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An optimization model for electrical vehicles scheduling in a smart grid

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ABSTRACT

Energy Management Systems (EMSs) are recognized as essential tools for the optimal management of smart grids. However, few of them consider, in their whole complexity, the integration of electrical vehicles (EVs) in smart grids, taking into account the requirements and the time specifications characterizing the service requests. In this paper, attention is focused on the formalization of a model for the optimal scheduling of charging of EVs in a smart grid, also considering the vehicle to grid process (i.e., the possibility for the EV to inject power during the charging process). In the formalization of an optimization problem for a smart grid, a deferrable demand is considered, which is represented by the charging demand of the set of EVs. The cost to be optimized for the considered problem includes the economic cost of energy production/acquisition (from the main grid) and the cost relevant to the delay in the satisfaction of the customers' demand (is represented as a tardiness cost). Also, the income coming from the service provided to vehicles is taken into account. The developed model is tested and applied in connection with a real case study characterized by a photovoltaic plant, two batteries, power production plants that use natural gas as primary energy, and a charging station.

1. Introduction and literature review

The integration of renewables, electrical vehicles, and microgrids is getting more and more importance in the last few years, to reduce greenhouse gas emissions, to increase the interactions between different systems, to improve the reliability of the distribution networks. In the recent literature, several articles analyze smart grids and how to integrate intermittent and distributed production and loads, often with reference to specific elements of the grid (renewables, electrical vehicles (EVs), storage systems).

The integration of EVs is becoming increasingly attractive for the following reasons. First, it is supposed that shortly there will be an increase of such a technology and thus they can result in a significant intermittent and distributed load. As a consequence smart charging strategies are necessary to reduce costs and peak loads. Second, EVs can be used as distributed storage systems. An example is reported in [1] where the authors propose the coordination between EVs fleets to mitigate energy imbalances caused by renewables, offering an essential service to electrical infrastructure by the use of the vehicle to grid (V2G) configuration. In fact, few of them consider, in their whole complexity, Energy Management Systems (EMSs) [2] that integrate smart grids and the facilities for charging of EVs, taking into account the requirements and the time specifications characterizing the service requests of the users relevant to the various EVs.

As regards the general theme of smart grid development and application, one can mention Shamshiri et al. [3], who present an overview of smart grids features and highlight the most recent developments. Optimization models are crucial to achieve a reduction in electricity costs and to maximize investments. In this connection, Monteiro et al. [4] develop a management architecture for the distributed micro-grid resource based on a multi-agent simulator that can optimize load scheduling. Nasrolahpour et al. [5] consider a microgrid and determine the optimal scheduling of each generator and some controllable loads during a day including the determination of the amount of energy purchased from the main grid.

As one of the critical issues in developing practical approaches towards the attainment of real smart cities, different authors have presented detailed models and methods to properly manage the scheduling of the charging of EVs and have studied the integration of electric mobility in the grid. Gonzalez et al. [6] review the state of the art related to ancillary service for smart grids provide by EVs, and two crucial examples are reported in [7] and [8]. In the former work, a real case study is presented and EVs' active and reactive power optimal injections are determined, satisfying both electrical

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demands and maintaining the distribution grid stability. Instead, the authors of [8] discuss the impact of reactive power support performed by EV charging stations in a low-voltage distribution grid. Zhao et al. [9] present the results of an investigation for the evaluation of different charging concepts and strategies. Delaimi et al. [10] propose a load management solution for coordinating the charging of multiple plug-in electric vehicles in a smart grid system. Allard et al. [11] compare the performance of different scenarios of smart charging and conventional charging applied to EVs integrated within a grid characterized by a high presence of renewables in particular wind energy.

Electric vehicles are equipped with efficient electric engines, which are powered by high-density lithium-ion batteries, which, through chemical reactions, generate electrical current. A typical drive for these vehicles is composed of a DC/DC converter and an inverter that feeds the engine [12], which allows bi-directional power flow. In fact, when there is a torque request from the traction system, the power flow is from the battery to the wheels, whereas during the regenerative braking the battery is recharged. The battery life is influenced not only by the itinerary and the activity [13] but also by the charging modes. There are different types of charging stations: for example, in [14] stations based on PV power are taken into account. Such stations combine a PV system with electric vehicles that are also connected to the main grid. In particular, the authors present a load scheduling model using data collected in two years. There are many different type of charging modes: the most common in smart grids are Smart Charging and Vehicle to Grid (V2G). The Smart Charging mode represents a flexible way of charging vehicles in order to modulate the feeding of the vehicles according to the grid necessities, for example during the peak hours. Instead, in V2G configuration, the power flow is bidirectional (from the grid to the vehicle and vice versa). In this way the vehicle storage can help the microgrid to sustain the power requirement of the entire system, whenever necessary, or to regulate the voltage at the charging station node. Two examples of the study of this configuration are [15] and [16]; in the first work authors investigate the cooperative evaluation of an EMS operation in a building considering different features like bidirectional energy flows of an EV fleet, the impact of PV uncertainty on EMS operation the effect of prioritization in selling energy to the main grid. The second one proposes a model to study the effects of power exchange between the grid and EVs on the power system's demand profile several indices are calculated for various vehicle-to-grid power level to estimate the impact of different level of power exchange on system's reliability.

However, these types of charging have also some drawbacks, among which the most important is the possibility of giving rise to a fluctuating power demand. This can cause problems to the main grid such as power imbalances. For this reason, the authors in [17] develop a strategy to regulate the vehicle's charging process, introducing different priorities for the various objectives, like the achievement of maximum flexibility, the effective management of the power flows in order to smooth the demand curve and increase the system's power quality. In [18] attention is focused on the active contribution (i.e., power modulation via different charging modes) of the electric vehicles in the grid optimization, considering the V2G mode. Differently, in [19] a mixed integer linear programming problem is formulated, with the objective of scheduling the charging of the vehicles, minimizing the energy costs and taking into account reliability and stability issues, considered in connection with both the microgrid and the customers (the vehicles). Wang et al. [20] study the configuration of a system wherein EVs are connected to the smart grid as mobile distributed energy storage. Bracco et al. [21] present an overall EMS, based on a dynamic optimization model to minimize operating costs and carbon emissions considering different technologies as micro gas turbines, photovoltaic, concentrating solar systems, and storage based on different battery technologies.

