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Research Article

Electric Vehicles and Storage Systems Integrated within a Sustainable Urban District Fed by Solar Energy

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In this paper, an optimization model is defined for the design of a smart energy infrastructure integrating different technologies to satisfy the electrical demand of a given site. The considered smart energy infrastructure includes a photovoltaic plant, electrical storage systems, electric vehicles (EVs), and charging stations. The objective function of the optimization model considers the costs related to the installation and maintenance of the considered technologies, as well as the costs associated with the energy exchanges with the external grid. A very extensive numerical analysis is reported in the paper, referred to a test case in a real site in Liguria Region, in the north of Italy. Many scenarios are analyzed and discussed, with specific attention to evaluate the role of electric mobility within a smart energy infrastructure and a focus on EVs acting as mobile storage systems.

1. Introduction

Several models have been proposed in the literature and are still under investigation by researchers to study the integration of renewable energy sources and storage technologies within smart urban districts [1–6]; some of them also deal with the integration of electric vehicles (EVs) and charging infrastructures in urban areas [7–11].

Some research works are devoted to the optimal design of distributed energy systems, in which both the thermal grid and the electric grid are considered (see e.g. [1, 2]). In these models, different technologies are integrated, such as combined heat and power units (reciprocating internal combustion engines and gas micro-turbines), renewable energy technologies including photovoltaic (*PV*) and solar thermal plants, heat pumps, chillers, boilers, electric, and thermal storages. In particular, the Distributed Energy System Optimal Design (DESOD) tool presented in Ref. [1] and the model proposed in Ref. [7] represent the main inspiration for the work described in the present paper. DESOD tool is based on Mixed Integer Linear Programming (MILP), i.e., it is a mathematical programming model that uses both continuous and binary decision variables and presents linear objective function and constraints. The considered system is composed of different technologies that provide heating/cooling and electrical energy to a district with different buildings. The optimization problem is solved in order to design the system layout, defining the technologies to be installed in each building and also the best configuration of the district heating network, as well as to define the optimal daily operation strategy of the whole infrastructure.

In Refs. [3, 12], the design of a distributed energy system is realized by means of a long-term planning problem, in which the main decisions concern which technologies, and of which size, must be installed in each building of the system. The determination of the optimal size of generation units is not easy because of the variability of electric and thermal demands, electricity, and fuel prices [13]. In Ref. [14], the authors propose to balance the intermittence of renewable sources using plants able to produce thermal energy and electricity in cogeneration or trigeneration modes. In Refs. [15, 16], storage technologies are also included, in order to study the optimal design of a more integrated system: the possibility to store the surplus of electrical and thermal energy helps the system to be more independent from the main grid and also to optimize the production of the different considered sources. The planning problem integrating storage systems is characterized by high complexity [4]. In addition, the problem becomes more complex when increasing the number of considered buildings and technologies, as described in Refs. [17, 18].

In the literature, the long-term planning of a distributed energy system is often realized through MILP models: the presence of only linear relations among decision variables allows to reduce the computational complexity of the problem and to properly model the performance of the technologies involved, while the presence of integer variables can improve the computational times required to find the optimal solution. In order to reduce the computational times, the authors in Ref. [19] propose a method to select a limited set of days that represent the typical daily energy demands of a specific user during the year. In Ref. [20], a MILP model is proposed in order to determine the optimal layout and operation strategy of a distributed cogeneration system: the objective function minimizes the annual capital, maintenance, and operation costs of the whole system. In Ref. [21], a MILP model useful to study the optimal layout of a distributed energy system in an eco-campus is discussed. The MILP models reported in the literature are characterized by different objective functions which refer not only to the minimization of costs but also to the reduction of primary energy consumptions and/or greenhouse gas emissions. For instance, the model presented in Ref. [22] is focused on environmental issues, that is, CO_2 emissions, in order to minimize the carbon footprint of the analyzed system.

In some cases, planning approaches different from MILP optimization are applied, such as non-linear programming models. For instance, in Ref. [23] a nonlinear mathematical programming model, with nonlinear constraints, is presented in order to describe the partial-load performance curves of different technologies. In some cases, there are some variables, such as the electrical and thermal loads, which are difficult to be forecasted and so the variability of such quantities can be accounted for by applying stochastic programming [24].

The innovation of the present work compared with the aforementioned models is related to the integration of EVs within a polygeneration urban system. The development and dissemination of EVs in urban areas is deeply discussed in Ref. [25], while [26, 27] provide, respectively, an overview of EV fleet management systems in smart grids and a focus on charging infrastructures integrated with distributed energy sources. Conventional EVs have to be considered as additional electrical loads, whereas EVs able to work in Vehicle-to-Grid (V2G) mode can be exploited in order to manage the energy production obtained from the different generation units, in particular the uncontrollable ones. As reported in Refs. [8, 28], the smart integration of EVs provides an improvement in the flexibility of power systems, reducing also investment costs. Furthermore, V2G technology allows a bidirectional energy exchange between the EVs and the power grid; EVs can offer numerous services to the power grid, such as power grid regulation, spinning reserve, peak load shaving, and load levelling.

In Refs. [29, 30], EVs are modelled as mobility loads whose main characteristics are charging time, power demand and rate of charge. In Ref. [8], four different charging schemes are described: "dumb" charging schemes (the EVs charging starts just when they are plugged-in), conventional controlled charging schemes (the charging process is time-delayed to avoid peak demand periods), smart charging schemes (the charging scheme is determined by an intelligent algorithm to improve the operation of the power network), V2G charging schemes (charging and discharging of the EVs can work in V2G mode in order to optimize power system operation). In Ref. [8], an optimization problem is proposed with the goal of defining the optimal charging scheduling of EVs to flatten the load profile of the transformer substation of a distribution network, considering peak demand shaving and technical networks limits.

A mixed-integer non-linear programming problem is proposed in Ref. [9] and solved using the Benders decomposition approach. In that case of study, a microgrid consisting of conventional thermal units, smallscale wind turbines, solar panels, and an EV parking facility is considered. The microgrid is connected to the power grid and can exchange energy in the electricity market. In addition, the microgrid uses an EV parking facility equipped with a bidirectional flow capability to perform a V2G program. The parking facility is assumed to be a virtual battery whose capacity depends on the batteries of the available EVs in the parking. This capacity is variable, as the available number of EVs in the parking facility changes over time, and it is stochastic since the arrivals and departures of EVs to/from the parking facility are not known with certainty.

In Ref. [31], a detailed battery-fading model for EVs is integrated into a general power management framework. Power management and renewable energy source sizing are optimized from the economic point of view, defining an intelligent operation of EVs in order to balance the renewable energy source generation, grid power, and electric demand, which are formulated and solved with a MILP model. The stochastic nature of the problem due to the involvement of renewable energy sources, EV operation, and electric demand is modelled using appropriate probability distribution functions to generate scenarios for several years.

Furthermore, an open source model called Electric Vehicles Learning Static (EVLS) model, able to simulate the relations between the EVs and the upstream energy system, is presented in Ref. [32]. The mathematical formulation is based on a linear programming problem that aims to satisfy the electricity demand for services at the lowest operating cost. The EVLS is adaptable to different cases, with the possibility to vary the time horizon according to the desired time steps, the available information and the type of analysis [33]. The modelling structure can be applied to different scale levels, from households to regional power systems, and can be expanded in each part of the reference energy system according to the needs of the user. The open source model presented in Ref. [32] can be exploited to investigate the integration of EVs and *PV* plants upon a broad range of combinations of penetration of both technologies. The combination of EVs and *PV* has not yet been fully explored, but some documentations can be found in Ref. [34], where a comprehensive list of the related studies and a thorough discussion can be found.

Another relevant application of electric mobility is the integration of EV smart charging infrastructures in buildings. The work in Ref. [10] analyzes different characteristics of control logics applied to V2G systems, when supporting an automatic controlled load, such as a smart building, supposed to be disconnected from the main grid. The positive effect of the integration of V2G on a smart building is shown, especially in case of an electric network failure. EVs are connected to their power stations in working hours: while in standard conditions power stations can only charge vehicle batteries, in emergency conditions a certain amount of energy can be withdrawn from vehicles, in order to increase the power/energy availability of the building. In Ref. [11], a storage model for both vehicle batteries and standard stationary batteries is proposed, whereas in Ref. [10] the parking facility is modelled as a set of storage units, each one with a certain capacity and power output; the power that one vehicle provides to the system is defined as a function of the vehicle capacity, the state of charge and the maximum available power from the battery. An MILP model to optimize the costs related to the management of a fleet of EVs is presented in Ref. [35], in which the charging points are located on urban roads and differ according to their charging rate (fast or ultra-fast). The model considers the average speed of the fleet, the battery states of charge, and a set of deliveries allocated to each vehicle to define an efficient charging strategy for each vehicle. An optimization problem is defined also in Ref. [36] for the optimal scheduling of the EV charging process in a smart grid, considering the V2G technology as well. In that paper, a deferrable charging demand of EVs is assumed, hence the objective function not only includes the cost of energy production and acquisition and the income of the provided services, but also the cost associated with the delay in the satisfaction of the customers' demand.

The adoption of EVs is presently constrained by some limiting factors. According to the authors of [37], such factors are the "range anxiety" of drivers, fearing that their vehicle has insufficient range to reach its destination, and the cost of batteries. These two limiting factors are addressed by some companies which have introduced a new concept of electric mobility that combines a network of battery switching stations and a payment system in which the driver is charged per mile driven and the company owns the batteries [37]. In battery switching stations, drivers can switch the depleted batteries of their vehicles for fully charged ones. This kind of systems implies new decision problems to be solved, regarding for instance the optimal allocation of spare batteries [38].

The mathematical model described in the present paper provides the following main contributions:

(i) To consider the interaction between EVs, seen also as storage systems, with stationary storage batteries.

(ii) To include different EV charging points, either conventional or of V2G type.

(iii) To compare different kinds of storage batteries.

Moreover, in the paper we show how the proposed mathematical model can be used to design a sustainable urban district through the analysis of different system configurations, characterized by an increasing complexity due to the incremental inclusion of new technologies.

The present paper is structured as follows. In Section 2, an MILP model is presented for the optimal design of a smart energy infrastructure used to provide electricity to an urban district, explicitly considering the presence of EVs. Section 3 is devoted to describe the application of this optimization model to a real case study, while some concluding remarks are drawn in Section 4.

2. The Mixed Integer Linear Programming Model

This section describes the proposed optimization model to define the optimal design of a smart energy infrastructure which is used to provide electricity to an urban district characterized by the presence of EVs. The main decisions regard the optimal number of PV panels and storage batteries to install in the buildings and the suitable number of EV charging points, with the aim of minimizing the overall costs (capital and operating). The site is connected to the distribution public grid and is described by known electrical load profiles of buildings and transportation demand of users that own EVs. The model is of the MILP type, so it is a mathematical model that uses both continuous and binary decision variables and presents linear objective function and constraints.

A given site is considered for the application of the model, with certain limits and data related to the available area for the installation of PV and batteries. The solar radiation in the considered zone is a known parameter, as well as the type of solar panels chosen for the installation. Moreover, in order to better manage the energy produced by exploiting the renewable sources, two different battery types (sodium nickel chloride and lithium ions) called respectively $B1$ and $B2$, are considered; in particular, sodium nickel chloride batteries are used for energy application, whereas lithium ion batteries are suitable for power application. It is worth noting that the formulation of the optimization model is general, so that the extension to include more types of batteries is straightforward.

