Optimal battery management for vehicle-to-home and vehicle-to-grid operations in a residential case study

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Paolo Lazzeroni[a,*], Sergio Olivero[a], Maurizio Repetto[b], Federico Stirano[a], Marc Vallet[c]

[a]*Fondazione LINKS - Leading Innovation & Knowledge for Society*
Via Pier Carlo Boggio, 61, 10138, Torino, Italy
[b]*Politecnico di Torino - Dipartimento Energia "Galileo Ferraris"*
Corso Duca degli Abruzzi, 24, 10129, Torino, Italy
[c]*École Supérieure d'Électricité - SUPELEC*
3 Rue Joliot Curie, 91190, Gif-sur-Yvette, France

Abstract

In the mobility sector Electric Vehicles represent one of the main opportunities to ensure strong reduction of local pollution. However, their higher costs compared to gas-fuelled cars are still a barrier for their large diffusions. One possible solutions to increase EVs penetration is their use as storage within households equipped with Renewable Energy Sources enabling a flexible energy management, for instance by the Vehicle-to-Grid and/or Vehicle-to-Home scheme.

The aim of this paper is to investigate possible management of the EV battery through an optimization approach capable to minimize the electricity supply costs for an Italian residential end-user with PV, considering battery constraints, such as driving habits. A statistical approach of

*Corresponding author
Email address: `paolo.lazzeroni@polito.it` (Paolo Lazzeroni)

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driver behavior is integrated within the optimization approach to define some possible daily driving patterns. The optimization takes into consideration mobility needs, prices for selling and purchasing electricity and hourly electrical, heating and cooling load profiles of the household. On the basis of these constraints the optimizer identifies when PV overproduction can be either used to charge batteries or to partially cover the load demand of the household. Finally, economic and energy evaluations are performed under Monte Carlo simulations to highlight reliability of potential benefits for the household case study.
Keywords: Electric Vehicle; V2H; V2G; Household case study; PV.

Nomenclature and units

$\alpha(t)$	availability of EV as energy storage unit
COP	Coefficient of Performance
c_c	energy consumption of EV battery for mobility needs (kWh/km)
C_p	price of electricity purchased from the grid €/(kWh)
C_s	price of electricity sold to the grid €/(kWh)
$d(t)$	distance travelled by EV in a time interval (km)
η_c	efficiency of EV battery during charge phase
η_d	efficiency of EV battery during discharge phase

η_{sd}	self-discharge efficiency of EV battery
E_{in}	electric power consumed by electric chiller (kW)
E_{out}	cooling power produced by electric chiller (kW)
EV	Electric Vehicle
PR	Performance Ratio of the PV system
PV	Photovoltaic
$P_{hp,in}$	electric power consumed by heat pump (kW)
$P_{hp,out}$	heating power produced by heat pump (kW)
P_p	electric power purchased from the grid (kW)
P_{pv}	electric power produced by PV (kW)
P_s	electric power sold to the grid (kW)
$P_{st,c}$	electric power during charge of the EV battery (kW)
$P_{st,d}$	electric power during discharge of the EV battery (kW)
SOC	State of Charge of EV battery (kWh)
SOC_{min}	Minimum State of Charge of EV battery (kWh)
S_{max}	EV battery capacity (kWh)
SC	Self-Consumption

U_c	cooling power demand of the household (kW)
U_e	electric power demand of the household (kW)
U_t	thermal power demand of the household (kW)
$V2G$	Vehicle to Grid
$V2H$	Vehicle to Home
YC	yearly electricity cost for household with V2H operation (€/y)
YC^*	yearly electricity cost for household without V2H operation (€/y)
YCS	yearly cost saving for household with V2H operation (%)

1. Introduction

Air pollution is still one of the main issue for people living in large and small cities, despite of implementation of emission reductions measures [1], at least at the European level, the transport sector still remains one of the main contributors to the reduction of the air quality. For this reason, a strategic approach for decarbonizing the transport sector is crucial to increase the quality of life and health condition of the people living in cities [2]. In this context, Electric Vehicles, especially if fed by Renewable Energy Sources, play an important role by significantly reducing pollutants emission [3]. However, even if the in the last years EV market is increasing [3, 4], EVs penetration is still difficult due to their higher costs and the short driving range with respect to usual gas-fuelled vehicles. Overcoming these aspects is crucial for promoting a large electrification in the transport sector especially in case of light duty vehicles. The EVs could become more economically attractive if Vehicle-to-Grid (V2G) or Vehicle-to-Home (V2H) schemes are implemented. V2G is intended as the possibility of selling stored energy to the grid, while V2H is the possibility of using stored energy later for home needs. In both cases, a more sophisticated management of the EV battery is required. EV battery can be managed as a stationary storage unit with bidirectional power fluxes to exploit local RES generation as, for example, Photovoltaic (PV). So, when EV is parked at home, the potential household PV overproduction can be stored in the EV battery for covering later, partially or fully, the domestic electric demand [5, 6, 7, 8]. As a consequence, the corresponding increased self-consumption level of PV generation also improves the resilience of those electric distribution grids subjected to a large penetration of distributed generation based on RES [9]. Similarly, if the energy market price is convenient, the stored PV overproduction could be sold to the grid [10].

However, the power exchanged with the battery needs to be optimally managed if the RES generation must be fully exploited also from the economic point of view [11]. For example, an optimization algorithm is proposed in [12] for EV battery management to minimize total electricity costs of households considering both battery technical constraints and a detailed modeling of user comfort preference, thermal dynamics and household occupancy patterns. Different optimization technique are instead compared in [13] for minimizing the electricity cost of the household within a residential energy management by means of EV battery management. A Mixed Integer Linear Programming (MILP) formulation is instead presented in [14] for minimizing electricity costs of household considering also the reactive power generation from EV battery inverter. In the literature presented above, all management strategies must cope with the driving patterns which strictly influence the EV battery availability to store energy. However, in general this aspect is investigated with simplified approaches where the car usage and the mobility need are assumed fixed, so no statistical analysis of driving patterns are considered.

In this paper a different approach for evaluating the optimal scheduling of EV battery for increasing the PV exploitation and minimizing the electric, heating and cooling energy supply costs at household level is presented. The optimal management of the EV battery here proposed is based on MILP formulation of household energy system, where driving patterns are statistically extrapolated by an existing database for considering the influence of the EV battery availability in V2G and V2H operations. The base of these data is the study on driving patterns in the six larger European Countries (Italy, France, Germany, UK, Spain and Poland) [16]. Statistic data are used to randomly generate different driving patterns within a Monte Carlo approach for estimating energy and economic benefits of a V2H and V2G management. Simulations considering the Italian context are performed and energy and economic results are presented and discussed.

The paper is organized as follows: in Section 2 the database concerning the driving pattern of Italian driver's living in small town and rural area is presented and a statistical analysis is discussed to randomly generate car usage profiles; in Section 3 the energy demand for an Italian household is presented; the MILP formulation of the optimization problem for the management of the EV battery is presented in Section 4; Monte Carlo simulations and results are finally discussed in Section 5.

2. Driving pattern

One of the main economic drivers for the application of V2G and V2H operations in household is the maximization of the self-consumption of the RES based generation system. In this way, an end-user can potentially benefit of the EV battery capacity for storing RES overproduction and supply its internal demand due to domestic appliances. In the Italian context, the wider RES distributed generation system installed in household is based on PV [15]. So, this RES technology was considered in this paper.

However, the use of the EV as an energy storage unit is strictly related to the driver's pattern behaviour. In fact, differently from battery for stationary applications, the availability of this "moving" storage system depends on how the EV is used by the drivers and on the scope of each trips. In this respect, two main classes of mobility can be identified [16]:

- Systematic mobility where the car is used by drivers for trips from home to workplace and vice versa: this class represents approximatively 35-40% of all trips in the six most populous EU countries

- Unsystematic mobility where the car is used by drivers for reasons not strictly related to work (e.g. shopping): this class accounts for around one-third of all the trips.

This classification is essential since the PV generation can be fully exploited in the household only if the EV is parked at home when PV overproduction occurs, so the energy surplus can be stored in the EV battery and used later for eventually supply the household appliances. If the car is used for systematic mobility, an unmatched condition can occur since the EV is typically not parked at home during daytime of working days (i.e.

Monday to Friday), and consequently the PV overproduction of the household cannot be stored in the EV battery [17]. On the other hand, different conditions could be obtained when unsystematic mobility is considered: in this case, an higher probability for finding car at home during PV overproduction could be instead expected. For this reason, this paper investigates the possibile implementation of V2G and V2H operation, within household with PV production, through the management of EV battery considering only unsystematic mobility needs for the driver's car.