The choice, among different modes of charging influences not only the statement of the charging scheduling problems, but also the routing of electrical vehicles. For instance, in [22] a double layer smart charging algorithm for electrical vehicles (EVs) is presented, having the objective of allowing the single vehicle to reach the more suitable recharging station, limiting the transformer load and the total energy costs. In [23] the authors study different routing strategies to smooth microgrid power fluctuations, caused by intermittent renewables and load, ensuring at the same time the grid power quality and the optimality of logistics services.

In the literature, there are also examples of stochastic approaches to model the integration between electric vehicles and power networks. For example in [24], a real case study is described (namely, the distribution network in Zaragoza, Spain). In particular, the authors formulate a stochastic problem for energy resource scheduling including uncertainties of renewable sources, electric vehicles, and market prices. In [25] a scheduling problem is considered, with the objective of maximizing the profit by charging the plug-in electric vehicles within the lowest price time intervals, considering the participation in the ancillary services market as an additional source of income. A stochastic problem formulation for V2G technology is also present in [26], where also uncertainties in the power flow are taken into account. Instead, in [27] attention is focused on energy aggregators that can help the management of multiple connected devices. In particular, the authors develop a stochastic model for one-day-ahead energy resource scheduling, integrated with the dynamic electricity pricing for electrical vehicles, to cope with the challenges related to the demand and renewable sources uncertainties. In [28] the authors propose the use of three metaheuristic optimization techniques, in order to solve the plug-in electric vehicle charging coordination problem in electrical distribution systems. Similar approaches are adopted in [29] and [30] using genetic algorithms and particle swarm optimization.

In the present paper, attention is focused on the formalization of a model for the optimal scheduling of charging of EVs in a smart grid. Concerning the existing literature, the original contribution of this paper is the formalization of an optimization problem for a smart grid with a deferrable demand, represented by the charging demand of the set of electrical vehicles. The cost to be optimized for the considered problem includes the economic cost of energy production/acquisition (from the main grid) and the cost relevant to the delay in the satisfaction of the customers' demand. The latter cost is represented as a tardiness cost. Besides, the income deriving from the service provided to the vehicle is taken into account. Note that [31], where the integration of plug-in EVs and renewable production plants is considered. However, the model proposed in this paper goes beyond the one in [31] as the scheduling problem of the vehicle's charging is explicitly considered.

To be more specific, the system considered in this paper is characterized by the presence of a renewable energy source (photovoltaic plant), energy storage facilities, power production plants that use natural gas as primary energy, and a recharging station for EVs. The decision variables include the active powers exchanged in the whole system, binary variables that describe the interaction between the EV and the charging station and the recharging unit price of each vehicle. In particular, the last decision variables represent one of the novelties introduced in this paper.

The rest of the paper is organized as follows. In the next section, the considered system is described in detail, highlighting its specifying features and introducing the optimization problem to be solved. In the third section, the optimization problem is formalized, and in Section 4 the application of the proposed approach to a case study is presented. Some concluding remarks are finally provided in the last section.

2. The considered physical system

The decision model presented in this paper is based on the fundamental concepts and tools that can be found in the literature for microgrids' operational management (like in [32]). Even though a new formalization is presented for the objective function and the constraints (including a demand–response model for the electrical vehicles charging). In the overall formalization, it is supposed that power losses can be neglected, and thus the microgrid is considered as a single node. Each component of the system is represented as an active power injection in the total power balance, following the active sign convention (the sign of the power is positive when it is generated).

The considered system consists of a microgrid composed of the following elements (see Fig. 1):

(a) One or more renewable energy sources (considered as a unique entity in the following, for the sake of simplicity); it is assumed that this renewable energy source is intermittent and not controllable and that the energy is generated without cost;
(b) One or more non-renewable high-efficiency energy sources, whose energy production is costly; in particular, two internal combustion engines are considered, with different maximum rated power;
(c) One or more electrical storage elements; in particular, the presence of two storage systems is assumed;
(d) A connection (PCC-Point of Common Coupling) with the main grid, which guarantees the bidirectional power flow between the microgrid and the main grid;
(e) A single facility (charging station) for the electrical charge of vehicles; it is assumed that the power flow between the microgrid and the charging vehicle may be bidirectional. The charging station may serve a single vehicle at a time, and the charging process is not pre-emptive, that is, a given vehicle cannot be disconnected from the charging station and reconnected later;
(f) An electric load characterized by a given pattern over the considered time horizon.

The objective function that will be considered in the decision problem statement includes different terms. Such terms include the cost due to the energy production from non-renewable sources and the energy bought/sold from/to the main grid. Also, a tardiness term is considered, as well as another term referring to the income due to the service provided to vehicles.

3. Formalization of the optimization problem

In this section, a mathematical programming problem will be formalized to represent the overall decision objective and the constraints to be taken into account. The formalization of the decision problem will be carried out within a discrete-time setting. The formalization of the problem is provided adopting the viewpoint and selecting the utility functions of a unique decision maker, that is, the manager of the microgrid. However, an attempt is made of modeling the customer's utility by introducing an elastic demand function. In other terms, the energy request by the vehicles is a function of the charging prices (which are considered as decision variables).