As far as electric mobility is concerned, it is assumed to have a certain number of EVs, already present in the site and, for this reason, not directly involved in the optimal design of the whole system. In the most general case, some of these EV are conventional, while others can work in V2G mode, being able to release energy when it is not used for transportation purposes. In particular, the daily transportation demand for each vehicle is known and has to be completely satisfied. In order to manage the fleet of EVs, the installation of a certain number of charging stations is required. In the proposed model, two types of charging stations are considered, denoted respectively as $S1$ and $S2$. Of course, the model can be easily extended to consider more types of stations. The two types $S1$

and $S2$ can correspond, for instance, to conventional and V2G charging stations, but they can be also two types of V2G stations with different technical characteristics. Finally, the power limits that characterize the connection of the site to the distribution network are known.

The main hypotheses considered in the proposed optimization model are listed below:

(i) Only the electrical needs of the site are considered, neglecting the thermal ones.

(ii) The type of *PV* modules (technology, material, size, and nominal power of each module) chosen for the installation is defined a priori; in addition, the position of the *PV* modules is not a decision variable of the problem, tilt and azimuth angles being assigned.

(iii) Since EVs are already present in the site, the costs related to their purchasing and maintenance are not taken into account in the objective function of the optimization model.

(iv) Referring to the EV charging infrastructure, the maximum power that can be absorbed or released (in V2G applications) by the EVs depends on the rated data of both the considered charging points and the charger of the EV battery.

(v) Each charging station has only one socket; consequently, it can be only connected to one vehicle at a time.

As aforesaid, the optimization problem is solved in order to define:

(i) The number of charging stations of type $S1$ and $S2$ necessary to satisfy the transportation demand of a certain number of EVs available in the site.

(ii) The number of *PV* modules to be installed on the roofs of the buildings included within the site.

(iii) The number of batteries of type $B1$ and $B2$ required to manage the energy flows in the system in order to maximize the exploitation of *PV* production and self-consumption.

(iv) The energy exchange with the power distribution network.

The objective is the minimization of the overall costs related to the purchase, installation, and maintenance of the whole infrastructure composed of EV charging stations, energy storage batteries, *PV* modules, and connection to the power distribution network.

In the following subsections, the constraints and the objective function of the optimization model are described in detail, while the definition of the decision variables is reported in the Appendix referring to each considered technology. The optimization model is formulated considering a yearly time horizon subdivided into M months, each one represented by a typical day divided into a number of T time intervals (each one having a length equal to Δt). Moreover, K indicates the number of days in a month, Ω represents the maximum number of charging stations (of $S1$ or $S2$ type) to be installed, while V is the number of vehicles of the considered fleet.

2.1. The Constraints. The constraints of the optimization problem are described by grouping them according to the subsystem which they refer to.

In Equation (1), the electrical balance of the whole site is represented, for each typical day and for each time interval, taking into account the power flows related to *PV* plant, $B1$ and $B2$ batteries, $S1$ and $S2$ charging systems, power distribution grid and the load request $D^{el}_{m,t}$.

$$\begin{aligned} &P^{PV}_{m,t} + P^{out,B1}_{m,t} + P^{out,B2}_{m,t} + \sum_{s=1}^{\Omega}\sum_{v=1}^{V}\left(P^{V,S1}_{s,v,m,t} + P^{V,S2}_{s,v,m,t}\right) \\ &+ P^{abs,G}_{m,t} - P^{in,B1}_{m,t} - P^{in,B2}_{m,t} - \sum_{s=1}^{\Omega}\sum_{v=1}^{V}\left(P^{S1,V}_{s,v,m,t} + P^{S2,V}_{s,v,m,t}\right) \\ &- P^{inj,G}_{m,t} - D^{el}_{m,t} = 0, m = 1\ldots M, t = 1\ldots T. \end{aligned} \tag{1}$$

Furthermore, Equations (2) and (3) impose the nonnegativity of the power that can be absorbed or injected from/into the power distribution grid and the associated upper bounds, respectively given by $\overline{P}^{abs,G}$ and $\overline{P}^{inj,G}$.

$$0 \le P^{abs,G}_{m,t} \le \overline{P}^{abs,G}, m = 1\ldots M, t = 1\ldots T, \tag{2}$$

$$0 \le P^{inj,G}_{m,t} \le \overline{P}^{\,inj,G}, m = 1\ldots M, t = 1\ldots T. \tag{3}$$

The constraints related to the *PV* plant are given by Equations (4)–(6).

$$0 \le P^{PV}_{m,t} \le P^{PV,mod} \cdot x^{PV}, m = 1\ldots M, t = 1\ldots T, \tag{4}$$

$$S^{PV} \cdot x^{PV} \le A, \tag{5}$$

$$P^{PV}_{m,t} = \eta^{PV}_{m} \cdot I_{m,t} \cdot A^{PV} \cdot x^{PV}, m = 1\ldots M, t = 1\ldots T. \tag{6}$$

In particular, Equation (4) defines that the power produced by the *PV* plant has to be non-negative and lower than the rated power of the plant obtained by multiplying the rated power of one module $P^{PV,mod}$ for the number of installed modules. The constraint reported in Equation (5) considers that the area occupied by the *PV* modules (obtained as the area S^{PV} of a single module multiplied for the number of installed *PV* modules) has to be lower than the maximum area A available in the considered site. Finally, as reported in Equation (6), the *PV* production depends on the solar radiation $I_{m,t}$, the plant efficiency η^{PV}_{m}, the active surface of each module A^{PV}, and the number of installed modules.

On the other hand, constraints in Equations (7)–(13) refer to storage batteries of type $B1$; the optimization model includes analogous constraints for $B2$ batteries. In Equations (7) and (8) the charging and discharging power is properly bounded considering the values of the maximum power that can be exchanged with the single battery ($\overline{P}^{in,B1}$ and $\overline{P}^{out,B1}$). Constraint in Equation (9) is used to ensure that the storage system cannot be simultaneously charged and discharged, while constraints in Equations (10) and (11) impose further upper bounds for the charging and discharging power, considering that the batteries can be either charged or discharged only when in operation (i.e., when the associated binary variables are equal to 1), assuming that U is a sufficient large number.

$$0 \le P_{m,t}^{in,B1} \le \overline{P}^{in,B1} \cdot x^{B1},\ m = 1 \dots M, t = 1 \dots T, \quad (7)$$

$$0 \le P_{m,t}^{out,B1} \le \overline{P}^{out,B1} \cdot x^{B1},\ m = 1 \dots M, t = 1 \dots T, \quad (8)$$

$$y_{m,t}^{in,B1} + y_{m,t}^{out,B1} \le 1,\ m = 1 \dots M, t = 1 \dots T, \quad (9)$$

$$P_{m,t}^{in,B1} \le U \cdot y_{m,t}^{in,B1},\ m = 1 \dots M, t = 1 \dots T, \quad (10)$$

$$P_{m,t}^{out,B1} \le U \cdot y_{m,t}^{out,B1},\ m = 1 \dots M, t = 1 \dots T. \quad (11)$$

Furthermore, Equation (12) represents the constraint for the energy stored in the storage system: the energy has to be lower than the overall capacity of the batteries, but at the same time higher than a minimum level, which depends on the minimum state of charge $SOC^{min,B1}$, the nominal capacity of each battery CAP^{B1} and the number of installed batteries. In Equation (13), the energy balance equation of the storage system is reported: the energy stored in the batteries at a certain time instant depends on the energy stored at the previous time instant, the energy injected into the batteries and the energy absorbed from the batteries, these latter evaluated considering charging and discharging efficiency values $\eta^{CH,B1}$ and $\eta^{DCH,B1}$.

$$SOC^{min,B1} \cdot CAP^{B1} \cdot x^{B1} \le E_{m,t}^{B1} \le \mathrm{CAP}^{B1} \cdot x^{B1}, \quad m = 1 \dots M, t = 1 \dots T, \quad (12)$$

$$E_{m,t+1}^{B1} = E_{m,t}^{B1} + \Delta t\left(\eta^{CH,B1} \cdot P_{m,t}^{in,B1} - \frac{1}{\eta^{DCH,B1}} \cdot P_{m,t}^{out,B1}\right), \quad m = 1 \dots M, t = 1 \dots T-1. \quad (13)$$

The set of constraints for EVs and charging points is given by Equations (14)–(21). Considering the charging stations of type $S1$, Equations (14) and (15) define feasible value ranges for the power exchanged between the vehicle and the charging station, considering the maximum values $\overline{P}_v^{S1,V}$ and $\overline{P}_v^{V,S1}$, respectively. Similar constraints are used to define the interactions between vehicles and charging stations of type $S2$.

$$0 \le P_{s,v,m,t}^{S1,V} \le \overline{P}_v^{S1,V} \cdot y_{s,v,m,t}^{S1,V},\ s = 1 \dots \Omega, \quad v = 1 \dots V, m = 1 \dots M, t = 1 \dots T, \quad (14)$$

$$0 \le P_{s,v,m,t}^{V,S1} \le \overline{P}_v^{V,S1} \cdot y_{s,v,m,t}^{V,S1},\ s = 1 \dots \Omega, \quad v = 1 \dots V, m = 1 \dots M, t = 1 \dots T, \quad (15)$$

Then, Equation (16) considers that, if the transportation demand $D_{v,m,t}^V$ of a certain vehicle is different from zero, the vehicle has not to be connected to any charging station (hence, the corresponding binary variables must be set equal to 0). In addition, it takes also into account that for each charging station, considering a certain time interval, only one of the binary variables can be set equal to 1; in other words, at a certain time instant, each vehicle can be either traveling or connected to one of the charging points (in charging or discharging mode). Note that Q is a sufficiently large number.

$$Q\left[1 - \sum_{s=1}^{\Omega}\left(y_{s,v,m,t}^{S1,V} + y_{s,v,m,t}^{V,S1} + y_{s,v,m,t}^{S2,V} + y_{s,v,m,t}^{V,S2}\right)\right] \ge D_{v,m,t}^V, v = 1 \dots V, m = 1 \dots M, t = 1 \dots T, \quad (16)$$

Furthermore, Equation (17) considers that a vehicle connected to a charging station of type $S1$, in a certain time interval, has the possibility to be either charged or discharged absorbing or transferring power from/to the charging station, but the two options are not possible at the same time. Equation (18) is used to define that, if a certain $S1$ charging station is absorbing/transferring power from/to vehicles in at least one time interval, this charging station has to be installed and so the associated binary variable referred to its installation has to be equal to 1; in Equation (18) H is again a sufficient large number. Note that, again, constraints analogous to Equations (17) and (18) must be reported also for charging stations of type $S2$.

$$\sum_{v=1}^{V}\left(y_{s,v,m,t}^{S1,V} + y_{s,v,m,t}^{V,S1}\right) \le 1, s = 1 \dots \Omega, m = 1 \dots M, t = 1 \dots T, \quad (17)$$

$$\sum_{v=1}^{V}\sum_{m=1}^{M}\sum_{t=1}^{T}\left(y_{s,v,m,t}^{S1,V} + y_{s,v,m,t}^{V,S1}\right) \le z_s^{S1} \cdot H, s = 1 \dots \Omega. \quad (18)$$

The constraint in Equation (19) allows to calculate the number of installed charging stations of type $S1$ summing the values of the binary variables referred to the installation of a charging station; a similar constraint is used to calculate the number of installed charging stations of type $S2$.

$$x^{S1} = \sum_{s=1}^{\Omega} z_s^{S1}. \quad (19)$$

The energy balance of each vehicle is reported in Equation (20); the energy stored in the vehicle in a time instant is given as a function of the energy stored in the previous time instant, the difference between the energy injected into the vehicle through charging stations and the energy released by the vehicle when operating in V2G mode (taking into account charging and discharging efficiencies η_v^{CH} and η_v^{DCH}), and the electrical consumption of the vehicle defined as the product between the transportation demand and the average energy consumption F_v expressed in kWh/km.

$$E_{v,m,t+1}^V = E_{v,m,t}^V + \Delta t\left[\eta_v^{\mathrm{CH}} \sum_{s=1}^{\Omega}\left(P_{s,v,m,t}^{S1,V} + P_{s,v,m,t}^{S2,V}\right) - \frac{1}{\eta_v^{\mathrm{DCH}}} \sum_{s=1}^{\Omega}\left(P_{s,v,m,t}^{V,S1} + P_{s,v,m,t}^{V,S2}\right)\right] - D_{v,m,t}^V \cdot F_v, \quad v = 1 \dots V, m = 1 \dots M, t = 1 \dots T-1. \quad (20)$$

Finally, in Equation (21), the operating range of the battery of each vehicle is defined by assuming minimum and maximum values of the state of charge, respectively equal to $SOC_v^{\min}$ and 1, and considering the capacity CAP_v of a single vehicle.

$$SOC_v^{\min} \cdot CAP_v \leq E_{v,m,t}^{V} \leq CAP_v, v = 1 \ldots V, \\ m = 1 \ldots M, t = 1, \ldots T. \quad (21)$$

Note that, if for some technical limitations some vehicles cannot be charged/discharged in some types of charging stations, the corresponding decision variables must be imposed to be equal to 0 in the optimization model.

