A coordinated optimal programming scheme for an electric vehicle fleet in the residential sector

F. Palmiotto [a], Y. Zhou [b], G. Forte [a,*], M. Dicorato [a], M. Trovato [a], L. M. Cipcigan [b]

[a] Dept. of Electrical and Information Engineering (DEI) – Politecnico di Bari
Via E. Orabona, 4 – 70125 Bari, Italy
f.palmiotto2@studenti.poliba.it
giuseppe.forte@poliba.it
maria.dicorato@poliba.it
micheleantonio.trovato@poliba.it

[b] School of Engineering, Cardiff University
Queen's Buildings, The Parade, Cardiff, CF24 3AA, United Kingdom
Zhouy68@cardiff.ac.uk
cipciganlm@cardiff.ac.uk

[*] corresponding author, mail to: giuseppe.forte@poliba.it

Abstract

The development of intelligent strategies to manage electric vehicle charging process is the key for fostering a proper diffusion of electric vehicles at customer premises. The presence of renewable generation and the exploitation of vehicle-to-grid can enhance this process. In this paper, two procedures are proposed for optimizing electric vehicle charging strategies, for an aggregation of consumers, with the objectives of load profile levelling and total cost minimization, in the presence of possible realistic diffusion of photovoltaic systems and electric vehicles. Moreover, the best compromise between the two objectives is evaluated by determining techno-economic merit indicators. The procedures are applied to a realistic case study in the UK, considering an aggregator managing a group of residential customers in a low-voltage distribution network, where multiple tariff schemes are assessed.

Keywords:

Electric Vehicles, Charging Strategy optimization, Aggregator, Residential load profile

Nomenclature

Sets and indices

i , t	Index of time interval
b	Index of Electric Vehicle (EV)
N	Number of time intervals in the considered time horizon
B	Number of EVs

Operation parameters

τ	Duration of time interval [h]
D_i	Load demand of residential users at the i-th interval [kW]
G_i	Power production level by photovoltaic system at the i-th interval [kW]
L_i	Net aggregated load at the i-th interval [kW]
i_b^{arr}	Arrival interval of the b-th EV at the charging point
i_b^{dep}	Departure interval of the b-th EV from the charging point
$u_{b,i}$	Binary parameter for the connection of the b-th EV to the charging point at the i-th interval
E_b^{cap}	Energy capacity of the b-th EV battery [kWh]
E_b^{arr}	Energy level of the b-th EV battery at arrival time [kWh]
E_b^{dep}	Minimum energy level of the b-th EV battery at departure time [kWh]
E_b^{tr}	Energy needed for the planned trip of the b-th EV [kWh]
P_b^{max}	Maximum charging power of the b-th EV [kW]
P_b^{min}	Maximum discharging (negative) power of the b-th EV [kW]

Uncontrolled case - operation parameters

$W_{b,i}$	Uncontrolled power exchange of the b-th EV at the i-th interval [kW]
D_i^{UC}	Total demand of the residential district in the uncontrolled case at i-th interval [kW]

Operation variables in procedures

$P_{b,i}$	Power exchange of the b-th EV with the internal grid at the i-th interval [kW]
$E_{b,i}$	Energy level of the b-th EV battery at the i-th interval [kWh]
y_i	Total power exchange by the EVs at the i-th interval [kW]

Load leveling – parameters and functions

f^{LL}	Objective function of the Load Levelling procedure [kW^2]
D^{tgt}	Target value of total demand of the residential district at i-th interval in Load Leveling procedure [kW]
L^{tgt}	Target value of net aggregated demand of the residential district at i-th interval in Load Leveling procedure [kW]

Cost minimization – parameters and functions

f^{CM}	Objective function of the Cost Minimization procedure [£]
π_i	Electricity price at the i-th interval [£/kWh]
π_i^p	Electricity purchase price at the i-th interval [£/kWh]
π_i^s	Electricity selling price at the i-th interval [£/kWh]

α_i , β_i Ancillary variables to linearize Cost Minimization objective function at i-th interval [kW]

Performance comparison

δ Mean absolute deviation of the demand from the target value [kW]

C Total cost for aggregated power exchange with the external distributor [£]

δ_{pu} Normalized value of δ

C_{pu} Normalized value of C

GMI Global merit indicator

ω Relative weighting factor for GMI determination

1. Introduction

The vehicle electrification is exerting an important impact on the existing distribution networks due to the increase in electricity consumption. If the charging process is uncontrolled, the charging of Electric Vehicles (EVs) would take place as soon as they reach the charging point, usually from afternoon until late evening, increasing the load peak of residential demand profiles [1]. If the peak demand exceeds the network capacity, the power network has to face voltage drops, power losses increase, power quality issues and overloading of distribution transformers, resulting in expensive network reinforcement.

On the other hand, EVs could provide support to the distribution networks. For example, smart charging of EVs could also provide ancillary services to the power grid such as peak shaving, spinning reserves and frequency regulation. These goals can be better achieved through the Vehicle-to-Grid (V2G) energy exchange mode.

The essential principle in the intelligent scheduling is to reshape the load profile by charging the EV from the grid at the time when the demand is low and discharging the EV to the grid when the demand is high [2], but similar strategies can be adopted during low and high price periods to improve economic performances. These actions take advantage of smart meters, which are able to communicate electricity consumption data with short time intervals and thus allow the deployment of dynamic pricing tariffs and can encourage change of customer habits.

Several scheduling schemes for EV charging and discharging to minimize the total energy cost have been described in the literature. In [2], a globally optimal scheduling is proposed, to minimize the total cost of all EVs which perform charging and discharging during the day, along with a locally optimal scheduling, focused at reducing the total cost of the EVs in the current ongoing set in the local group. The locally optimal scheduling scheme is not only scalable to a large EV population but also resilient to the dynamic EV arrivals. A decentralized valley-filling charging strategy is adopted in [3], in which a day-ahead pricing scheme is designed by solving a minimum-cost optimization problem, to be offered to EV owners, and to indirectly coordinate the individual charging behaviors. Optimal pricing strategy for the EV fast charging using double-layer optimization model was developed in [4] for voltage control in distribution network. A procedure for microgrid operation planning is presented in [5], able to integrate EV fleet management adopting a non-linear daily cost minimization subject to dynamic operating constraints, according to suitable load demand and source availability forecast, controlled by an EV aggregator. Minimum cost scheduling of a DC microgrid including Photovoltaic (PV), energy storage and EVs with V2G is analyzed in [6], with a focus on realistic features of devices and providing performance indicators. Minimization of day-ahead EV charging cost in a residential area is proposed in [7], exploiting Monte-Carlo simulation for uncertainties on initial state of charge and on arrival/departure time, and considering low voltage feeders. In [8], a stochastic mixed integer programming method is employed to schedule the operation of a system including commercial buildings, involving thermal and electric power, and EV charging stations in order to minimize the total energy cost. Different energy exchanges with EVs in a building complex are evaluated in [9] with an economic objective. The presence of different tariffs for EVs according to their participation level in smart charging action is considered in [10], considering an EV aggregator with power exchange limits at grid interface. In [11], a double-layer EV management is investigated, involving cost minimization through active power control and grid integration enhancement through reactive power control.

Peak shaving models using scheduling of EV charging and discharging have also been widely addressed in the literature. In [12], optimal EV battery charging/discharging scheduling is assessed to achieve peak shaving and reduction of load variability for 63 households connected to distribution network, by comparing a business-as-usual scenario (without any intelligent charging), an intelligent local charging optimization without V2G, and charging optimization with V2G. A mathematical model is proposed in [13] to peak-shave and valley-fill the power consumption profile of a university building by scheduling the charging/discharging process in an EV parking lot, validated by real-world data of power consumption and parking lot occupancy. A Local Energy Management System (LEMS) is used in [14] to predict the most probable half hours for a triad peak, forecasts the electricity demand of a building facility at those times and control the EVs charging using scheduling algorithms [14]. An EV aggregator is proposed in [15] to perform load peak shaving and to subsequently allocate power among EVs according to charging priority. These aggregators can use multi-agent models considering EV charging limits given by distribution network feeder rating as proposed in [16]. Loss minimization and voltage constraints on a distribution network accounting for EV paths and correlation is proposed in [17]. In [18], a probabilistic study on EV charging trends is carried out, according to energy state and travel distances, to individuate feasible integration quotas in distribution grid.

Moreover, an increasing number of studies have considered EVs and stochastic renewable energy sources integration in small- or large-scale applications. In [19], a number of scenarios are examined for peak-shaving and valley-filling the power consumption profile of a university building with PV systems using plug-in EVs, while emphasis is given on solar irradiance forecasting and simulation of the PV power output. EVs can be used to consume local PV generation and reduce the potential impact on the grid [20,21]. In order to address the uncertainty of PV power output for load scheduling of smart homes, where EVs are only considered as charging load, a robust formulation is proposed and further transformed to an equivalent quadratic programming problem in [22]. A system with PV, loads and different types of EVs is managed in [23] by means of real-time procedures and a linear programming aimed at maximizing self-consumption. The uncertainty of EV demand should be tackled as well in the residential sector, as illustrated by [24]. In [25], a procedure for net load minimization in a microgrid is proposed.

