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# On the characterization and evaluation of residential on-site E-car-sharing

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ABSTRACT

E-car-sharing concepts can play a key role in future urban areas as a new and sustainable transport system. When it comes to residential buildings, the added values of sharing systems are reduced parking space and increased use of solar photovoltaics generation on-site. This work proposes a simple and complete method to define residential building tenants' optimal investment and operation, switching from car ownership to an e-car-sharing system. A mixed-integer linear optimization framework describes technologies such as battery storages, solar photovoltaics, electric vehicles, and charging stations. Furthermore, different scenarios are defined and simulated in order to investigate and evaluate the economic potential of residential on-site e-car-sharing. It is shown that with the actual grid tariff design in Austria, the integration of bidirectional charging stations is not cost-effective if considering only the Day-Ahead spot market. The results show that integrating an e-car-sharing system in a residential building allows for fewer cars and charging stations with higher nominal power, reducing the annual total costs of the residential building tenants by up to 29%. On the other hand, the results indicate that e-car-sharing systems can also lead to lower optimal installed solar photovoltaic power.



## 1. Introduction

Electric vehicles (EVs) represent the most prominent mean of transportation that can contribute to the transition to greener and more sustainable urban mobility. The 2015 Paris declaration on electro-mobility, which brings together the individual and collective commitments to increase electro-mobility to levels compatible with the goals mentioned in the Paris Agreement [1], stated the need to electrify at least 20% of all road transport vehicles by 2030 [2]. However, there are still multiple determinant barriers for the successful electrification of road vehicles, such as lack of charging infrastructures, cost concerns, and technical and operational restrictions, as investigated in Refs. [3,4].

At the same time, there is rapid growth in car-sharing applications, mainly in urban centers [5]. Electric vehicle car-sharing systems can become essential components of future urban transport systems [6]. As a new and more sustainable means of transportation, car-sharing services are taking over private mobility replacing ownership with service use [7]. When it comes to residential buildings, the added value of shared mobility is reducing the required parking space while maintaining the mobility offer. Several studies investigate the impact of a large number of smart EVs on the self-consumption degree of renewable energy [8]. In fact, in recent years, the share of renewable energy sources in global electricity generation has grown rapidly [9].

Research, such as [10,11], show how EVs' demand management can positively influence the integration of renewables in the electrical power supply system. EVs can assist in integrating volatile renewable electricity sources in power systems by contributing to the electrical grid stability, balancing the generation and the demand side, as investigated in Ref. [12]. Furthermore, the use of EVs for grid stabilization reduces the deployment of fossil fueled power stations to balance the electricity grid and, therefore, $CO_2$-emissions [13].

Moreover, the growing share of renewable energy sources significantly increases the price volatility in the wholesale electricity markets, as investigated in Refs. [14,15]. Electricity price volatility implies profit opportunities for flexible electricity consumers and producers [16]. Flexibility is the capability of electrical systems to alter their scheduled injection and consumption in reaction to external signals (e.g., spot market prices) [17].

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**Abbreviations**

| | |
|---|---|
| BS | Battery Storage |
| CS | Charging Station |
| DA | Day-Ahead Spot Market |
| EV | Electric Vehicle |
| GCP | Grid Connection Point |
| LCOS | Levelized Cost of storage |
| PV | Solar Photovoltaic Panel |
| RL | Residential Load |
| V2G | Vehicle-to-Grid |