2.1. Data analysis

The maximization of the PV self-consumption is based on an optimal management of the EV battery capacity. However, this optimal management can not ignore the statistical variability of the driver's pattern behavior, since it strictly influences the EV battery availability as energy storage unit. So, a preliminary statistical analysis of driver's car usage was performed for the Italian context to defines:

- the intervals when the car is parked at home during a day (i.e. the identification of the time when car is leaving home and when it is coming back)
- the distance travelled by the car when it is moving out of home

The statistical analysis was performed considering the data used for investigating the driver's car usage in the reports [18, 19]. The database contains data of each car trips (e.g. duration, scope, departure and arrival time, place of departure and arrival, etc.) for people living in the six most populous country of European Union (Italy, France, Germany, UK, Spain and Poland). Data regarding trips for systematic and unsystematic mobility are available from this database where a further classification is introduced concerning the people's living area: metropolitan area, large city, large town, small town and rural area. Each drivers is identified by an ID, so its corresponding trips are recorded according to this anonymous classification.

The analysis was performed by considering only people living in single-family building, since the installation of the infrastructure for charging the EV battery is easier to be implemented, if compared to people living in a multi-family building where reduced spaces for parking and other barriers can occur. Thus, since single-family buildings are supposed to be mainly located in small towns or in rural area, data for driver's pattern behavior were extracted from the database considering people living in those areas of Italy.

Firstly, the extracted data were subdivided in two main groups according to weekday (i.e. from Monday to Friday) or weekend day classification, since the car usage in Saturday or Sunday is typically different than during the working days. Then for each j-th ($j = 1, \dots, ID_{tot}$) driver's ID extracted from the database, the times when the car leaves home and when it comes back were observed for each trips. In the database, a day of 24 hours is discretized in consecutive intervals of 5 minutes, so the results were aggregated in two vectors L and R where each of them is formed by 288 elements. Each elements of L counts the number of trips where the cars leave from home in a given i-th time interval and each elements of R counts, instead, the number of trips where the cars return at home in a given i-th time interval of 5 minutes.

$$L = (l_1, l_2, \dots, l_{288}) \tag{1}$$

$$R = (r_1, r_2, \ldots, r_{288}) \tag{2}$$

Essentially, the aggregation process consists in summing up the number of times that cars start from home and come back at home in a given i-th time interval, as follows:

$$l_i = \sum_{j=1}^{ID_{tot}} l_{i,j} \tag{3}$$

$$r_i = \sum_{j=1}^{ID_{tot}} r_{i,j} \tag{4}$$

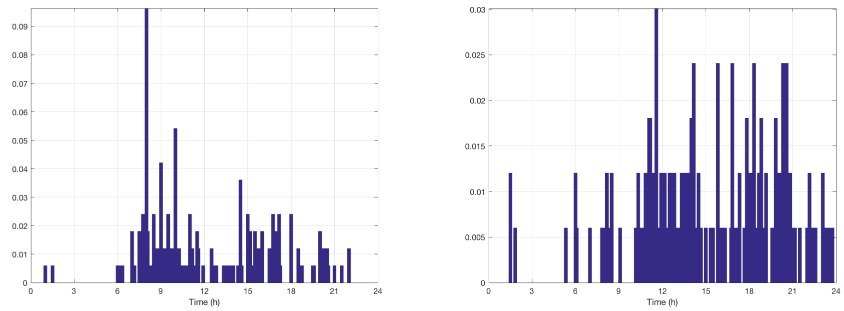
Consequently, each element of the first vector L represents the total number of trips starting from home observed in a given time interval for living home, while each element of the second vector R represents the total number of trips that end at home in a given time interval.

A discretized probability was subsequently calculated by a simplified approach for defining when cars lives home and comes back during weekday and during the weekend. The probability in the i-th time interval is defined as the ratio between the number of trips in that interval and the sum of all trips, as follows:

$$p(l_i) = \frac{l_i}{\sum_{i=1}^{288} l_i} \tag{5}$$

$$p(r_i) = \frac{r_i}{\sum_{i=1}^{288} r_i} \tag{6}$$

Figure 1 shows that Italian drivers, engaged on unsystematic mobility during weekdays and living in small towns or in rural area, usually leave home at 8 a.m.. Instead, users prefer coming back home at 11 a.m., but in general drivers can also return in the afternoon up to 8 p.m.



(a) (b)

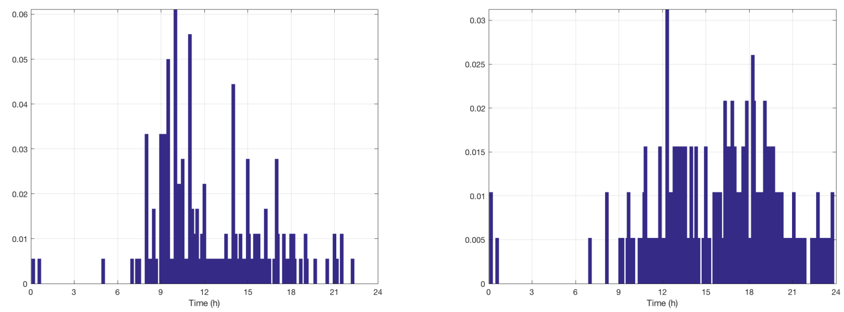
Figure 1: Probability distribution for cars living home a) and coming back home b) during weekday.

Figure 2 shows instead the probability for leaving and coming back home calculated in the weekend. It is noticeable that Italian drivers usually leave home later in the weekend for unsystematic mobility needs (around 10 a.m. or 2 p.m.) compared to weekdays, while they back home with higher probability at 1 p.m. or around 6 p.m.

2.2. Driving pattern generation

A daily driving pattern behavior can be randomly generated according to the four previous discrete distributions. The generation of the departure and the arrival times of a car at home permits to estimate the periods when the EV battery capacity can be used at home for increasing PV self-consumption in weekdays and weekend days.

However, once the time when a car leaves home and comes back is defined, both for weekdays and weekend days, the number of trips per day



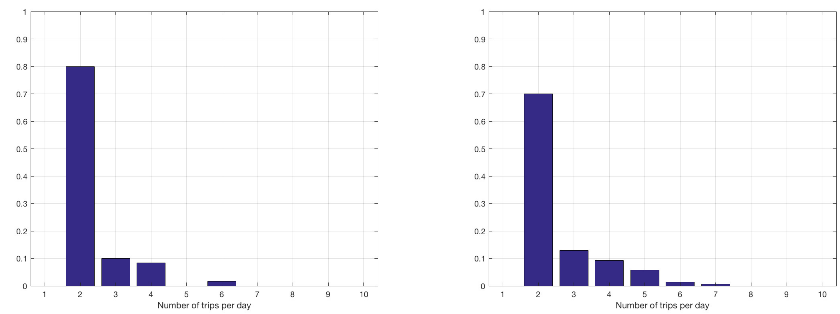
(a) (b)

Figure 2: Probability distribution for cars living home a) and coming back home b) during weekend.

should be considered as well. In fact, this factor influences the energy consumption of the EV battery capacity due to mobility needs and consequently the available energy storage content to supply household appliances. Even if the driver's pattern suggests that only two trips per day occurs in most of the cases (i.e. about 80%), more than two trips per day are generally observed in the database according to the discrete probability distribution shown in Figure 3.

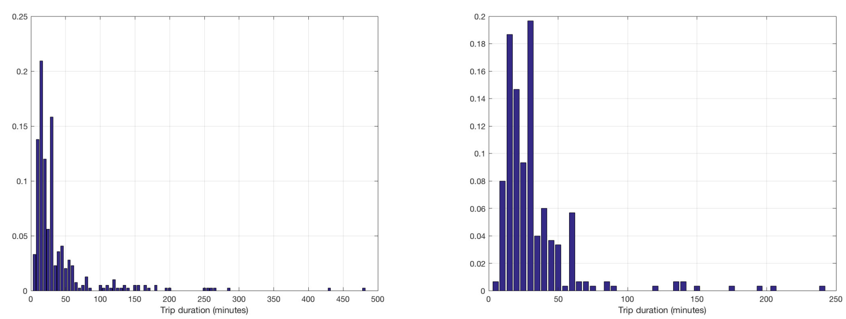
Finally, the trip duration is randomly generated for each journey according to the discrete probability distribution of Figure 4 extrapolated by the database. This distribution highlights how the trip duration for unsystematic mobility for people living in small town or rural area are typically within the range of 10-30 minutes both for weekday and weekend days.

However, a simplified approach is proposed here to make easier the analysis and the generation of daily driving pattern. In particular, if two trips per day are generated, the first one is assumed from home to an outdoor destination and the second one from outside to home, so their duration D



(a) (b)

Figure 3: Probability distribution of number of trips per day in weekdays a) and weekend b).



(a) (b)

Figure 4: Probability distribution of trip duration in weekdays a) and weekend b).

is supposed to be the same.