In some studies, several objectives are jointly analyzed and considered. In particular, in [26], the optimization of residential load profile involving EV and demand response techniques is based on a multi-objective approach involving customer satisfaction on bills and on time shifting actions. By contrast, in [27], minimization of costs, emissions and losses in a network with residential loads with EV is obtained by separate objective functions and determining the best compromise through Pareto front and fuzzy technique.

From literature analysis, it can be argued that the presence of technical and economic objectives in a residential EV-oriented energy management system is seldom investigated, and the need of synthetic performance indicators, useful for flexible strategy evaluation for system management and for users, can be pointed out.

In this paper, two procedures for optimizing electric vehicle charging strategies are carried out, for an aggregation of consumers, in the presence of possible realistic diffusion of photovoltaic systems and EVs. In particular, the objectives of load profile levelling and total cost minimization are considered by means of proper optimization formulation. Moreover, the best compromise between the two objectives is evaluated by determining the variation of suitable techno-economic merit indicators. The proposed methodologies are applied in a UK residential district in the presence of realistic EV diffusion and according to EV mobility data based on field measurements.

The main contributions of this work with respect to the studies in the existing literature can be summarized in the following points:

- Proper linearization technique for the nonlinear objective of cost reduction is applied in order to improve solution performances.
- A set of tariffs is analysed in order to individuate the more adequate solution to provide benefits for users depending on EV usage.

- A comparative study of normalized performance indicators is proposed, determining the best compromise in different conditions according to relative weighting factor.

The paper is organized as follows. The proposed procedures are illustrated in Section 2. Test case is characterized in Section 3, and simulation results and comments are reported in Section 4. Conclusions are drawn in Section 5.

2. EV management models in the residential sector

In this work, two scenarios are analyzed in order to highlight the benefits of EVs. In particular, in the uncontrolled scenario, the EVs can only charge for the energy needed for the next trip according to statistical data of charging request, until a suitable final energy state is reached. By contrast, in the coordinated charging scheme, two optimization procedures are elaborated, i.e. the load levelling and the cost minimization, on a day-ahead programming horizon, regulating the EVs charging and discharging processes. The influence of renewable-based distributed generation facilities is assessed in the coordinated charging.

The basic assumption is to examine the power exchange levels of a residential district over the daily horizon, evenly divided in N time intervals with a duration τ and denoted by the index $i = 1, \cdots, N$. For each i-th interval, the electric load demand D_i of the residential users of the district is properly forecasted, along with possible PV power production G_i. The charging and discharging process of EVs, denoted by the index $b = 1, \cdots, B$, is therefore introduced, assuming an exact correspondence between EVs and residential charging points, installed at user premises.

2.1. Reference case – uncontrolled charge

In order to create a reference case for the optimization procedures, the uncontrolled charge is studied. It is assumed that the arrival interval i_b^{arr} and the departure interval i_b^{dep} of the b-th EV at the relevant charging point are known in advance. The battery of the b-th EV has an energy capacity E_b^{cap}, and its operation is characterized by the initial energy level E_b^{arr} at arrival and by the energy for forecast mobility needs E_b^{tr}.

In the uncontrolled case, the values of power exchange of EVs during the parking interval are represented by known values $W_{b,i}$, directly obtained from typical EV charging patterns, given that the energy E_b^{tr} has to be fed to the EV during b-th EV parking time. Therefore, the total demand of the residential district in the uncontrolled case D_i^{UC} is obtained for each time interval as:

$$D_i^{UC} = D_i + \sum_{b=1}^{B} W_{b,i} \tag{1}$$

2.2. Load levelling procedure

The load levelling procedure works on the total net load of the residential district. In particular, the net aggregated load at i-th time interval L_i is obtained by dealing with PV generation G_i as negative load, as detailed in equation (2):

$$L_i = D_i - G_i \tag{2}$$

The goal of the procedure is to reduce as much as possible the variation, in each interval, of total demand of the residential district from the target value L^{tgt} (or D^{tgt}) defined as the average between minimum and maximum load levels, as follows:

$$L^{tgt} = \frac{1}{2} \cdot \left[\max_{i=1,\cdots,N} (L_i) + \min_{i=1,\cdots,N} (L_i) \right] \tag{3}$$

In the procedure, a decision variable is the EV power exchange $P_{b,i}$, which by convention is negative when the b-th EV is discharged and positive when the b-th EV is charged. Moreover, the parameter for EV presence at charging point $u_{b,i}$ is defined by equation (4):

$$\begin{aligned} u_{b,i} &= 1 \quad \text{if } i_b^{arr} \leq i \leq i_b^{dep} \\ u_{b,i} &= 0 \quad \text{otherwise} \end{aligned} \tag{4}$$

In this way, the total power exchange by the EVs at the i-th interval, y_i, is determined as follows:

$$y_i = \sum_{b=1}^{B} P_{b,i} \cdot u_{b,i} \quad i = 1, \cdots, N \tag{5}$$

Therefore, the goal of the load levelling procedure is the minimization of the function f^{LL}, corresponding to the sum of square values of deviation from target in each time interval, as reported in equation (6):

$$f^{LL} = \sum_{i=1}^{N} [(L_i + y_i) - L^{tgt}]^2 \tag{6}$$

where, in the absence of PV generation, L_i and L^{tgt} are replaced by D_i and D^{tgt} respectively.

Power exchange of EVs is limited by the features of the charging point it is connected to. By assuming that each EV can be connected to a single charging point characterized by P_b^{max} (positive) and P_b^{min} (negative or zero in the absence of V2G), the following limits hold:

$$P_b^{min} \leq P_{b,i} \leq P_b^{max} \quad i = 1, \cdots, N; \; b = 1, \cdots, B \tag{7}$$

Therefore, the total power exchange from EVs is limited by the sum of charging and discharging power boundaries, as follows:

$$\sum_{b=1}^{B} P_b^{min} \leq y_i \leq \sum_{b=1}^{B} P_b^{max} \quad i = 1, \cdots, N \tag{8}$$

The energy level of the b-th EV battery in the i-th interval $E_{b,i}$ is obtained by equation (9):

$$E_{b,i} = E_b^{arr} + \sum_{t=1}^{i} (\tau \cdot P_{b,t} \cdot u_{b,t}) \quad i = 1, \cdots, N;\ b = 1, \cdots, B \tag{9}$$

where the second term represents the sum of all energy exchanges experienced by the EV from the beginning of the time horizon up to the i-th interval. The EV energy level is bounded by means of the following expression:

$$0 \leq E_{b,i} \leq E_b^{cap} \quad i = 1, \cdots, N;\ b = 1, \cdots, B \tag{10}$$

Further constraints apply on EV battery management. In particular, at departure time i_b^{dep} the energy level should be enough to cover the energy needed for the next trip, as explicated in equation (11):

$$E_{b,i_b^{dep}} \geq E_b^{dep} = E_b^{arr} + E_b^{tr} \quad b = 1, \cdots, B \tag{11}$$

In order to prioritize EV use for mobility with respect to energy provision, it is supposed that the total daily EV charging should be higher than the total daily discharging, as follows:

$$\sum_{i=1}^{N} (\tau \cdot P_{b,i} \cdot u_{b,i}) \geq 0 \quad b = 1, \cdots, B \tag{12}$$

In order to limit energy exchange of EVs only in parking periods, the equation (13) applies:

$$P_{b,i} \cdot (1 - u_{b,i}) = 0 \quad i = 1, \cdots, N;\ b = 1, \cdots, B \tag{13}$$

This implies that, for the scope of managing EV charging/discharging with the distribution system, the energy level of EVs out of the parking time is not of interest

The explained procedure can be posed in the form of a quadratic optimization problem, assuming the following general formulation:

$$\begin{gathered} \min_{x} \left(\frac{1}{2} \boldsymbol{x}^T \cdot \boldsymbol{H} \cdot \boldsymbol{x} + \boldsymbol{k}^T \cdot \boldsymbol{x} \right) \\ s.t. \begin{cases} \boldsymbol{A_d} \cdot \boldsymbol{x} \leq \boldsymbol{b_d} \\ \boldsymbol{A_e} \cdot \boldsymbol{x} = \boldsymbol{b_e} \\ \underline{\boldsymbol{x}} \leq \boldsymbol{x} \leq \overline{\boldsymbol{x}} \end{cases} \end{gathered} \tag{14}$$

For the described problem, the state variable vector $\boldsymbol{x}$ includes the decision variables $P_{b,i}$, y_i and $E_{b,i}$, and has a dimension of $(2 \cdot B + 1) \cdot N$. In the objective function, the matrix $\boldsymbol{H}$ and the vector $\boldsymbol{k}$ can be obtained by explicating the expression of f^{LL} in equation (6). Inequality constraints $\boldsymbol{A_d} \cdot \boldsymbol{x} \leq \boldsymbol{b_d}$ include equations (11) and (12), whereas equality constraints $\boldsymbol{A_e} \cdot \boldsymbol{x} = \boldsymbol{b_e}$ involve equations (5), (9), (13), and finally max/min limits $\underline{\boldsymbol{x}} \leq \boldsymbol{x} \leq \overline{\boldsymbol{x}}$ include equations (7), (8) and (10).