*Mathematical Notations*

| | |
|---|---|
| $\mathcal{T} = \{1, \ldots, T\}$ | Time periods |
| $\mathcal{J} = \{1, \ldots, J\}$ | Tenants |
| $\mathcal{J}^* = \{1, \ldots, J^*\}$ | Tenants and e-car-sharing company |
| $\mathbf{\Gamma}_j = \{1, \ldots, \Gamma_j\}$ | Travel cycles of tenant $j$ |
| $\mathbf{\Gamma} = \{1, \ldots, \Gamma\}$ | Travel cycles of the tenants in $\mathcal{J}$ |
| $\mathbf{\Phi} = \{\varphi_0, \ldots, \varphi_\Phi\}$ | Nominal powers of the charging stations |
| $A^x_{n^x,r}$ | Annuity factor of $x$ |
| $p^x_{j,t}$ | Power of $x$ of tenant $j$ at time step $t$ |
| $p^x_t$ | Power of $x$ at time step $t$ |
| $p^{x,I}_j$ | Installed power of $x$ of tenant $j$ |
| $c^x$ | Specific costs of $x$ |
| $C^x$ | Costs of $x$ |
| $C^x_j$ | Costs of $x$ of tenant $j$ |
| $P^x_t$ | Price of $x$ at time step $t$ |
| $P^x$ | Price of $x$ |
| $d^x$ | E/P of $x$ |
| $p^{x,L_\%}$ | Percentage standby-losses of $x$ |
| $\eta^x$ | Efficiency of $x$ |
| $N^x$ | Number of cycles of $x$ |
| $p^{EV,C}_{j,\gamma_j,t}$ | EV consumption of tenant $j$ and travel cycle $\gamma_j$ at time step $t$ |
| $p^{EV,C}_{j,t}$ | EV consumption of tenant $j$ at time step $t$ |
| $E^x$ | Capacity of $x$ of tenant $j$ |
| $\sigma^x_{j,t}$ | Binary variable $x$ of tenant $j$ at time step $t$ |
| $\sigma^x_j$ | Binary variable $x$ of tenant $j$ |
| $C_\varphi$ | Costs of the charging station $\varphi$ |
| $m^{EV}$ | Number of EVs |
| $\sigma^{EV,\,c}_{\theta,\gamma}$ | Binary variable of EV $\theta$ and travel cycle $\gamma$ |

The main objective of this study is to investigate and evaluate the economic potential of residential on-site e-car-sharing. Profit opportunities incentivize residential tenants to invest in several technologies, such as battery storages (BSs), Solar photovoltaic panels (PVs), EVs and their charging stations (CSs). Likewise, price signals may incentivize residential tenants to apply flexible energy consumption patterns to their energy supply schedules. Hence, the tenants' investments in different technologies strongly depend on the potential savings their operations can provide.

In this paper, a mixed-integer linear optimization framework is developed. The optimization aims to define the optimal investments and the operational strategy of the residential tenants' technologies to minimize the overall costs allocating the flexibilities on the Day-Ahead spot market (DA), considering the grid cost components. However, a detailed description of the investigated technologies' economic aspects and technical operation is needed to efficiently coordinate multiple flexible components and determine the optimal investment. In this work, we describe the technologies of the tenants using linear relationships only, which are implemented in the mixed-integer linear optimization framework using the *Python* toolbox *Pyomo* [18].

The paper is organized as follows. Section 2 provides an overview of the state of the art in scientific literature. The optimization framework and the mathematical methods to describe each technology and their interactions are outlined in section 3. Section 4 provides the description of the investigated case study and section 5 presents the comprehensive results of the case study. Finally, section 6 concludes the paper and elaborates on possible directions for future research.

## 2. State of the art

Car-sharing services are becoming increasingly important because they represent a potential and more sustainable alternative to various means of transportation, including private cars. This trend matches with the contemporary interest in sharing economy concepts [19]. The study [20] reveals that people with e-car-sharing experience rate the usefulness of EVs higher than non-experienced people, proving how e-car-sharing concepts involve higher acceptance of EVs.

E-car-sharing systems can lead to reductions of up to 37% in mobility-related $CO_2$-emissions in urban areas [21]. In particular [22], quantifies the effects of car-sharing on car ownership and car use, showing how car sharers drive 15%–20% fewer car kilometers than before using a car-sharing service. Moreover [23], demonstrates the positive correlation between car-sharing vehicle availability and vehicle ownership reduction, which leads to greater parking availability in metropolitan areas. For these reasons, e-car-sharing systems appear to play an essential role in future transportation systems.