Instead, if the simulation randomly generates a number of trips per day greater than two, only two "equivalent" trips per day are considered: two trips represents the leaving and coming back trips as described before, while additional trips are counted differently. Under the hypothesis that each additional trips is travelled out of home (i.e. intermediate trips do not consider stops at home), half duration for the outdoor trips ϵ belongs to the first "equivalent" trip (from home to outside) and the remaining half duration belongs to the second "equivalent" trip (from outside to home), as follows:

$$D' = \begin{cases} D & \text{if } N_{trips} = 2 \\ D + \sum_{h=3}^{N_{trips}} \frac{\epsilon_h}{2} & \text{if } N_{trips} > 2 \end{cases} \tag{7}$$

where N_{trips} is the number of trips randomly generated, D is the duration of the first and the last trip of a day and ϵ_h is the duration of each h-th additional trip travelled out of home. Substantially, the duration D' of the two equivalent trips is equal to the sum of the duration of each trips travelled in a day. Figure 5 shows an example of how the trips duration is arranged in the random generation of driving pattern

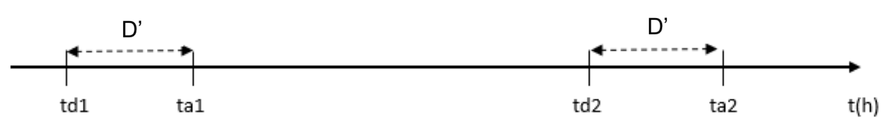


Figure 5: Arrangement of the trips duration in the random trip generation.

Finally, the trip duration can be suitably converted in a distance travelled in each trip by multiplying the trip duration for the average speed of the car observed in the database and reported in Table 1.

Table 1: Average speed of cars for Italian drivers living in small town and rural area.

	Weekdays	Weekend
Average speed (km/h)	38.3	40.8

The estimation of the average distance travelled by each trips is fundamental to evaluate the energy consumption of the EV battery capacity for mobility needs.

2.3. Daily driving distance and availability profiles

The result of the data analysis is the creation of an automatic procedure to randomly generate different daily time profiles, describing the driver's pattern behavior, according to the discrete probability functions presented in Section 2.1 and 2.2. Since the time of leaving home and the time of coming back home were extracted from the analysis of the two vectors L and R, in which a day is discretized in 288 time intervals, the corresponding daily driving pattern time profile, that describes the driver's behavior, is still a vector discretized in consecutive intervals of 5 minutes.

Two different time profiles were created. The first one represents the availability of the EV battery to be used as energy storage systems in the household to store the electricity overproduction of PV and release it when economically profitable. For this reason, this time profile assumes only 0/1 value according to the EV availability (1) or unavailability (0) to be parked at home and connected to the household electric system. The second time profile represents instead the distance travelled by the EV when out of home.

Figure 6 and 7 show an example of these time profiles during one week. It is noticeable how the generation of different daily driving patterns influences the presented weekly profile.

The average distance calculated for each trip allows also to estimate the energy consumption needed during the trips of the day. This consumption influences the State Of Charge (SOC) of the EV battery and the available energy content to be used to satisfy household electricity needs. Table 2 shows the average specific energy consumption of EV used here during different season of the year and reported in [19, 20, 21].

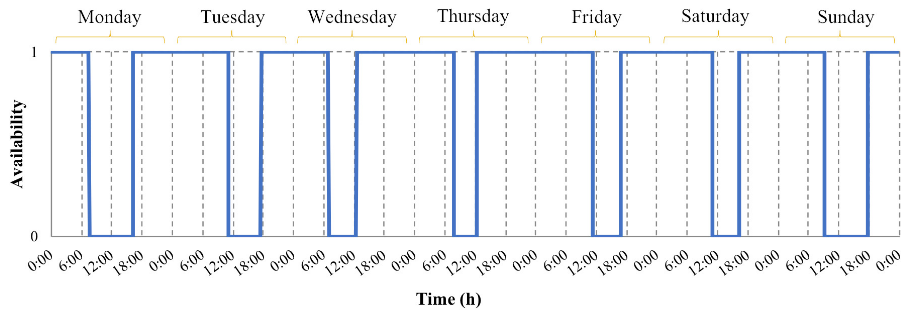


Figure 6: Weekly time profile of the availability for the car to be parked at home.

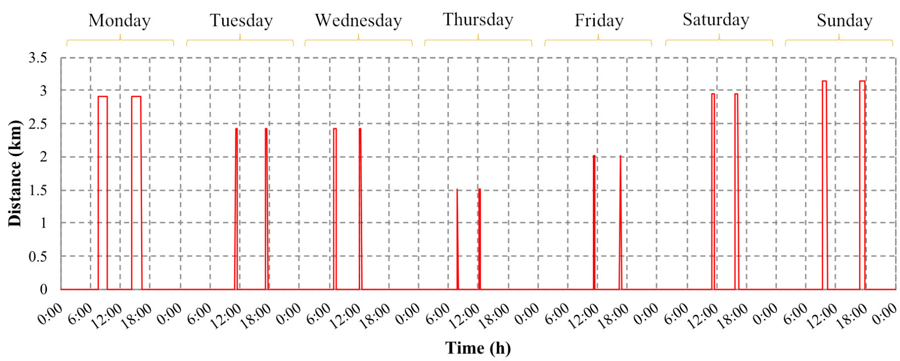


Figure 7: Weekly time profile of the distance travelled by car.

Table 2: Average energy consumption of EV for mobility needs.

	EV consumption (kWh/km)
winter	0.25
summer/mid	0.20

It is noticeable that energy consumption in winter is generally higher than one in summer or mid seasons, because of the consumption required from the ventilation and heating system of the EV.

3. Household case study

A single-family household with PV generation located in the Northern part of Italy was identified as simple case study. The household is equipped by an EV used to satisfy unsystematic mobility needs according to the definition introduced in Section 2. Figure 8 shows the layout of the energy system analyzed in this paper, where EV can provide V2H and V2G operation for increasing PV self-consumption and consequently energy self-sufficiency.

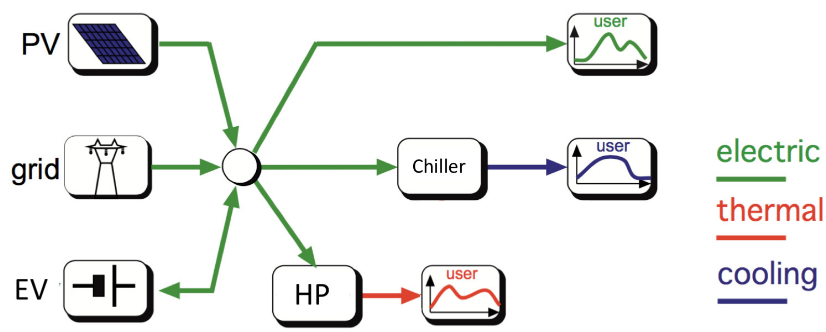


Figure 8: Layout of the energy fluxes in the domestic case study.

The heating and cooling energy generation within household is based on electricity-driven systems instead of traditional one based on fossil fuel, since this configuration allows to fully exploit the benefit from the management of the EV battery: a heat pump is used to cover the space heating and Domestic Hot Water (DHW) demand, while an electric chiller supplies the space cooling need in summer. Table 3 summarizes the main technical characteristics of these energy sources, under the hypothesis that their average Coefficient of Performances (COPs) are supposed to be constant along the year. Electric appliances can be supplied by the grid, by the PV during its daylight production or by the EV battery during its V2H operation.

Table 3: Main characteristics of the energy sources in the case study.

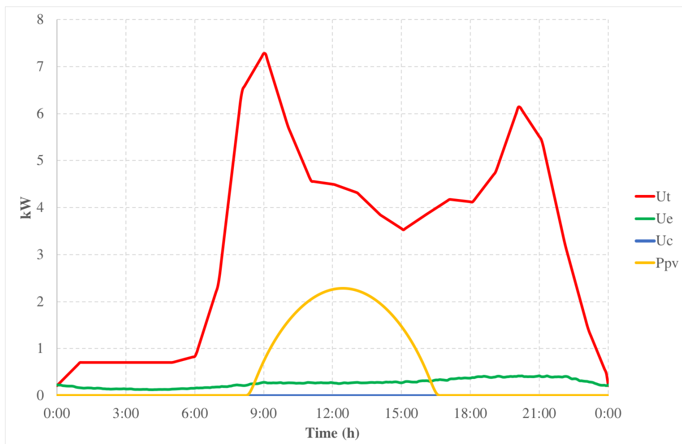
	Technical characteristics	
Heat Pump	P_n=15 kW_t	COP=4
Electric Chiller	P_n=5 kW_c	COP=3
PV	P_n=6 kW_p	PR=0.75

The time profile of the heating load was obtained considering the normalized load profiles presented in [22, 23], an yearly energy consumption for space heating of 145 kWh/m^2/y and for DHW of 30kWh/m^2/y according to a climatic zone E as classified by the Italian regulation [24] with an overall surface of approximatively 120 m^2.

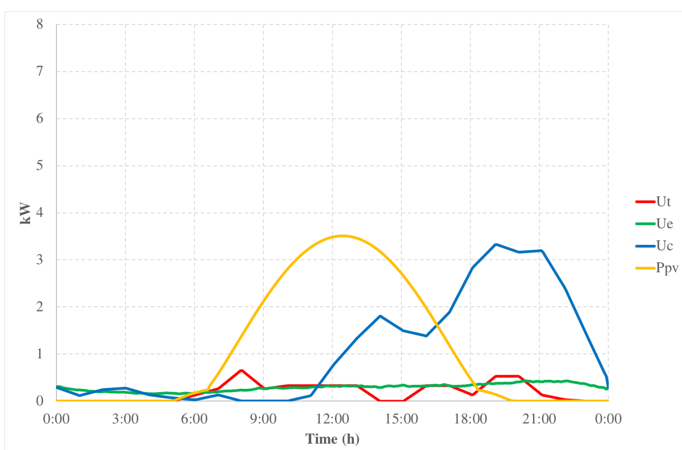
The cooling demand time profile was instead obtained by means of the normalized load profiles presented in [25, 26] for typical Italian domestic end-users assuming a yearly cooling demand of 25 kWh/m^2/y. Cooling load profiles were also further rescaled through the analysis of the cooling degree days.

