x\F. Aleotti[1], A. Rollo[1,*], P. Marcolin[1], V. Angelucci[1], D. Cilio[1], M. Zulianello[1],

A new smart charging strategy for electric vehicles in energy communities: An Italian case study

[1]Ricerca sul Sistema Energetico – RSE s.p.a., Via R. Rubattino 54, 20134 Milano
*Corresponding author: federico.aleotti@rse-web.it

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Abstract

The aim of this study is to evaluate the energy and economic benefits of different Electric Vehicles (EV) charging strategies within Renewable Energy Communities (REC) in Italy. The electrification process for mobility purposes will lead to increased and concentrated electricity demand that may lead to network congestion and other issues. Distributed self-consumption combined with RECs and optimal control of EVs' charging profiles may reduce the network stress and improve the economic benefits of stakeholders. A simulated case study is used to explore three cases in which 20 EVs (domestic and commercial): (i) are charged independently using a "standard" charging strategy, (ii) join a REC with other users and there aren't modifications of EV charging profiles, (iii) implement smart charging strategies to integrate with the REC via real-time control infrastructure. In this last case, EV charging power is controlled by a remote controller that monitors the production and consumption of all REC members and controls the EV charge to maximize energy sharing while respecting infrastructure and users' constraints (e.g., guarantees of minimum SOC, EV maximum charging power, etc.). The developed algorithm firstly simulates all EV trips in a year starting from probability distributions for different parameters, recreating their location and availability for charging on a 15min timestep granularity; secondly, it computes the REC energy flows and assigns the charging power to all vehicles, based on the charging logic which changes across the cases. In conclusion, the paper shows how the EV smart charging and load shift can generate additional value in the form of incentives (+50%) to the REC, without creating disruptions in terms of mobility.

Keywords*: Renewable Energy Community (REC), Electric Vehicles, Load Shifting, Smart Charging, Shared Energy, Italian Policy*

1. Introduction

The European Union has set the objective of achieving climate neutrality by 2050. To enable this energy transition, the *European Green Deal* proposes a series of legislative reforms. Its key objectives include reducing greenhouse gas emissions, increasing the share of renewable energy, promoting electrification, and enhancing energy efficiency. The central element of this strategy is *empowerment and consumer engagement*; the aim is to raise end-user awareness, facilitate access to information, and encourage active participation. For this purpose, new consumption models such as Energy Communities have been introduced at European level thanks to the *Clean Energy for All Europeans Package*. This package includes the *RED II Directive (2018/2001)* [1], which introduced the concept of Renewable Energy Communities (REC), and *Directive 2019/944* [2], which established Citizens' Energy Communities (CEC). According to the *RED II Directive*, a REC is a legal entity based on open and voluntary participation by individuals, small and medium-sized enterprises (SMEs), or local authorities located in proximity to renewable energy plants. Its primary purpose is not the financial profit, but the generation of environmental, economic, and social benefits for its members and the local community. In Italy, the *RED II Directive* was implemented in two phases: an experimental phase with *Legislative Decree 162/2019* [3] and an operative phase with *Decree-Law 199/2021* [4] with the full transposition of the RED II. The key aspects such as the incentive tariff for shared energy, the funds of the *National Recovery and Resilience Plan* (PNRR), and the requirements for accessing the incentives are defined in the *Integrated Text for Diffused Self-Consumption* (TIAD) published by the *Regulatory Authority for Energy, Networks and the Environment* [5], the *Ministry Decree 414/2023* which regulates the incentives [6] and the Operating Rules issued by the *Gestore Servizi Energetici* (GSE) [7]. The legislation was subsequently updated to clarify certain provisions and to broaden access to PNRR funding. Italian legislation has introduced three specific configurations for renewable energy sharing, known as *Self-Consumption Configurations for Renewable Energy Sharing* (CACER):

- **Renewable Energy Communities (REC):** members share energy "virtually" through the national distribution grid.
- **Group of Renewable Energy Self-Consumers Acting Collectively:** all members and systems are located within the same building or condominium.
- **Individual Remote Self-Consumers of Renewable Energy:** a single end customer produces renewable energy for their own consumption using systems that are not physically connected to their point of delivery.

The GSE incentivizes virtually shared energy in these configurations for 20 years, with a premium tariff that varies between approximately €80 and €130/MWh, depending on plants' capacities.

The empowerment of end consumers through these new consumption models aims to promote a more intelligent use of electricity and a more efficient use of the grid. In recent decades there has been a growing diffusion of distributed generation systems, and the electricity sector has undergone a deep transformation, moving from a *centralized generation model* (with a few large-scale power plants located "upstream" of the grid) to a *decentralized generation model* (with many small-scale plants distributed across the grid) [8]. These "distributed" generation plants mainly exploit renewable sources, in particular photovoltaic systems [9]. Photovoltaic generation plants have a "bell-shaped" production curve where the production is concentrated in the central hours of the day. However, the electricity consumption follows an inverse trend, peaking in the late afternoon and evening hours. This temporal mismatch between generation and consumption can lead to several problems, such as difficulty in managing new bidirectional power flows, voltage and frequency variations, overheating and consequent cable deterioration, and the well-known "*Duck Curve*" effect [10]. These phenomena can lead to greater grid instability, progressive deterioration of cables and protection devices, lower quality of service, etc. To ensure proper functioning of the electrical system, it is therefore necessary to invest in modernizing the national grid by developing the *smart grid paradigm* [11] and, at the same time, encourage more conscious electricity use by end consumers. Load management techniques such as load shifting allow part of consumption to be shifted to photovoltaic generation peak hours with consequent benefits for the electrical system. These load management techniques should be applied in sectors with a minimum level of consumption flexibility, such as domestic sector (in this case, flexible loads are, for example, washing machines and dishwashers). The effects on the electricity system caused by load shifting of flexible household appliances have already been studied [12]. That research highlighted the impacts on the grid promoted through different load management methodologies within a REC, in particular: (i) *Demand Side Engagement*, which involves spontaneous shifting of consumption by household users; and (ii) *Optimal Demand Side Management*, which involves optimized shifting of flexible loads to maximize the shared energy within the configuration. The impact of load shifting was analysed from both an energetic and economic prospective. The results highlighted how load management techniques can favour greater revenues deriving from incentives and from greater direct self-consumption of the energy produced by the systems. Within this study, however, the potential of storage systems and electric vehicles (EVs) to generate greater flexibility of final consumption was not evaluated. Several researchers have attempted to quantify the benefits generated by smart management of EV charging. Karameros et al. [13] analysed the environmental and economic impacts promoted by applying a "hybrid" optimization algorithm based on a Hierarchical Analytical Process and a genetic algorithm in a microgrid. An optimization algorithm is proposed, where buildings, photovoltaic plants, storage systems, and EVs (utilization of Vehicle to Grid technology, V2G) can efficiently meet the energy requirements and peak-hour energy demand, in both economic and sustainability terms. Moura et al. [14] investigated the increase in shared self-consumption and the reduction in electricity costs enabled by smart management of EVs in a case study located in Portugal. In this study, an optimization methodology was applied to correctly schedule EVs charging with vehicles managed at a "community" level. The results show a significant reduction in costs and increased local self-consumption of renewable energy under a "community based" EV management strategy compared to an "individual" management strategy for each building. Marcolin et al. [15] analysed various smart charging strategies for EV charging profile scheduling based on data from a real workplace infrastructure. By applying a MILP–based control algorithm, they demonstrated the potential to significantly mitigate system-level impact of EV charging, achieving a 40% reduction of total energy consumption from the grid and a 70% decrease in peak demand, without causing any incomplete charging events for end users and while generating operating cost savings ranging between 33% and 70% depending on the considered case.

The international literature on EV smart charging mainly frames charging control as an optimization problem aimed at reducing costs, limiting grid impacts, or increasing renewable self-consumption, often using forecasts of PV generation, demand, prices, or vehicle availability. However, real-time approaches have also been proposed to control EV charging directly from currently observed system conditions. Shern et al. [16] are one example of real-time EV smart control based on AI-based demand response relying on load and generation forecasting.