On the other hand, the increase of high-power CSs in urban centers and the growing share of renewable energy sources currently represent a big challenge for the distribution operators [24]. For this reason, Vehicle-to-Grid (V2G) charging technology is gaining importance. The operational benefits that V2G can provide are varied. In Ref. [25], the authors investigated the operation of a V2G-capable EV fleet and its impact on electric grid operation, showing how small changes in charging patterns can significantly benefit the end-user and the grid operation [26,27]. analyze the effects of bidirectional CSs on grid stability and power quality and demonstrate how V2G operation can improve both.

EVs can provide flexibility for the grid and increase the consumption of variable and unpredictable renewable energy generation [8]. Several studies, such as [28,29], investigated the impact of the active participation of EVs in spot markets and the potential economic benefits that new business models may create. In particular [29], recognizes the need for centralized coordination with other market participants, such as energy suppliers, aggregators, grid operators, and other consumers to implement EV market participation successfully.

Therefore, several studies explore different methods to describe the flexibility of EVs mathematically. Shi et al. [30] establish a robust multi-objective optimization dispatching model, where the flexibility of EVs is used to increase renewable energy injection and reduce operational and environmental costs. Luo et al. [31] introduce a charging scheduling simulation platform and demonstrate that optimal charging strategies can improve the safety and economics of the electrical grid operation. Pirouzi et al. [32] compared a linear and nonlinear optimization approach for flexible bidirectional power management of EVs and shows how linear models can

replace more complex nonlinear ones. Additionally, Chinneck et al. [33] present the twelve most significant advantages of linear models in comparison to nonlinear ones. In particular, an essential benefit of representing EVs with the exclusive use of linear relationships in mathematical optimizations is the model's characteristic of being scalable and capable of handling a large number of components.

Complementing to existing literature, this paper aims to investigate the economic impact of residential on-site e-car-sharing and the monetary benefits that new e-car-sharing business models may create in different scenarios. The work presents a simple and comprehensive method to define residential energy management systems' optimal investment and operation with different technology options and set-ups. Specifically, we investigate the case of the adoption of the residential on-site e-car-sharing system defining the optimal investment of each tenant in multiple technologies, such as PVs, BSs, EVs and CSs. For this purpose, a mixed-integer linear optimization framework is developed. The main contributions of this paper beyond state of the art are the following.

- The novel mathematical method to determine the optimal number of EVs and the optimal type of CSs for the tenants of a residential building willing to switch from private cars to an e-car-sharing system.
- The mixed-integer linear optimization framework to determine the optimal technology portfolio of residential building tenants considering different scenarios. The optimal solution is found considering the tenants' electrical and driving needs, the physical limits of the grid and of the technologies, the grid cost components, and the spot markets price signals.
- The application of the methods to an Austrian case study to demonstrate the optimal technology portfolio determination in practice.
- The definition of the corresponding benefit indicators and the presentation of the cost-benefit analysis of residential on-site e-car-sharing based on the optimization results.

## 3. Methods

This chapter presents the mixed-integer linear optimization framework used to determine the optimal investment and operation of different technologies in a residential building. Section 3.1 provides the mathematical description of the residential building's components, which are implemented in the optimization framework. The mathematical method aims to efficiently coordinate multiple components and to determine the optimal investment in multiple technologies, considering their physical limits and costs. Moreover, in section 3.2, the investigated scenarios are defined. The scenarios differ from one another in varied organizational aspects and investment possibilities. Therefore, in the optimization framework, a distinct objective function is defined for each scenario.

The optimization framework simulates the operation of the residential building for one year. Hence, the equivalent annual cost method is used to calculate the cost-effectiveness of investment in the different technologies. This method allows determining the convenience of multiple investments that have unequal lifespans in the same optimization period. In general, the annuity factor for a technology $x$ is calculated as follows,

$$A^{x}_{n^x,r} = \frac{1 - \frac{1}{(1+r)^{n^x}}}{r} \tag{1}$$

where $n^x$ is the lifespan of the technology $x$ and $r$ indicates the annual interest rate.