3.1. The considered variables

The state variables

The state of the considered system is made of the following information:

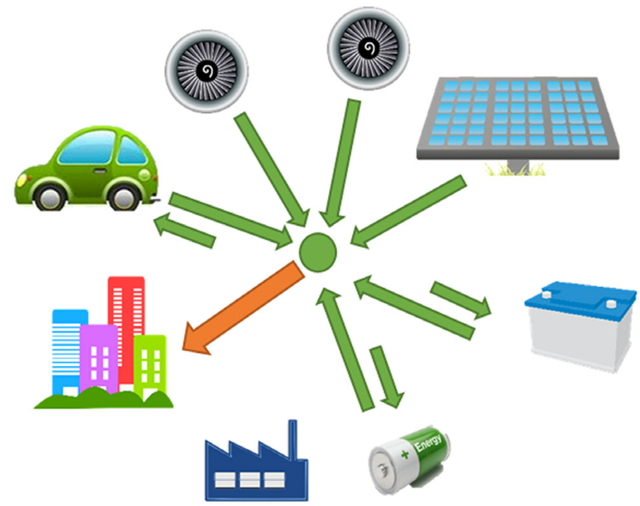

Fig. 1. Microgrid design.

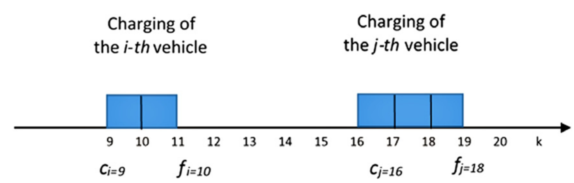

Fig. 2. Charging of two different vehicles.

– the state of charge of the two storage systems [kWh] (i.e., $x_{sl}(t_k)$ is related to a lithium battery and $x_{ss}(t_k)$ for a sodium battery, both with the capacity of 40 [kWh]);
– the state of charge of vehicle i [kWh]$x_{sveh,i}(t_k)$ for $i = 1, \ldots, N$.

Each vehicle is identified by an integer number i, which may be assigned, for instance, according to the arrival order. Note that all variables are considered in discrete time instants t_k, $k = 0, 1, 2, \ldots$. The length of the discrete time interval will be denoted as Δt, while the overall optimization horizon is (t_0, t_T) and consists of T time intervals.

Variables and data relevant to the set of vehicles

The charging process of a vehicle has an integer duration, namely

– $\left(t_{c_i}, t_{c_i+1}\right)$ is the time interval in which vehicle i begins the charging process;
– (t_{f_i}, t_{f_i+1}) is the time interval in which vehicle i concludes the charging process.

In Fig. 2 an example, concerning the charging of two different vehicles is represented.

Each vehicle i, $i = 1, \ldots, N$, is characterized by the following apriori information:

– $D_{i,max}$ [kWh] is the aspiration level of the amount of energy to be acquired by the vehicle i; this is the maximum amount of the energy requested by the vehicle;
– (t_{rel_i}, t_{rel_i+1}) is the release time interval (this may be thought as corresponding to the time interval in which the vehicle is made available for the charging state process);
– (t_{dd_i}, t_{dd_i+1}), that is, the time interval at which the charging process of the vehicle *should* be concluded. In particular,

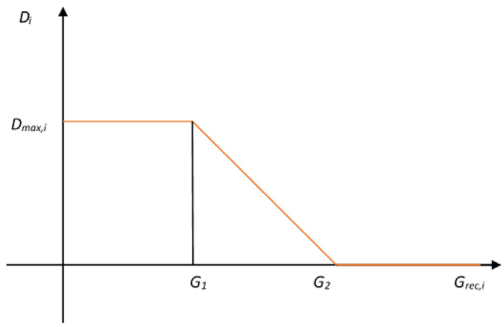

Fig. 3. The elastic demand function.

t_{dd_i+1} is the due-date of the charging of vehicle i. A tardiness with respect to a due date induces the payment of a penalty cost;

– α_i [€/h] is the unit (tardiness) penalty cost.

The optimization problem considered in this paper is relevant to the sequencing and timing of the charging process of the vehicles.

In the formalization of the problem, it is taken account the possible reduction of the actual energy demand by vehicle i (from the value $D_{i,max}$ down to zero) owing to the prices for the charging service.

More specifically, it is assumed that the actual demand for vehicle i, namely D_i, is *elastic*. This means that D_i is determined by the *unit charging* $Grec_i$ [€/kWh] through the application of the *demand function* represented in Fig. 3.

The function expressing the demand is given by the following expression

$$D_i = \begin{cases} D_{max,i} & \text{if } Grec_i \le G_1 \\ \dfrac{D_{max,i}}{G_1 - G_2}(Grec_i - G_2) & \text{if } G_1 < Grec_i \le G_2 \\ 0 & \text{if } Grec_i > G_2 \end{cases}$$
$$i = 1, \ldots, N \tag{1}$$

where G_1 and G_2 are given constants, assumed independent from i. Naturally it may turn out that the actual number of vehicles requiring the charging service is reduced, concerning the initial number of N, as some of them require zero demand.

The charging price $Grec_i$ for vehicle i is considered as a decision variable, whose value is determined as the product between the unit cost for purchasing energy from the main grid (that is given and known) in the time interval (t_{rel_i}, t_{rel_i+1}) and the value of a function $\theta(t_{rel_i})$, namely

$$Grec_i = \theta\left(t_{rel_i}\right) \cdot \beta_{PURCHASE}\left(t_{rel_i}\right) \qquad i = 1, \ldots, N. \tag{2}$$

Indeed, the values of the decision variables $\theta(t_{rel_i})$, for any possible (discrete) value t_{rel_i}, are the decision variables (determined by solving the optimization problem) whose values have to be found taking into account the overall objective function of the decision maker (i.e., the microgrid manager). For instance, higher values of such variables for some time intervals may have the effect of lowering the actual service demand by vehicles arriving at the service station in those intervals. This lowering, in turn, may be convenient in order to achieve a globally better solution over the entire time horizon.

The following notation is adopted:

- $\beta_{PURCHASE}(t_k)$ is the unit purchase cost (price) from the main grid, in time interval (t_k, t_{k+1});
- $\beta_{SELL}(t_k)$ is the unit selling price to the main grid, in time interval (t_k, t_{k+1}).