Despite this progress, existing research still pays limited attention to approaches that reduce reliance on AI, forecasting algorithms, and historical data. An example is represented by Wang et al. [17], which proposed a carbon-aware EV charging flexibility model which uses a Lyapunov prediction-free optimization responsive to grid carbon intensity. Forecasting-free approaches are relevant for REC applications too, where heterogeneous users, uncertain mobility patterns, and limited observability can make forecast-based scheduling difficult or expensive to implement. Accordingly, this paper evaluates a transparent real-time rule-based methodology for distributed self-consumption within a REC, in which the activation logic relies only on real-time consumption and generation. Instead of scheduling EV charging in advance or solving a forecast-based objective function, the controller estimates the current shared energy potential of the community and allocates charging power among connected EVs according to SOC, charging-station limits, contractual power constraints, and user-comfort thresholds. The novelty of the study therefore lies in assessing whether a forecast-free and objective-function-free control logic can still provide measurable energy and economic benefits, bridging the gap between highly optimized scheduling models and implementable REC-level control architectures.

2. CASE STUDY

The objective of this analysis is to assess the energy and economic benefits achievable through smart control of EV charging within a REC located in Italy, while proving whether a low technology and prediction-free algorithm can meet the users' needs in terms of EV charge availability for mobility demand. Accordingly, the calculation of

revenues refers to the current Italian regulatory framework, considering the incentive to the amount of energy shared within the Energy Community [5]. The analysis highlights variation in energy self-consumption levels, both in terms of energy directly self-consumed at the user's point of delivery (i.e., *directly self-consumed energy*) and in terms of energy "virtually" shared within the Energy Community (i.e., *shared energy*). Increased direct self-consumption of electricity from photovoltaic systems results in electricity bill savings, while increased shared energy generates additional revenues for the REC due to higher incentive.

It is observed that in the domestic sector, users who own an EV tend to recharge frequently outside the generation hours of photovoltaic systems [18]. In fact, these users often use their cars for commuting, meaning that during the central hours of the day the EV is not connected to the charging station (CS). Conversely, a company with a fleet of EVs that does not operate on weekends has greater charging flexibility [15]. In fact, on holidays the EVs are connected to the CSs but since there is no need to complete the charging quickly, the charging power can be controlled to maximize the energy shared within the Energy Community. This paper proposes a control algorithm which reduces the EV fast charging in favor of more flexible, incentive-driven, forecast-free and low-power recharge without occurring in service disruptions. Further details will be provided later regarding the modelling of the state of charge (SOC) of EVs, patterns of vehicle use, and the methodology adopted to control charging power with the aim of increasing shared energy within the Community. Based on these considerations, an Energy Community was modelled in which a company equipped with a PV system for self-consumption and a fleet of Commercial Electric Vehicles (CEVs) participates alongside various domestic users with different characteristics, who also own Domestic Electric Vehicles (DEVs). The following case studies have been identified:

- **Reference Case (i.e. Ref Case):** This scenario assesses the energy expenditure and energy flows of the configuration in its current state without the establishment of a REC (therefore, there are no revenues related to the incentive) and without the smart control of EV charging. Photovoltaic generation systems and EVs are still considered in this configuration. Table 1 summarizes the number of users by type, the capacity of the generation systems, the capacity of the storage systems and the number of EVs. The reported values for the various parameters refer to individual users. Therefore, there are users (domestic and commercial) who self-consume energy from generation plants (prosumers) and users who own an electric vehicle. The latter typically charge their vehicles based on their needs, always maintaining a minimum charging rates and without any smart charging control. Since there is no REC, there are no revenues linked to the incentives applied to the shared energy. It is assumed that the commercial user has two points of delivery: a main point of delivery (i.e., *main POD*) to which all loads and the photovoltaic generation plant are connected, and a secondary point of delivery dedicated solely to the charging infrastructure (i.e., *CSs POD*). It is assumed that the number of CSs equals the number of cars in the company fleet (a total of 10 CSs). Domestic users who own generation plants are also equipped with electric storage systems.
- **Renewable Energy Community Case (i.e. REC Case):** Compared to the Reference Case, there are no changes to the configuration, the same characteristics and number of users are reported in Table 1. However, in this case, users participate in a REC and benefit from the revenues associated with the incentive on energy virtually shared through the electricity grid. Consequently, revenues and thus energy expenditure for each individual user change. No modifications are applied to EV charging strategies, and the charging profiles remain unchanged compared to the Reference Case The only variations occur in economic flows: the REC introduces a new revenue stream and additional cost items for both the initial investment and operating costs, while energy flows remain unchanged. All assumptions regarding the systems and the commercial user's points of delivery also remain the same. All assumptions regarding the systems and the commercial user points of delivery also remain unchanged.
- **Renewable Energy Community and Smart Charging Case (i.e. REC – SC Case):** Once again, there are no changes to the configuration; the same characteristics and number of users are reported in Table 1. In this case, users also participate in REC and benefit from the revenues associated with shared energy incentives. However, the charging profiles of EVs differ, and a "smart" charging strategy is applied to maximize the energy shared by the REC at any given

Table 1. Characteristics of the analyzed configuration.

ID	Typology user	Number	Contractual power [kW]	PV	PV capacity [kW]	Storage capacity [kWh]	EV	EV Number
Prosumer	Commercial	1	100	Yes	300	0	No	-
Charging stations	Commercial	1	500	No	-	-	Yes	10
HH	Domestic	5	6	No	-	-	No	-
HH_PV	Domestic	5	6	Yes	6*	10*	No	-
HH_EV	Domestic	5	6	No	-	-	Yes	1*
HH_PV_EV	Domestic	5	6	Yes	6*	10*	Yes	1*

*For each user

time. Further details on the smart charging strategy are provided in the following sections. Smart control of EVs entails higher initial investment costs as well as higher operating costs related to measurement instruments, control tools, management platform, and so on. However, these extra costs and details on hardware and software of the controlling equipment are not in the scope of this study.

The assumptions made for the various cases analyzed are summarized in Table 2.

The characteristics of the EVs and charging infrastructure simulated in this study are summarized in Table 3.

The main parameters influencing the simulation of EVs are battery capacity, maximum charging power, and efficiency (i.e. average electricity consumption per 100 km).

Table 2. Summary of the hypothesis for the different cases.

Cases	Photovoltaic plants	Vehicles electric	Energy Community	Smart charging for EVs
Reference Case (Ref Case)	Yes	Yes	No	No
Renewable Energy Community Case (REC Case)	Yes	Yes	Yes	No
Renewable Energy Community and Smart Charging Case (REC - SC Case)	Yes	Yes	Yes	Yes

Table 3. Characteristics of EVs and charging stations.

Variable	Domestic EV – DEV	Commercial EV - CEV
Vehicle type	Multi-purpose car	Delivery Van
Battery capacity [kWh]	42	80
Battery Roundtrip efficiency [%]	90%	
Dept of Discharge [%]	80%	
Battery derating factor [%/cycle]	0.00635 (hypothesis SOH = 80% @ 3500 cycles)	
EV max charging power [kW]	11	22
Charging station capacity [kW]	3.7	22
EV efficiency [kWh / 100km]	18.9 [19]	
Yearly distance covered [km] (approximate)	10,000 [20]	15,000 [20]

3. METHODOLOGY

The various case studies are compared from both an economic and energy perspective. Specifically, the following KPIs are evaluated:

- **Total annual energy shared by the REC:** as shared energy increases, revenues from incentives rise, thereby improving the benefits for users within the configuration.
- **Total annual incentive generated by the REC:** as the incentive grows, the benefits for users of the configuration increase accordingly.
- **Charging power (PC) of EVs:** charging power profiles of EVs are extracted, and average profiles are determined for each typical day. Comparing these profiles across the different cases, it is possible to understand how charging power varies with the chosen charging strategy.
- **State of Charge (SOC) of EVs:** SOC profiles of EVs are extracted, and average profiles are determined for each typical day. Comparing these profiles across the different cases, allows an understanding of how SOC varies depending on the charging strategy. Furthermore, additional statistical insights can be obtained from box plots generated for each individual vehicle.

All these KPIs make it possible to evaluate how the economic benefits vary and to assess how users' "comfort" conditions change under different charging strategies.

To simulate the energy and economic flows of various users in the configuration and to model the operation of an Energy Community, the open-source Python library developed by RSE [21] was employed. The modelling of the EV charging with a "standard" strategy (*StC logic*) and with a "smart" strategy (*SC logic*) required the development of a dedicated simulation module; the corre-

sponding implemented logic is described in the following sections. All the functions used to model EV charging profiles (with different control strategies), along with the related documentation, are available in the open-source repository [21]. The following paragraphs briefly introduce the key concepts underlying the methodology for simulating individual users' energy and economic flows, the REC simulation framework, and the methodology for simulating EV charging profiles with different control strategies. More detailed information is available in the documentation attached to the online repository.