2.2. The Objective Function. The objective function to be minimized is the annual total cost of the whole smart energy infrastructure, given by the sum of six terms, i.e. the annual total cost of the PV plant, the annual total cost of $B1$ and $B2$ batteries, the annual total cost of $S1$ and $S2$ charging stations and the overall cost related to the power exchange with the distribution grid. For the ith technology, the annual total cost is given by the sum of the capital cost and the maintenance cost $C^{M,i}$, the former being calculated multiplying the purchase and installation cost for the capital recovery factor defined as $\omega^i = r(1+r)^{L^i}/\left((1+r)^{L^i} - 1\right)$, where r is the discount rate and L^i is the useful life of the i-th technology.

Consequently, the objective function can be written as:

$$\min \quad C^{tot,PV} + C^{tot,B1} + C^{tot,B2} + C^{tot,S1} + C^{tot,S2} + C^{tot,G}, \quad (22)$$

where

$$C^{tot,PV} = x^{\mathrm{PV}}\left(\omega^{\mathrm{PV}} c^{I,PV} P^{PV,mod} + C^{M,PV}\right), \quad (23)$$

$$C^{tot,B1} = x^{B1}\left(\omega^{B1} c^{I,B1} CAP^{B1} + C^{M,B1}\right), \quad (24)$$

$$C^{tot,B2} = x^{B2}\left(\omega^{B2} c^{I,B2} CAP^{B2} + C^{M,B2}\right), \quad (25)$$

$$C^{tot,S1} = x^{S1}\left(\omega^{S1} C^{I,S1} + C^{M,S1}\right), \quad (26)$$

$$C^{tot,S2} = x^{S2}\left(\omega^{S2} C^{I,S2} + C^{M,S2}\right), \quad (27)$$

$$C^{tot,G} = K \cdot \sum_{m=1}^{M} \sum_{t=1}^{T} \Delta t\left(P_{m,t}^{abs,G} \cdot p_{m,t} - P_{m,t}^{inj,G} \cdot r_{m,t}\right). \quad (28)$$

Note that, in Equation (23), the capital cost related to the PV plant is calculated considering the purchase and installation cost $c^{I,PV}$ proportional to the PV rated power; in Equations (24) and (25) the purchase and installation cost of batteries depend on $c^{I,B1}$ and $c^{I,B2}$, respectively, which are proportional to the capacity of the battery, while Equations (26) and (27) consider a fixed cost $C^{I,S1}$ and $C^{I,S2}$ per charging station. In Equation (28), the grid cost is evaluated: for each time interval of each typical day, the purchasing cost related to the electricity withdrawn from the grid and the selling revenue due to the electricity injected into the grid are defined, assuming appropriate buying and selling prices ($p_{m,t}$ and $r_{m,t}$).

3. Application of the Optimization Model: Discussion of Results for Different Scenarios

In this section the application of the optimization model to a real test case is described considering different scenarios, each one based on different assumptions. In particular, the test case is represented by a real site located in Liguria Region, in the north of Italy.

A typical day has been selected for each month of the year and the time-dependent data have been defined with a time interval Δt equal to 30 min, in order to accurately represent the variation of the loads, and in particular the EV transportation demand. As a consequence, each time-dependent input quantity is characterized by 48 values (T) for each month.

The optimization model has been used to study different scenarios for the same site; specifically, in the present paper, attention is focused on the following cases:

(i) Case 1—"AS IS scenario": all the electrical demand of the site is completely satisfied by buying electricity from the power distribution grid; in other words, the possible installation of PV modules, storage batteries, and the EV charging stations is not considered.

(ii) Case 2—"Installation of a PV field": the electrical demand of the site can be satisfied by benefitting from the possible installation of a PV field in addition to the already present connection with the power distribution grid.

(iii) Case 3—"Installation of a PV field and storage batteries": the possible installation of storage batteries is considered in order to maximize the self-consumption of PV production.

(iv) Case 4—"Installation of a PV field, storage batteries, and charging stations for EVs": starting from Case 3, this case considers the presence of EVs and the possibility to install charging stations, operating also in V2G mode.

The previous cases are compared through the evaluation of the following indicators: optimal value of the objective function, installation costs, annual maintenance costs, annual grid costs, and optimal values of energy quantities associated with the different technologies.

The following set of technologies has been chosen for the present analysis:

(i) PV modules: Polycrystalline, 250 W peak power, active surface equal to 2.64 m^2, plant average efficiency equal to 12.9%.

(ii) $B1$ storage batteries: Sodium nickel chloride technology, 23 kWh rated capacity of the single battery (ST523 FZSoNick type), maximum charging/discharging power values respectively equal to 6 kW /8 kW, charging/discharging efficiency of 88%.

(iii) *B*2 storage batteries: Lithium ion technology, 40 kWh rated capacity of the single battery (CH75-6 Hitachi model), maximum charging/discharging power equal to 31 kW, charging/discharging efficiency of 90%.

(iv) EV fleet: 3 "Nissan Leaf" vehicles (30 kWh battery rated capacity, Type 1 and CHAdeMO connectors, suitable to be operated in V2G mode, 7.4 kW maximum AC charging power, average consumption equal to 0.166 kWh/km, charging/discharging efficiency equal to 86%) and 2 "Smart fortwo" vehicles (17.6 kWh battery rated capacity, Type 2 connector, not suitable to be operated in V2G mode, 22 kW maximum AC charging power, average consumption equal to 0.129 kWh/km, charging/discharging efficiency equal to 86%).

(v) *S*1 charging station: V2G type, CHAdeMO connector, V2G maximum power equal to 9 kVA, G2V maximum power equal to 10 kW.

(vi) *S*2 charging station: Conventional charging station, Type 2 connector, maximum power equal to 7.4 kW (when charging "Nissan Leaf", an adapter cable is necessary since "Nissan Leaf" has an AC Type 1 connector) and 22 kW (when charging "Smart for two").

Regarding purchase and installation costs, the following values have been assumed: 1000 €/kW for the *PV* technology, 800 €/kWh for *B*1 batteries, 1000 €/kWh for *B*2 batteries, 15000 € for *S*1 charging stations, 1700 € for *S*2 charging stations, 300 € for the adapter cable necessary to charge "Nissan Leaf" in AC mode.

The number of variables involved in the optimization model is 79503 (42624 are continuous, 36874 are binary and 5 are integer), while the number of constraints is equal to 148623. The time required for solving the optimization model is in the range of 7.5–9 min using a personal computer with RAM of 8 GB and a processor AMD FX-7500 Radeon R7.

3.1. Case 1–"AS IS Scenario". In Case 1, all the electrical demand of the site is satisfied by withdrawing electricity from the power distribution grid. Storage batteries, *PV* modules, charging stations and EVs are not taken into account. The value of the objective function is 222 k€/year, whereas the energy absorbed from the grid is 1142 MWh, equal to the annual total demand.

3.2. Case 2–"Installation of a PV Field". This case considers the possibility to install *PV* modules in order to satisfy the electric demand of the site. This leads to the reduction of both the grid costs and the overall objective function. Since there are several months in which the solar radiation is quite high, there are periods during which electricity is injected into the external grid. In particular, the optimal solution is characterized by:

(i) The objective function is 158 k€/year, lower (−29%) than in Case 1.

(ii) The number of installed *PV* modules is 2551, which corresponds to a peak power of 638 kW.

(iii) The total *PV* production, related to 1 year, is equal to 813 MWh.

(iv) The energy absorbed from the grid is 613 MWh, with an annual cost equal to 115 k€.

(v) The energy injected into the grid is 284 MWh, with an annual revenue of 18 k€.

The installation cost of the *PV* modules is equal to 638 k€, while the maintenance cost amounts to about 11 k€ per year. Note that the installation cost is subdivided on the useful life of the *PV* plant (25 year), using an appropriate capital recovery factor.

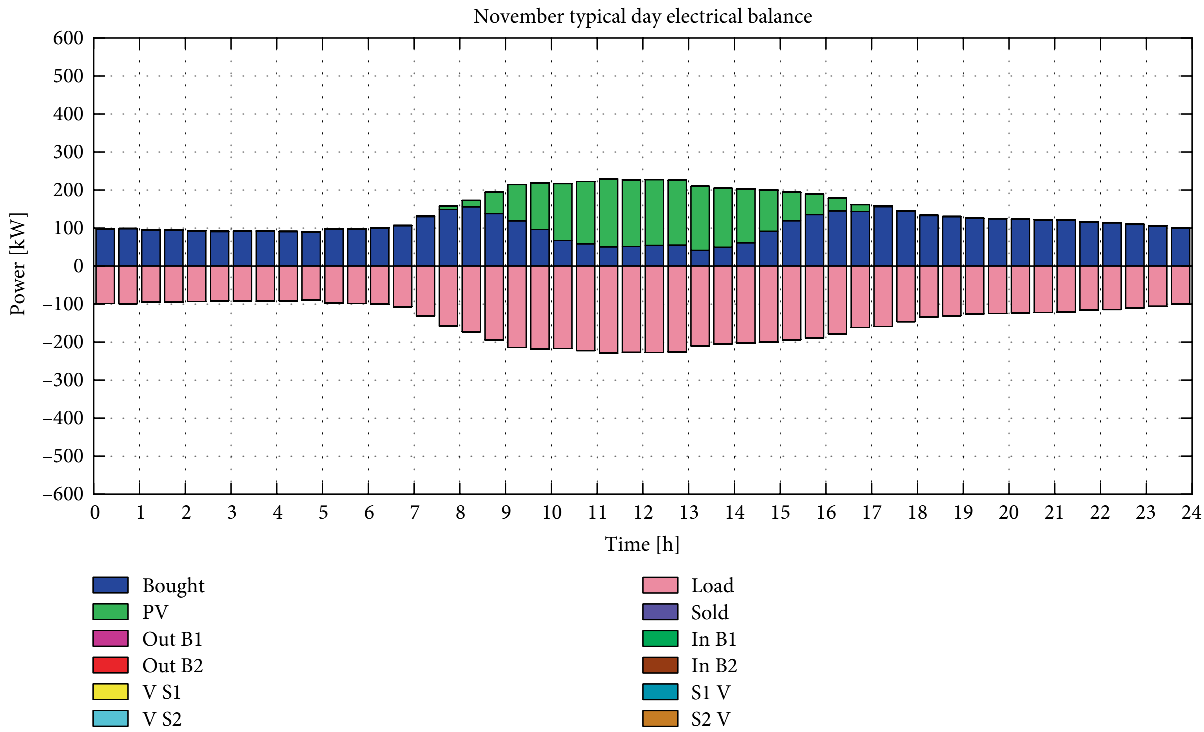
In Figures 1(a) and 1(b), the electrical balance of a typical November and June day is reported. The two graphs, like many other graphs reported in this section, show through coloured bars the power absorbed from the grid ("Bought"), the *PV* power output ("*PV*"), the power absorbed from storage batteries ("Out *B*1" and "Out *B*2"), the power released by EVs ("V *S*1" and "V *S*2"), the electrical load of the site ("Load"), the power injected into the grid ("Sold"), the power transferred to storage batteries ("In *B*1" and "In *B*2"), and the power provided to EVs ("*S*1 V" and "*S*2 V").