2.3. Cost minimization procedure

In order to implement cost minimization, the electricity price π_i is introduced. It is assumed that an aggregator is called to manage the total demand, that is $L_i + y_i$ for each time interval, towards the electricity distributor. Therefore, the objective function of the procedure f^{CM} is determined as follows:

$$f^{CM} = \sum_{i=1}^{N} \tau \cdot \pi_i \cdot (L_i + y_i) \tag{15}$$

The pricing level π_i depends on the sign of the total demand, corresponding to the direction of aggregated power exchange with the electricity distributor. If the total demand is positive, a purchase price π_i^p is applied, whereas for negative demand a selling price π_i^s is considered, thus generating a revenue (negative total cost), as described in equation (16):

$$\begin{aligned} \pi_i &= \pi_i^p \quad \text{if } (L_i + y_i) \geq 0 \\ \pi_i &= \pi_i^s \quad \text{if } (L_i + y_i) < 0 \end{aligned} \tag{16}$$

In order to keep in the framework of linear programming although with price coefficients varying with variable sign, an alternative formulation is provided, by first converting the objective function to a form with absolute values, and then by introducing ancillary variables α_i and β_i, to eliminate the absolute values – without physical meaning – thus linearizing the expression. Full proof of the linearization is demonstrated in [22]. Therefore, for the equation (15) the following expression can be adopted:

$$f^{CM} = \sum_{i=1}^{N} \frac{\tau}{2} \cdot \left[\left(\pi_i^p - \pi_i^s\right) \cdot (\alpha_i + \beta_i) + \left(\pi_i^p + \pi_i^s\right) \cdot (L_i + y_i) \right] \tag{17}$$

where ancillary variables assume only positive values:

$$\begin{aligned} \alpha_i &\geq 0 \quad i = 1, \cdots, N \\ \beta_i &\geq 0 \quad i = 1, \cdots, N \end{aligned} \tag{18}$$

An additional equality constraint is defined, as reported in equation (19), in order to link ancillary variables to net demand components:

$$y_i + \alpha_i - \beta_i + L_i = 0 \quad i = 1, \cdots, N \tag{19}$$

Note that a further non-linear constraint for ancillary variables α_i and β_i is included in [22], which is $\alpha_i \cdot \beta_i = 0$. However, it can be neglected in the formulation of this paper, considering that ancillary variables are used for removing absolute value in (17) only, and thus the condition $\alpha_i \cdot \beta_i = 0$ is always verified when the objective function is minimized. In more detail, with $\pi_i^p > \pi_i^s$ which is true in most practical cases, if $\alpha'_i \cdot \beta'_i \neq 0$ and $\alpha'_i \geq \beta'_i$, we can always find $\alpha_i = \alpha'_i - \beta'_i$ and $\beta_i = 0$ resulting in a smaller value of the objective function at the same time satisfying the equality constraint (19), indicating that the optimal solution that minimizes the objective function (17) must satisfy $\alpha_i \cdot \beta_i = 0$ by keeping linear formulation. Similar considerations can be made for the case $\alpha'_i \cdot \beta'_i \neq 0$ and $\alpha'_i < \beta'_i$.

The general form of the linear programming problem for cost minimization is defined as follows:

$$\min_{\boldsymbol{z}}(\boldsymbol{f}^T \cdot \boldsymbol{z})$$
$$s.t. \begin{cases} \boldsymbol{A'}_{\boldsymbol{d}} \cdot \boldsymbol{z} \leq \boldsymbol{b'}_{\boldsymbol{d}} \\ \boldsymbol{A'}_{\boldsymbol{e}} \cdot \boldsymbol{z} = \boldsymbol{b'}_{\boldsymbol{e}} \\ \underline{\boldsymbol{z}} \leq \boldsymbol{z} \leq \overline{\boldsymbol{z}} \end{cases} \tag{20}$$

In this case, the state variable vector $\boldsymbol{z}$ includes the decision variables $P_{b,i}$, y_i and $E_{b,i}$, along with ancillary variables α_i and β_i, and has a dimension of $(2 \cdot B + 3) \cdot N$. Moreover, the objective function $\boldsymbol{f}^T \cdot \boldsymbol{z}$ corresponds to f^{CM} in equation (17), having non-null coefficients for y_i , α_i and β_i. Inequality constraints $\boldsymbol{A'}_{\boldsymbol{d}} \cdot \boldsymbol{z} \leq \boldsymbol{b'}_{\boldsymbol{d}}$ include equations (11) and (12), whereas equality constraints $\boldsymbol{A'}_{\boldsymbol{e}} \cdot \boldsymbol{z} = \boldsymbol{b'}_{\boldsymbol{e}}$ involve equations (5), (9), (13) and (19). Finally, max/min limits $\underline{\boldsymbol{z}} \leq \boldsymbol{z} \leq \overline{\boldsymbol{z}}$ involve equations (7), (8), (10) and (18).

2.4. Performance indicators and global merit indicator

In order to compare the alternative scheduling strategies described so far, a set of merit indicators of EV programming is defined.

In particular, to test the flattening action on the total demand, the daily mean absolute deviation δ of the optimized demand from the target value is chosen as a technical indicator, defined as follows:

$$\delta = \frac{1}{N} \cdot \sum_{i=1}^{N} |(L_i + y_i) - L^{tgt}| \tag{21}$$

The total cost for aggregated power exchange with the external distributor C is selected as economic indicator, defined by equation (22):

$$C = \sum_{i=1}^{N} \tau \cdot \left[\pi_i^p \cdot \max(L_i + y_i\,, 0) + \pi_i^s \cdot \min(L_i + y_i\,, 0)\right] \tag{22}$$

To compare the two performance indicators, one expressing power level and the other an economic indicator, each of them is normalized according to a proper reference value, and therefore per unit values δ_{pu} and C_{pu} are obtained.

The global merit indicator GMI is inspected by determining the weighted average of the two per unit indicators according to relative weighting factor ω, representing the outweigh of δ_{pu} with respect to C_{pu}, as reported in equation (23):

$$GMI = \frac{\omega}{1 + \omega} \cdot \delta_{pu} + \frac{1}{1 + \omega} \cdot C_{pu} \tag{23}$$

The case with minimum value of GMI for a given ω represents the highest combined increase of system performance, therefore it is taken as the best compromise.

A schematization of the proposed analysis framework is depicted in the flowchart of Figure 1.