### 3.1. Optimization framework

In this work, tenants are characterized by a residential load (RL) and a driving need. In addition, depending on the scenario, each tenant can invest in different technologies such as CSs, PVs and BSs. In this model, we distinguish between private and shared EVs. Depending on the scenario, the tenants of the residential building adopt an e-car-sharing system or private EVs to cover their driving needs. A comprehensive mathematical description of the components' physical limits and costs is required to determine the optimal tenants' investment and components operation. A visual representation of a residential building and the power flows of the components are shown in Fig. 1.

We consider a discrete-time optimization problem in which the time range $\mathcal{T}$ is divided into equally-spaced time intervals $\Delta t$ with a 15 min resolution. Furthermore, the residential building is composed of the tenants $j \in \mathcal{J}$. The components of the different tenants are connected to the same residential grid connection point (GCP) and their power flows are traded in the DA. In order to satisfy the electrical power balance at the GCP, the following equations are derived,

$$p^{\text{GCP, in}}_{j,t} - p^{\text{GCP, out}}_{j,t} = p^{\text{RL}}_{j,t} - p^{\text{PV}}_{j,t} + p^{\text{EV, in}}_{j,t} - p^{\text{EV, out}}_{j,t} + p^{\text{BS, in}}_{j,t} - p^{\text{BS, out}}_{j,t} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{2}$$

$$p^{\text{GCP, in}}_{j,t} - p^{\text{GCP, out}}_{j,t} = p^{\text{DA, Buy}}_{j,t} - p^{\text{DA, Sell}}_{j,t} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{3}$$

where $p^{\text{DA, Buy}}_{j,t}$ and $p^{\text{DA, Sell}}_{j,t}$ indicate the power flows traded in the DA.

The costs of each tenant can be summarized in 5 elements: the DA costs ($C^{\text{DA}}_j$), the grid costs ($C^{\text{Gr}}_j$), the PV costs ($C^{\text{PV}}_j$), the BS costs ($C^{\text{BS}}_j$) and the EV costs ($C^{\text{EV}}_j$), as depicted below.

$$C^{\text{Tot}}_j = C^{\text{DA}}_j + C^{\text{Gr}}_j + C^{\text{PV}}_j + C^{\text{BS}}_j + C^{\text{EV}}_j \quad j \in \mathcal{J} \tag{4}$$

The following subsections aim to mathematically define the costs of the components and the operations on which they are based, in order to implement them in the optimization framework as constraints.

#### 3.1.1. Day-Ahead spot market

In this work, the DA prices are implemented in the optimization framework as an exogenous time-series, as shown in 5.

$$P^{\text{DA}}_{\mathcal{T}} = (P^{\text{DA}}_1, P^{\text{DA}}_2 \ldots, P^{\text{DA}}_T) \tag{5}$$

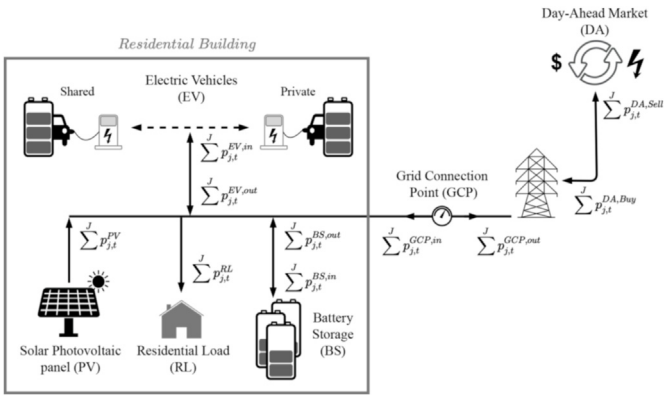


**Fig. 1.** Residential buildings' components and their power flows.

Hence, the DA costs ($C_j^{\mathrm{DA}}$) of a generic tenant $j$ are given as the product of the energy traded in each time step $t$ as follows.

$$C_j^{\mathrm{DA}} = \sum_{t=1}^{T} \left( P_t^{\mathrm{DA}} \cdot \left( p_{j,t}^{\mathrm{DA,\ Buy}} - p_{j,t}^{\mathrm{DA,\ Sell}} \right) \cdot \Delta t \right) \quad j \in \mathcal{J} \tag{6}$$

Furthermore, according to the constraints, the optimization framework determines the power flows ($p_{j,t}^{\mathrm{DA,\ Buy}}$ and $p_{j,t}^{\mathrm{DA,\ Sell}}$) at each time step, which are traded in the DA.