Since in November the solar radiation is lower and the *PV* production is not sufficient to completely satisfy the load, the site needs to buy electricity from the grid and no energy is sold (see Figure 1(a)). On the other hand, during summer months, as reported in Figure 1(b), there is a high *PV* production in the central hours of the day; this allows, first of all, to satisfy the electricity demand of the site and, secondly, to inject a significant amount of energy into the grid.

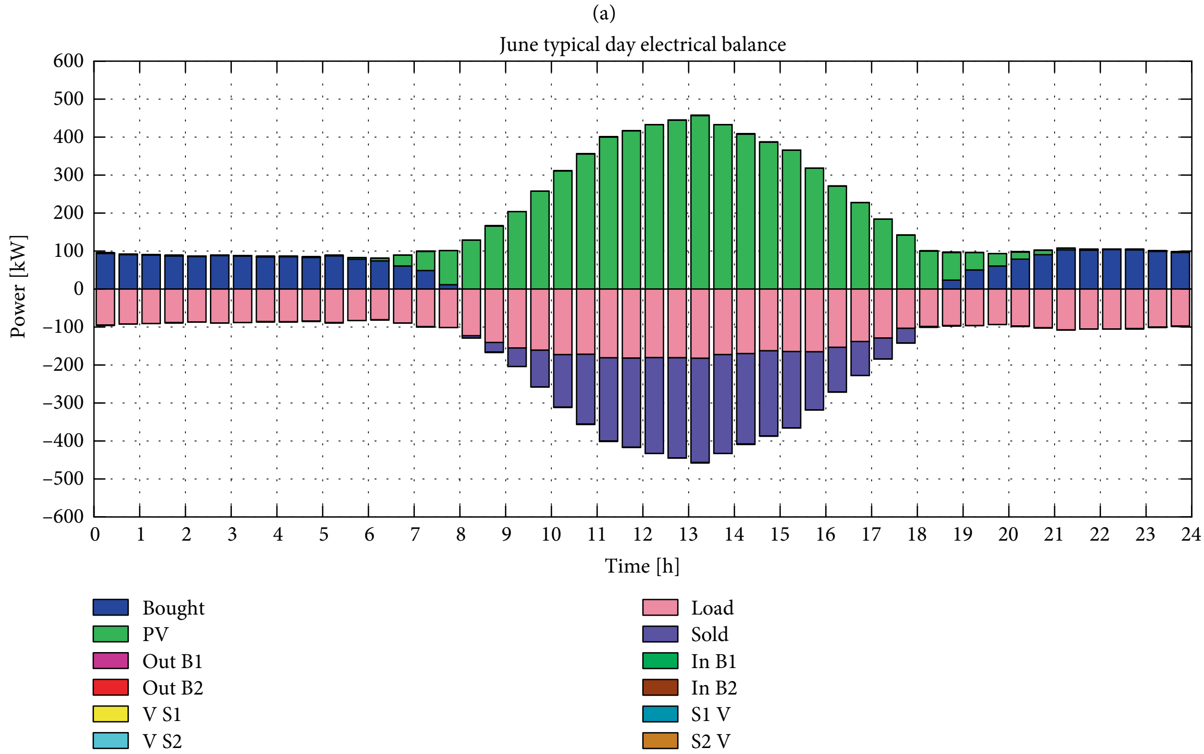
3.3. Case 3–"Installation of a PV Field and Storage Batteries". Case 3 has been studied to consider the possibility of installing *PV* modules and storage batteries. The installation of batteries allows the site to be more autonomous, reducing the overall amount of energy exchanged with the grid in order to better satisfy the load. Currently, the purchasing price of these devices is still very high. Starting from this latter consideration and remembering that the main objective of the optimization problem is the minimization of the overall costs of the system, the amount of battery modules installed in Case 3 is equal to zero, for both types of the considered batteries, when actual prices are considered. Hence, the optimal results of this case are exactly the same as those of Case 2. In order to evaluate the possibility of integrating storage batteries in a smart energy infrastructure, the following subsections discuss two sub-cases, corresponding to a decrease in the prices of the storage systems.

3.3.1. Case 3.1: 50% Reduction of the Storage Battery Prices. The first sub-case refers to a 50% reduction of the battery prices, thus assuming 400 €/kWh and 500 €/kWh, respectively for *B*1 and *B*2. Even if the prices have been halved, no batteries are installed. As a consequence, the optimal results remain similar to those of Case 2.

3.3.2. Case 3.2: 75% Reduction of the Storage Battery Prices. A second sub-case corresponds to a 75% reduction of the battery prices, i.e., 200 €/kWh and 250 €/kWh, respectively for *B*1 and



(a)



(b)

FIGURE 1: (a) November day electrical balance for Case 2, (b) June day electrical balance for Case 2.

*B*2. In this case, some *B*2 batteries are installed. In particular, the optimal results indicate that:

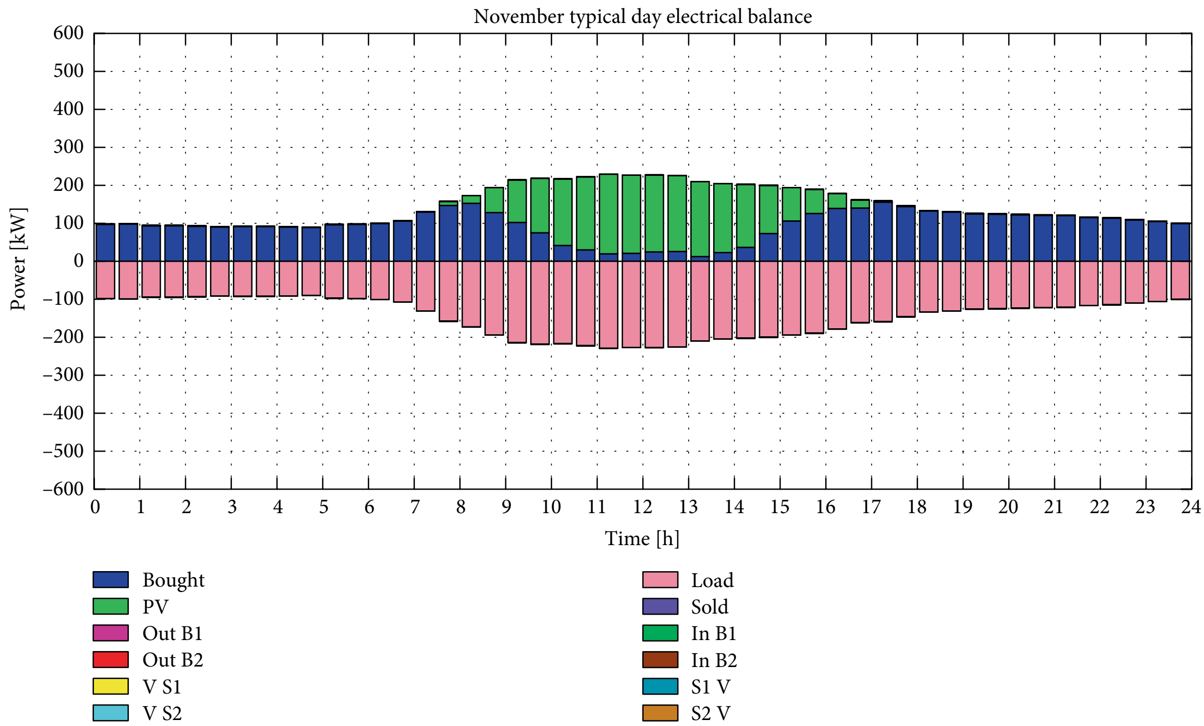
(i) The objective function is 157 k€/year, lower (−0.8%) than in Case 2.

(ii) The number of installed *PV* modules is 2989, having a peak power of 747 kW, 17% higher than in Case 2.

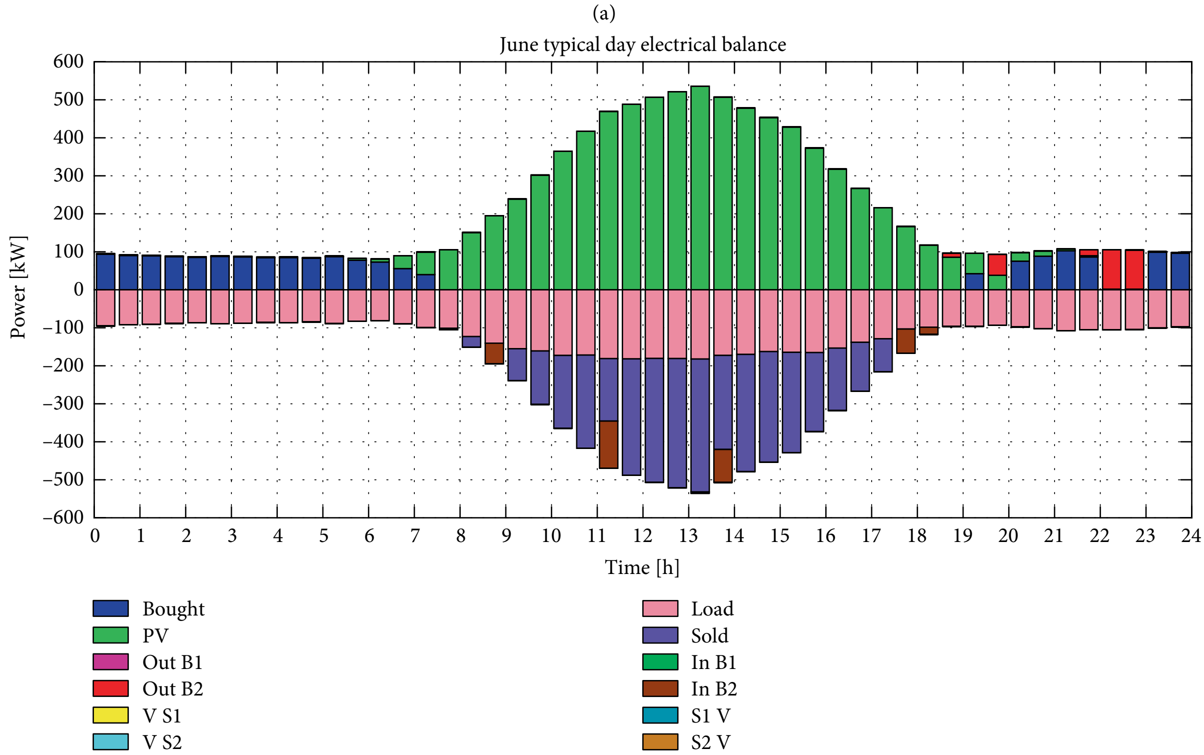
(iii) The annual *PV* production is equal to 952 MWh.