4. Energy Community Simulator

Figure 1 shows the operating scheme of the REC simulator. While the electric vehicle model can be generalized, the energy shared and incentives calculations are tailored on the Italian context and regulatory framework, which play a relevant role in determining the EV smart charging control logics.

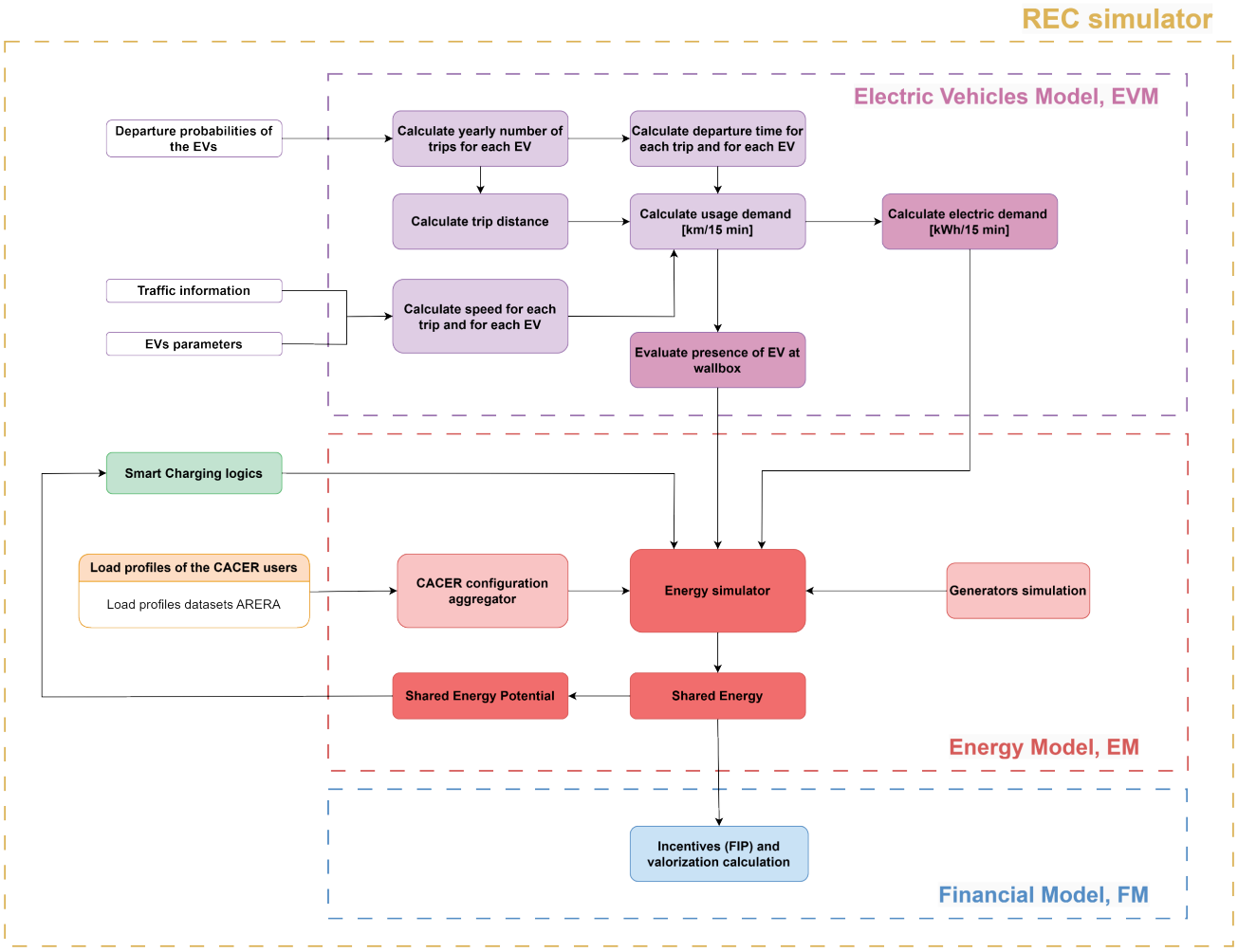


Fig. 1. Simulator workflow.

The simulator is composed of three different modules:

1. **Electric Vehicle Model (EVM)**, This module determines the consumption profiles of electric vehicles (kWh/15min) and their presence at the charging infrastructure. EV consumption profiles represent the vehicles' electricity use during different trips, while presence indicates whether the vehicle is connected to the charging station. To calculate these parameters, it is necessary to know the EV characteristics (particularly its efficiency), the traffic conditions affecting vehicle speed, the type of trip (local road, connecting road, or arterial road), the number of annual trips, and the departure time of each individual trip. More detailed information on the electric vehicle simulation methodology is provided later.

2. **Energy Model (EM)** simulates the electricity consumption of each individual user (both domestic and commercial) as well as the production of photovoltaic systems. In addition, EM calculates the net exchange profiles with the electricity grid for each user. Specifically, at each timestep it evaluates:
   a. **Electricity consumption for charging EVs**, which depends on the state of charge of the vehicles when connected to the CS.
   b. **Energy consumed**, i.e., the energy consumed by the user for each instant of time, including the EVs consumption.
   c. **Energy produced**, i.e. the energy generated by production plants at each instant of time.
   d. **Direct Energy self-consumption**, i.e. the amount of energy produced by the generation plants that is immediately consumed by user loads.
   e. **Energy injected into the grid**, i.e. surplus energy produced that is not directly consumed by the user.
   f. **Energy drawn from the grid**, i.e. the energy consumed by the user net of direct self-consumption.

Shared energy, defined by Italian law as the minimum between the total withdrawn energy by users participating in the REC and the total injected energy by users participating in the REC on an hourly basis [5]. Shared energy is calculated using Equation 1.

$$shared\ energy\ (t) = \min\left(\sum_{i}^{N} withdrawn\ energy_{i,t}\ ;\ \sum_{i}^{N} injected\ energy_{i,t}\right) \quad (1)$$

Here N represents the number of members of the REC (consuming and/or producing) and t represents the specific hour.

Shared Energy Potential, defined as the difference between the total energy injected by users participating in the REC and the total energy withdrawn by those users on an hourly basis. Only positive values are considered, while negative values are set to zero. This metric evaluates the REC's hourly potential for shared energy. It indicates the additional amount of user withdrawals required in each hour to maximize shared energy and, consequently, incentive revenues. In this study, higher consumption is achieved by adjusting the charging power of EVs. The "smart" charging strategy is described in more detail in the following sections. The shared energy potential is calculated using Equation 2.

$$shared\ energy\ potential(t) = max\left[\left(\sum_{k}^{M} injected\ energy_{k,t} - shared\ energy\ (t)\right); 0\right] \quad (2)$$

3. **Financial Model (FM):** these modules calculate the revenues obtained by participation in the REC. According to Italian legislation [5] an incentive is granted on the amount of energy shared within the configuration. Shared energy is calculated using Equation 1, while the corresponding incentive revenues are obtained through Equation 3, again calculated on an hourly basis.

$$yearly\ incentive\ revenues = \sum_{t=1}^{8760} FIP(t) \times energy\ shared\ (t) \quad (3)$$

Where is the hourly premium tariff, which depends on the power of the generation plants () and the hourly zonal price of electricity (). The hourly FIP is calculated using Equation 4.

$$FIP = \begin{cases} min[100; 60 + \max(0; 180 - ZP)] & if\ (P_{gen} > 600\ kW) \\ min[110; 70 + \max(0; 180 - ZP)] & if\ (200\ kW < P_{gen} < 600\ kW) \\ min[120; 80 + \max(0; 180 - ZP)] & if\ (P_{gen} \leq 200\ kW) \end{cases} \quad (4)$$

The FIP also includes a correction factor based on the location of the systems, which accounts for the different levels of solar radiation across Italian territory (providing additional financial support for region with lower irradiation levels).

In addition to the FIP, a bill tariff component is refunded, corresponding to the reduced network losses resulting from increased local self-consumption (*valorization*). This incentive is less significant than the FIP, but it is nevertheless calculated by the simulator. Further details on the calculation of this revenue component are provided in the *Integrated Text for Diffused Self-Consumption* [5].