### 3.1.2. Grid connection point

Grid tariffs differ from the grid connection level, but in general, the tenant's grid costs are made up of three distinct cost components: a power-related cost component ($C_j^{\mathrm{Gr,\ P}}$), an energy-related component ($C_j^{\mathrm{Gr,\ E}}$) and a fixed rate ($C_j^{\mathrm{Gr,\ FR}}$). The power-related cost component is the product of the peak power at the GCP ($p_{j,max}^{\mathrm{GCP,\ in}}$) and the grid power price ($P^{\mathrm{Gr,P}}$). The energy-related cost component depends linearly on the amount of energy withdrawn from the grid, which multiplies the grid energy price ($P^{\mathrm{Gr,E}}$) as described in 8. Hence, total grid costs ($C_j^{\mathrm{Gr}}$) for a generic tenant $j$ are given by the sum of these three components, as depicted in 9.

$$C_j^{\mathrm{Gr,\ P}} = p_{j,max}^{\mathrm{GCP,\ in}} \cdot P^{\mathrm{Gr,\ P}} \quad j \in \mathcal{J} \tag{7}$$

$$C_j^{\mathrm{Gr,\ E}} = \Delta t \cdot \sum_{t=1}^{T} \left( p_{j,t}^{\mathrm{GCP,\ in}} \right) \cdot P^{\mathrm{Gr,\ E}} \quad j \in \mathcal{J} \tag{8}$$

$$C_j^{\mathrm{Gr}} = C_j^{\mathrm{Gr,\ E}} + C_j^{\mathrm{Gr,\ P}} + C_j^{\mathrm{Gr,\ FR}} \quad j \in \mathcal{J} \tag{9}$$

In accordance with the grid constraints, the optimization algorithm defines the peak power ($p_{j,max}^{\mathrm{GCP,\ in}}$) and the power flows ($p_{j,t}^{\mathrm{GCP,\ in}}$ and $p_{j,t}^{\mathrm{GCP,\ out}}$) in each time step.

### 3.1.3. Residential load

The RL represents, together with the driving need, the consumption requirements of the residential building tenants. Each tenant $j$ is characterized by different consumption patterns, defined as exogenous time-series of power needs, described as follows.

$$p_{j,\mathcal{T}}^{\mathrm{RL}} = (p_{j,1}^{\mathrm{RL}}, p_{j,2}^{\mathrm{RL}} \ldots, p_{j,T}^{\mathrm{RL}}) \quad j \in \mathcal{J} \tag{10}$$

### 3.1.4. Solar photovoltaic panel

In this work, the PV is a technology in which the tenants of the residential building can invest. In order to implement the PV in the optimization framework, an exogenous time-series of PV-specific power generation per installed $kW_p$ is given, as follows.

$$p_{\mathcal{T}}^{\mathrm{PV,\ p}} = (p_1^{\mathrm{PV,\ p}}, p_2^{\mathrm{PV,\ p}} \ldots, p_T^{\mathrm{PV,\ p}}) \tag{11}$$

Therefore, the PV generation of a generic tenant $j$ at the time step $t$ is defined as the product of the PV-specific power generation per installed $kW_p$ and the installed power ($p_j^{\mathrm{PV,I}}$), as depicted in 12.

$$p_{j,t}^{\mathrm{PV}} = p_t^{\mathrm{PV,\ p}} \cdot p_j^{\mathrm{PV,I}} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{12}$$