(iv) The energy absorbed from the grid is 547 MWh (−10.8% with respect to Case 2), corresponding to an annual cost of 102 k€.

(v) The energy injected into the grid is 349 MWh (+22.9% with respect to Case 2), determining an annual revenue of 22 k€.



(a)



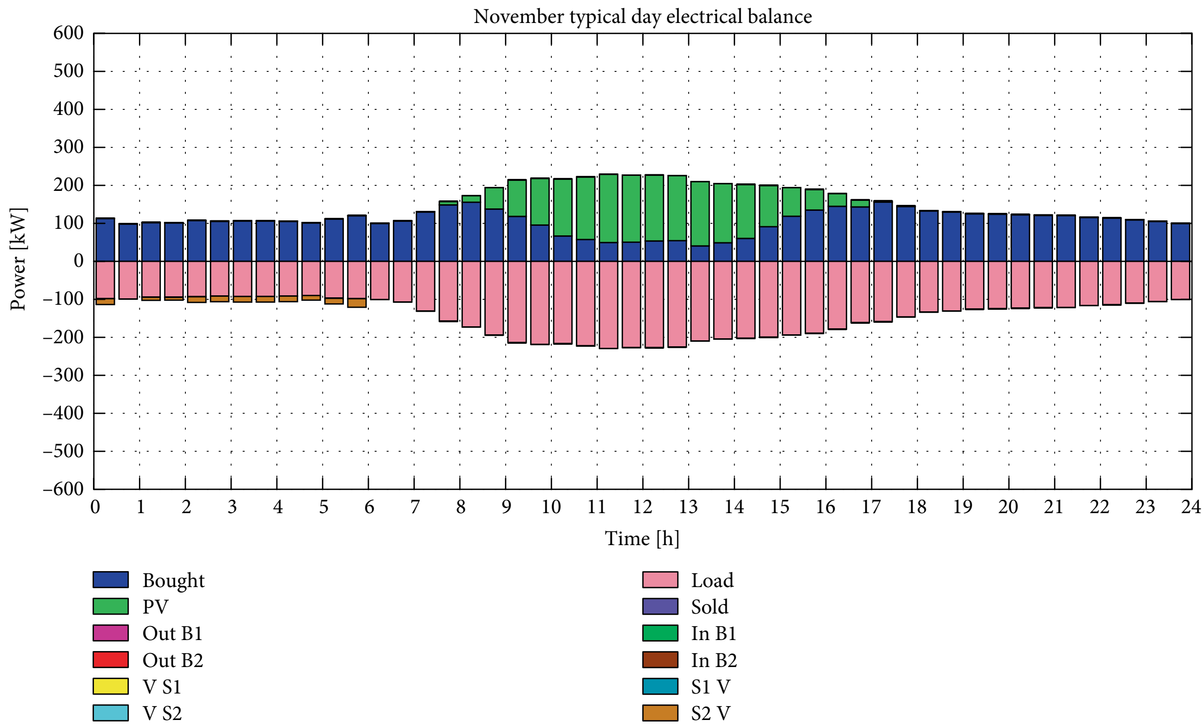
(b)

Figure 2: (a) November day electrical balance for Case 3.2. (b) June day electrical balance for Case 3.2.

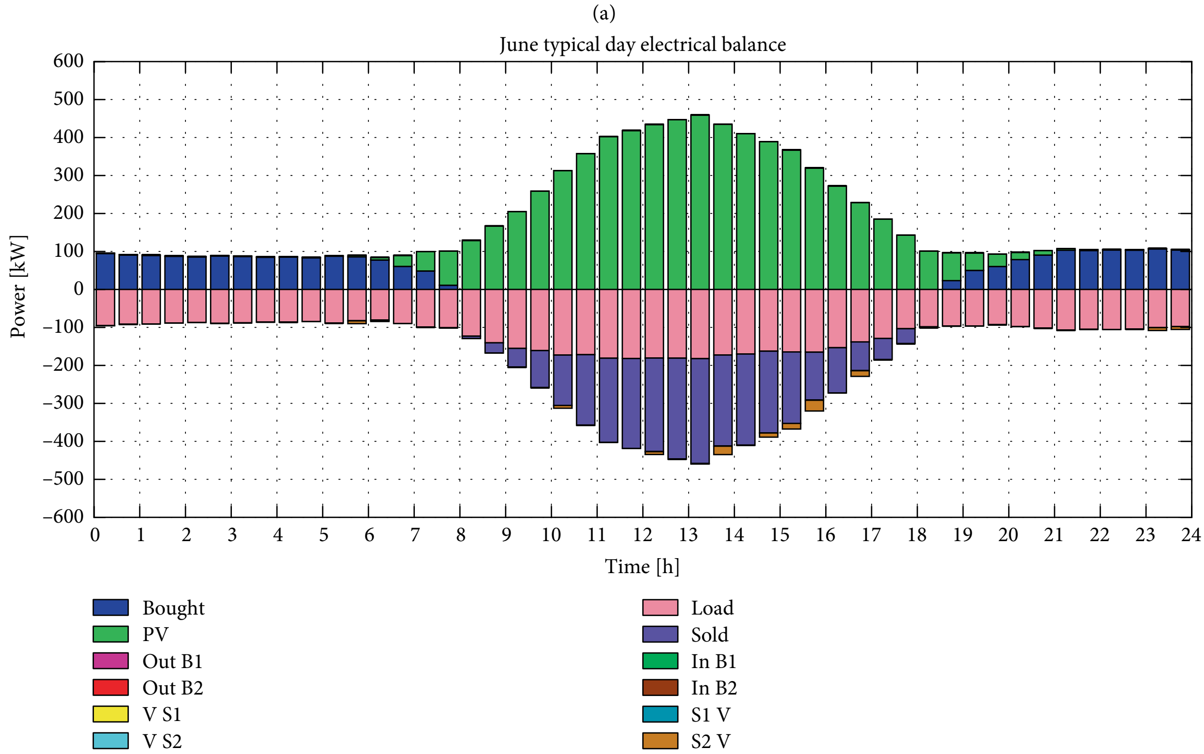
(vi) The total number of installed *B*2 batteries is equal to 4, with a total capacity of 160 kWh.

The installation cost of the *PV* modules is equal to 747 k€, whereas their annual maintenance cost is about 13.5 k€. The purchase and installation cost of storage batteries is near 40 k€, while their annual maintenance cost amounts to a value of 1.6 k€.

The objective function in Case 3.2 is a bit lower than in Case 2, and other differences can be highlighted. First of all, there is an increase of the *PV* plant size (adding 438 modules), with some lithium ion storage batteries installed. In this way,



(a)

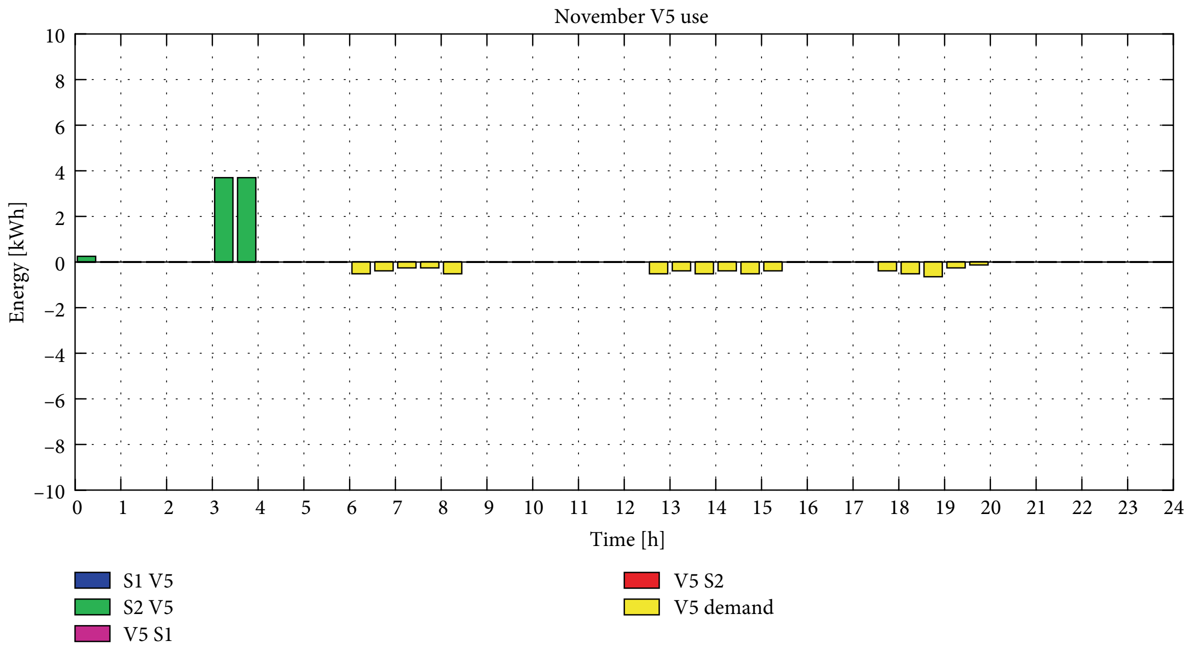


(b)

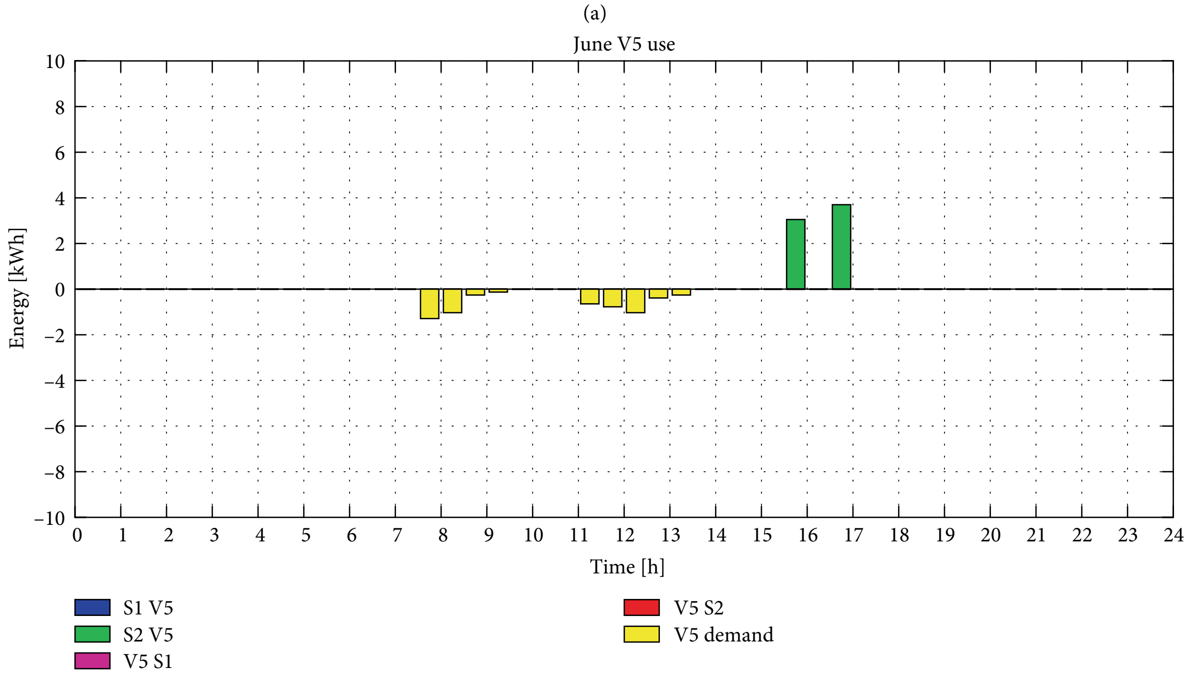
Figure 3: (a) November day electrical balance for Case 4. (b) June day electrical balance for Case 4.

the smart energy infrastructure is able to produce a surplus of energy that can be stored in the batteries and used to satisfy the load, thus avoiding to buy energy from the grid in some hours of the day. Indeed, the energy absorbed from the grid is lower than in Case 2 and more energy is sold; consequently, the energy bill of the site decreases of about 17 k€ (−17.5%).