The sequences $\beta_{PURCHASE}(t_k)$ and $\beta_{SELL}(t_k)$, $k = 0, 1, \ldots, T-1$ are considered as given, whereas the sequence $\theta(t_k)$, $k = 0, 1, \ldots, T-1$ consists of decision variables.

Further decision variables of the problem

In the problem formulation, we admit the possibility that the decision maker (that is, the microgrid manager) recognizes the impossibility of providing service to one or more vehicles. This possibility is modeled through the introduction of the binary decision variables ε_i, where $\varepsilon_i = 1$ means that a service is provided to vehicle i, whereas in case $\varepsilon_i = 0$ this vehicle is not served. Besides, , to ensure the consistency of the model, we impose that $\varepsilon_i = 0$ when $D_i = 0$, that is, when the actual demand of the customers corresponding to vehicle i becomes equal to zero, owing to a value $Grec_i \ge G_2$.

Also, for each time interval (t_k, t_{k+1}), $k = 0, 1, 2, \ldots T-1$, the decision maker has to find the optimal value of the following variables [kW]:

- $P_{G\to v,i}(t_k)$, the power flow from the microgrid to the i-th vehicle, unrestricted in sign, $i = 1, 2, 3, \ldots N$;
- $P_{eng1}(t_k)$, $P_{eng2}(t_k)$, the power flows from the two engines to the microgrid;
- $P_{sl\to G}(t_k)$, the power flow from the lithium storage to the microgrid, unrestricted in sign;
- $P_{ss\to G}(t_k)$, the power flow from the sodium storage to the microgrid, unrestricted in sign;
- $P_{MG\to G}(t_k)$, the power flow from the main grid to the microgrid, unrestricted in sign.

In the above notation, the orientation of the arrow in the subscript relevant to the variables representing power flows identifies the direction in which the power flow (if unrestricted in sign) is considered as positive.

Further, it is necessary to define the set of the binary variables $\delta_i(t_k)$, $k = 0, 1, 2, \ldots, T-1$, $i = 1, 2, \ldots, N$, where $\delta_i(t_k) = 1$ if vehicle i is connected to the charging station in time interval (t_k, t_{k+1}) and 0 otherwise.

Summing up, the decision variables of the problem are:

- $P_{G\to v,i}(t_k)$, $P_{eng1}(t_k)$, $P_{eng2}(t_k)$, $P_{sl\to G}(t_k)$, $P_{ss\to G}(t_k)$, $P_{MG\to G}(t)$ $k = 0, 1, \ldots, T-1$
- $\varepsilon_i \quad i = 1, 2, \ldots, N$
- $c_i, f_i \quad i = 1, 2, \ldots, N$
- $\delta_i(t_k) \quad k = 0, 1, \ldots, T-1 \quad i = 1, 2, \ldots, N$
- $\theta(t_k) \quad k = 0, 1, \ldots, T-1.$

3.2. The constraints affecting the system behavior

Constraints representing the system state evolution

The following storage state equations (for the two batteries and the EVs, respectively) have to be taken into account in the statement of the optimization problem:

$$x_{sl}(t_{k+1}) = x_{sl}(t_k) - P_{sl\to G}(t_k) \cdot \Delta t \qquad k = 0, \ldots, T-1 \tag{3}$$

$$x_{ss}(t_{k+1}) = x_{ss}(t_k) - P_{ss\to G}(t_k) \cdot \Delta t \qquad k = 0, \ldots, T-1 \tag{4}$$

$$x_{sveh,i}(t_{k+1}) = x_{sveh}(t_k) + P_{G\to v,i}(t_k) \cdot \Delta t$$
$$i = 1, \ldots, N \quad k = 0, \ldots, T-1. \tag{5}$$

Constraints affecting the vehicle charging process

Next, we consider the constraints relevant to the dynamics of the charging process. First, it is necessary to prevent that more than a single vehicle is connected to the charging station, in the same time interval, namely

$$\sum_{i=1}^{N} \delta_i(t_k) \le 1 \qquad i = 1, \ldots, N \quad k = 0, \ldots, T-1. \tag{6}$$

Moreover, we must impose that the time interval at which the charging starts should be greater than or equal to the release time interval:

$$c_i \geq rel_i \qquad i = 1, \ldots, N. \tag{7}$$

Besides, we have to impose that the charging process (if any) must finish before the end of the time horizon

$$f_i \leq T - 1 \qquad i = 1, \ldots, N. \tag{8}$$

A further constraint has the function of relating the state of the charging station with the time interval during which the charging of a vehicle i takes place:

$$\delta_i(t_k) = \begin{cases} 0 & \text{if } t_k \leq t_{c_i-1}, \text{ or } t_k \geq t_{f_i+1} \text{ or if } D_i = 0 \\ \varepsilon_i & \text{else} \end{cases}$$
$$i = 1, \ldots, N \; k = 0, \ldots, T-1. \tag{9}$$

The above constraint allows the connection of a vehicle only when the demand expressed by the vehicle is not zero, and the microgrid manager agrees to the service. In this case, the vehicle is connected only during time interval (t_{c_i}, t_{f_i+1}).

Another constraint prevents the service with no demand, that is

$$\varepsilon_i = 0 \text{ when } D_i = 0, \text{ that is, when } Grec_i > G_2 \quad i = 1, \ldots, N. \tag{10}$$

It is necessary to introduce a constraint that prevents that a vehicle departs from the station before reaching the desired state of charge (that is, without having received an amount of energy equal to its demand D_i). To this end, it is sufficient to enforce

$$x_{sveh,i}(t_k) = \begin{cases} x_{sveh,i_{in}} + D_i & \text{if } t_k \geq t_{f_i+1} \text{ and } \varepsilon_i = 1 \\ x_{sveh,i}(t_k) & \text{else} \end{cases}$$
$$i = 1, \ldots, N \qquad k = 1, \ldots, T. \tag{11}$$

At time instant $t_k = t_{rel_i}$, the state of charge has to be equal to the given initial value, that is

$$x_{sveh,i}\left(t_{rel_i}\right) = x_{sveh,i_{in}} \qquad i = 1, \ldots, N \quad k = 0, \ldots, T-1. \tag{12}$$

Constraints expressing upper and lower bounds

The evolution of the system state variables is constrained by upper and lower bounds, namely

$$x_{sveh\,min,i} \leq x_{sveh,i}(t_k) \leq x_{sveh\,max,i}$$
$$i = 1, \ldots, N \; k = 1, \ldots, T \tag{13}$$

where $x_{sveh\,min,i}$ and $x_{sveh\,mmax,i}$ are lower and upper bounds, respectively, for the state of charge of vehicle i.