The rooftop area, and consequently, the potential PV power of a residential building is generally limited to a maximum installed power ($p_{max}^{\mathrm{PV,\ I}}$), which is distributed among the tenants. Hence, the tenants' installed PV power is bounded, as described in 13 and 14.

$$\sum_{j=1}^{J} p_{j,max}^{\mathrm{PV,\ I}} = p_{max}^{\mathrm{PV,\ I}} \tag{13}$$

$$p_j^{\mathrm{PV,\ I}} \leq p_{j,max}^{\mathrm{PV,\ I}} \quad j \in \mathcal{J} \tag{14}$$

Furthermore, the PV costs of a generic tenant $j$ are defined as the product of the installed power and the PV-specific power costs ($c^{\mathrm{PV}}$) considering its annuity factor as described below.

$$C_j^{\mathrm{PV}} = p_j^{\mathrm{PV,\ I}} \cdot \frac{c^{\mathrm{PV}}}{A_{n^{PV},r}^{PV}} \quad j \in \mathcal{J} \tag{15}$$

According to the physical constraints and the costs, the optimization framework determines the optimal installed PV power ($p_j^{\mathrm{PV,\ I}}$) for each tenant of the residential building.

### 3.1.5. Battery storage

This section presents the linear battery model implemented in the mixed-integer linear optimization framework employed to investigate the optimal size and operation of the tenants' BSs. In order to preserve the linearity of the model, the ratio between installed capacity and installed power (E/P) will be given by a fixed parameter: the duration $d^{\mathrm{BS}}$. Each tenant's BS input and output power ($p_{j,t}^{\mathrm{BS,\ in}}$ and $p_{j,t}^{\mathrm{BS,\ out}}$) is bounded to the installed power ($p_j^{\mathrm{BS,\ I}}$) at each time step $t$, as follows.

$$0 \leq p_{j,t}^{\mathrm{BS,\ in}} \leq p_j^{\mathrm{BS,\ I}} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{16}$$

$$0 \leq p_{j,t}^{\mathrm{BS,\ out}} \leq p_j^{\mathrm{BS,\ I}} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{17}$$

Also, it is necessary to initialize the state of charge of the BSs ($soc_{j,0}^{\mathrm{BS}}$) and to bound it to the installed capacity for each time step, as depicted in 19.

$$soc_{j,0}^{\mathrm{BS}} = soc_{j,Start}^{\mathrm{BS}} \quad j \in \mathcal{J} \tag{18}$$

$$0 \leq soc_{j,t}^{\mathrm{BS}} \leq p_j^{\mathrm{BS,\ I}} \cdot d^{\mathrm{BS}} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{19}$$

The batteries' state of charge ($soc_{j,t}^{\mathrm{BS}}$) is calculated according to the input-output power and the standby-losses ($p^{\mathrm{BS},L_{\%}}$), as described below,

$$soc_{j,t}^{\mathrm{BS}} = soc_{j,t-1}^{\mathrm{BS}} \cdot \left(1 - p^{\mathrm{BS,L_{\%}}}\right) + \left(p_{j,t}^{\mathrm{BS,\ in}} \cdot \eta^{\mathrm{BS,\ in}} - \frac{p_{j,t}^{\mathrm{BS,\ out}}}{\eta^{\mathrm{BS,out}}}\right) \cdot \Delta t \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{20}$$

where $\eta^{\mathrm{BS,\ in}}$ and $\eta^{\mathrm{BS,\ out}}$ are the batteries' charging and discharging efficiency, respectively.