The household electric load profiles due to other internal appliances was instead defined according to [27] as already presented in [23]. The corresponding estimated average daily and yearly electricity demand are respectively close to 7.5 kWh/day and 2700 kWh/y, in line with the average electricity demand for an Italian domestic end-user as reported by the Italian Energy Authority (ARERA) [28]. The resulting yearly electricity demand, obtained summing up the consumption of heat pump, electric chiller and internal appliances, is close to 7280 kWh.

The PV generation time profile was obtained through an analysis on the solar irradiation data from PVGIS database [29] as described in [30]. Since the PV installation is located in the Northern part of Italy, a yearly production of 7350 kWh is estimated corresponding to around 1200 of equivalent full-load hours. Figure 9 shows an example of the load and the PV profiles extrapolated for the household case study, where Ut, Ue and Uc represent the energy demand for space heating/DHW, electricity and space cooling, respectively.



(a)



(b)

Figure 9: Example of load profiles (heating U_t, cooling U_c, electric U_e and PV P_{PV}) generation profiles in weekdays during a) winter and b) summer.

Since the aim of this paper is based on the evaluation and minimization of the household energy supply costs through the management of EV battery, also time profile for the electricity bought from the grid and sold to the grid were defined. The former refers to a common flat tariff for residential and domestic costumers equal to 220 €/MWh [31] (including taxes and excises), while the latter is derived from [32] and it has an yearly average value of 42€/MWh. Figure 10 shows an example of the electricity price variability for the PV production sold to the grid.

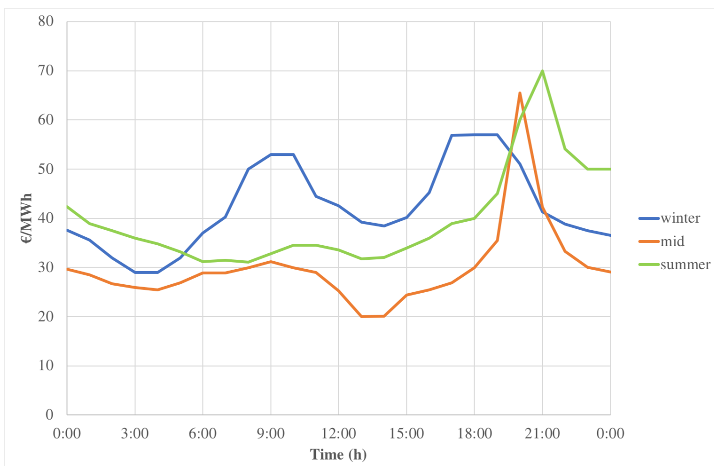


Figure 10: Italian selling electricity prices during different seasons.

The driving pattern of the EV, that influences the management of V2H operation, is taken into account through the availability and the distance travelled daily time profiles randomly generated according to the driving pattern described in Section 2. The EV battery considered in this case study have different size according to the market segmentation of vehicles [33] in order to evaluate the impact of different battery capacity. So, three main classes were identified, as follows:

- A for mini cars with a battery capacity equal to 20kWh.
- B for small cars with a battery capacity equal to 40kWh.
- C for medium cars with a battery capacity equal to 60kWh.

Moreover, different minimum values of SOC (SOC_{min}) for the EV battery were assumed from 40% to 80%, to take into account different possible driver's range anxiety [34, 35]. In fact, a lower SOC_{min} reflects drivers who do not need a high SOC to be used for traveling. Vice versa, an higher SOC_{min} reflects drivers that want preserve battery capacity to be used for traveling needs. Finally, a limit on the electric power exchanged to the battery is fixed at 3.3 kW to avoid fast charging operation and a consequent peak demand. Furthermore, the maximum power exchanged to the grid is fixed at 4.5 kW equal to the average installed power capacity for an Italian household.

4. Problem formulation

The management of the EV battery was investigated by means of an optimization tool named `XEMS13` [36, 37] developed in partnership between the Energy Department of Politecnico di Torino and Fondazione LINKS - Leading Innovation & Knowledge for Society. The tool is capable to identify the scheduling of different sources which minimize the energy supply costs within a multi-energy system.

A Mixed Integer Linear Programming (MILP) formulation is used to describe the behavior of complex energy system, so all the equations and constraints representing the energy system are linear or should be linearized. Two different kind of linear equations can be found for describing the energy systems: topological or balance equations depending on the system structure; component or constitutive equations, representing the energy modules. When non-linear behavior occurs, the functions are typically approximated by means of piecewise linear functions. Binary (integer) variables are also introduced to describe the on/off status of the components and to consider their operational limits. A detailed description of the models representing the sources within the household case study (i.e. electric chiller and heat pump) can be found in [37, 38].

The time horizon of the simulation is discretized by subdividing it in N_i intervals with equal length Δt, equal to 5 minutes in this particular application for exploring V2H operation, since driving pattern has the same discretization.

4.1. Objective Function

In this paper the complex energy systems is represented by an electricity-driven single-family building with PV where EV is connected to the household. Under the linear constraints, the energy supply costs is the objective function calculated, as follows:

$$OF = \sum_{i=1}^{N_i} \left[C_p(t_i)P_p(t_i) - C_s(t_i)P_s(t_i)\right] \Delta t \tag{8}$$

where P_p and P_s represent the electric power purchased from and sold to the grid, respectively. Instead, C_p and C_s are the prices for buying and selling electricity, respectively.

4.2. Modeling EV battery

The daily time profiles generated by procedure described in Section 2 were integrated within the existing optimization tool designed for the management of complex energy systems. In particular, an upgrade of the existing battery model developed in [39] was implemented to consider the availability of the EV battery and the SOC variation due to the energy consumed for traveling by the car. The EV battery is described as a passive components, so that the energy released by the battery is assumed positive, while the energy stored is negative. Under this consideration, the energy content of the EV battery at a time instant t+1 can be expressed by means of a linear equation, as follows:

$$SOC(t+1) = \eta_{sd} SOC(t) + \left(\eta_c P_{st,c} - \frac{P_{st,d}}{\eta_d} \right) \Delta t - c_c d(t) \tag{9}$$

where η_{sd} is the self-discharge efficiency, η_c and η_d are the charge and discharge efficiencies, $P_{st,c}$ and $P_{st,d}$ are the power exchanged with the EV battery respectively in charge and discharge phase, d is distance travelled by the car in a given time interval (see Figure 7) and c_c is the car energy consumption described in Table 2. The power exchanged to the EV battery is then bounded by its technical limits, so that other constraints were also added, as follows:

$$0 \leq P_{st,d}(t) \leq \delta_d(t) \frac{S_{max}}{T_d} \tag{10}$$

$$0 \leq P_{st,c}(t) \leq \delta_c(t) \frac{S_{max}}{T_c} \tag{11}$$

$$0 \leq \delta_d(t) + \delta_c(t) \leq \alpha(t) \tag{12}$$

where S_{max} is the maximum energy stored in the battery, T_c and T_d are the minimum charge and discharge time. δ_c and δ_d are instead binary variables introduced to avoid charge and discharge phase at the same time in Eq. 8 and $\alpha(t)$ is the availability in a given time interval as shown in Figure 6. When the car is parked at home and connected to electric system of the household $\alpha(t) = 1$ and consequently $d(t) = 0$, so Eq. 9 is equivalent to one used in the stationary application [39]. Otherwise, when $\alpha(t) = 0$ (i.e. the car is not parked at home) the binary variables δ_c and δ_d are forced to be zero and the SOC variation is only due to the energy consumption of car trips.

4.3. Energy balance of household

According to the definitions and the modellng of the different components within `XEMS13`, the energy balances in the household can be expressed, as follows:

$$P_p(t_i) - P_s(t_i) + P_{pv}(t_i) - P_{hp,in}(t_i) - E_{in}(t_i) + P_{st,d}(t_i) - P_{st,c}(t_i) = U_e(t_i) \tag{13}$$

$$P_{hp,out}(t_i) = U_t(t_i) \tag{14}$$

$$E_{out}(t_i) = U_c(t_i) \tag{15}$$

Equations (13), (14) and (15) represent the electricity, the heating and the cooling balance, respectively. In (15), the cooling generation by the electric chiller E_{out} must equate the demand of the space cooling U_c of the household in each time interval. Equation (14) shows that the heat produced by the heat pump $P_{hp,out}$ can be used to supply the space heating and DHW demand U_t of the household. Finally, (13) highlights that the electricity bought from the grid P_p, produced by PV P_{pv} and from the EV battery $P_{st,d}$ can feed the electric demand of the household appliances U_e as well as the electric demand required by the heat pump $P_{hp,in}$ and the chiller E_{in}. Moreover, EV battery can be charged by electricity bought from the grid and from PV.