Similarly, constraints limiting the value of the state of charge of the storage elements have to be taken into account:

$$x_{ss}^{min} \leq x_{ss}(t_k) \leq x_{ss}^{max} \qquad k = 1, \ldots, T \tag{14a}$$
$$x_{sl}^{min} \leq x_{sl}(t_k) \leq x_{sl}^{max} \qquad k = 1, \ldots, T \tag{14b}$$

where symbols have an obvious meaning.

In addition, a series of constraints have to be considered in order to limit the values of the power flows which are considered as decision variables in the model:

$$-P_{G\to v,i}^{max}\delta_i(t_k) \leq P_{G\to v,i}(t_k) \leq P_{G\to v,i}^{max}\delta_i(t_k) \quad i = 1, \ldots, N$$
$$k = 0, \ldots, T-1 \tag{15}$$
$$-P_{MG\to G}^{max} \leq P_{MG\to G}(t_k) \leq P_{MG\to G}^{max} \qquad k = 0, \ldots, T-1 \tag{16}$$
$$0 \leq P_{eng1}(t_k) \leq P_{eng1}^{max} \qquad k = 0, \ldots, T-1 \tag{17}$$
$$0 \leq P_{eng2}(t_k) \leq P_{eng2}^{max} \qquad k = 0, \ldots, T-1 \tag{18}$$
$$-P_{G\to ss}^{max} \leq P_{G\to ss}(t_k) \leq P_{G\to ss}^{max} \qquad k = 0, \ldots, T-1 \tag{19}$$
$$-P_{G\to sl}^{max} \leq P_{G\to sl}(t_k) \leq P_{G\to sl}^{max} \qquad k = 0, \ldots, T-1 \tag{20}$$

where all symbols have a straightforward meaning. Note that we have taken into account that some of the power flows are bidirectional.

Finally, the power balance constraint has to be fulfilled for any time instant, namely

$$P_R(t_k) + P_{S\to G}(t_k) + P_{MG\to G}(t_k) - \sum_{i=1}^{N} P_{G\to Vi}(t_k) - P_{EXT}(t_k)$$
$$+ P_{eng1}(t_k) + P_{eng2}(t_k) = 0 \qquad k = 0, \ldots, T-1 \tag{21}$$

where $P_{EXT}(t_k)$ is the non-deferrable (external) power demand that has, in any case, to be satisfied in time interval (t_k, t_{k+1}) and $P_R(t_k)$ is the forecasted power flow from renewable sources in the same interval.

Constraints limiting the variations of the power flow to/from storage elements

It is necessary to introduce constraints in order to prevent too high variations in the power flows from/to the storage elements (including the storage of the vehicles). Such variations may accelerate the degradation of these elements.

$$\left|P_{ss\to G}(t_k) - P_{ss\to G}(t_{k+1})\right| \leq \Delta P_{ss\to G}^{max} \qquad k = 0, \ldots, T-2 \tag{22}$$
$$\left|P_{sl\to G}(t_k) - P_{sl\to G}(t_{k+1})\right| \leq \Delta P_{sl\to G}^{max} \qquad k = 0, \ldots, T-2 \tag{23}$$
$$\left|P_{G\to v,i}(t_k) - P_{G\to v,i}(t_{k+1})\right| \leq \Delta P_{G\to v,i}^{max}$$
$$k = 0, \ldots, T-2 \quad i = 1, \ldots, N. \tag{24}$$

3.3. The overall optimization problem

The overall cost to be minimized is composed of the sum of economic production costs plus net energy buying costs (from the grid) and the overall weighted tardiness cost.

Thus, the optimization problem consists in the following minimization under constraints from (1) to (24).

$$min\left\{C_{eng1} + C_{eng2} + C_{purchase} - C_{sell} + C_{tard} - C_{serv}\right\} \tag{25}$$

where:

- $C_{eng1} = \sum_{k=0}^{T-1}\gamma P_{eng1}(t_k)\,\Delta t$ and $C_{eng2} = \sum_{k=0}^{T-1}\gamma P_{eng2}(t_k)\,\Delta t$ are the energy overall production costs at the two engines, where γ is the unit cost for producing power from engines (this cost is assume to be equal for the two engines);
- $C_{purchase} = \sum_{t=0}^{T-1}\beta_{PURCHASE}(t_k)\max\{P_{G\to MG}(t_k), 0\}\,\Delta t$ is the cost paid to buy energy from the main grid;
- $C_{sell} = \sum_{t=0}^{T-1}\beta_{SELL}(t_k)\max\{-P_{MG\to G}(t_k), 0\}\,\Delta t$ is the income due to the sale of energy to the main grid;
- $C_{tard} = \sum_{i=1}^{N}\varepsilon_i\alpha_i \max t_{f_i} - t_{dd_i}, 0$is the total tardiness cost;
- $C_{serv} = \sum_{i=1}^{N}\varepsilon_i\theta\left(t_{rel_i}\right)\beta_{PURCHASE}\left(t_{rel_i}\right)D_i$ is the income due to the charging services actually provided to the customers.

4. Application to a case study

For all cases, the optimization problem presented in the previous section has been solved by using Lingo [33] invoking the global solver, on a PC Intel i7, 16 GB RAM. Runtime is about 30 min for Scenario 1 and 2, while for Scenario 3 is about 90 min. Real data have been taken from a real case study located in the Savona (Italy) municipality.