5. Electric Vehicle Simulator

The module was developed from the perspective of the individual user's mobility demand, following a *bottom-up approach*. The algorithm is divided into two sections: the first defines the mobility demand of EVs and their presence at the charging station (purple section in Figure 1), while the second defines their charging strategy (green box in Figure 1). The first section of the algorithm therefore characterizes each individual trip of the different vehicles using a probabilistic approach, as described in the following steps:

1. The parameters of each vehicle, the characteristics of the charging infrastructure, and the usage habits of different user types (e.g. annual mileage, number of trips, etc.) are specified.
2. Daily probability distributions of vehicle movements are provided on a quarter-hourly basis and for typical days (workdays, Saturdays, and Sundays). In addition, weekly correction factors are applied to simulate different usage patterns across seasons. User-defined quarter-hourly departure probability profiles are then generated for the entire simulation period (1 year, 20 years, etc.), for each type of vehicle use (e.g., family use, commuting, commercial vehicle, heavy transport, forklift, etc.). Figure 2 shows the departure probability distributions for different day types and uses (Commercial EVs and Domestic EVs).
3. Depending on the specified type of use, an arbitrary value is assigned to the shape factor of the Weibull function, which defines the distribution of trip distances. This factor describes the shape of the distribution and affects both the standard deviation and the proximity of the mean value to zero. Based on the shape factor and the number of trips provided by the user, a function then calculates the scaling factor of the Weibull function to match the desired annual distance travelled (within a tolerance of a few hundred km).
4. Once these values are defined, a function iteratively simulates vehicle's movements, based on:
   a. **Departure time** derived from the probability of distribution of trip departures.
   b. **Distance** generated using the Weibull function.
   c. **Vehicle destinations** are defined as either a charging point (e.g., a wall box at home) or a generic destination without charging. Public charging stations are not considered in this study, as they are irrelevant to the current research.

Given the departure time and destination, each trip is divided into 15-minute intervals, considering the average vehicle speed according to the road type assumed for that segment (*Local* or "L", *Connection* or "C", *Arterial* or "A") and the estimated traffic conditions based on the time of day and day of the week. Table 4 summarizes the average speeds and distances travelled for the different road types.

Figure 3 shows the speed correction factors as a function of the time and type of day.

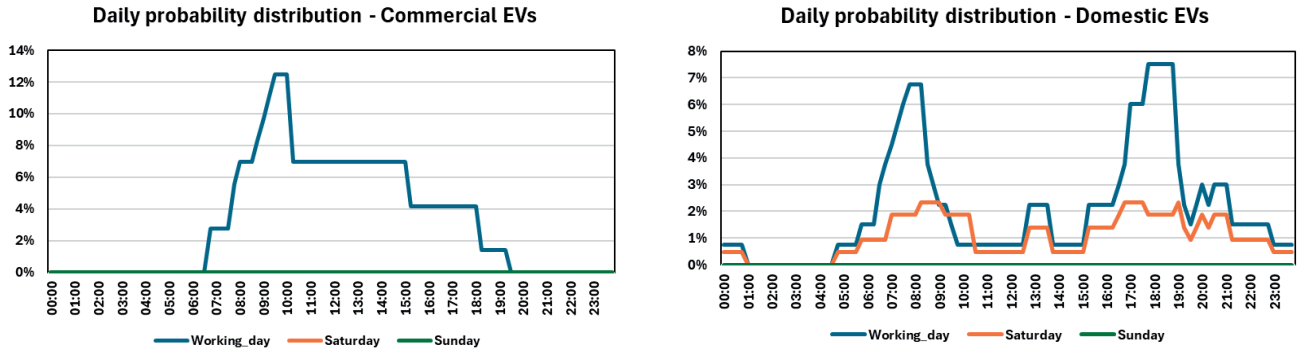


Fig. 2. Probability of electric vehicle departure for different days of the week and for different vehicle types (commercial on the left and domestic on the right).

Table 4. Average travel speed and average distance traveled for different types of roads.

Functional Road Class	Section	Average speed [km/h]	Distance from departure/ arrival venue [km]
Local Roads	L	15	2
Connector Roads	C	30	5
Arterial Roads	A	100	n.a.

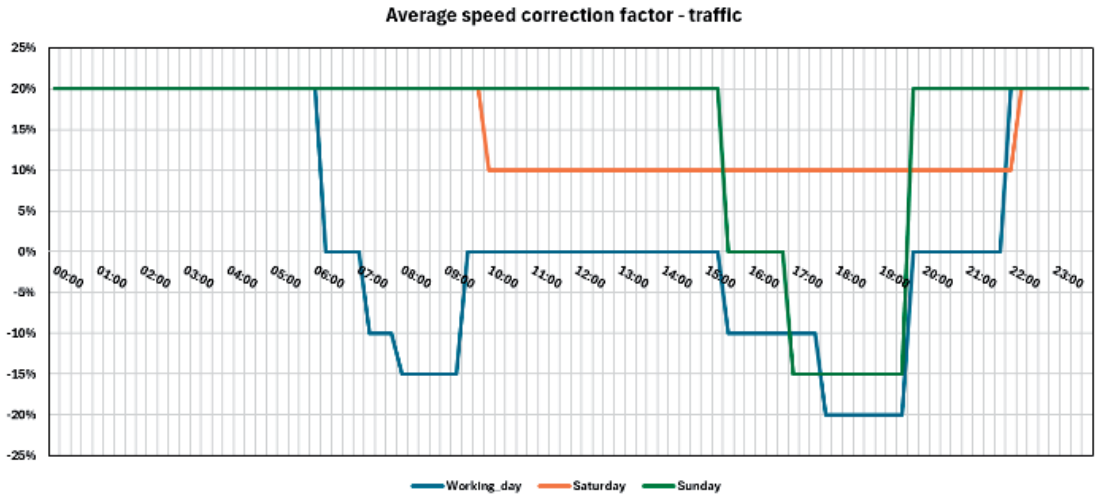


Fig. 3. Average speed correction factors due to traffic on different days of the week.

The average speed of the vehicle, the distance travelled, and the arrival time at the destination are then calculated. Once at its destination, the vehicle remains idle until the next trip. This procedure is repeated for each trip and each vehicle over the entire simulation horizon, resulting in a mobility demand matrix expressed in km per 15 min.

5. From the mobility demand matrix, the travel-related electricity consumption matrix is derived, converting km per 15 min into kWh per 15 min by applying an appropriate conversion factor. This factor may depend on the average speed at that moment, the outside temperature (and thus the season), and the characteristics of the individual vehicle (different make and model with varying performance). At present, a fixed conversion factor is applied.
6. For each trip, the vehicle's position relative to its reference charging point is tracked at each moment in time. A function determines whether the user, upon arriving at the charging point, connects the vehicle to the CS or not. This makes it possible to simulate different behaviors among users with varying charging habits, including those who may choose not to connect their EV to the CS.

This entire section of the algorithm is used to determine mobility demand (expressed in kWh per 15 minutes) and the presence of the electric vehicle at the CS.

At this point, as the energy demand for mobility is obtained, the EV charging and discharging algorithm steps in governing the battery energy flows. For each simulation timestep t, the model receives a theoretical energy flow at the battery terminals (positive if the charging power, negative if requested by the EV engine) and determines the actual battery behavior by considering charging/discharging efficiencies and SOC operational constraints. The model considers also losses for roundtrip efficiency, battery derating from aging effect. Starting from the SOC from the t-1 interval (here considered in kWh) and the theoretical energy flows at time t, the model computes the real flows by checking the battery constraints and applying the losses (gross and net are before and after applying the conversion efficiency). The model replicates the calculation iteratively. The model provides a computationally efficient representation suitable for large-scale energy simulations while neglecting voltage dynamics, thermal behavior, and power-dependent battery characteristics.

Describing the process with the equations, at each timestep, the theoretical energy exchanged at the battery terminals is partitioned into charging and discharging components:

$$E^{theor}_{charge,gross,t} = max\left(0;\ E^{theor}_{terminal,t}\right) \tag{5}$$

$$E^{theor}_{discharge,gross,t} = min\left(0;\ E^{theor}_{terminal,t}\right) \tag{6}$$

Conversion losses are represented through a half-cycle efficiency parameter, assumed identical for charge and discharge processes:

$$\varepsilon_{halfcycle} = \sqrt{\varepsilon_{roundtrip}} \tag{7}$$

where ε denotes the efficiency. The upper and lower charge boundaries (SOC, indicated in kWh) are computed based on the cycling historical information of the battery:

$$SOC_{max,t} = \ (1-d)^{N_t} * C \tag{8}$$

$$SOC_{min,t} = \ SOC_{max,t} * (1 - DoD) \tag{9}$$

where d is the battery derating factor to include loss of capacity due to aging (for single cycle, assumed constant during the battery lifetime), N the number of cycles at time t since commissioning, C is the battery rated capacity and DoD is the Dept od Discharge.