As already observed EV battery can not be charged and discharged simultaneously due to the constraint in Equation 12. Similarly, binary variable are also introduced to avoid that household can contemporarily purchase electricity from the grid and sold electricity P_s to the grid.

5. Simulations and Results

The optimal management of the EV battery was applied through the `XEMS13` tool considering the different time profiles defined in the previous Section. A Monte Carlo approach was used here for considering the different possible driving patterns of Italian driver's living in small town and rural area. So, 1000 time profiles describing different driver's habits were randomly extrapolated following the approach in Section 2.2.

For each driving patterns, simulations with `XEMS13` were performed for three days in different seasons: winter, mid and summer. The results of the daily energy supply costs obtained by the optimization procedure were then aggregated according to the season distribution in Table 4 to calculate the yearly costs YC potentially achievable by the household by using the EV as a storage unit to perform V2G and V2H operation. As a general remark, it can be observed that winter days marginally contribute to the yearly cost saving, because of lower PV production and higher electricity demand of the heat pump for space heating. This combination of factors reduces, in fact, possible PV overproduction storable in EV battery. Differently, mid and summer days can instead significantly promote the V2H operation, since higher PV overproduction is expected. The yearly result of each Monte Carlo simulations was finally compared to the yearly electricity cost YC^{*} for an household where V2H/V2G operations are not considered. Thus, the yearly cost saving obtained in each simulation was calculated, as follows:

$$YCS = \left(1 - \frac{YC_{V2H}}{YC^{*}}\right) * 100 \tag{16}$$

In addition, energy aspects were analyzed by considering and calculating the Self-Consumption level SC in each Monte Carlo simulations. The SC was compared to one where V2H/V2G operations are not allowed for highlighting possible additional energy benefits due to V2H and V2G operations. The energy indicator SC, is calculated as the ratio between the self-consumed PV production and the yearly electricity generated by the PV installation [40], as follows:

$$SC = \left(\frac{E_{sc}}{E_{pv}}\right) * 100 \tag{17}$$

When the optimal management by `XEMS13` finds solution oriented towards V2H operations, the corresponding SC level is strongly increased. Otherwise, if SC level remains unchanged or it has a limited variation, the battery management either does not consider V2H operation or V2G is acted greater than V2H, respectively.

Table 4: Season assignement during the year

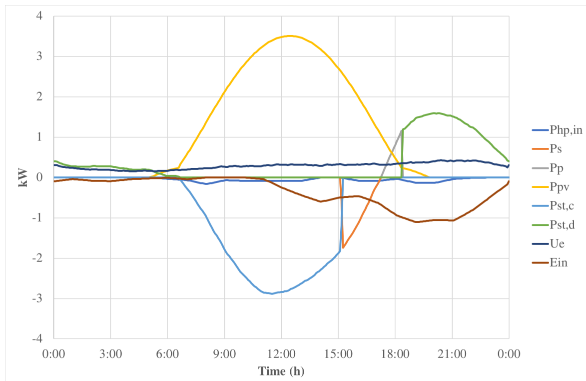
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
winter	✓	✓	✓	-	-	-	-	-	-	-	✓	✓
mid	-	-	-	✓	✓	-	-	-	✓	✓	-	-
summer	-	-	-	-	-	✓	✓	✓	-	-	-	-

The two most widely diffused technologies for EV battery were considered for V2G and V2H operations in the simulations [41]: nickel-metal hydride (Ni-MH) and lithium-ion (Li-ion). The main operational characteristics of these technologies are summarized in Table 5, where the relevant difference, in energy terms, is the charge/discharge efficiency. In fact, typically the Li-ion EV battery has a roundtrip efficiency substantially higher than Ni-MH one. Self-discharge effect is instead substantially negligible in both cases.

Table 5: Charge and discharge efficiency for EV battery [42, 43].

Technology	Charge, Discharge efficiency (η_c, η_d)
Ni-MH	0.85
Li-ion	0.975

Figure 11 shows an example of the scheduling for the different sources within household with EV in a summer day with the same driving pattern. Since, the technologies considered for EV battery have different efficiency, the observed results can differ. In general, it is noticeable that the optimal scheduling of EV battery stores part of the PV production (P_{pv}) during daytime. The power injected into the batteries ($P_{st,c}$) is used later ($P_{st,d}$) to cover the household electric demand (U_e) during nighttime due to the appliances, the electric chiller (E_{in}) and heat pump ($P_{hp,in}$) demand, where the latter operates during summer only for DHW production. The PV overproduction stored in the Li-ion batteries is also sold (P_s) to the grid (see Figure 11b) for V2G opeartion, because of its higher charge/discharge efficiency compared to Ni-MH technology.



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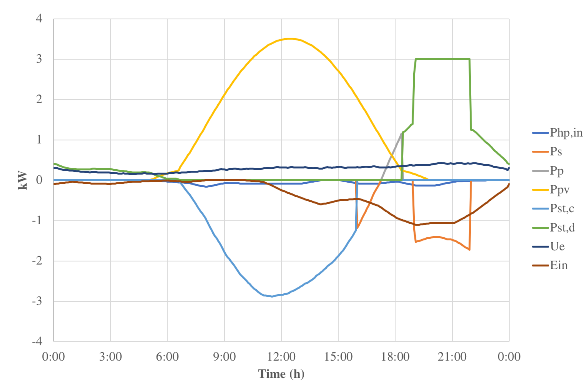
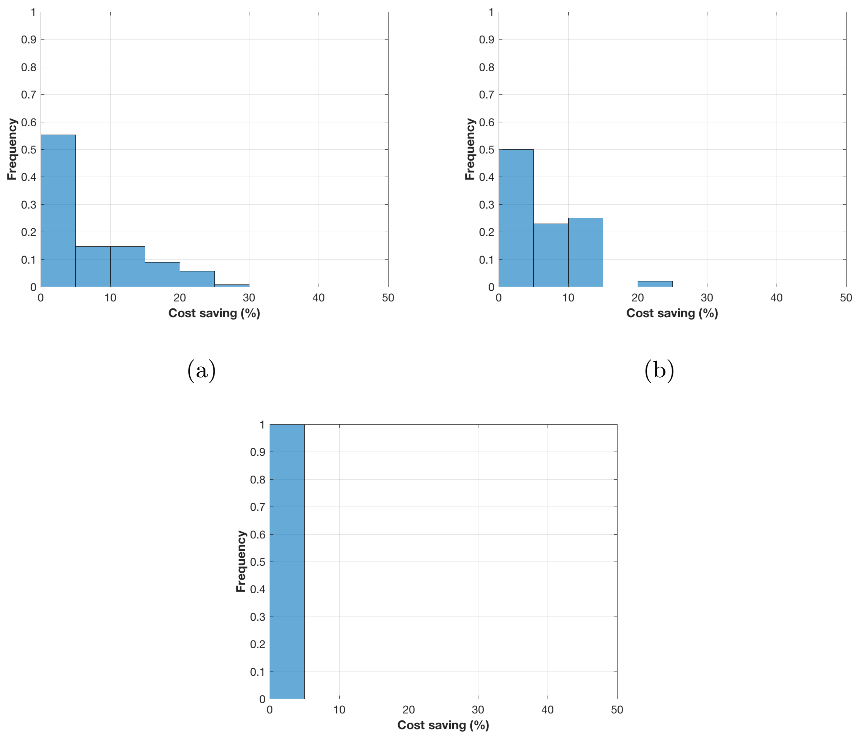


(b)

Figure 11: Scheduling of the sources with EV equipped by battery capacity of 60kWh and SOC_{min}=40% for a) Ni-MH and b) Li-Ion technologies.