First, let us provide, in Table 1, the values of the parameters of the elements of the microgrid of the considered case study

Scenarios 1 and 2 refer to the case in which the distribution of demand over time is certain and relatively light and thus the optimization of the vehicles' charging schedule can be carried out over a time horizon of 24 h.

Table 1
Power flow data.

Parameter	Value
P_{eng1}^{Max}	30 [kW]
P_{eng2}^{Max}	65 [kW]
$P_{G\rightarrow ss}^{max}$	40 [kW]
$P_{G\rightarrow sl}^{max}$	40 [kW]
$P_{G\rightarrow v,i}^{max}$	30 [kW]
$P_{MG\rightarrow G}^{max}$	1000 [kW]
γ	0,237
$\Delta P_{ss\rightarrow G}^{max}$	10 [kW]
$\Delta P_{sl\rightarrow G}^{max}$	10 [kW]
$\Delta P_{G\rightarrow v,i}^{max}$	7 [kW]

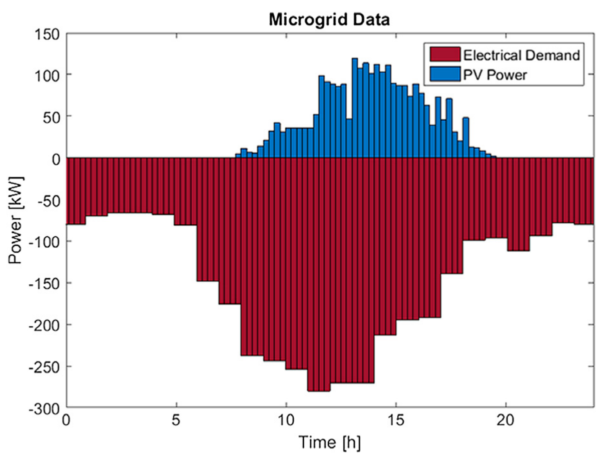

Fig. 4. Not deferrable electrical demand, PV power production.

Instead, Scenario 3 considers a more heavy service request (i.e. a higher number of vehicles within a shorter time). In this case, the prior knowledge the distribution of service request over time is quite difficult. For this reason, the application of the so called "receding horizon" scheme can be reasonably chosen. That is, optimization is carried out only with respect to a limited time horizon (over which the distribution of the service demand is relatively certain). Then, after the application of the first decisions, a new instance of the optimization problem is considered and solved again, taking into account possible previously unsatisfied service requests and possible new service requirements.

For Scenarios 1 and 2 we consider an optimization horizon consisting of 96 time intervals, each ones of 15 min. Thus $\Delta t = 0.25$ [h] and on the whole, the horizon length is equal to 24 h. Instead, in the third Scenario the optimization horizon is restricted to 2 h with a discretization interval of 5 min.

In Fig. 4, the patterns (obtained by real measurements) of the known *not deferrable* demand and of the renewable energy power are represented, over a whole day. The unit cost ($\beta_{PURCHASE}(\cdot)$) and benefit ($\beta_{SELL}(\cdot)$) for the power exchanged with the external grid are taken equal to

$$\beta_{PURCHASE}(t) = \begin{cases} 0.2\dfrac{€}{\text{kWh}} & 0 \leq t \leq 36 \text{ or } 81 \leq t \leq 95 \\ \dfrac{0.26€}{\text{kWh}} & 37 \leq t \leq 80 \end{cases}$$

$$\beta_{SELL}(t) = 0.15\frac{€}{\text{kWh}} \quad \text{for any } t.$$

Scenario 1

In this case, we consider 3 different vehicles. All data are summarized in Table 2.

Table 2
Data for the first scenario.

Vehicle data	Vehicle 1	Vehicle 2	Vehicle 3
rel_i	40	35	65
dd_i	65	59	79
$D_{max,i}$ [kWh]	30	30	30
$x_{sveh,i,in}$ [kWh]	5	5	5
α_i [€/h]	0.1	0.3	0.1
G_1, G_2 [€/kWh]	0.5, 0.6	0.5, 0.6	0.5, 0.6

Table 3
First scenario results.

Vehicle output	Vehicle 1	Vehicle 2	Vehicle 3
$\theta(t_{rel})$	2	2	2
c_i	56	44	80
f_i	61	54	96
D_i [kWh]	30	30	30
ε_i	1	1	1

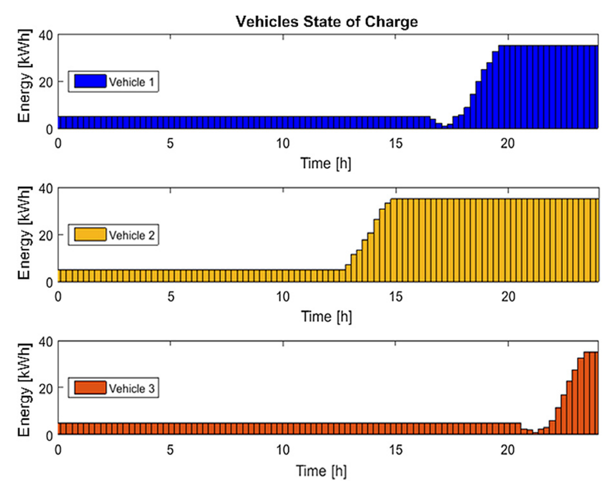

Fig. 5. The evolution of the state of charge of the three vehicles (Scenario 1).

The results obtained are shown in Fig. 5, as regards the evolution of the state of charge of the vehicles.

It can be noted that vehicle 2 is charged, but never discharged, whereas the other two vehicles are sometimes discharged (i.e., vehicle to grid is performed and the EVs serve as temporary energy sources), but eventually charged. The values of the other important decision variables, as determined in the solution of the problem, are reported in Table 3.

We can note from these results that in this scenario no vehicle reduces its demand with respect to $D_{max,i}$, and that the microgrid manager satisfies all service requests.