The SOC evolution is obtained by applying the corresponding efficiency-adjusted energy variation and enforcing minimum and maximum SOC constraints that represent the allowable operating range of the battery. Whenever the unconstrained SOC exceeds these limits, the stored energy is saturated accordingly:

$$\begin{cases} SOC_t = SOC_{\max,t}; if\ SOC_{t-1} + E^{theor}_{halfcycle,t} > SOC_{max,t} \\ SOC_t = SOC_{min,t}\ ; if\ SOC_{t-1} + E^{theor}_{halfcycle,t} \leq SOC_{min,t} \\ SOC_t = SOC_{t-1} + E^{theor}_{halfcycle,t};\ otherwise \end{cases} \quad (10)$$

$$SOC_{\%,t} = \frac{SOC_t}{SOC_{max,t}} \quad (11)$$

Conversion losses are represented through a half-cycle efficiency parameter, assumed identical for charge and discharge processes. The actual terminal energy exchange and the associated energy losses are subsequently recalculated from the constrained SOC variation, ensuring consistency between battery operation, efficiency effects, and capacity limitations:

$$E^{real}_{halfcycle,t} = SOC_t - SOC_{t-1} \quad (12)$$

$$E^{real}_{charge,net,t} = max\left(0;\ E^{real}_{halfcycle,t}\right) \quad (13)$$

$$E^{real}_{charge,gross,t} = \frac{E^{real}_{charge,net,t}}{\varepsilon_{halfcycle}} \quad (14)$$

$$E^{real}_{discharge,gross,t} = min\left(0;\ E^{real}_{halfcycle,t}\right) \quad (15)$$

$$E^{real}_{discharge,net,t} = E^{real}_{discharge,gross,t} * \varepsilon_{halfcycle} \quad (16)$$

$$E_{loss,t} = \left|E^{real}_{charge,net,t} - E^{real}_{charge,gross,t}\right| + \left|E^{real}_{discharge,gross,t} - E^{real}_{discharge,net,t}\right| \quad (17)$$

The outputs of the module are the updated SOC and the corrected charging/discharging energy flows at the terminals for timestep t.

At this stage, the EVs charging strategy can be defined, which determines the user's electricity consumption due to charging. Two charging strategies are modelled:

- **Standard charging strategy (StC logic)**, in this case EVs, once connected to the CS, are charged at the maximum available charging power. This maximum charging power depends on the contractual power of the delivery point, the user's concurrent consumption, the maximum power deliverable by the CS and the EV maximum charging power. The maximum charging power is calculated using Equation 18.

$$P_{C,max}(t) = min\left[\left(P_{POD} - \sum_i P_{load,i}(t)\right);\ P_{CS,max};\ P_{EV,max}\right] \quad (18)$$

Where is the contractual power of the delivery point, reported in Table 1, is the power of the i-th load at time , is the maximum charging power of the CS, and is the maximum charging power of the electric vehicle. It was assumed that the commercial user's EV charging point includes a contractual power limiter, even though Italian legislation allows the installation of delivery points without a limiter and thus without any contractual power restriction.

- **"Smart" charging strategy (SC logic)**, This charging strategy is applied to both Commercial and Domestic EVs). Charging is prevented if no shared energy potential is available, and it can be partially limited or even suspended when necessary. Charging power is modulated by adjusting the variation ranges as the SOC changes. Specifically, a minimum charging power () and a maximum charging power () are defined as a function of the EV's SOC (Figure 4). The charging measurement, management, and control system checks whether shared energy potential is available in the configuration and adjusts charging power accordingly within the power ranges described below. On working days (except for Friday, Figure 4a), vehicles always charge at maximum power up to a SOC equal to . Between and of the SOC, partial power can be achieved up to of . Beyond , charging can be further reduced without limits, even to the point of cancellation. On Fridays (Figure 4b), vehicles charge at the maximum power when SOC is less than , while SOC values above charging can be reduced to , since rapid completion of charging is not required. On Saturdays and Sundays (Figures 4c and 4d respectively), charging power ranges are wider, allowing for greater flexibility. After Sunday midnight, however, a stricter limit is reinstated as the weekday strategy applies again. The SOC threshold ensures a minimum level of charge, reducing the risk of EVs not having sufficient energy for travel. The specific different distribution adopted for Fridays was designed to avoid full charging and to preserve flexibility that can be exploited during the weekend, when EVs are generally unused. Summarizing, part of the charging is prioritized for workdays and during the production period of the generation plants.

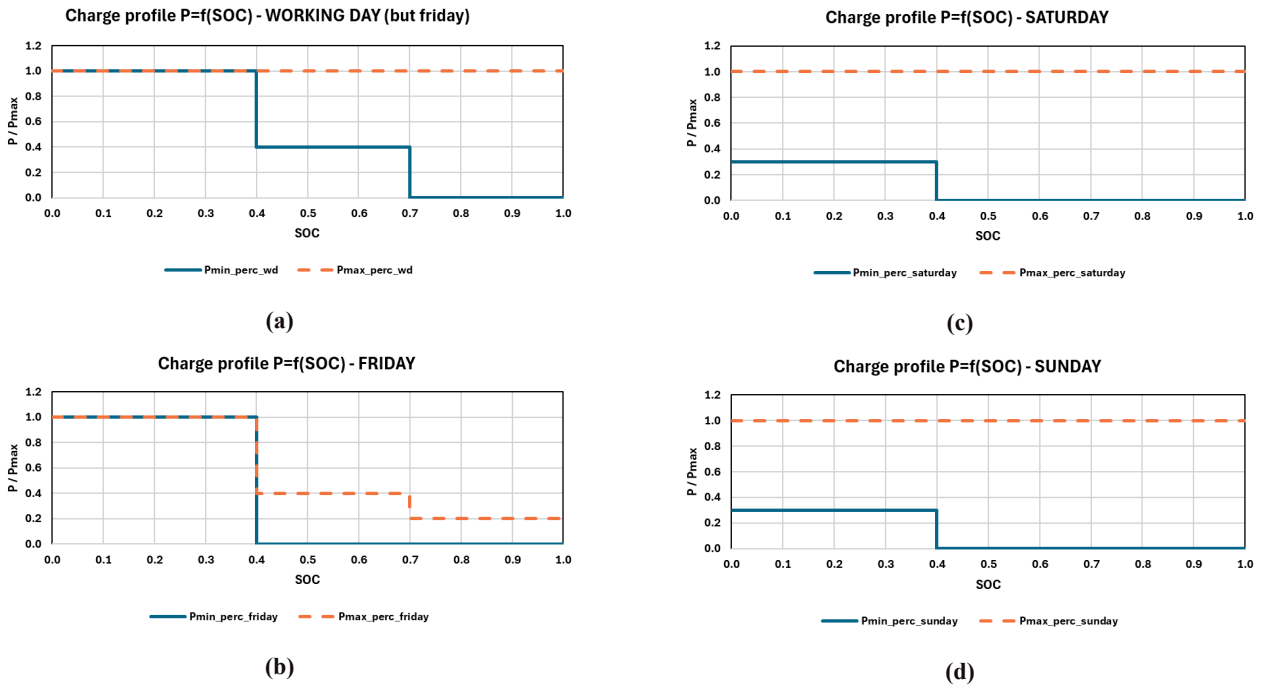


Fig. 4. Minimum and maximum power limits (nominal values compared to the maximum charging power Pmax) as function of SOC, for different days of the week: (a) - Working day but Friday; (b) - Friday; (c) - Saturday; (d) - Sunday.