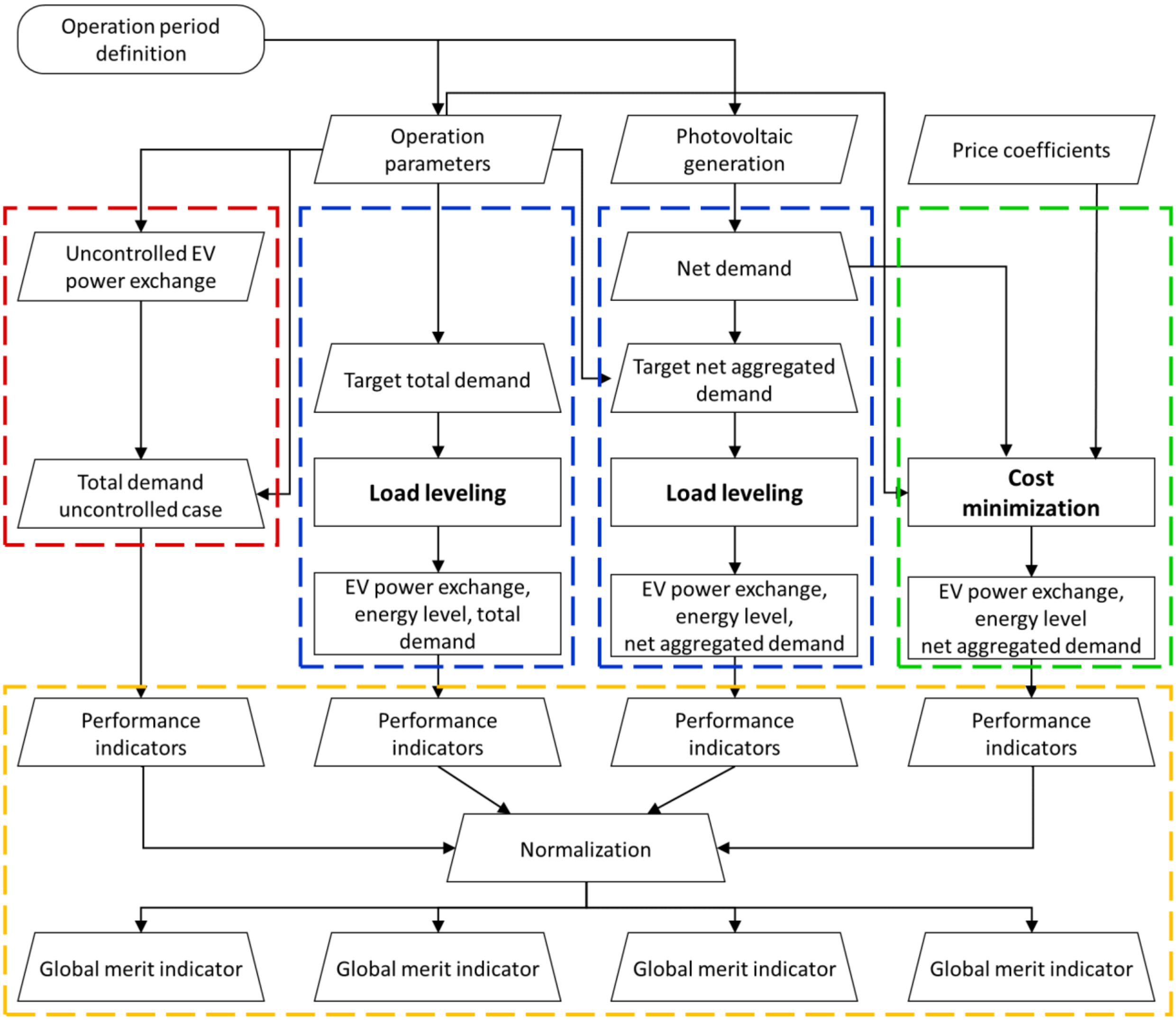

Figure 1: Flowchart of the proposed analysis framework: in red, uncontrolled charge; in blue, load leveling; in green, cost minimization; in orange, performance analysis.

3. Test case description

In order to evaluate the effectiveness of the proposed procedures, the case study involves an aggregation of 96 residential customers connected to a radial low-voltage network feeder. It is supposed that 22 customers have photovoltaic panels installed on the roof with an installed power of 3.5 kWp for each and 40 of them use an EV with relevant residential charging point allowing bidirectional V2G option. Assumptions on PV and EV diffusion in the residential framework are consistent with most ambitious UK outlook scenarios at 2030 [28]-[31].

Each EV can be charged/discharged with maximum rates P_b^{max} = 3.5 kW and P_b^{min} = -3.5 kW respectively, in order to inspect the fact that bidirectional exchange could be available on residential-size charging points instead of more powerful public charging stations. The daily horizon is divided in half-hour intervals, hence N = 48 and τ = 0.5 h. Therefore, the total number of variables is

$(2 \cdot B + 1) \cdot N = 3888$ for load levelling quadratic problem and $(2 \cdot B + 3) \cdot N = 3984$ for cost minimization linearized problem.

The power consumption of customers is set up according to data from [32]. In this context, a reference week for the summer and one for the winter are selected, and consumption values of a set of 96 Domestic Unrestricted Customers in each interval of the day are properly mediated to get the aggregated profile for a typical winter and summer weekday. The resulting half-hourly power consumption profiles are shown in Fig. 2, where two peaks are observed, in the early morning and in the afternoon, caused by the presence of active household appliances and electric heating. Winter peak reaches 85 kW, whereas summer demand does not exceed 60 kW.

Moreover, PV power production profiles are obtained from [33][34], considering the generation profile of a single house PV installation in the considered location. The aggregated profiles are presented in the Fig. 3. As a consequence, in the winter case the aggregated net demand reaches a minimum of 12 kW in central hours of the day, whereas in the summer case the PV production exceeds load demand, attaining a minimum net demand of -36 kW.

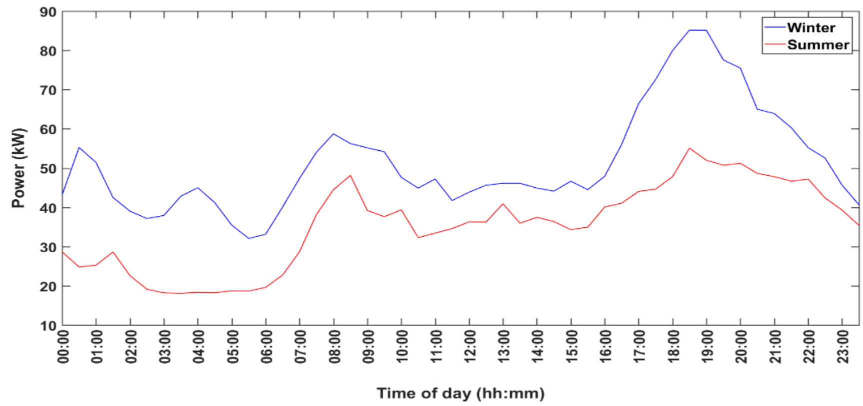

Figure 2: Aggregated power consumption profiles of the winter and summer.

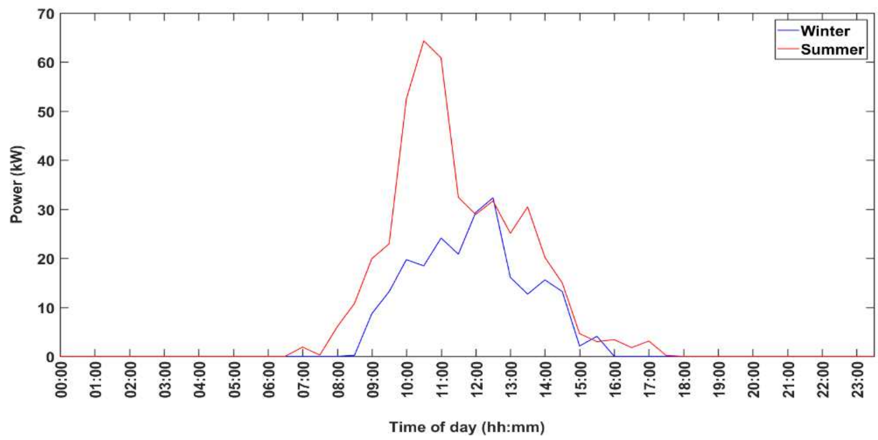

Figure 3: Aggregated PV generation profiles of the winter and summer.

EV exploitation patterns are taken from [33][35], extracting proper samples from the collected field data, while respecting the general dispersion features of parking time and charging needs. In particular, the extremes of parking time for the 40 EVs are shown in the first two columns of Table 1, where it can be seen that the majority of parked EVs are present in the afternoon. For each EV, the energy capacity E_b^{cap} is assumed equal to 24 kWh [36].

According to the considered data source, the energy needed for the next trip of each EV E_b^{tr} ranges between 1.1 kWh and 7.3 kWh (i.e. from 5% to 25% of E_b^{cap}), corresponding to trips from 10 to 50 km, as reported in the relevant column of Table 1. The relevant measurements of charging power are accounted to build the uncontrolled charging in the reference case, usually lower than maximum level of 3.5 kW. The influence of uncontrolled EV charge on the total demand profile is reported in Fig. 4 and Fig. 5 for winter and summer days, respectively. The total demand increases due the charging of EVs which reaches at most 10 kW between 17:00 and 20:00.

For each EV, it is assumed that the minimum energy state at departure time E_b^{dep} is a random number between 19.2 kWh and 24 kWh (i.e. 80% and 100% of E_b^{cap}) with a uniform distribution, as reported in the last columns of Table 1. Therefore E_b^{arr} is determined by subtracting E_b^{tr} to E_b^{dep}, so that it does not fall below 50% of E_b^{cap}.

Table 1: Parking time and energy features of the considered EVs.