The plot of the state of charge of the two storage systems is provided in Fig. 6.

Finally, the various power flows in the microgrid are represented in Fig. 7.

Fig. 8 shows the pattern of $\delta_i(t_k)$ over time This allows to identify the service sequence of the vehicles.

Scenario 2

In the second scenario, the number of vehicles is increased to 4. Table 4 reports the data for each vehicle.

In Fig. 9, the patterns of the state of charge of the four vehicles are reported.

The micro grid manager accepts to charge every vehicle. Note that in this case vehicle 1 is initially overcharged, with respect to its demand, in order to use it later as a temporary storage (V2G).

The values of the most relevant decision variables are reported in Table 5.

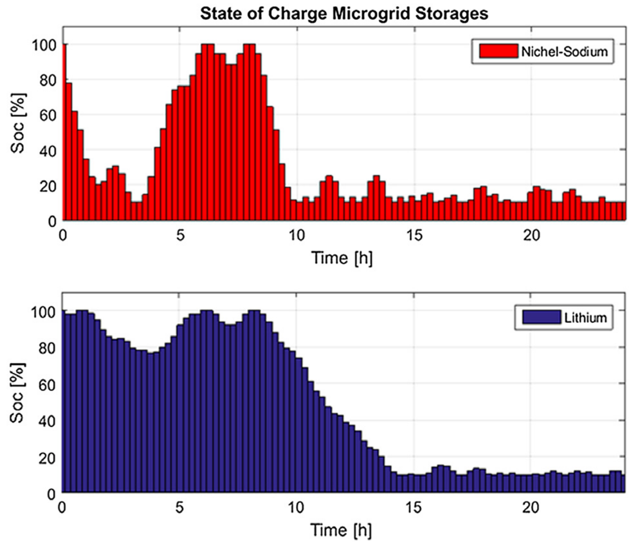

Fig. 6. The evolution of the state of charge of the two microgrid storage systems.

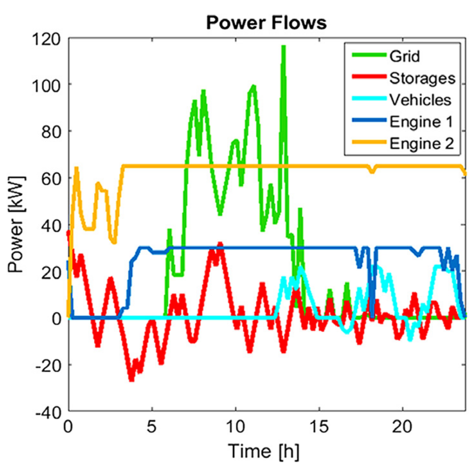

Fig. 7. Power flows in the microgrid (Scenario 1). *Ps* is the sum of $P_{sl\to G}(t_k)$ and $P_{ss\to G}(t_k)$. *P* vehicles is the sum of power flows $P_{G\to v,i}(t_k)$ for all *i*.

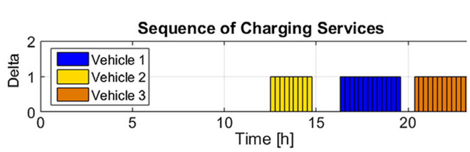

Fig. 8. Evolution of $\delta_i(t_k)$ in Scenario 1.

Table 4
Vehicles data for the second scenario.

Vehicle data	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
rel_i	20	40	35	65
dd_i	35	65	59	79
$D_{max,i}$ [kWh]	30	30	30	30
$x_{sveh,i,in}$ [kWh]	5	5	5	5
α_i [€/h]	0.2	0.1	0.3	0.1
G_1, G_2 [€/kWh]	0.5, 0.6	0.5, 0.6	0.5, 0.6	0.5, 0.6

Scenario 3

In this scenario a receding horizon approach is applied, considering a higher number of vehicles within a shorter time horizon (2 h). At the completion of the service of the last vehicle served (i.e., accepted) a new instance of the optimization problem, again over a time horizon of 2 h, is defined and solved. Within this instance, the arrivals of new vehicles are taken into account. In addition, also the vehicles that have not been accepted and whose due-dates are greater than the initial time instant of the new optimization horizon. Obviously this procedure can be repeated indefinitely. Here we show only two steps of this procedure. Table 6 reports vehicles' data for the first step

Table 5
Second scenario results.

Vehicle output	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
$\theta(t_{rel})$	2	2	2	2
c_i	20	48	54	74
f_i	35	53	60	95
D_i [kWh]	30	30	30	30
ε_i	1	1	1	1

We report in Fig. 10 the evolution of $\delta_i(t_k)$ over time, and in Table 7 the values determined for the most relevant decision variables

In the solution of the first optimization step, vehicle 2, 5 and 7 are not serviced. Note that the service sequence in the solution is *not* in accordance with the order of release times. In fact, it is possible to say that the presented approach jointly optimizes timetabling and sequencing.

When the second optimization step is defined, two of the above three vehicles (namely, 2 and 5) are definitively discarded, since both their due-dates(10,5 and 13 discretization steps, corresponding to 52,5 and 65 min, respectively) are overcome by the initial discretization step (24, that is 2 h), that represents the starting time of the second optimization step. Instead, vehicle 7 is considered in the statement of the problem (as its due date is 30, that is 2,5 h), along with 4 new vehicles arriving within the new optimization interval. Table 8 reports the data for the second optimization step. Note that time values are referred to a new "zero", corresponding to the initial time instant of the optimization interval in the second step.

Fig. 11 shows the sequence of services of step 2. In this case the microgrid manager does not accept vehicle 12, but this one can be considered in the next step.

Table 9 shows the output variables for this second step.

Finally, it is important to note that the run time turns out to be acceptable for each Scenario considered. Namely, For Scenarios 1 and 2 the maximum run time is 1 h, whereas for Scenario 3 (both steps) is lower than 3 min.