5.1. Economic results

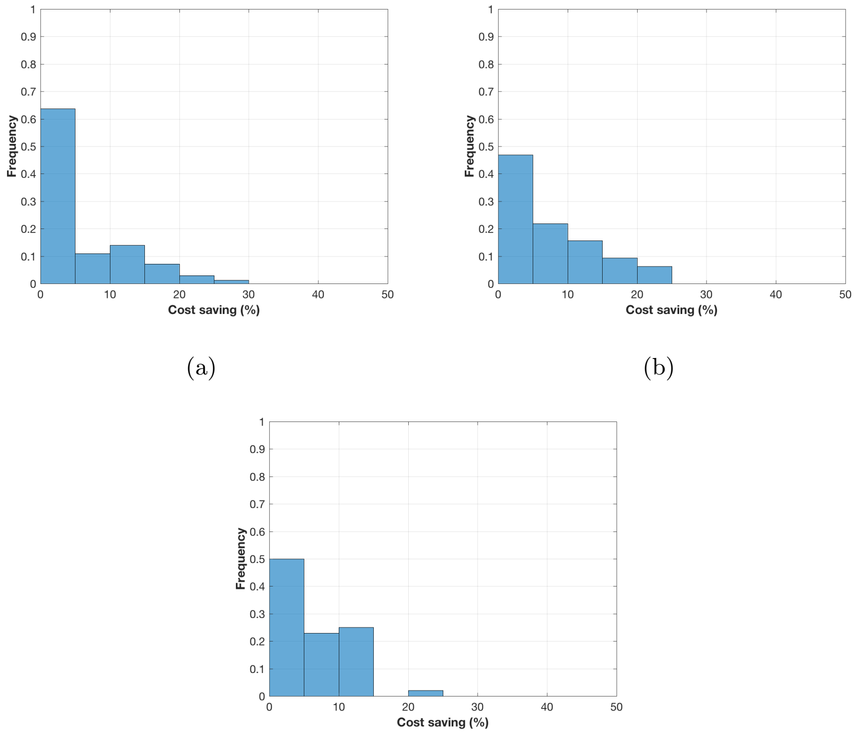
Figure 12, 13 and 14 show the different frequency distribution of cost savings resulting by the Monte Carlo simulation when Ni-MH technology and different EV battery sizes are considered. As expected, higher SOC_{min}, that correspond to lower battery capacity available for V2H/V2G operation, reflects reduced cost saving. In general, it can be noticed that the energy consumption for mobility needs strongly influences the battery usage, since around 50-55% of the results highlights cost savings lower than 5% due to the driver's habits. In particular, when small car is considered (i.e. SOC_{max}=20kWh) and SOC_{min} is set to 80%, the cost saving is always lower than 5% (see Figure 12c).



(a) (b) (c)

Figure 12: Frequency distribution of cost saving for a 20 kWh Ni-MH EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

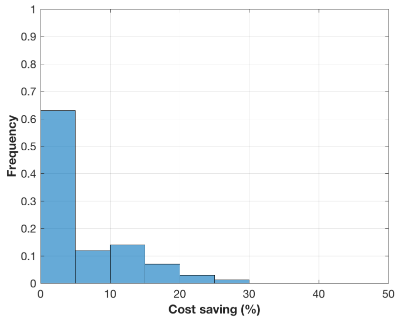
When battery capacity increases (i.e. SOC_{max}=40kWh or 60 kWh), V2H operation ensures in general higher cost saving. In fact, it can grow up to 15-20% in around 30% of the Monte Carlo simulations. The cost saving can be further increased up to 30% when medium cars are analyzed (see Figure 14).



(a) (b) (c)

Figure 13: Frequency distribution of cost saving for a 40 kWh Ni-MH EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

Similarly, economic results are also highlighted in Figure 15, 16 and 17 for Li-ion technology. Li-ion EV battery can ensure an increased costs saving due to the higher efficiency shown in Table 5 capable to explore both V2H and V2G operations. In fact, the frequency distribution for low cost saving (i.e. $\leq 5\%$) is generally reduced down to 40-45% of the Monte Carlo simulations, if compared to Ni-MH battery where the frequency reach 50-55%. Contemporarily, the maximum cost saving potentially achievable also increased up to 35%. Only small battery size (see Figure 15c) with stringent range anxiety (i.e. $SOC_{min} = 80\%$), that are related to the A market



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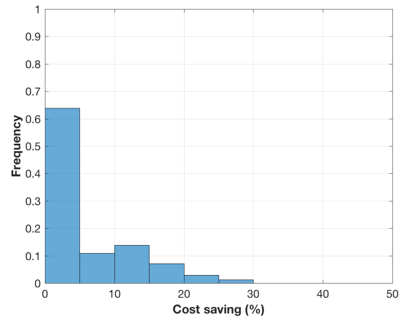

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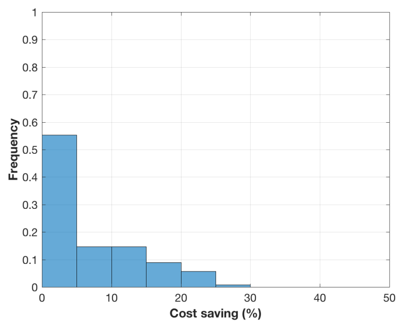


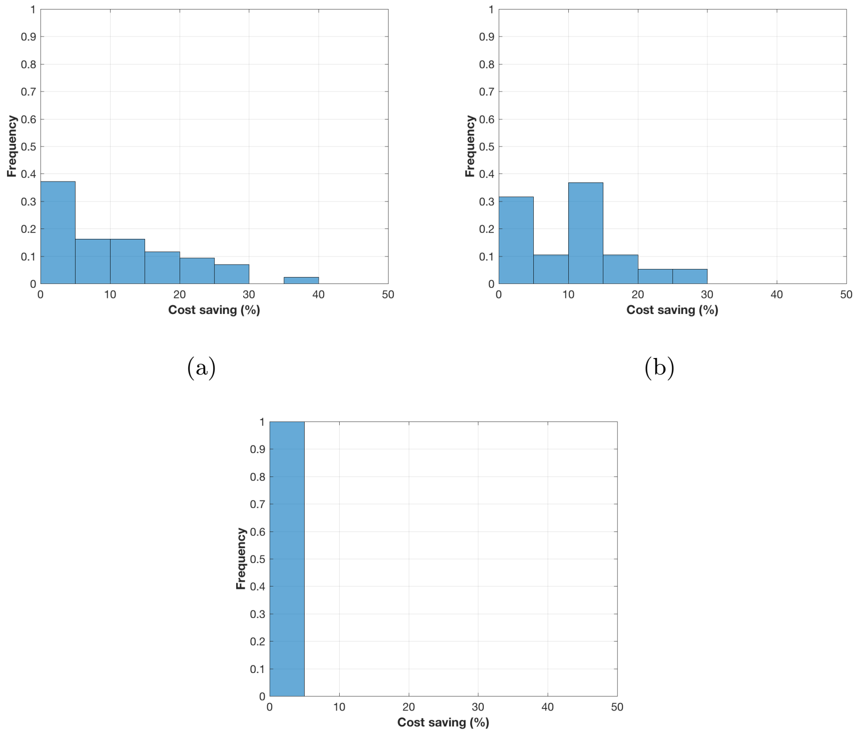
(c)

Figure 14: Frequency distribution of cost saving for a 60 kWh Ni-MH EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

segmentation, still shows not enough battery capacity for fully exploiting V2H and V2G operations.

Again, the increase of battery capacity (i.e. SOC_{max}=40kWh or 60 kWh),corresponds to higher cost saving where around 20-25% of the Monte Carlo simulations reflect cost saving within a range between 10% and 20%.

Summarizing, the results exposed above underline that economic benefits, in terms of costs saving, are strongly influenced by the combination of two different effects. Firstly, the driving pattern modifies the energy consumption for covering the mobility needs and consequently it strongly limits

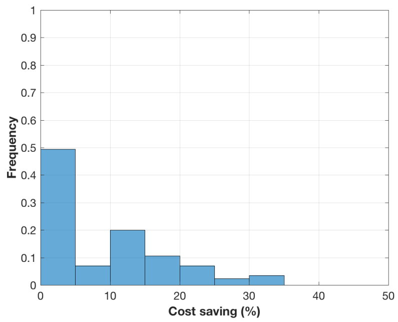


(a) (b)

(c)

Figure 15: Frequency distribution of cost saving for a 20 kWh Li-ion EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

the availability of battery capacity for storing PV overproduction. Secondly, the range anxiety, that is represented by different level of SOC_{min}, limits the V2H and V2G operation, since high SOC_{min} (i.e. kept high to preserve battery capacity for covering mobility needs) reduce the band of battery capacity potentially available for V2H. Moreover, it can be noticed that Li-ion technology is more suitable for exploring both V2H and V2G operation due to its high round trip efficiency (i.e. around 95%). While Ni-MH battery seems to be more suitable only for V2H operation due to its limited round trip efficiency (i.e. around 75%).



