation starts and the binary variable $h^t_{n,m}$, while constraints (10) ensure that for each vehicle there is only 1 charging start interval. Constraints (11) $\div$ (13) specify the feasible values for the charging starting time: in particular, (11) impose that the charging operations of a specific EV cannot start before the stated *release time*, (12) ensure that such a value can be different from zero only if the considered vehicle has been assigned to that specific charging station and, finally, (13) take into account the time required by the EV to reach the assigned facility. (14) are the charging stations capacity constraints, while constraints (15) guarantee that charging operations of each vehicle end within the specified deadline. (16) ensure that an assigned vehicle is effectively recharged, while constraints (17) impose that an EV seizes a charging station only if it still needs to be charged. (18) impose that the battery capacity of each vehicle is not exceeded during the charging operations and only the required amount of energy is supplied; constraints (19) describe the update rules of the vehicle residual SoC, (20) express the maximum possible amount of energy that a certain vehicle can receive during a time interval and (21) describe the amount of energy requested by each EV at each time interval. Constraints (22) and (23) and constraints (24) and (25) express the relationship between decision variables $s_{n,m}$ and $w^t_{n,m}$ for $t = 1$ and for $t \neq 1$, respectively. Constraints (26) $\div$ (29) ensure that the amount of energy received by each vehicle during a specific time interval is equal to the minimum value between the amount of energy requested by such a vehicle and the maximum possible amount of energy that the charging station it has been assigned to can supply to it.

4. PRELIMINARY RESULTS

In this section, an example of application of the lower-level optimization problem is presented. To solve it, we assume as given the parameters that have to be determined by the upper-level problem (i.e., p^t_n, $cost^t_n$).

We consider a planning horizon of 12 hours discretized into 48 time intervals, each lasting 15 minutes. The objective is to optimally assign a population of 50 EVs to a set of 5 charging stations and to determine the optimal charging operations scheduling.

The main parameters of the model are based on typical values from the related literature and settled as listed in Tab. 1. Furthermore, in order to take into account the effects of the traffic on the time required to reach the assigned charging station, vehicles are characterized by values of speed typical of the urban areas. In future works, a more detailed traffic simulator will be considered.

Table 1. Example parameters

Parameter type	Name	Value	Condition
charging station	r_n	1	$n = 1$
		2	$n \geq 2$
	$cost^t_n$ [€]	$[0.10, 0.20]$	$\forall n, t$
	p^t_n [kW]	$[3, 24]$	$\forall n, t$
vehicle	cap_m [kWh]	$[10, 25]$	$\forall m$
	$d_{n,m}$ [km]	$[0, 5]$	$\forall n, m$

Table 2. Results

Performance Index (average)	Case 1	Case 2	Case 3
waiting time [time slots]	2.82	0.00	0.50
unit charging cost [€]	0.16	0.15	0.12
distance [km]	3.02	1.50	1.90
incomplete charging [kWh]	0	0	5

Three different cases, characterized by different assignment policies, are taken into account by varying the values of the objective function weights α_i (2). In particular, in *Case 1* only the penalty fot incomplete charging is considered and, so, we assume $\alpha_4 = 1$ and $\alpha_i = 0$ for $i = 1, 2, 3$. In *Case 2* we consider $\alpha_1 = \alpha 3 = \alpha 4 = 1$, while the charging costs are not optimized. Finally, in *Case 3* all the objective function entries are taken into account and, therefore, $\alpha_i = 1$ for $i = 1, \ldots, 4$.

The problem is solved using IBM ILOG CPLEX 12.5 on a PC with a 1.40 GHz processor and 6 GB RAM: in the worst case, the computation time required to find the optimal solution is 62 seconds. Moreover, additional tests have enhanced that such a time is affected more by the initial spatial and temporal distribution of the charging requests than by the size of the problem. Furthermore, considering an istance with a strongly imbalance in the demand distribution (i.e., most of the requests are concentrated in the same area and in the same time periods), it takes about 400 seconds to assign optimally 50 EVs to 5 charging stations taking into account all the objective function entries. On the other hand, for an istance with similar distribution but with 100 EVs and 10 charging stations, 700 seconds are required.

Table 2 summarizes the solution performance indexes in the three cases previously described . In addition, for each case, a diagram representing the optimal solution is reported (Fig. 2, Fig. 3 and Fig. 4). Time slots are on the x-axis, while on the y-axis the different charging stations, with their different outlets, are listed. Finally, bars of different colors identify the vehicles. As can be seen, in all the cases all the vehicles are succesfully distributed.

5. CONCLUSIONS AND FUTURE WORKS

The paper presents a management strategy for the *EVs charging management problem*. In particular, charging operations involving the public charging infrastructure are considered and a hierarchical bilevel structure able to fulfil simultaneously drivers' and grid requirements is proposed. More precisely, the *upper-level optimization* determines the optimal charging infrastructure configuration, while the *lower-level optimization* assigns optimally EVs that need to be recharged to the available charging stations. Moreover, a MILP formulation for the lower-level problem is introduced and a preliminary example of application

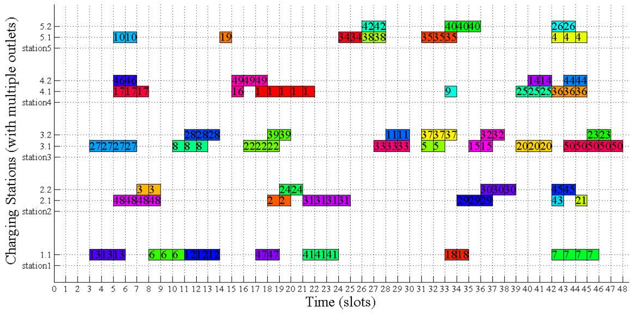

Fig. 2. Optimal assignment and charging operations scheduling (*Case 1*)

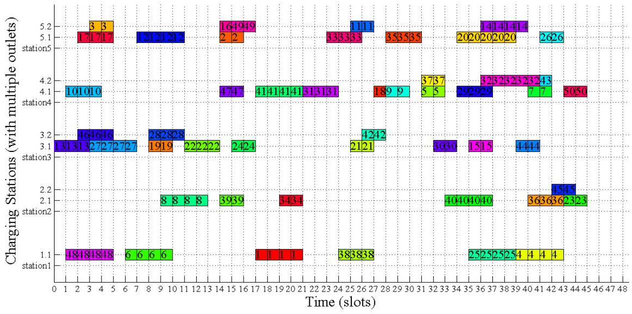

Fig. 3. Optimal assignment and charging operations scheduling (*Case 2*)

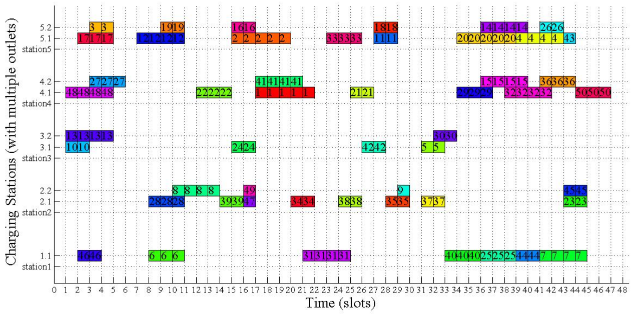

Fig. 4. Optimal assignment and charging operations scheduling (*Case 3*)

proves its effectiveness in providing the optimal solution considering different users' utility functions.
Future works will concern the formulation of the upper-level optimization problem and the identification of the best strategy to deal with the whole *EVs Charging Smart Management Procedure*.

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