EV # (b)	i_b^{arr}	i_b^{dep}	E_b^{tr} [kWh]	E_b^{dep} [kWh]	**EV #** (b)	i_b^{arr}	i_b^{dep}	E_b^{tr} [kWh]	E_b^{dep} [kWh]
1	17:00	20:00	2.89	22.31	**21**	12:30	17:00	4.89	21.99
2	10:30	13:30	3.07	22.46	**22**	19:00	23:00	4.14	21.80
3	12:30	16:30	3.85	22.25	**23**	20:00	22:00	2.18	23.38
4	12:00	15:30	3.50	23.74	**24**	15:00	18:00	1.70	20.47
5	17:00	21:30	4.84	20.20	**25**	22:30	23:30	1.10	20.73
6	12:30	15:30	3.13	22.60	**26**	13:00	18:00	4.35	19.77
7	11:00	12:30	1.64	20.33	**27**	04:00	08:00	3.86	23.71
8	17:00	21:00	4.35	19.77	**28**	11:00	13:30	2.70	22.30
9	16:30	18:00	1.12	22.12	**29**	07:00	11:00	4.30	21.50
10	01:30	05:30	4.48	21.36	**30**	00:00	08:00	7.28	22.27
11	17:00	20:30	3.70	21.40	**31**	13:30	16:00	2.29	21.81
12	11:30	16:30	4.06	22.38	**32**	22:00	24:00	1.54	22.31
13	15:30	19:00	3.74	22.90	**33**	17:00	20:00	2.48	21.81
14	13:00	16:30	3.28	20.88	**34**	09:00	12:00	3.10	22.66
15	18:00	21:00	3.25	22.38	**35**	10:00	13:00	3.44	21.71
16	17:30	20:00	2.72	21.20	**36**	10:30	13:00	2.99	23.97
17	17:00	20:30	3.26	23.24	**37**	07:30	10:00	2.99	20.25
18	13:30	16:30	3.19	23.20	**38**	21:00	24:00	3.00	19.71
19	18:00	19:30	1.49	20.43	**39**	19:30	23:00	3.41	19.73
20	17:00	22:00	4.65	22.14	**40**	20:00	23:30	3.89	19.50

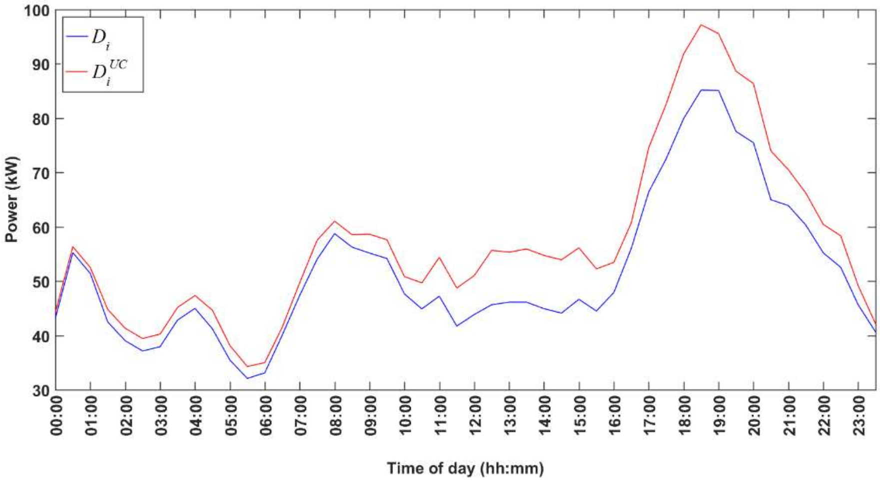

Figure 4: Impact of reference EV charging on the winter demand.

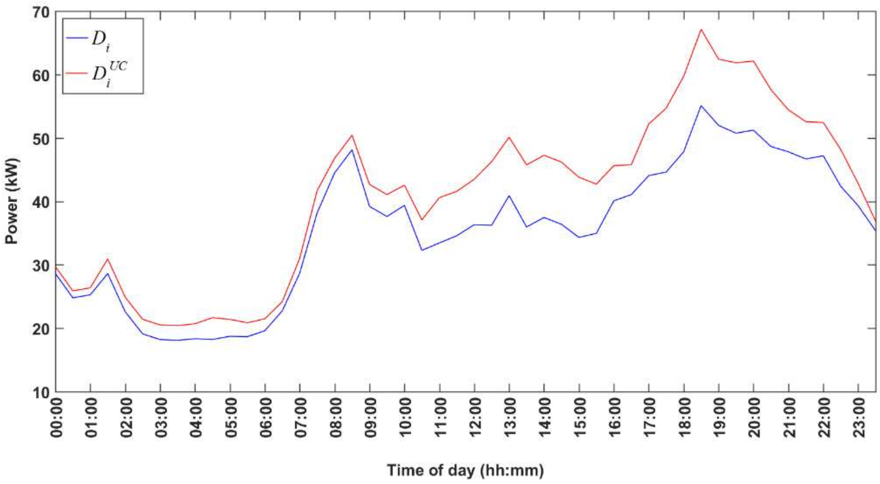

Figure 5: Impact of reference EV charging on the summer demand.

As regards pricing schemes, a comparison between standard flat tariff and the Time of Use (TOU) tariff scheme is considered, in order to analyze possible implications on EV exploitation pattern. Therefore, the residential district is considered in the UK retail market, where the retail price plays the role of π_i^p, and the feed-in tariff price is assumed as π_i^s. On these premises, three cases are analyzed, exploiting three pricing schemes provided by Scottish and Southern Energy utility provider (Standard, Evening and Economy 10), which are valid for a location coherent with load data [37]. Relevant values are reported in Table 2. The Standard tariff has a constant price throughout the day, whereas Evening tariff offers off-peak electricity in the evening, and in Economy 10 the peak hours are split in three different periods, although two price levels are considered. Finally, feed-in tariff is equal to 5.24 pence/kWh, as reported in [38] for export.

Table 2. Retail price description in the three tariff schemes

Tariff Type	Standard Rate (pence/kWh)	Off-Peak Rate (pence/kWh)	Standard Period	Off-Peak Period
Standard	17.82	/	0:00-24:00	/
Evening	15.10	24.73	7:30- 19:30	19:30-7:30
Economy 10	12.81	21.30	5:00-13:00 16:00-20:00 22:00-24:00	0:00-5:00 13:00-16:00 20:00-22:00

4. Results and discussion

The procedures are implemented in MATLAB 2017 framework, exploiting *quadprog* and *linprog* optimization tools for the load levelling and cost minimization procedures, respectively, according to the standard forms given in equations (14) and (20).

4.1 Load levelling procedure

In the presence of PV production, the net demand is accounted, and the effect of load levelling procedure is depicted in Fig. 6 and Fig. 7 in winter and summer days, respectively. It can be seen that the duck curve effect due to the presence of PV production can be effectively flattened by the load levelling procedure with the EVs. For the comparison of results, outcomes of procedure application in the absence of PV are reported as well by dashed lines.

In particular, in the winter day the target value L^{tgt} is 49.25 kW and the demand valley is filled up to 38.05 kW between 10:00 and 12:30, while the target is reached between 15:00 and 16:00. In the early morning and late evening, the total demand keeps the same profile of the case without PV, since the EV parking intervals seldom overlap the demand valley period. This can yield a decreased stress on the electrical network, while improving the integration of both PV systems and EVs. The maximum level of total demand is equal to 67.6 kW.

In the summer day, the target value L^{tgt} is 11.5 kW and the significant variation of daily demand is reduced. In fact, the morning peak between 07:00 and 09:00 is cut to 31.5 kW thanks to the EV discharging, at the expenses of demand flattening in the first hours of the day. EV charging helps reduce the minimum net demand at 10:30, reaching -14.6 kW as compared to the original value of -32.1 kW. EV discharging starts to prevail from 14:30, and the evening peak reaches the same value of 44 kW obtained in the case without PV.

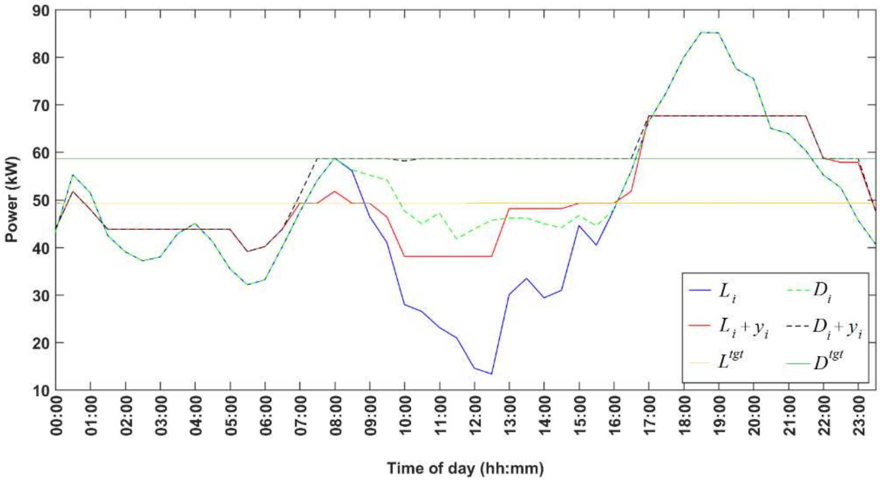

Figure 6: Demand variation in the winter day with load levelling procedure application.