An important consideration is that, even if a reduction of the purchasing prices for both battery types has been considered, the optimal solution suggests to install only lithium ions batteries, setting the number of sodium nickel chloride batteries equal to zero. This result can be explained considering that sodium nickel chloride batteries are cheaper than lithium ions



(a)



(b)

Figure 4: (a) November day electrical profiles for one "Nissan Leaf" in Case 4. (b) June day electrical profiles for one "Nissan Leaf" in Case 4.

batteries, but they have a storage capacity which is half of the lithium ions battery capacity and they are able to exchange lower values of charging/discharging power.

In Figure 2(a), the electrical balance of November is reported, whereas that of June is shown in Figure 2(b). It should be noted that storage batteries are not used during November since the *PV* production is not so high and, consequently, at every hour of the day energy has to be withdrawn from the external grid in order to satisfy the load; in other words, there is no surplus production to charge the storage system. On the other hand, during summer, the *PV* production is very high and the batteries are well exploited, during the central hours of the day, to store energy than can be used in the evening in order to reduce the amount of energy bought from the grid.

3.4. Case 4–"Installation of a PV Field, Storage Batteries and Charging Stations for EVs". Case 4 has been developed adding a certain transportation demand for a fixed number of EVs present within the site that, as previously mentioned, consist of three "Nissan Leaf" and two "Smart for two" vehicles. For this reason, a charging infrastructure has to be installed in this

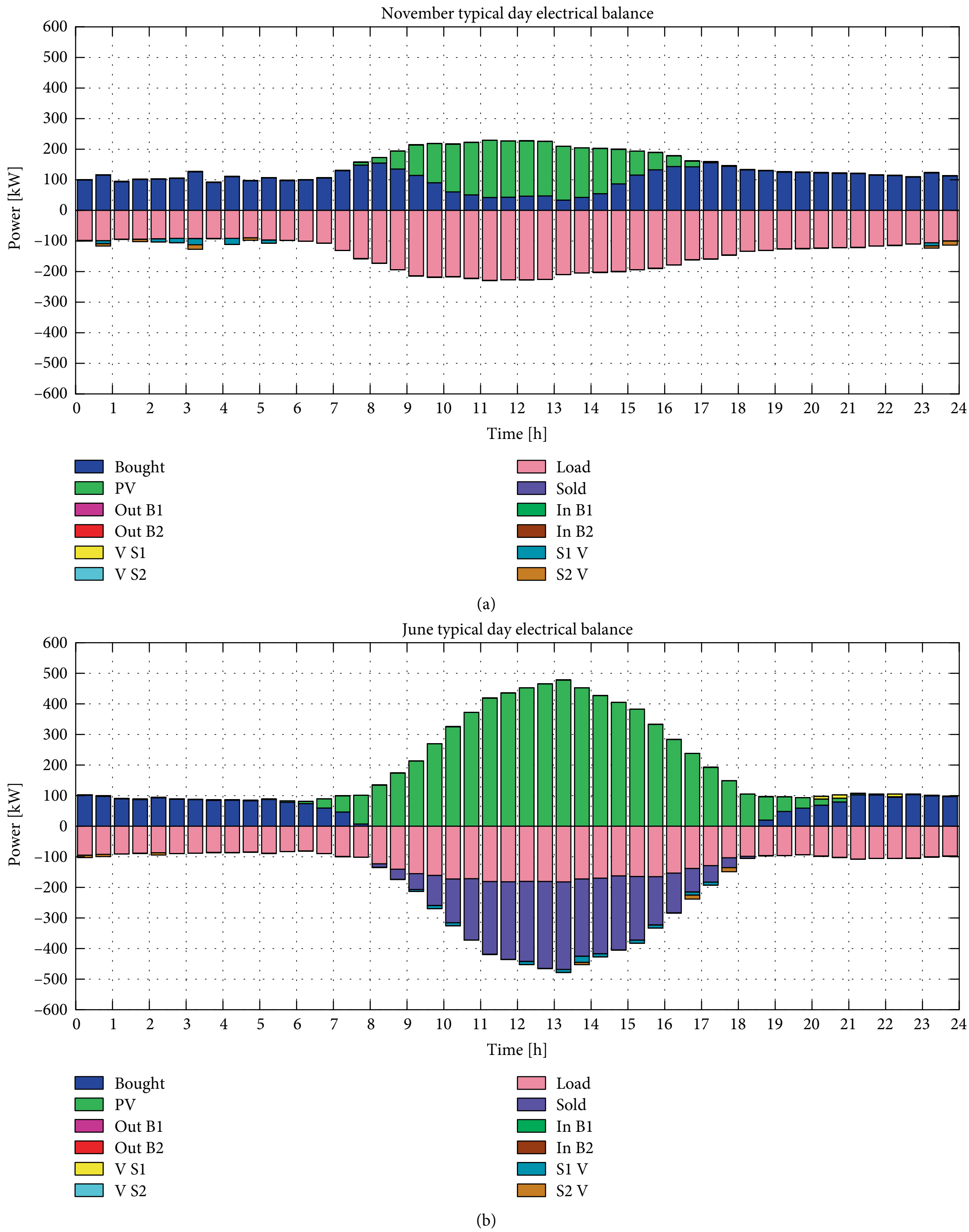


Figure 5: (a) November day electrical profiles for Case 4.1. (b) June day electrical profiles for Case 4.1.

case: in particular, the optimization model has to define the optimal number of charging stations required to satisfy the transportation demand.

Case 4 is the most interesting scenario, because it integrates the highest number of technologies. Furthermore, this case is also innovative since it considers the application of V2G technologies, nowadays under research and development, within a smart urban context.

Case 4 considers the real prices of storage batteries and EV charging stations. In particular, the price of the conventional charging stations is extremely lower than the price of V2G charging stations. For this reason, in the present case,

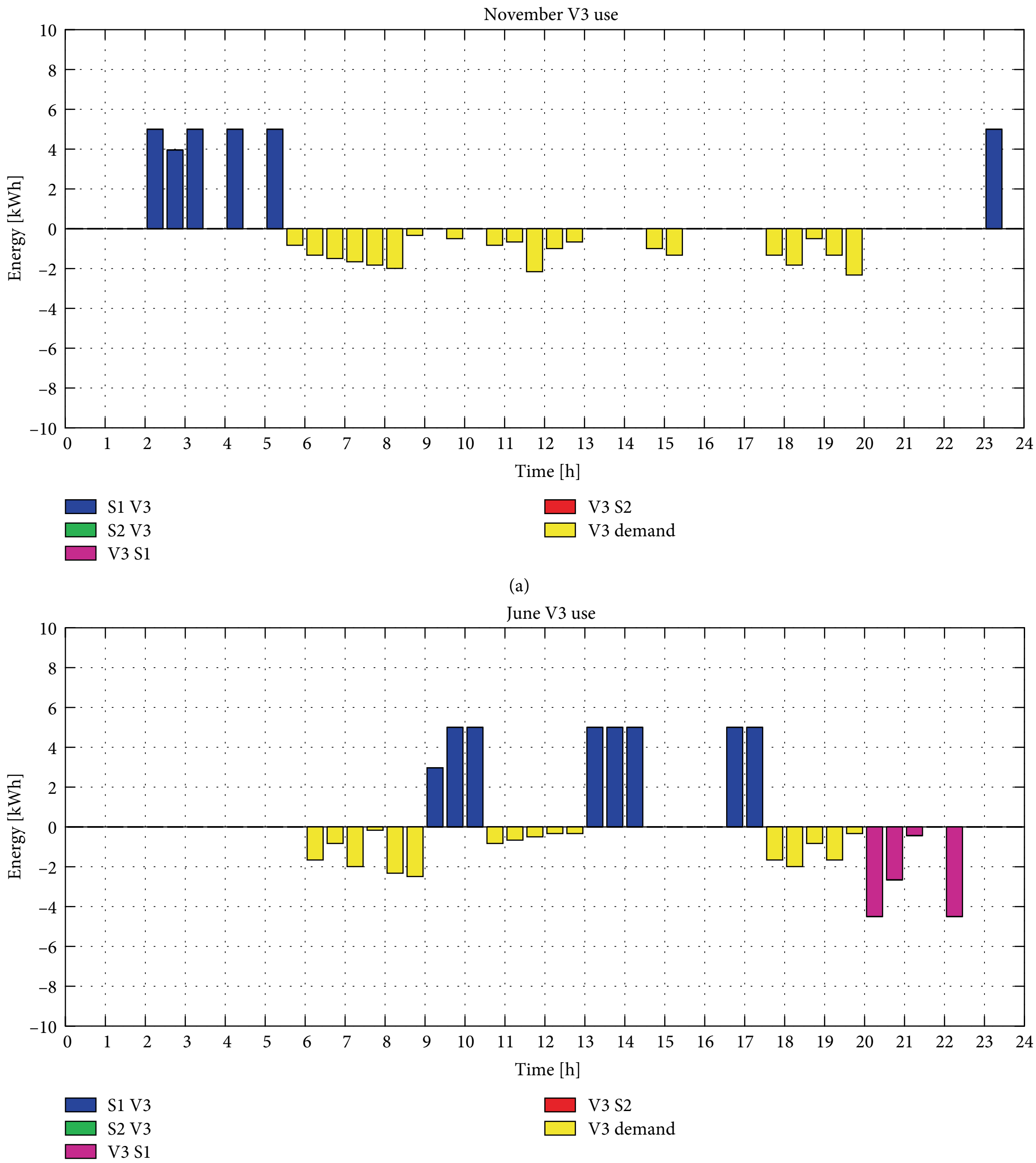


Figure 6: (a) November day electrical profiles for one "Nissan Leaf" in Case 4.1. (b) June day electrical profiles for one "Nissan Leaf" in Case 4.1.

only conventional charging stations are installed. As described in Case 3, the current prices of both types of battery systems are quite high; consequently, none of them is installed in the optimal configuration of the site. The optimal results are the following:

(i) The objective function is 163 k€/year (3% lower than in Cases 2 and 3, 27% lower than in Case 1).

(ii) The number of installed *PV* modules is 2563, with a peak power of 641 kW, similar to Cases 2 and 3, corresponding to an annual *PV* production of 816 MWh.

(iii) The energy absorbed from the grid is 623 MWh, corresponding to an annual cost equal to 117 k€.

(iv) The energy injected into the grid is 277 MWh, corresponding to an annual revenue of 18 k€.

(v) The number of installed conventional charging stations is 5, with an installation cost equal to 10 k€ and an annual maintenance cost of about 1 k€; the energy released by them corresponds to 20 MWh.