5. Conclusions and future developments

A new optimization model is here formalized to include electrical vehicles in a smart grid. On the basis of the requests and preferences of users of EVs, the grid's manager decides the optimal schedule of its generation plants and storage systems, taking into account the non deferrable internal demand and renewable availability. The developed model is applied by using real data, and different scenarios related to the demand of EVs' charging have been considered.

In the proposed model, an attempt has been made to model the behavior of different decision makers. Namely, the vehicles' owners may reduce their service request on the basis of an elastic demand function (assumed to be the same for vehicles, for the sake of simplicity). Instead, the service station manager has different degrees of freedom, as he/she can vary the unit price for service, and may even decide against servicing one or more vehicles. Besides, also the time intervals during which the various services take place

Table 6
Vehicles data second scenario Step 1.

Vehicle data	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5	Vehicle 6	Vehicle 7	Vehicle 8
rel_i	0	5.5	3.5	2	7.5	8.5	18	15
dd_i	9.5	10.5	10	28.5	13	15.5	30	19
$D_{max,i}$ [kWh]	15	8	13	12	10	15	17	19
$x_{sveh,i,in}$ [kWh]	5	5	5	5	5	5	5	5
α_i [€/h]	0.2	0.1	0.3	0.1	0.2	0.1	0.3	0.1
G_1, G_2 [€/kWh]	0.5, 0.6	0.5, 0.6	0.5, 0.6	0.5, 0.6	0.5, 0.6	0.5, 0.6	0.5, 0.6	0.5, 0.6

Table 7
Third scenario Output step 1.

Vehicle output	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5	Vehicle 6	Vehicle 7	Vehicle 8
$\theta(t_{rel})$	2	0	2	2	0	2	0	2
c_i	0	–	6	21	–	15	–	10
f_i	5	–	9	24	–	10	–	15
D_i [kWh]	10	–	8	7	–	10	–	14
ε_i	1	0	1	1	0	1	0	1

Table 8
Vehicles data second scenario Step 2.

Vehicle data	Vehicle 7	Vehicle 9	Vehicle 10	Vehicle 11	Vehicle 12
rel_i	0	10	12	7	18
dd_i	6	20	19	21	32
$D_{max,i}$ [kWh]	17	22	13	20	10
$x_{sveh,i,in}$ [kWh]	5	5	5	5	5
α_i [€/h]	0.2	0.1	0.3	0.1	0.2
G_1, G_2 [€/kWh]	0.5, 0.6	0.5, 0.6	0.5, 0.6	0.5, 0.6	0.5, 0.6

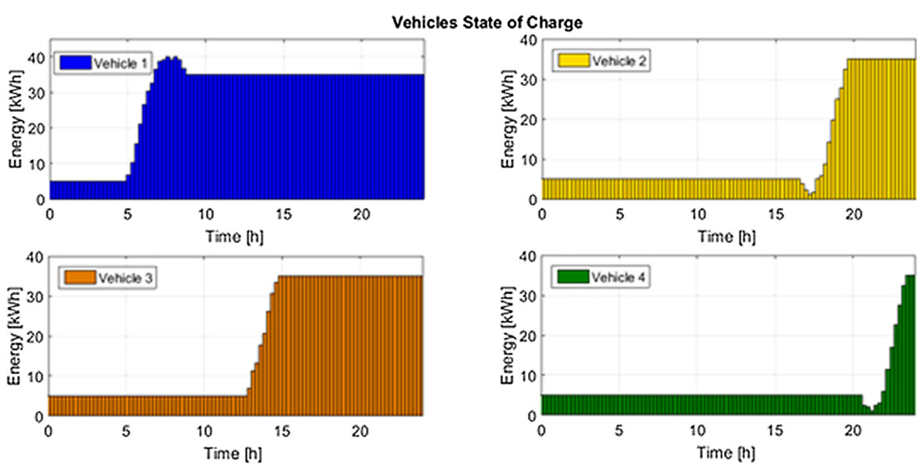

Fig. 9. The evolution of the state of charge of the four vehicles (Scenario 2).

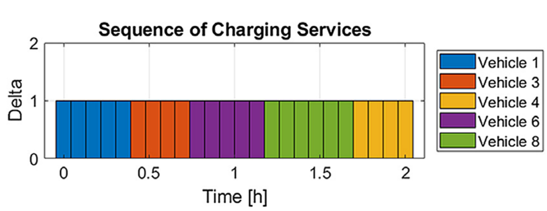

Fig. 10. Evolution of $\delta_i(t_k)$ in Scenario 3 Step 1.

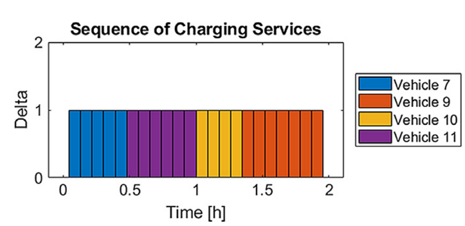

Fig. 11. Evolution of $\delta_i(t_k)$ in Scenario 3 Step 2.

are determined through the solution of the optimization problem. These services are imposed to be non preemptive and their order does not necessarily reproduces the order of the arrivals of the vehicles. Thus, is possible to say that *even the service sequence* is determined by the solution of the optimization problem. Of course, different interaction schemes among the various decision makers can be conceived, and this is matter of current research.

The problem has been formalized in a discrete-time setting. Obviously, this choice is not the unique possible. In fact, also a discrete-event formalization of the model is possible, in which the only time instants represented are those corresponding to decisions to be taken. The development of a decision model based on a discrete-event representation of the dynamics of the system is actually in progress.

Table 9
Third scenario Output step 2.

Vehicle output	Vehicle 7	Vehicle 9	Vehicle 10	Vehicle 11	Vehicle 12
$\theta(t_{rel})$	2	2	2	2	0
c_i	1	17	13	7	–
f_i	6	23	16	12	–
D_i [kWh]	12	17	7	15	–
ε_i	1	1	1	1	0

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