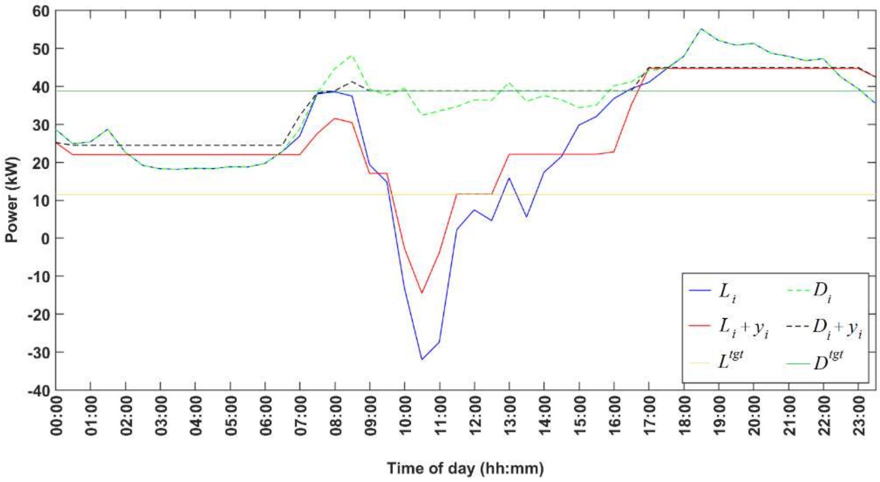

Figure 7: Demand variation in the summer day with load levelling procedure application.

The charging and discharging power of EVs in each time interval are shown in the Fig. 8 and Fig. 9 for winter and summer days, respectively. As predicted, in the winter day the EVs parked between 09:00 and 16:00 are assigned to charge reaching the maximum value of 24.7 kW at 12:30 from nine EVs, to fill the demand valley. By contrast, in late afternoon the EV discharging prevails, with a peak of -17.6 kW by eleven EVs at 18:30, in order to decrease the power demand of the aggregation.
In the summer day, the demand peak between 07:00 and 09:30 is flattened by discharging the only five EVs parked in that interval at maximum rate, acting a preventive charge for EV29 and EV26 and a successive charge for EV37 and EV34 in order to comply with next trip energy level constraint. A peak charge of 24.5 kW is reached at 11:00, due to seven EVs charging at maximum rate. Simultaneous charging and discharging are observed at 13:00 and in the afternoon, whereas the maximum discharging of -21 kW is observed at 16:00 to shave the peak. On average, the energy

exchanges of EVs are more intense in winter due to higher differences to be covered between minimum and maximum peak demand.

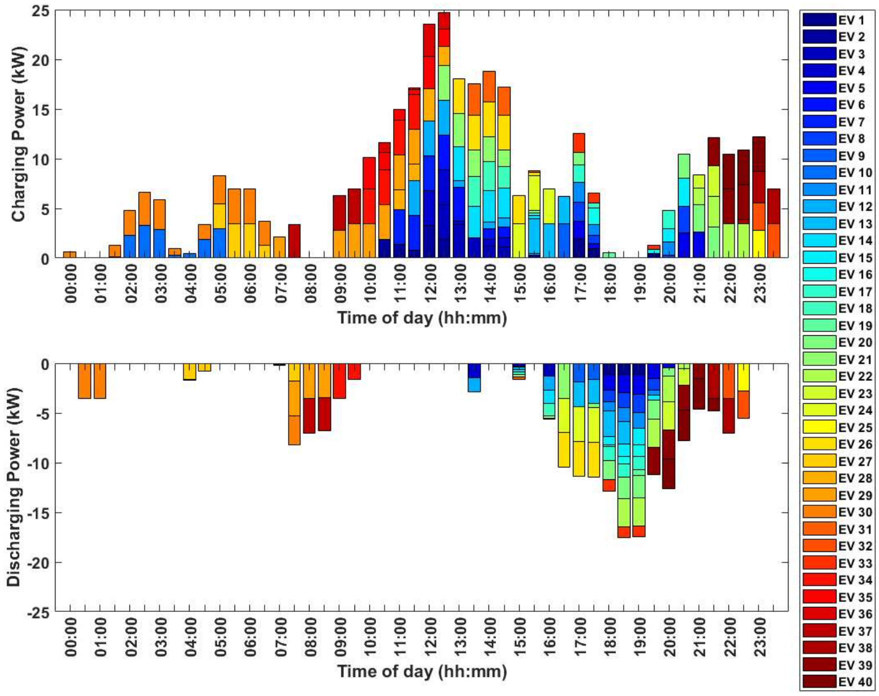

Figure 8: Detail of EV charging/discharging in the winter day with load levelling procedure application.

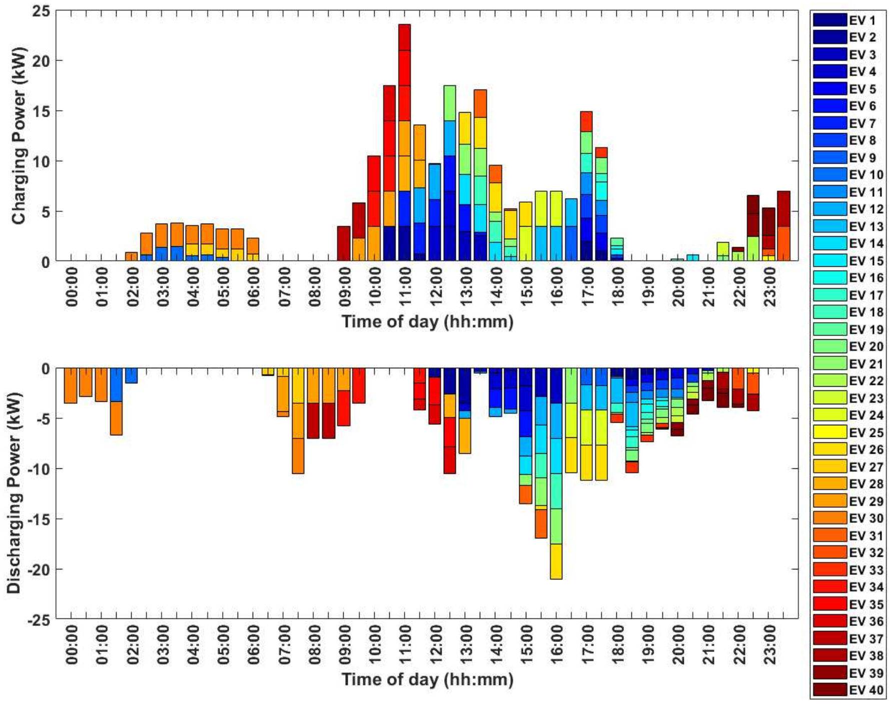

Figure 9: Detail of EV charging/discharging in the summer day with load levelling procedure application.

4.2 Cost reduction procedure

Results of the cost reduction problem for the winter and summer days are illustrated in Fig. 10 and in Fig. 11, respectively. In these figures, the top plot is obtained for Case 1 (Standard tariff), the middle one for Case 2 (Evening tariff) and the bottom one for Case 3 (Economy 10 tariff scheme).

For the winter day, in Case 1, EVs are discharged during the night in order to reduce the demand, and subsequently charged due to the energy constraints. During PV production, EV charging enables to reach null power exchange between 11:00 and 12:00. In the early afternoon, two peaks are formed as EVs alternate charging and discharging. After sunset, EVs first tend to charge, increasing the peak demand to 118.9 kW at 18:30, and then discharging is performed until the end of the day, making the optimized net demand lower than initial net demand. In Case 2, the behavior of EVs varies in the afternoon, since the procedure solution involves EV discharging until the end of peak period, and then they are charged at maximum rate as the price gets lower, obtaining a peak of 109.1 kW at 19:30. In Case 3, the net demand is increased in the three off-peak periods of Economy 10 tariff due to the intense EV charging. However, the peak occurs in an on-peak period, at 18:30, since the EVs are still energetically constrained. Moreover, this is the only interval during peak price in which y_i assumes positive value, i.e. the aggregation of EVs is charging.

For the summer day, in Case 1 the charging of EVs is observed as soon as the PV production exceeds original demand, given that the feed in tariff is significantly lower than the retail price. Afterwards, they return power to the network, bringing total net demand equal to 0 kW from 11:30 to 15:00. Between 15:00 and 16:00, many vehicles are ready to leave, so they charge at least the energy needed to tackle the next trip. Finally, in the central afternoon hours, there is a peak of 88.8 kW, while in the late evening a flatter consumption profile is achieved. In Cases 2 and 3, variations are similar to the winter day. In particular, it should be noted that in all the cases, the negative peak of the optimized net demand is equal to -2.7 kW.