The installation cost of the *PV* modules is equal to 641 k€ and the annual maintenance cost is around 12 k€. It is possible to note that the objective function is slightly higher than in Cases

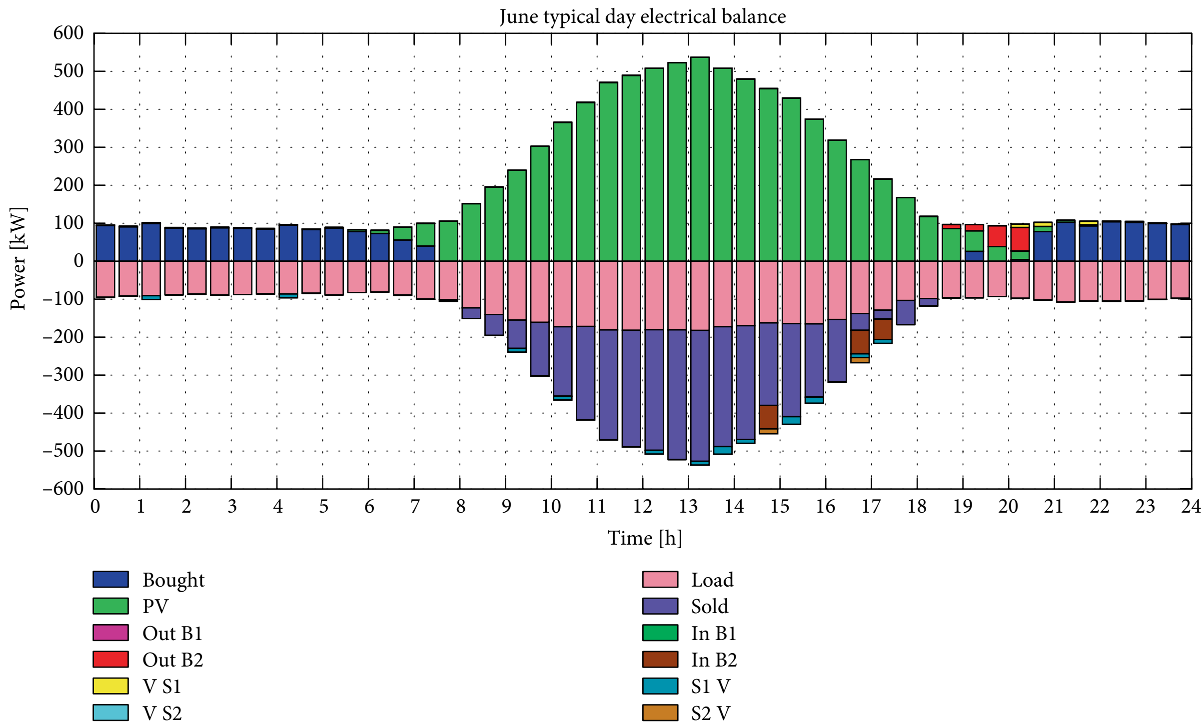


Figure 7: June day electrical profiles for Case 4.2.

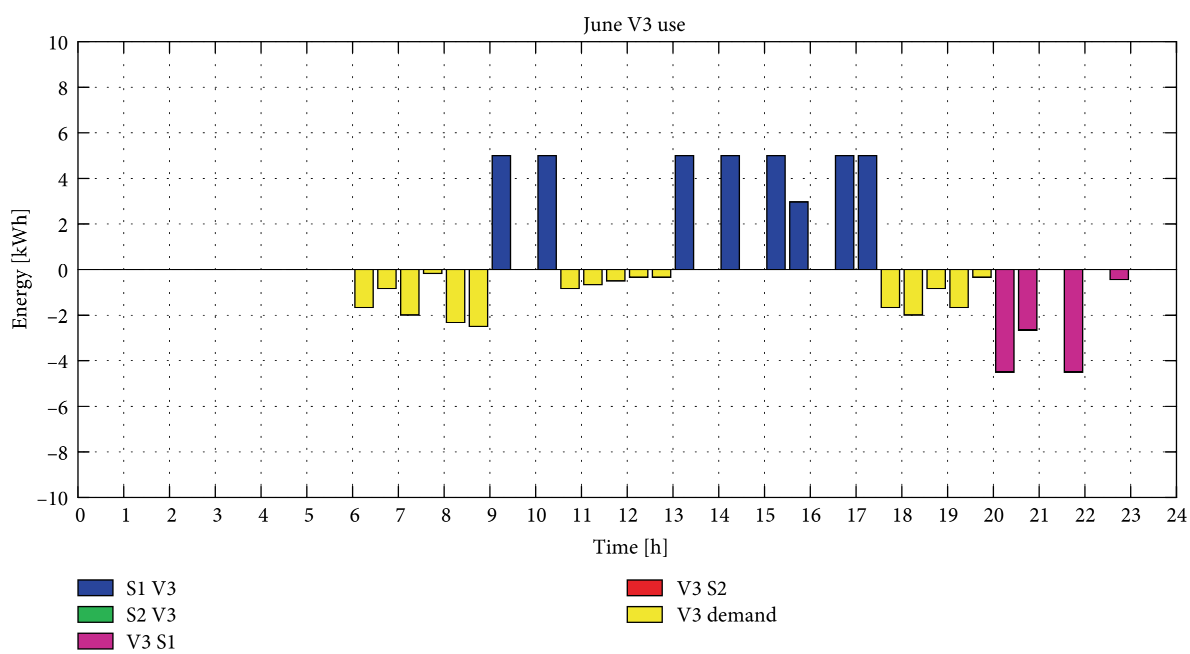


Figure 8: June day electrical profiles for one "Nissan Leaf" in Case 4.2.

2 and 3, and obviously lower than in Case 1 (where the external grid is the unique energy source). This is mainly due to the installation cost of charging stations, which are not considered in the other cases. The number of *PV* modules is higher than in Cases 2 and 3, since the overall electrical demand is increased because of the transportation demand of EVs. For the same motivation, the energy absorbed from the grid is higher, whereas the one injected into the grid is lower, thus confirming the increased value of the objective function.

The electrical balance of the November typical day is shown in Figure 3(a), whereas Figure 3(b) is relative to the June day. During June, the *PV* production in the central hours of the day is high enough to satisfy the electrical demand of the site, and the surplus production is injected into the external grid. The absence of batteries determines the need to buy energy in the remaining hours.

As far as the EV charging is concerned, EVs are charged when electricity prices are lower, especially during the night of the November day, or when the *PV* production attains higher values. In Figures 4(a) and 4(b), the charging profile and the energy consumption during traveling of one of the three "Nissan Leaf" are reported. Obviously, since no V2G charging stations are installed, the vehicle can only be charged, without the possibility to act as a storage system.

In order to analyze the role of storage batteries and V2G charging stations within the site, some sub-cases characterized by the reduction of purchase and installation costs of the aforementioned technologies are investigated. In particular, 50% and 75% price reductions are considered for storage batteries and V2G charging stations, while real prices are taken for the *PV* technology and the conventional EV charging stations.

3.4.1. Case 4.1: 50% Reduction of Batteries and V2G Charging Stations Prices. Considering a 50% reduction of prices for batteries and V2G charging stations, the obtained optimal results are:

(i) The objective function is 162 k€/year.

(ii) The number of installed *PV* modules is 2668, with a total peak power of 667 kW, corresponding to an annual *PV* production equal to 850 MWh; the installation cost of the *PV* modules is 667 k€ and the maintenance cost amounts to 12 k€/year.

(iii) No storage batteries are installed.

(iv) The energy absorbed from the grid is 609 MWh, giving an annual expense of 114 k€.

(v) The energy injected into the grid is 294 MWh, corresponding to an annual revenue of 19 k€.

(vi) The number of installed V2G charging stations is 2 and the energy released by these stations to the EVs is about 19 MWh, whereas the energy provided by the vehicles when operated in V2G mode amounts to 5 MWh.

(vii) The number of installed conventional charging stations is 3; they provide 8 MWh to annually charge the vehicles.

First, it is possible to note that, in the present case, both types of stations are installed, due to the reduction of the V2G charging station price. Compared to Case 4, the number of installed conventional charging stations is lower, since there is the possibility to charge the Nissan vehicles also using V2G stations.

The optimal value of the objective function is very close to the one of Case 4. This is explained by considering that, on the one hand, the V2G option allows to absorb energy from the vehicles that are not completely discharged, thus determining a consequent reduction of the energy acquired from the grid, but, on the other hand, the reduction of the objective function is mitigated since V2G stations are more expensive than conventional ones. Another aspect that keeps the objective function almost unchanged is that, even if the prices are reduced, no batteries are installed, because the prices are still too high. The electrical balances, respectively for November and June, are reported in Figures 5(a) and 5(b).

Referring to the summer day, the *PV* production in the central hours of the day is high enough to satisfy the electrical load and the surplus is sold. At the beginning and in the central hours of the day (from midnight to 2:30 p.m. and from 9:30 a.m. to 6 p.m.), a certain amount of energy is delivered to the EVs since some vehicles are not travelling. Instead, at the end of the day (from 8 p.m. to 9 p.m. and from 10 p.m. to 10:30 p.m.) some vehicles are discharged, being operated in V2G mode. On the other hand, during the winter day, the *PV* production in the central hours of the day is not high enough to completely satisfy the electrical demand; consequently, a certain amount of energy is absorbed from the external grid. The absence of batteries determines the need to buy energy at the beginning and at the end of the day in order to fulfill the site load and also the EV transportation demand. For instance, from midnight to 5 a.m., a certain amount of energy is delivered to the EVs by conventional and V2G stations. Then, in the central hours of the day, the vehicles travel and then come back to the charging points at the end of the day; for example, from 11 p.m. to midnight, the vehicles are recharged.

The charging and discharging of a Nissan vehicle is depicted in Figures 6(a) and 6(b). It is worth noting that the transportation demand is quite low and, for this reason, in June the optimal solution corresponds to charge the vehicle with an amount of energy larger than what is required for the transportation in order to operate the vehicle in V2G mode (from 8 p.m. to 10:30 p.m.). In this way, the vehicle operates as a mobile storage system reducing the dependence of the smart energy infrastructure on the external grid.

3.4.2. Case 4.2: 75% Reduction of Batteries and V2G Charging Stations Prices. With a 75% reduction of prices for batteries and V2G charging stations, the optimal results can be summarized as follows:

(i) The objective function is 160 k€/year.

(ii) The number of installed *PV* modules is 2996, corresponding to a total peak power of 749 kW, very close to the one registered in Case 3.2, and annual *PV* production of 954 MWh; the installation cost of the *PV* modules is 749 k€, while the annual maintenance cost is 13 k€.

(iii) The energy absorbed from the grid is 566 MWh, which implies an annual cost of 105 k€.

(iv) The energy injected into the grid is 351 MWh, with an annual revenue of 22 k€.

(v) The number of installed V2G charging stations is 3; they release 25 MWh when they are used to charge the vehicles, while they provide 7 MWh when operated in V2G mode.

Table 1: Optimal size of technologies.

Case of study	No. of *PV* modules	*PV* rated power [kW]	No. of *B*1 batteries	*B*1 installed capacity [kWh]	No. of *B*2 batteries	*B*2 installed capacity [kWh]	No. of *S*1 stations	No. of *S*2 stations
Case 1	0	0	0	0	0	0	0	0
Case 2	2551	638	0	0	0	0	0	0
Case 3	2551	638	0	0	0	0	0	0
Case 3.1	2551	638	0	0	0	0	0	0
Case 3.2	2989	747	0	0	4	160	0	0
Case 4	2563	641	0	0	0	0	0	5
Case 4.1	2668	667	0	0	0	0	2	3
Case 4.2	2996	749	0	0	2	80	3	2
Case 4.3	2871	718	0	0	1	40	3	2

Table 2: Optimal economic values.