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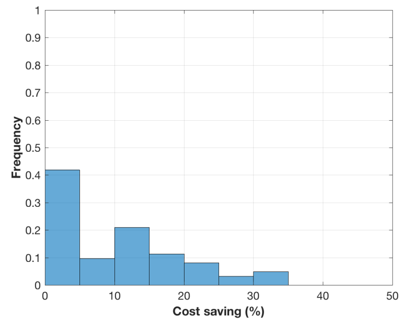

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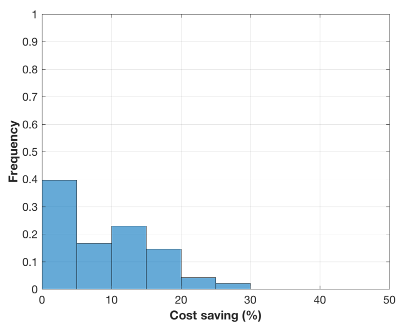


(c)

Figure 16: Frequency distribution of cost saving for a 40 kWh Li-ion EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

5.2. Energy results

The increase of self-consumption level is shown in Figure 18, 19 and 20 for different Ni-MH EV battery sizes. When small cars are considered, the limited availability of the EV battery to V2H and V2G operations affects the increase of self-consumption level, that generally is lower than 5% for around 35% of Monte Carlo simulation (see Figure 18a and 18b). A relevant range anxiety effect (see Figure 18c) further contributes to strongly limits the self-consumption increase. However, for example, an increase of SC level close to 20-25 % can be observed in around 20% of Monte Carlo simulations

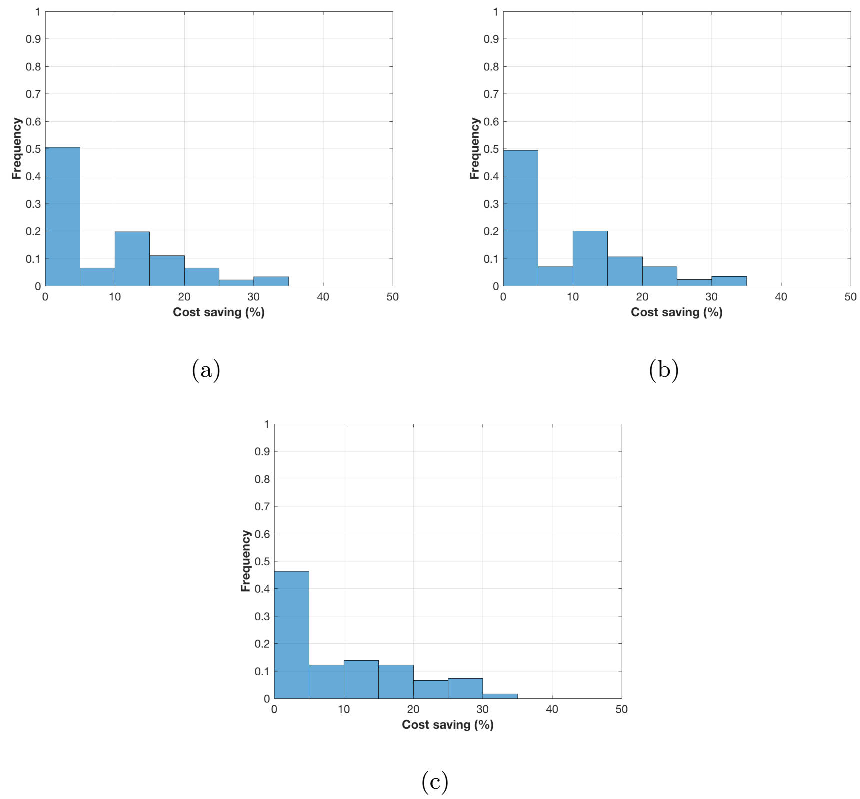
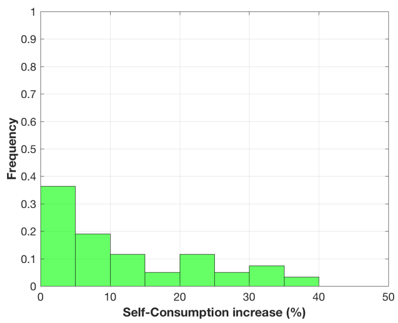


Figure 17: Frequency distribution of cost saving for a 60 kWh Li-ion EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

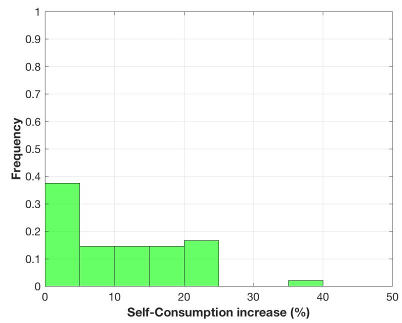
with lower range anxiety (i.e. SOC_{min}=40% and 60%).

If larger battery sizes is considered, the SC level increases as well also in case of higher range anxiety effect (i.e. SOC_{min}=80%). However, in around 40% of Monte Carlo simulations, the increased level of self-consumed PV production still remains lower than 5% due to the significant impact of energy consumption for mobility needs, similarly to the trends shown for the cost savings. Figure 19a, 20b and 20c finally show that an increase of self-consumption level up to 50% can be reached in a small number of cases.

The energy results for Li-ion EV battery are instead shown in Figure 21,



(a)



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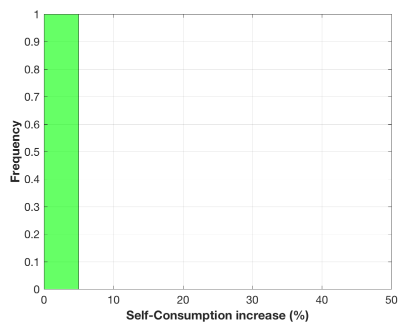
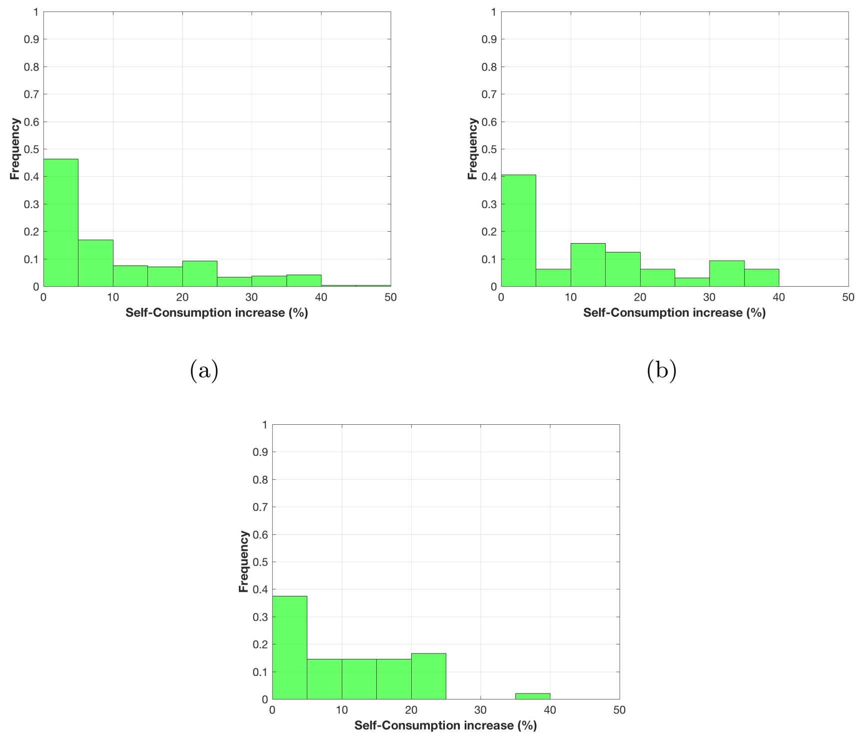


(c)

Figure 18: Frequency distribution of Self-Consumption increase for a 20 kWh Ni-MH EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

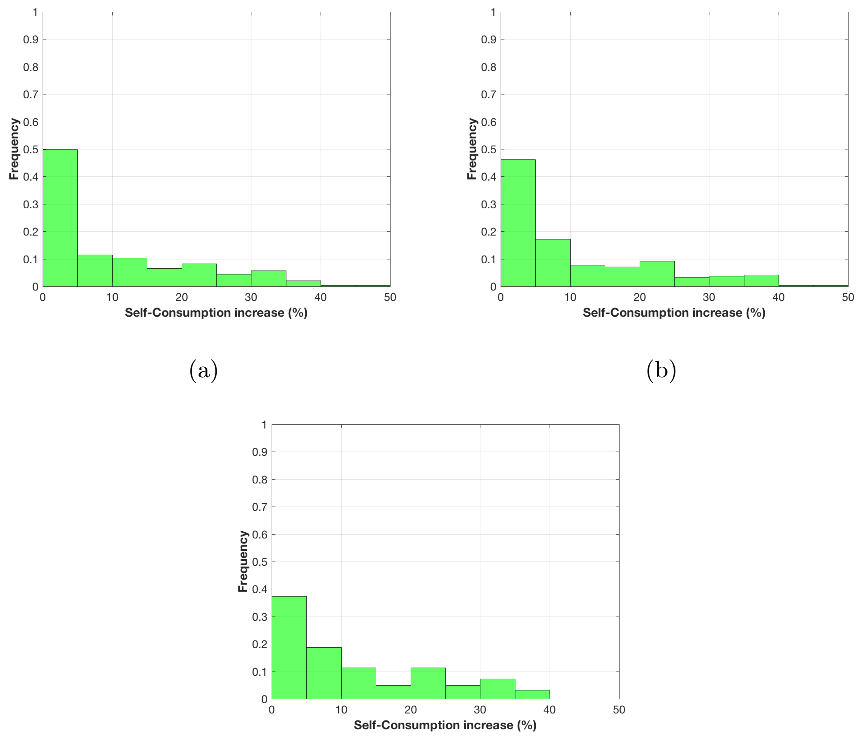
22 and 23. In general, the increase of self-consumption seems to be lower if compared to Ni-MH techology, even if the roundtrip efficiency is higher. This result is mainly due to the optimal management of the EV battery for reducing household electricity costs. The high efficiency of Li-ion EV battery seems lead to solutions where part of the stored PV overproduction can be profitably sold the grid, enabling both V2H and V2G operations for the EV. As a consequence, the self-consumption level appears reduced instead of increased, in contrast to one observed for Ni-MH technology where only V2H operation occur.