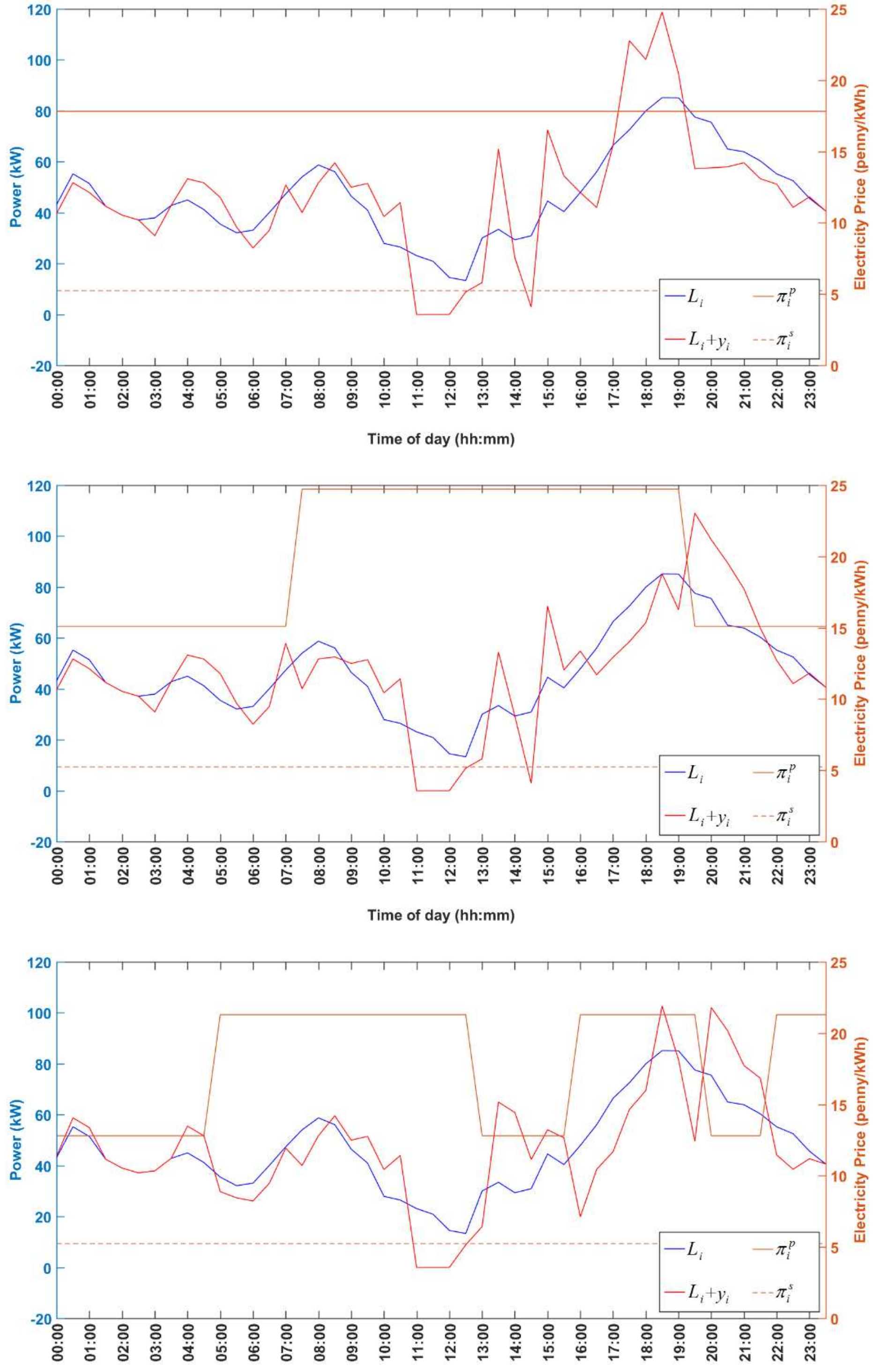

Figure 10: Demand variation in the winter day with cost minimization in Case 1 (top), Case 2 (middle) and Case 3 (bottom).

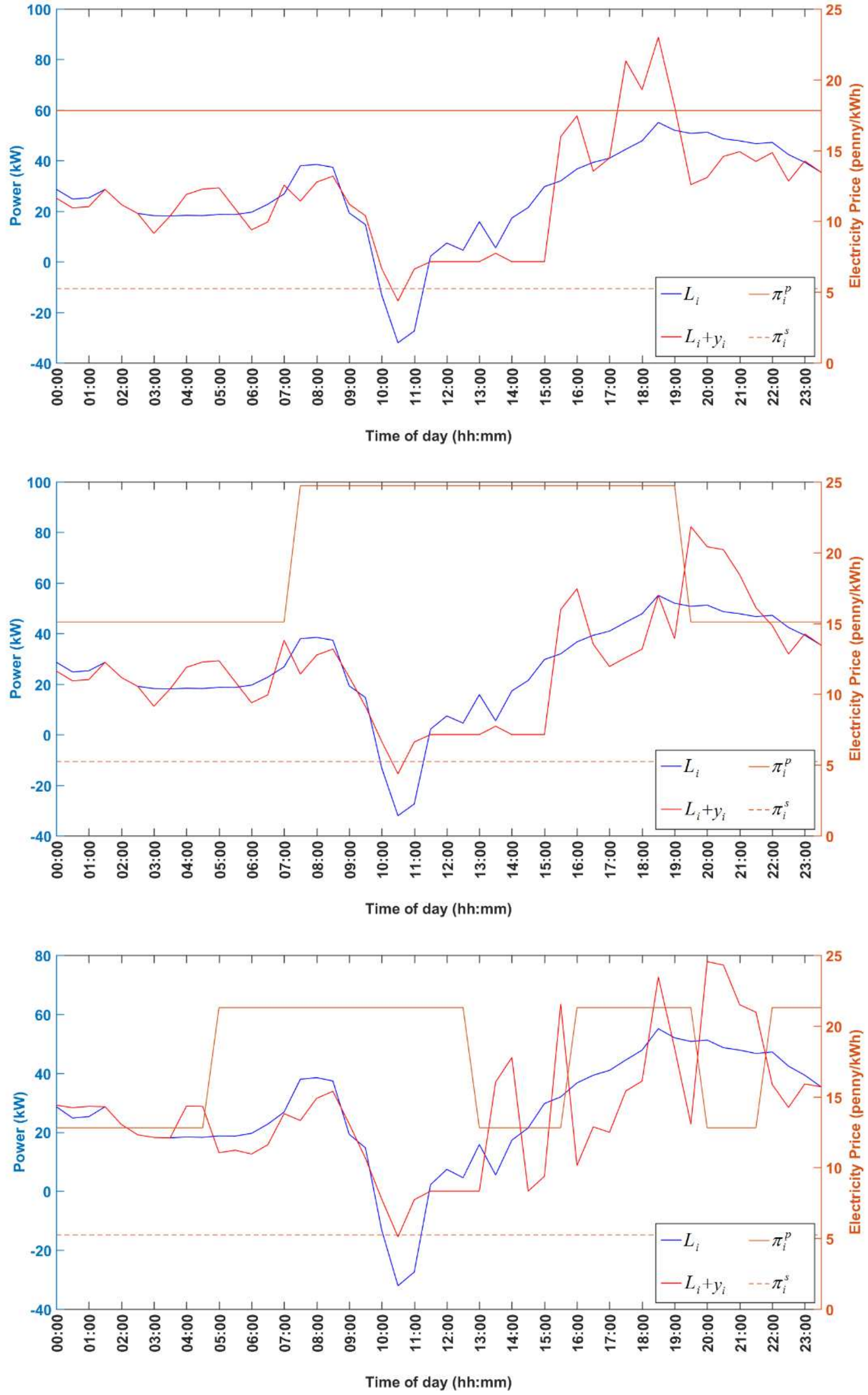

Figure 11: Demand variation in the summer day with cost minimization in Case 1 (top), Case 2 (middle) and Case 3 (bottom).

4.3 Comparisons through merit indicators and discussion

As reported in Section 2.4, technical and economic performance indicators are determined.

The values of δ are shown in Table 3 for initial demand, uncontrolled charge, load levelling methodology and cost reduction methodology, with the three tariff cases.

It can be initially noted that the presence of PV production involves higher variations with respect to initial demand, and EV uncontrolled charge has little influence in winter while it worsens the performances in summer, involving higher stress for the network. By contrast, the optimized EV behavior in load levelling flattens the initial winter and summer demand by 50.3% and 20.7% respectively, and by 46.3% and 14.3% respectively in the presence of PV production. With respect to load levelling, aiming to reduce the determined deviation, results in cost minimization are quite worse in winter and comparable in summer, and Case 3 shows the best behavior among tariff schemes.

Table 3. Demand daily mean absolute deviation [kW]

Scenario	Winter	Summer
Initial demand	13.13	8.69
Net demand	14.34	20.41
Uncontrolled charge	14.36	24.27
Load levelling	7.70	17.49
Cost minimization – Case 1	17.22	20.87
Cost minimization – Case 2	16.80	20.89
Cost minimization – Case 3	16.84	19.96

The results for the economic indicator $\boldsymbol{C}$ in the three cases of tariff schemes, are illustrated in Table 4 for initial values, uncontrolled charging and the two procedures.

At a first look, it can be seen that values obtained by the cost minimization procedure are much lower than the uncontrolled scenario in all cases, showing the effectiveness of the proposed approach. Furthermore, the Evening tariff exploited in Case 2 is not convenient in all scenarios with respect to other investigated tariffs. This is due to the fact that almost half of the 40 EVs have the parking interval within the on-peak period of Evening tariff and that the Standard price is slightly higher than the off-peak rate of the Evening tariff but much lower than the Evening standard rate. Moreover, it can be noted that the presence of off-peak hours charging is not sufficient to reduce expenses, showing that off-peak hours would be better concentrated where there is a high number of EVs, as in the Case 3.