Case of study	Objective function [k€]	Purchase & installation costs [k€]					Annual operating costs/revenues [k€]	
		PV	B1	B2	S1	S2	For energy absorbed from the grid	For energy injected into the grid
Case 1	222	0	0	0	0	0	222	0
Case 2	158	638	0	0	0	0	115	18
Case 3	158	638	0	0	0	0	115	18
Case 3.1	158	638	0	0	0	0	115	18
Case 3.2	157	748	0	40	0	0	102	22
Case 4	163	641	0	0	0	10	117	18
Case 4.1	162	667	0	0	15	6	114	19
Case 4.2	160	749	0	21	11	4	105	22
Case 4.3	162	718	0	16	18	4	109	21

Table 3: Optimal energy values.

Case of study	Annual *PV* production [MWh]	Annual energy injected into the grid [MWh]	Annual energy absorbed from the grid [MWh]	Annual energy transferred from *S1* stations to EVs [MWh]	Annual energy transferred from EVs to *S1* stations [MWh]	Annual energy transferred from *S2* stations to EVs [MWh]
Case 1	0	0	1142	0	0	0
Case 2	813	284	613	0	0	0
Case 3	813	284	613	0	0	0
Case 3.1	813	284	613	0	0	0
Case 3.2	952	349	547	0	0	0
Case 4	816	277	623	0	0	20
Case 4.1	850	294	609	19	5	8
Case 4.2	954	351	566	25	7	4
Case 4.3	915	331	583	25	7	4

(vi) The number of installed conventional charging stations is 2, and they are used to charge around 4 MWh into the vehicles.

(vii) The total number of lithium ions batteries installed is 2 with a total capacity of 80 kWh.

The objective function is lower than the one of Case 4 and the size of the *PV* plant is very similar to Case 3.2, where four batteries are installed. In the present case, on the contrary, only two batteries are adopted since vehicles also act as storage systems. No sodium nickel chloride batteries are installed for the same reasons reported for Case 3.2.

The daily management of the different technologies is highlighted in Figure 7 referring to the summer typical day. It is possible to note that the EVs are mainly charged when the *PV* production is higher and then used in V2G mode during the evening. Storage batteries are preferably charged during the afternoon and discharged during the evening, when the *PV* production decreases. A consistent amount of electricity is injected into the grid. For the same month, the energy profiles of one of the Nissan vehicles is shown in Figure 8. The charging is concentrated when there is a high *PV* production and the vehicle is parked, whereas the discharging occurs from 8 p.m. to 11 p.m.

3.4.3. Case 4.3: At Which Price Do Lithium Ions Batteries Become Cost-Effective? Several tests have been performed considering different storage battery price reductions in the range between 50% and 75% of the current market prices. The installation of Lithium Ions batteries becomes cost-effective when the price reduction is equal to 60%, that is when it is around 400 €/kWh. In such a condition, again, the batteries of the other type are not installed for the technical and economic reasons described before.

In particular, with a 60% reduction of lithium ions battery prices, the results of the optimization problem are:

(i) The objective function is 162 k€/year.
(ii) The number of installed *PV* modules is 2871, giving a peak power of 718 kW and an annual *PV* production of 915 MWh; the installation cost of the *PV* plant is 718 k€ and the annual maintenance cost is 13 k€.
(iii) The energy absorbed from the grid is 583 MWh, corresponding to a cost of 109 k€.
(iv) The energy injected into the grid is 331 MWh, giving an annual revenue of 21 k€.
(v) The number of installed V2G charging stations is 3; they transfer 25 MWh to the EVs, while these latter are used in V2G mode to provide 7 MWh to the site.
(vi) The number of installed conventional charging stations is 2 and the energy released by them is 4 MWh.
(vii) Only 1 lithium ions battery is installed, having a total capacity of 40 kWh.

Even if the overall costs are different from the other cases, the management of the smart energy infrastructure does not undergo relevant differences, and so daily electrical balances and EV charging/discharging profiles are very similar to those of Case 4.2.

3.5. Comparison of Results. In Tables 1–3 the main results of the study are reported referring to the nine analyzed cases. In particular, the optimal size of the technologies is shown in Table 1, whereas Table 2 reports purchase and installation costs, as well as operating costs, together with the optimal values of the objective function. Finally, in Table 3 the focus is on annual energy quantities: production of the *PV* plant, exchange with the power distribution grid, and energy exchanged with EVs.

4. Conclusions

The main goal of the present work has been the formulation of an optimization model for the design of a smart energy infrastructure, within an urban area, that integrates different on-site generation systems to satisfy the electrical loads and that is connected to the power distribution grid. The considered technologies are *PV* and storage batteries; moreover, EVs with charging stations are also accounted for, as the main aim of the study is the evaluation of the role of the electric mobility within a smart energy infrastructure. The optimization model is formulated in order to minimize purchase, installation and maintenance costs of the aforementioned technologies and the costs related to the energy exchange with the external grid.

Several cases, based on different assumptions, have been analysed and optimized. In Case 1 (As-IS scenario), all the electrical demands of the site are completely satisfied withdrawing electricity from the external grid without considering the possibility to install *PV* plants and storage systems; the presence of EVs and charging stations is not considered. In Case 2, the electrical demand of the site can be satisfied by a *PV* field in addition to the connection with the external grid. Then, Case 3 considers the possibility to couple a storage system with the *PV* plant. Finally, in Case 4, electric mobility is also taken into account.

It is important to highlight that all the cases permit to decrease the energy bill of the site. More in general, all the treated scenarios allow to reduce the operating costs, if compared with the case in which all the energy is bought from the external grid. This is an important point because it confirms that the accurate design of a smart energy infrastructure, such as the one proposed in this work, allows to decrease the overall cost, in addition to determining environmental benefits. In particular, there is a reduction of fossil fuel utilization because of the use of technologies based on the exploitation of renewable sources; moreover, a significant reduction of transportation emissions can be obtained through the use of EVs powered by energy mainly produced from renewable sources.

Nowadays, the main barriers to the large scale deployment of a smart energy infrastructure are the still high capital cost of storage systems. Furthermore, the technologies related to electric mobility and, in particular, the charging stations able to operate in V2G mode are still too expensive and standardization issues remain to be solved.

Starting from the study proposed here, it is possible to foresee a series of future developments. One improvement can be the integration of other technologies based on the exploitation of renewable sources (for instance, wind microturbines, geothermal heat pumps, cogeneration units fuelled by biogas, hydro microturbines, etc.). These technologies could permit to increase the amount of energy locally produced and to reduce carbon dioxide emissions. Moreover, a second enhancement could be the development of an optimization model for different interconnected sites where EVs can be recharged or can release energy when managed in V2G mode. Finally, EV smart charging strategies could be included in the optimization model, also computing charging costs and discharging revenues.

Appendix

List of the decision variables of the optimization problem.

A. Connection to the Power Distribution Grid

(i) $P_{m,t}^{inj,G}$: power injected into the grid in month m, at time $t [kW], m = 1 \dots M, t = 1 \dots T$,

(ii) $P^{abs,G}_{m,t}$: power absorbed from the grid in month m, at time $t[kW], m = 1 \ldots M, t = 1 \ldots T$.

B. PV Plant

(i) x^{PV}: number of PV modules $[-]$;
(ii) $P^{PV}_{m,t}$: power output of PV plant in month m, at time $t[kW], m = 1 \ldots M, t = 1 \ldots T$.

C. Energy Storage System

(i) x^{B1}: number of $B1$ batteries to be installed $[-]$;
(ii) x^{B2}: number of $B2$ batteries to be installed $[-]$;
(iii) $P^{in,B1}_{m,t}$: power injected into $B1$ batteries in month m, at time $t[kW],\ m = 1 \ldots M, t = 1 \ldots T$;
(iv) $P^{in,B2}_{m,t}$: power injected into $B2$ batteries in month m, at time $t[kW], m = 1 \ldots M, t = 1 \ldots T$;
(v) $P^{out,B1}_{m,t}$: power withdrawn from $B1$ batteries in month m, at time $t[kW], m = 1 \ldots M, t = 1 \ldots T$;
(vi) $P^{out,B2}_{m,t}$: power withdrawn from $B2$ batteries in month m, at time $t[kW], m = 1 \ldots M, t = 1 \ldots T$;
(vii) $E^{B1}_{m,t}$: energy stored in $B1$ batteries in month m, at time $t[kWh], m = 1 \ldots M, t = 1 \ldots T$;
(viii) $E^{B2}_{m,t}$: energy stored in $B2$ batteries in month m, at time $t[kWh], m = 1 \ldots M, t = 1 \ldots T$;
(ix) $y^{in,B1}_{m,t}$: binary variable equal to 1 if $B1$ battery is charging in month m, at time t, and equal to 0 otherwise, $m = 1 \ldots M, t = 1 \ldots T$;
(x) $y^{in,B2}_{m,t}$: binary variable equal to 1 if $B2$ battery is charging in month m, at time t, and equal to 0 otherwise, $m = 1 \ldots M, t = 1 \ldots T$;
(xi) $y^{out,B1}_{m,t}$: binary variable equal to 1 if $B1$ battery is discharging in month m, at time t, and equal to 0 otherwise, $m = 1 \ldots M, t = 1 \ldots T$;
(xii) $y^{out,B2}_{m,t}$: binary variable equal to 1 if $B2$ battery is discharging in month m, at time t, and equal to 0 otherwise, $m = 1 \ldots M, t = 1 \ldots T$.

D. Charging Stations and EVs

(i) x^{S1}: number of $S1$ charging stations to be installed $[-]$;
(ii) x^{S2}: number of $S2$ charging stations to be installed $[-]$;
(iii) $P^{S1,V}_{s,v,m,t}$: power from charging station s of type $S1$ to vehicle v, in month m, at time t $[kW], s = 1 \ldots \Omega, v = 1 \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(iv) $P^{S2,V}_{s,v,m,t}$: power from charging station s of type $S2$ to vehicle v, in month m, at time t $[kW], s = 1 \ldots \Omega, v = 1 \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(v) $y^{S1,V}_{s,v,m,t}$: binary variable equal to 1 if power is transferred from charging station s of type $S1$ to vehicle v, in month m, at time t, and equal to 0 otherwise, $s = 1 \ldots \Omega, v = 1 \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(vi) $y^{S2,V}_{s,v,m,t}$: binary variable equal to 1 if power is transferred from charging station s of type $S2$ to vehicle v, in month m, at time t, and equal to 0 otherwise, $s = 1 \ldots \Omega, v = 1 \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(vii) $P^{V,S1}_{s,v,m,t}$: power from vehicle v to charging station s of type $S1$, in month m, at time t $[kW], s = 1 \ldots \Omega, v = 1 \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(viii) $P^{V,S2}_{s,v,m,t}$: power from vehicle v to charging station s of type $S2$, in month m, at time t $[kW], s = 1 \ldots \Omega, v = 1 \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(ix) $y^{V,S1}_{s,v,m,t}$: binary variable equal to 1 if power is transferred from vehicle v to charging station s of type $S1$, in month m, at time t, and equal to 0 otherwise, $s = 1 \ldots \Omega, \nu = 1 \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(x) $y^{V,S2}_{s,v,m,t}$: binary variable equal to 1 if power is transferred from vehicle v to charging station s of type $S2$, in month m, at time t, and equal to 0 otherwise, $s = 1 \ldots \Omega, \nu = \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(xi) $E^{V}_{v,m,t}$: energy stored in the battery of vehicle v in month m, at time $t[kWh], v = 1 \ldots V, m = 1 \ldots M, t = 1 \ldots T$;
(xii) z^{S1}_{s}: binary variable equal to 1 if the charging station s of type $S1$ is installed, and equal to 0 otherwise;
(xiii) z^{S2}_{s}: binary variable equal to 1 if the charging station s of type $S2$ is installed, and equal to 0 otherwise.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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