At each timestep t, the shared energy potential is calculated and allocated among the EVs according to their availability (Figure 5). Specifically, the shared energy potential is divided into equal portions for all available vehicles, so the controller makes the power injection request and checks whether each vehicle can absorb it. In the example shown in Figure 5, during the iteration *n*, vehicle EV4 cannot retrieve the allocated share and is therefore excluded from the calculation, while vehicle EV3 can only partially. This energy that is left out becomes the input of the second iteration and thus redistributed into equal shares between updated list of vehicles EV1 and EV2 (as EV3 and EV4 are no longer available). The power allocation request is again checked at vehicles level, and it is found that vehicle EV2 can only partially absorb it (iteration). Finally, the remaining excess is absorbed by vehicle EV1, which still had available capacity in this example (iteration). At certain timesteps, it may also happen that the vehicles do not have sufficient availability to meet the controller's requests, meaning that not all the potential is converted into shared energy. The availability of EVs depends on the vehicle's SOC, infrastructure constraints and the power available at the point of delivery at given time, given by the difference between the contracted power and the user's current electricity consumption ().

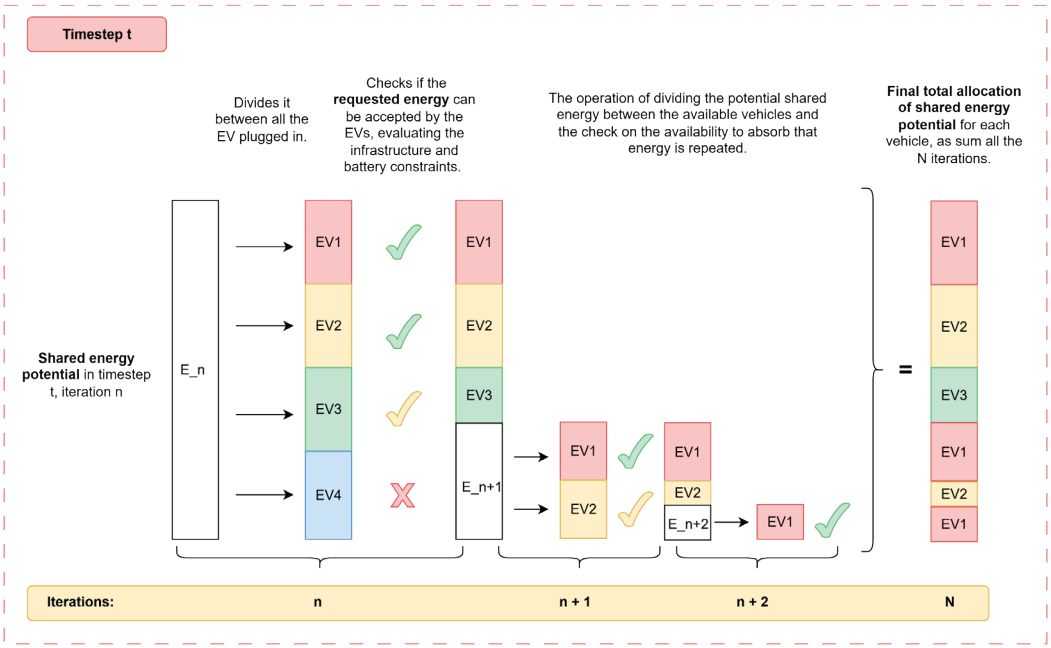


Fig. 5. Logic for allocating shared energy potential to different EVs (example for 4 EVs).

6. RESULTS

Figure 6 shows the average charging powers of the different EVs on various types of days (working day, Friday, Saturday, and Sunday), under different charging strategies (6-a for *StC logic* and 6-b for *SC logic*).

As expected, *SC logic* shifts EV charging from nighttime to daytime, thereby increasing the energy shared within the community. In the SC case, charging is significantly reduced since it only occurs when the SOC falls below the thresholds of 40% or 70%, as described in Figure 4.

Simulation results indicate that under *StC logic*, vehicles generally reach full charge by Friday night. Consequently, little charging is required over the weekend, except for domestic users who use their cars on Saturday, while commercial vehicles remain parked. Using the *SC logic*, EVs do not fully recover SOC during workdays due to power limitations, but they compensate over the weekend, when abundant solar energy is available and industrial loads are low.

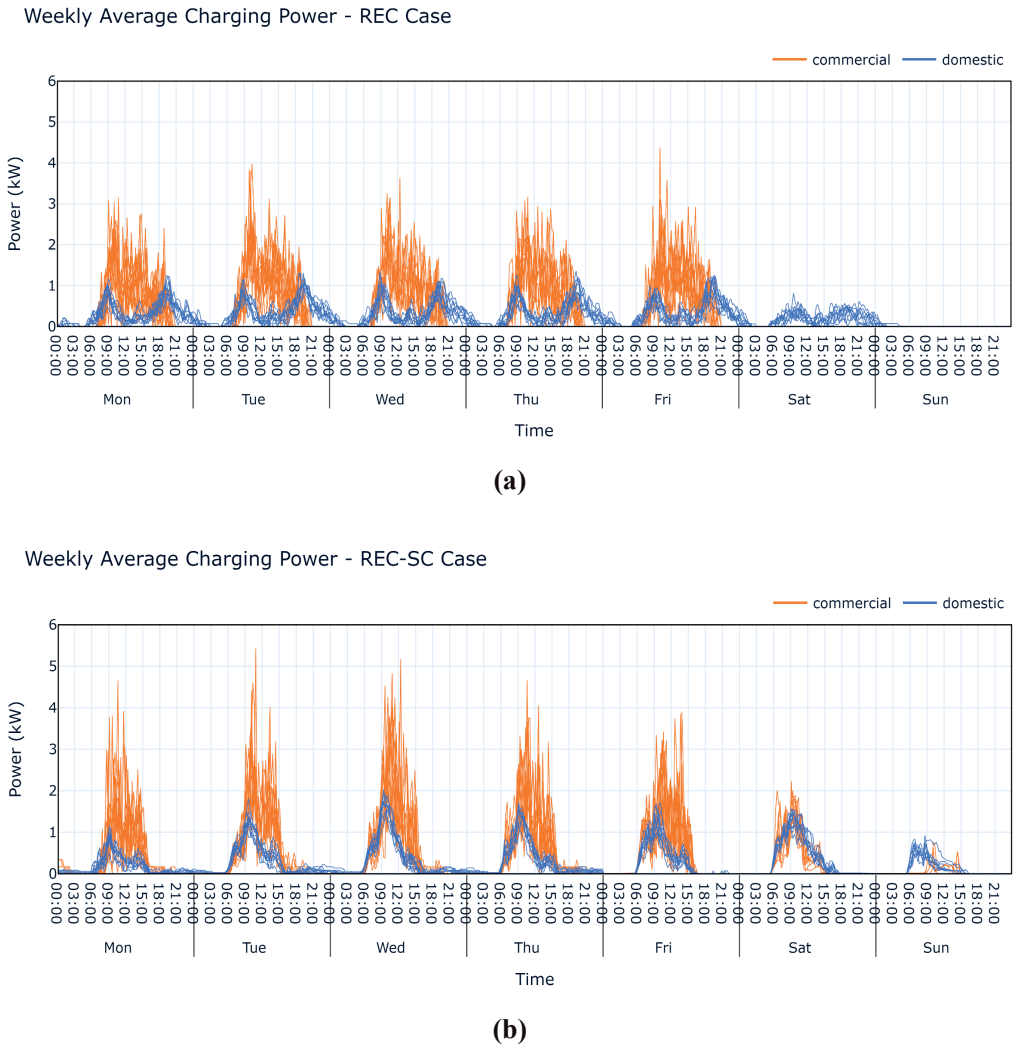
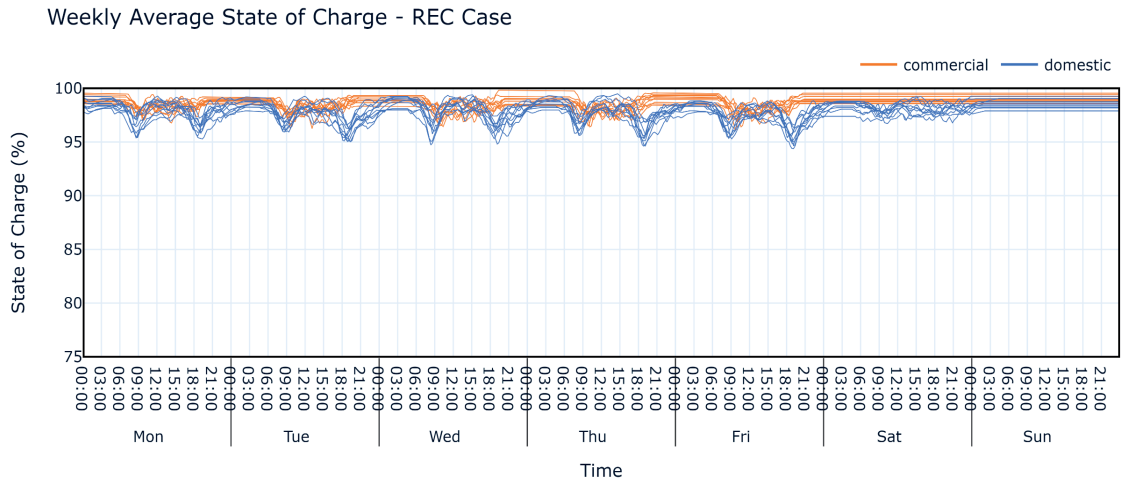