Table 4. Daily electricity cost indicator [£]

Scenario	Winter			Summer		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
Initial demand	220.51	250.17	222.29	151.86	175.13	154.50
Net demand	199.97	221.66	200.44	117.29	127.99	117.73
Uncontrolled charge	223.46	249.90	223.90	139.83	154.75	139.97
Load levelling	216.55	241.48	215.91	115.47	125.25	115.50
Cost minimization	199.97	217.11	192.25	114.05	118.41	107.58

In order to determine δ_{pu} and C_{pu}, given that the initial demand scenario is useful as an external comparison, each merit indicator is normalized according to the value assumed in the scenario of net demand with Case 1 tariff.

The evaluation of GMI for $\omega = 1$, i.e. considering the two indicators with the same importance, is synthesized in Table 5. According to the previous considerations, in the winter day the best compromise is provided by using the load levelling mechanism in Case 3 (Economy 10 tariff scheme), due to the higher peaks that can be efficiently flattened. By contrast, in the summer day there is a lower difference between the load levelling with Case 1 and Case 3 and cost minimization with Case 3. Therefore, it can be argued that, for an aggregator aiming to balance technical and economic needs, the load levelling procedure, along with a proper time-of-use tariff scheme, can bring advantage in most periods.

Table 5. Global merit indicator values with equal techno-economic weighting.

Scenario	Winter			Summer		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
Initial demand (ID)	*1.009*	*1.083*	*1.014*	*0.860*	*0.959*	*0.872*
Net demand (ND)	1.000	1.054	1.001	1.000	1.046	1.002
Uncontrolled charge (UC)	1.059	1.126	1.061	1.191	1.254	1.191
Load levelling (LL)	0.810	0.872	0.808	0.921	0.962	0.921
Cost minimization (CM)	1.100	1.129	1.068	0.997	1.017	0.948

The impact of weighting factor variation is illustrated in Fig. 12 and Fig. 13 in winter and summer days, respectively, indicating each scenario with the abbreviations reported in Table 4 and investigating the relation of varying ω among scenarios in each Case.

In the winter conditions, as long as ω increases, i.e. the importance given to technical indicator increases, it can be noted that the advantage of load leveling improves and uncontrolled becomes more performant than cost minimization even with TOU tariff application. In particular, for $\omega > 2$ cost minimization in Case 1 becomes as less convenient as in Case 2, whereas in Case 3 cost minimization is comparable to load levelling for $\omega < 0.2$.

In the summer conditions, the increase of ω implies a remarkable advantage for initial demand and net demand, whereas the influence on optimized scenarios is less evident. Moreover, in Case 3 cost minimization becomes preferable to load leveling for $\omega < 0.5$.

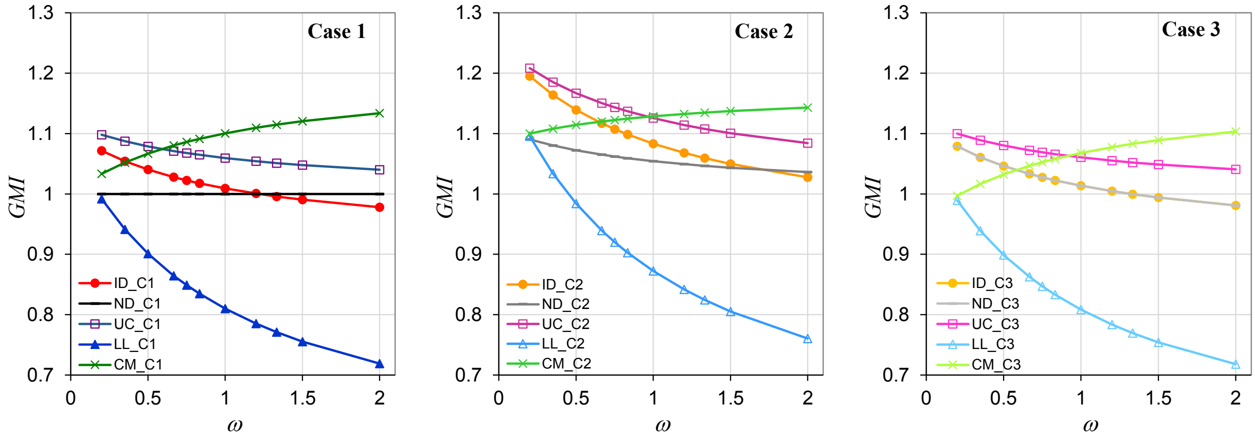

Figure 12: Influence of weighting factor on global merit indicator in winter day in Cases 1 (left), 2 (middle) and 3 (right).

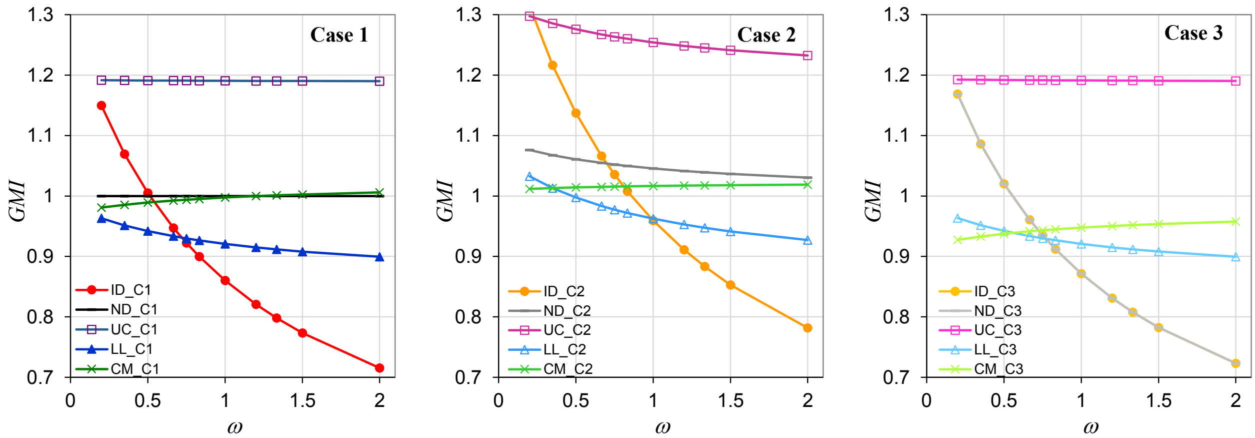

Figure 13: Influence of weighting factor on global merit indicator in summer day in Cases 1 (left), 2 (middle) and 3 (right).

According to the proposed analysis, it can be envisaged that different entities would consider suitable different values of the weighting factor ω for the determination of GMI.

In the residential framework and aggregator would analyze the case of $\omega = 1$, caring for economic aspects of demand coverage and technical issues of network operation and EV exploitation. Whereas, a network operator, managing electricity network connections for the residential settlement with EV charger, could rely on values of $\omega > 1.5$, giving more attention to the load leveling action that would infer lower stress in the distribution network. On the other hand, an energy provider, acting on behalf of residential customers with EVs in energy purchasing mechanisms, would better exploit $\omega < 0.5$ in order to satisfy the goal of reduced economic efforts.

Moreover, although the dependence of results on the considered conditions is undoubtable, the performed analysis in the presence of input variation, such as load demand trend, PV production and electricity tariff, proves the flexibility of the method, and the tailoring of the weighting factor can provide further adaptability.

5. Conclusions

The anticipated large penetration of EVs into the market brings forward many potential technical problems to be addressed, resulting in the need to better characterize the interface between EVs and the grid. In this framework, the present work has examined a case study exploiting V2G concept with the aim to analyze the potential of load levelling and cost minimization for a district of residential consumers in the presence of an aggregator, considering possible realistic diffusion of PV arrays and EVs. The obtained results demonstrate the feasibility of the proposed approach to achieve the two main targets, while the PV production involves a lower aggregated demand, with a consequent potential increase of distribution network benefits. Regarding the cost minimization problem, considerable monetary savings have been achieved with respect to uncontrolled EV charge, both in summer and winter for all the considered rates. However, the mere presence of time-of-use tariff has been revealed not sufficient to reduce cost, since off-peak hours should be concentrated in periods with intense EV parking. The best compromise between the two minimization techniques is obtained by determining techno-economic indicators and by defining a global merit indicator according to a proper weighting factor. It is observed that load levelling with proper time-of-use tariff involves greater advantages considering technical and economic performances with the same importance. Moreover, the proposed approach, involving two different objectives compared by means of consistent performance indicators, can pose the basis for a wide range of applications, evaluating different operation strategies for EV charging points in the residential framework by varying the weighting factor according to the viewpoint of the managing entity (network operator, aggregator, or energy provider). Future work could focus on demand response and the possibility of modulating the parking time of EVs. In parallel, complementary work could include the development of models that take into account the impact of ambient conditions of the EV battery, and the incorporation of stochastic process with respect to EV behaviors.

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