(a) (b) (c)

Figure 19: Frequency distribution of Self-Consumption increase for a 40 kWh Ni-MH EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

More in details, the increase of self-consumption level is generally lower than 5% for around 35-40% of Monte Carlo simulation due again to the energy consumption for mobility needs. Similarly to Ni-MH technology, when lower battery size is considered, the range anxiety effect (see Figure 18c) further contributes to strongly limit the self-consumption increase. If larger battery size is analyzed, a general increase of SC can be observed, but it is lower if compared to Ni-MH technology according to the V2G operation described above.



(a)

(b)

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Figure 20: Frequency distribution of Self-Consumption increase for a 60 kWh Ni-MH EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

6. Conclusions

The implementation of V2H and V2G operation represents an interesting option for reducing energy costs and increasing RES exploitation at household level. This paper presents an example of possible applications of V2H and V2G operation based on a optimal management of EV battery in an Italian electricity-driven household with PV. Driver's behaviour has been taken into account and analyzed from an EU database to better identify when EV is available and parked at home for operating as an equivalent

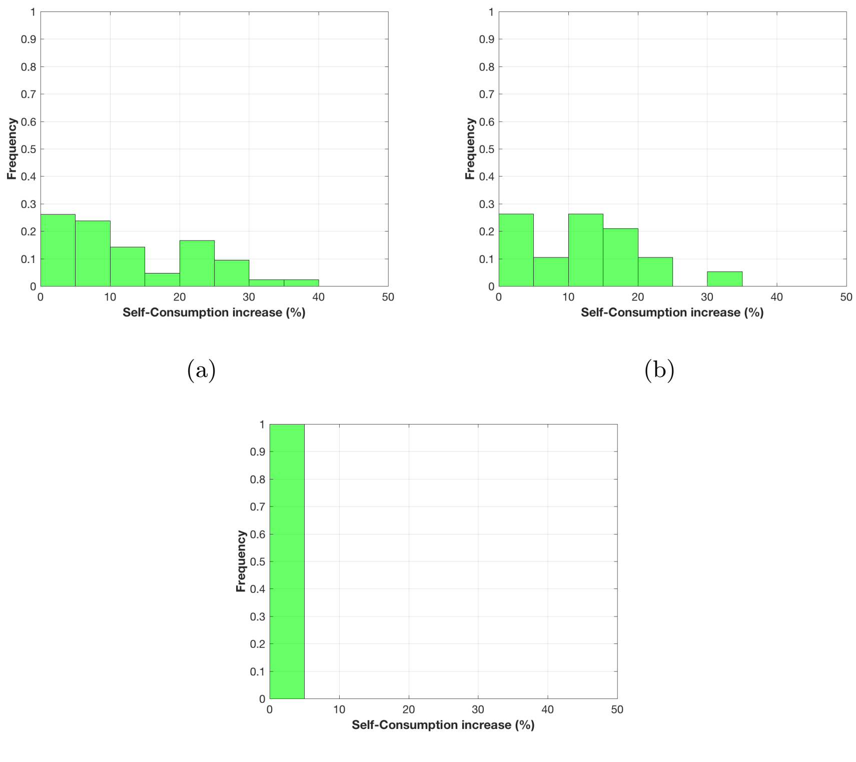
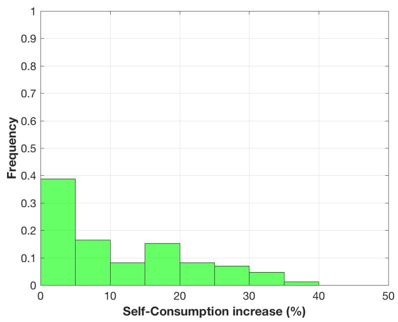


Figure 21: Frequency distribution of Self-Consumption increase for a 20 kWh Li-ion EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

stationary storage unit. So, an availability time profile, that is randomly generated according to statistical data, was used to represent the unsystematic mobility habitudes of Italian people living in small town and rural area. Moreover, different minimum SOC were considered to highlight different driver's range anxiety. A Monte Carlo approach was used here for considering the statistical variation of driving patterns to evaluate economic and energy benefits of V2H and V2G operation by considering two main EV battery technologies: Ni-MH and Li-ion.

The results obtained from the application of the optimal management



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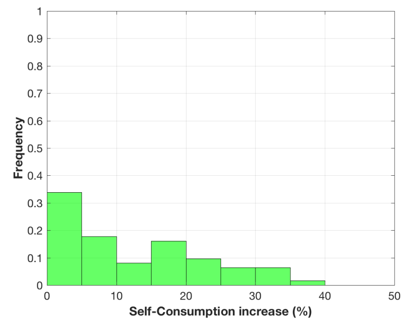

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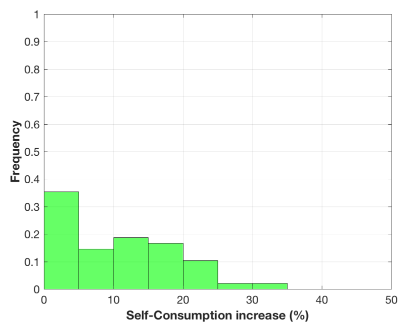
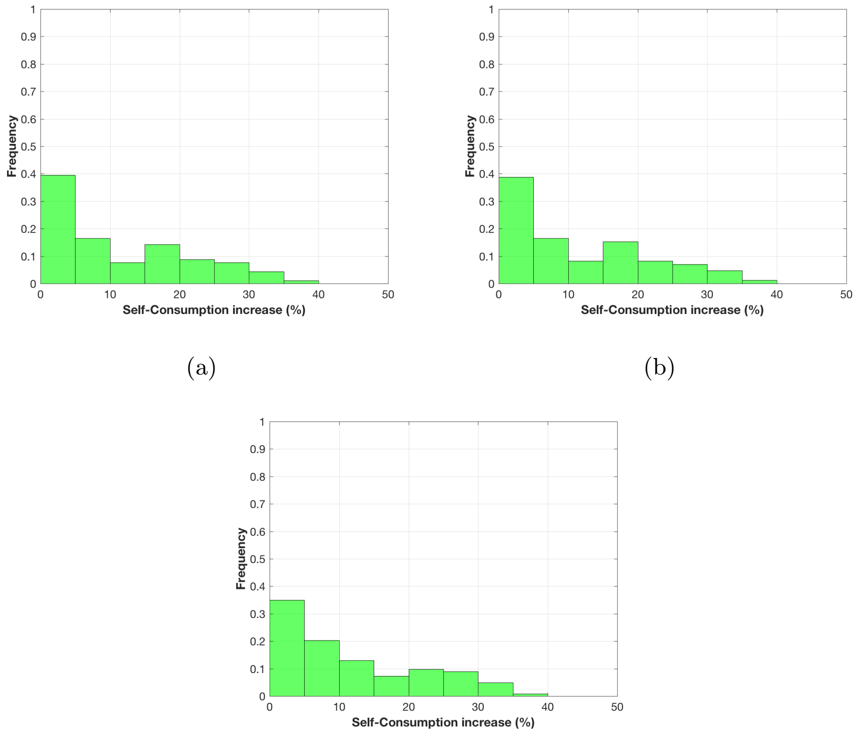


(c)

Figure 22: Frequency distribution of Self-Consumption increase for a 40 kWh Li-ion EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

of the EV battery, within the Monte Carlo approach, show that, in general, a lower range anxiety (i.e. lower SOC_{min}) allows to better exploit the PV production increasing the self-consumption of RES generation and consequently reducing the household energy supply costs. On the other hand, higher range anxiety leads to a reduction of the benefits. The statistical analysis underlines how the driving patterns for Italian people living in small town and rural area have a significant effect on the economic and energy benefits. In fact, around 50% of the Monte Carlo simulations reveals a significant energy consumption for covering mobility needs, so just a re-



(a) (b)

(c)

Figure 23: Frequency distribution of Self-Consumption increase for a 60 kWh Li-ion EV battery with a) 40% of SOC_{min}, b) 60% of SOC_{min} and c) 80% of SOC_{min}.

duced band of EV battery capacity is available for V2H and V2G operation with a corresponding cost saving lower than 5%. Nevertheless, yearly cost saving up to 20-30% may be potentially reached in 25/30% of the scenarios of the Monte Carlo simulations. As a consequence, the self-consumption of PV production is increased as well.

Moreover, the EV battery technologies considered in this study show some differences. The higher roundtrip efficiency of Li-ion battery, compared to Ni-MH, reflects the ability of this system to act both V2H and V2G operation for minimizing household electricity cost. While, the lower efficiency for storing electricity in Ni-MH technology, combined to a context with low electricity selling price, forces the EV battery to be used only for V2H operation.

However, the impacts of V2H and V2G operation on battery aging and deterioration are not considered here. So future work, where also different contexts and countries are considered, will be developed to include also these aspects within the optimal management.

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