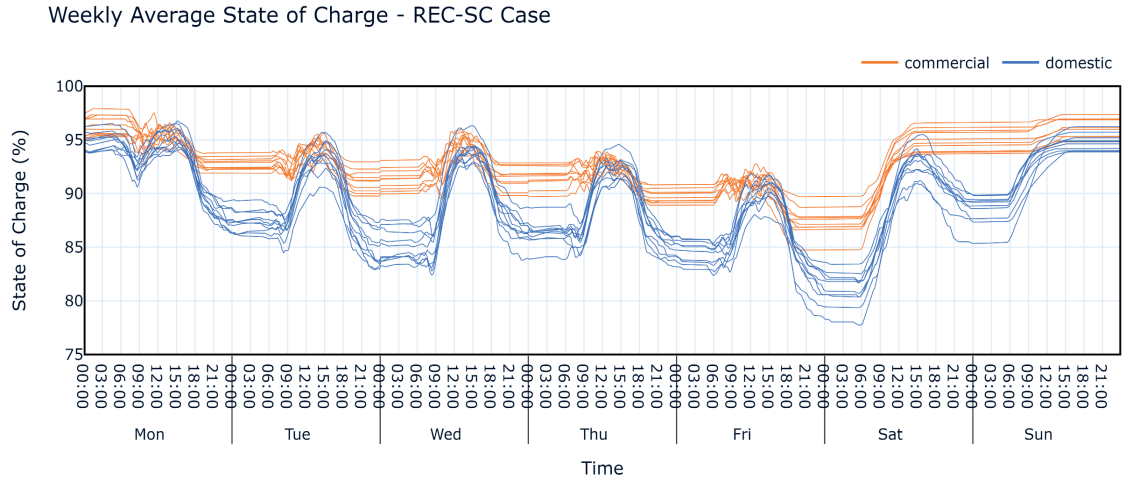
Fig. 6. Average weekly charging power profiles for all EVs (domestic in blue and commercial in orange) on different days of the week, for (6a) StC logic and (6b) for SC logic.

Figure 7 shows the average weekly SOC using *StC* (Figure 7-a) and *SC logics* (Figure 7-b). In general, SOC levels are lower in the *SC case*, reaching a minimum between Friday and Saturday, while remains relatively high and stable in the *StC case*. As expected, the SOC patterns reflect the combination of mobility demand (SOC decreases when EV is in use), charging events described above (SOC increases when EV is plugged and charging), and idle conditions when the vehicle is parked but not charging (SOC remains stable, typically at night, in the early morning, or during weekends).

By adopting *SC logic*, SOC becomes more stable during evening and nighttime hours, as consequence of the controller's charging limitations. Conversely in the SC case, SOC increases in the morning as solar irradiance and PV production rise and then stabilizes when users begin driving their vehicles.



(a)



(b)

Fig. 7. Average SOC profiles for different EVs (domestic in blue and commercial in orange) on different days of the week, for (7a) StC logic and (7b) SC logic.

As shown in the previous graphs, the average SOC of EVs decreases when *SC logic* is applied. This trend is also evident in the boxplots shown in Figure 8, which illustrates the SOC distributions for different vehicles. Using the *StC logic* (REC and reference cases), SOC values are generally very high, with the 5th percentile typically above . In contrast, using *SC logic* (REC – SC case), SOC values are considerably lower, with the 5th percentile around for commercial EVs and for domestic EVs. This occurs because *SC logic* imposes several charging limitations based on PV production and real-time SOC, forcing EVs to wait for optimal charging conditions. Regarding the lowest recorded values, represented by outliers (dots), they never fall below . This means that vehicles always maintain a state of charge sufficient to meet user's mobility needs. Using the *SC logic*, however, SOC values exhibit a wider distribution, highlighting the variability introduced by this charging strategy. Even in this case, SOC levels generally remain high, although outliers may drop to low value without ever reaching zero. Consequently, the "smart" charging strategy reduces user comfort but does not cause service disruptions. It is worth noting that the SOC levels are determined by the charging power constraints imposed according to the SOC thresholds (40% and 70%) illustrated in Figure 4. An increase in these thresholds would lead to higher allowable charging power and, consequently, higher SOC levels; however, this would occur at the expense of reduced charging flexibility, thereby diminishing the potential for additional incentives.

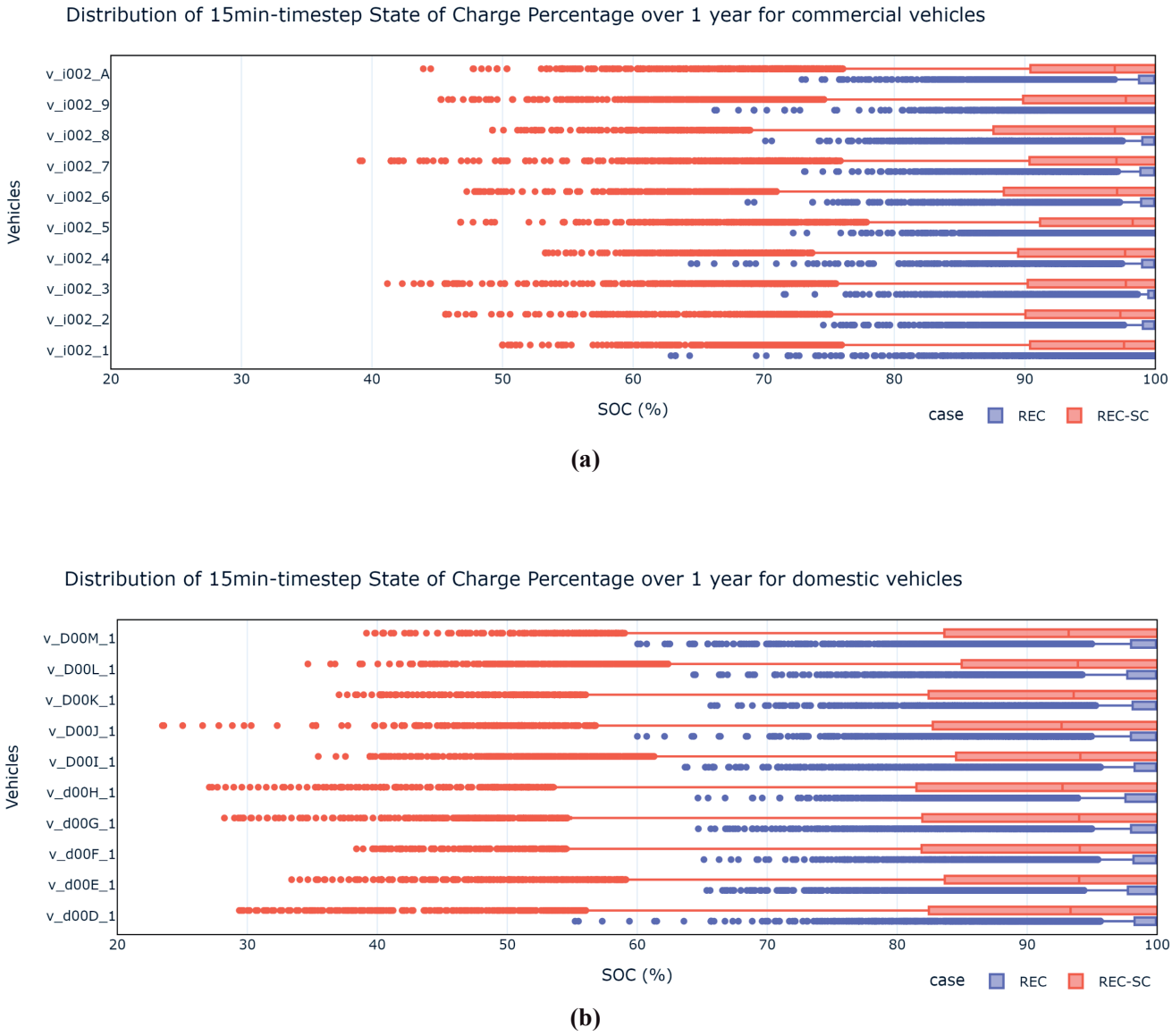


Fig. 8. Boxplot of the SOC for different EVs - commercial EVs in Figure 8-a and domestic EVs in Figure 8-b - using StC logic (REC case) and SC logic (REC-SC case).

To investigate a real behavior rather than averaged values, Figure 9 shows the energy flows results for the REC and REC-SC scenarios during a specific week in March. Non-shiftable REC base load is shown in yellow (household and commercial user consumption), while EV charging is highlighted in blue. In the REC scenario, charging is distributed between day and night and depends solely on the vehicles' SOC and their presence at the charging station.

In the REC-SC scenario, however, the "smart" charging strategy concentrates charging during PV system production hours (the production curve is represented by the red line). Moreover, on days with low PV generation and insufficient shared energy potential (as on Monday in the figure), vehicles charge only to meet minimum SOC requirements (hence the small blue lines on Monday and Tuesday evenings in Figure 9-b).

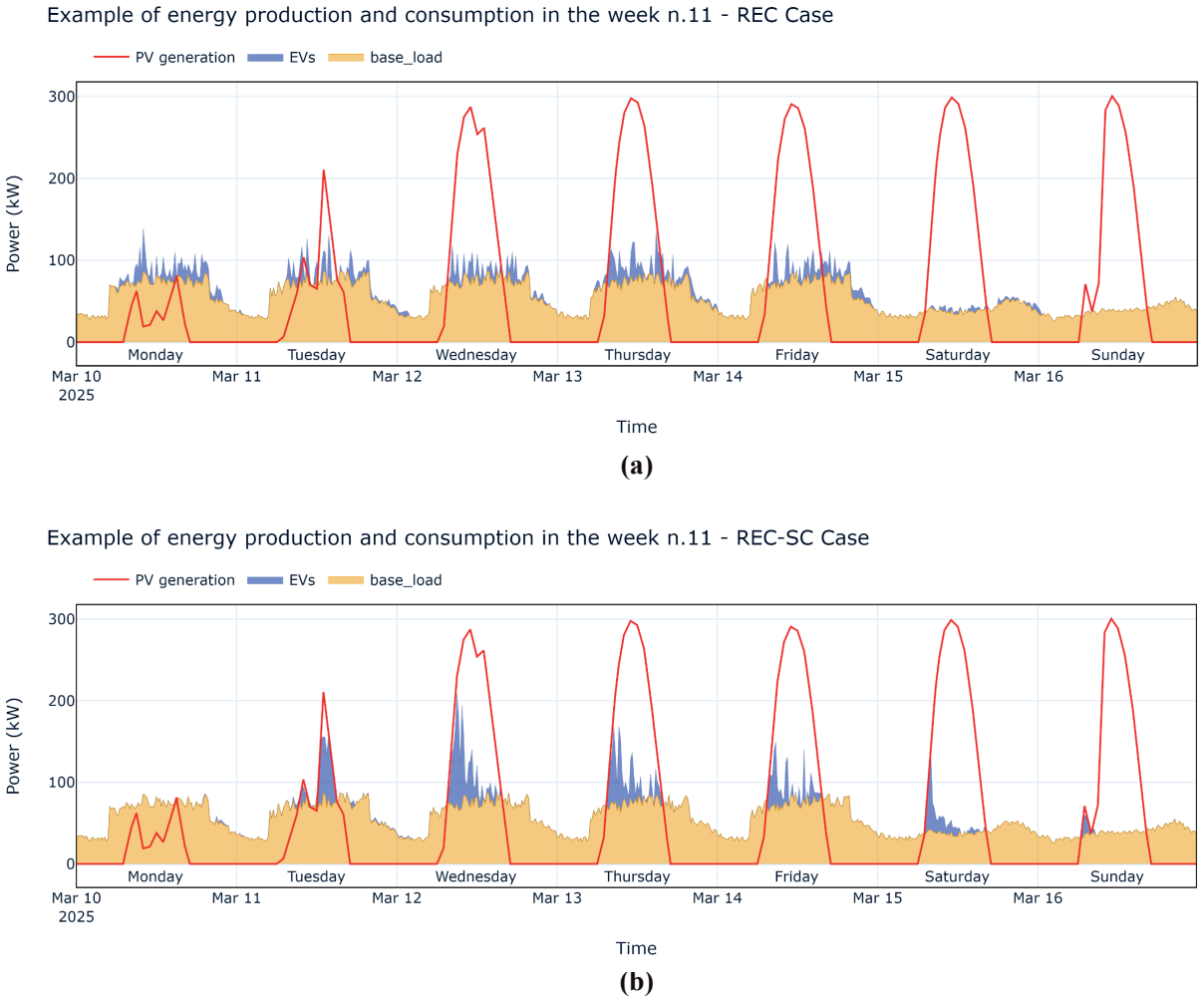


Fig. 9. Aggregate production profiles of photovoltaic systems (red line), aggregate base load of the configuration (yellow area), and aggregate load of EVs (blue area) for a specific week under consideration. Figure 9-a uses StC logic and Figure 9-b uses SC logic.

To conclude, Table 5 reports the results for the REC's annual shared energy and the annual incentive-related revenues obtained in the different case studies. Aggregating all users within a REC generates approximately thousand in incentives, without requiring any changes in energy generation and consumption (including EV charging) compared to the reference case.

Moreover, adopting a smart charging system increases shared energy by , raising incentive revenues to thousand (), all without causing any disruptions to users' mobility services. These results highlight the relevant benefits that can be achieved by participating in an energy community and by additionally adopting the "smart" charging strategy proposed in this study.

Table 5. Annual shared energy and annual incentive revenues in different cases.

Case study	Yearly Shared Energy [MWh]	Yearly Incentive Revenues [€]
Ref case	n.a.	n.a.
REC case	56.3	€ 5,684.86
REC – SC case	82.8	€ 8,527.83

When results are normalized to the average vehicle of the REC fleet, each smartly controlled generates an additional of shared energy and in incentives per year, with the potential to be maintained over a 20-year period.

7. CONCLUSIONS

The simulations and output data show that the REC can leverage these storage resources to generate approximately 47% increase in energy sharing and 50% additional incentives, by adopting a centralized smart charging for the 20 EV without disruptions in services. In other words, EV users do not experience any shortage of charge availability for their mobility needs over the 1-year simulation. Although the smart charging strategy leads to greater variability in the state of charge during the week, no vehicle ever suffers from insufficient charge. This was demonstrated by investigating the 15-min SOC distributions, which show that none of the EVs' bottom outliers ever reach critical states. The smart charging logic proposed in this study has the advantage of avoiding the need to forecast the configuration's consumption and production data. Specifically, EV charging power is regulated based on the shared energy potential of the Energy Community, while maximum and minimum charging limits are defined as function of the EVs state of charge. Naturally, implementing this charging strategy in a real-world context requires investment in measurement, control, and management systems for both EVs and the Energy Community, which architecture and costs were not the scope of this study. Furthermore, EV charging load shifting was demonstrated to increase local self-consumption, with simulations reporting still high SOCs which may leave room for other applications, such as V2G or other flexibility purposes. In conclusion, smart load shifting in electric mobility applications can generate relevant additional value to energy communities with relatively simple optimization solutions.

8. Nomenclature

Parameter notation	Parameter definition	Unit
REC	Renewable Energy Community	-
EV	Electric Vehicle	-
CEV	Commercial Electric Vehicle (EVs of the commercial user)	-
DEV	Domestic Electric Vehicle	-
CS	Charging Station	-
FIP	Premium Feed-in	€/kWh
ZP	Zonal Price	€/kWh
	Installed capacity of the generators	kW
SOC	State of Charge	%
	Maximum charging power (Equation 3)	kW
	Contractual power	kW
	Power absorbed by the load	kW
	Maximum charging power of the Charging Station	kW
	Maximum charging power of the Electric Vehicle	kW
	Minimum charging power of the Electric Vehicle	kW

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