The equivalent annual cost of technologies, as mentioned in 1, is related to the lifespan of the technology itself. In the case of BSs, the lifespan and, therefore, the specific cost ($c^{\mathrm{BS}}$) depends on the number of cycles performed. Based on the analysis of [34], in this model, the number of yearly cycles is bounded to a maximum ($N^{\mathrm{BS}}$) so that the specific cost can be expressed in a linear system. Hence, the battery cycles limitations and the investment costs for each tenant are defined as below.

$$\Delta t \cdot \sum_{t=1}^{T} p_{j,t}^{\mathrm{BS,\ in}} \leq p_j^{\mathrm{BS,\ I}} \cdot d^{\mathrm{BS}} \cdot N^{\mathrm{BS}} \quad j \in \mathcal{J} \tag{21}$$

$$C_j^{\mathrm{BS}} = p_j^{\mathrm{BS,\ I}} \cdot d^{\mathrm{BS}} \cdot \frac{c^{\mathrm{BS}}}{A_{n^{BS},r}^{BS}} \quad j \in \mathcal{J} \tag{22}$$

In accordance with the constraints and the BSs' related costs, the model aims to determine the optimal installed power ($p_j^{\mathrm{BS,\ I}}$) for each tenant $j$ under consideration of the specific investment costs ($c^{\mathrm{BS}}$) and the BSs' operation. The optimization framework defines the tenants' BS operation, specifying the input and output power ($p_{j,t}^{\mathrm{BS,\ in}}$ and $p_{j,t}^{\mathrm{BS,\ out}}$) and the state of charge ($soc_{j,t}^{\mathrm{BS}}$) in each time step $t$.

### 3.1.6. Private electric vehicles

In this model, tenants are characterized by a RL and a driving need. The driving need of a tenant $j$ is formed by multiple travel cycles ($\gamma_j \in \mathbf{\Gamma}_j$). A travel cycle expresses the consumption of an EV when it is not plugged in, i.e., the driving need. Furthermore, a travel cycle represents a single trip, and the consumption of each travel cycle $\gamma_j$ is formally defined as follows.

$$p_{j,\gamma_j,\mathcal{T}}^{\mathrm{EV,C}} = (p_{j,\gamma_j,1}^{\mathrm{EV,C}}, p_{j,\gamma_j,2}^{\mathrm{EV,C}} \ldots, p_{j,\gamma_j,T}^{\mathrm{EV,C}}) \quad j \in \mathcal{J}, \gamma_j \in \mathbf{\Gamma}_j \tag{23}$$

Hence, the driving need of a tenant $j$ can be resumed in an exogenous time-series, defined as the sum of the travel cycles $\mathbf{\Gamma}_j$ in each time step $t$, as depicted in the following equation.

$$p_{j,t}^{\mathrm{EV,C}} = \sum_{\gamma_j=1}^{\Gamma_j} p_{j,\gamma_j,t}^{\mathrm{EV,C}} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{24}$$

Since the tenants are characterized by a driving need, each tenant $j$ invests in a car to cover its driving demand in the case of private EVs. Like in BSs, it is necessary to initialize the state of charge of the EV's batteries and confine it to the EV's battery capacity ($E^{\mathrm{EV}}$) for each time step, as described below.

$$soc_{j,0}^{\mathrm{EV}} = soc_{j,Start}^{\mathrm{EV}} \quad j \in \mathcal{J} \tag{25}$$

$$0 \leq soc_{j,t}^{\mathrm{EV}} \leq E^{\mathrm{EV}} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{26}$$

Also, the state of charge of the tenants' EVs batteries ($soc_{j,t}^{\mathrm{EV}}$), considering the standby-losses ($p^{\mathrm{EV},L_{\%}}$) and the charging-discharging efficiency ($\eta^{\mathrm{EV,\ in}}$ and $\eta^{\mathrm{EV,\ out}}$), can be defined in each time step $t$ as follows.

$$soc_{j,t}^{\mathrm{EV}} = soc_{j,t-1}^{\mathrm{EV}} \cdot \left(1 - p^{\mathrm{EV,L_{\%}}}\right) + \left(p_{j,t}^{\mathrm{EV,\ in}} \cdot \eta^{\mathrm{EV,in}} - \frac{p_{j,t}^{\mathrm{EV,\ out}}}{\eta^{\mathrm{EV,out}}}\right) \cdot \Delta t \cdot \sigma_{j,t}^{\mathrm{EV,\ Pi}} - p_{j,t}^{\mathrm{EV,C}} \cdot \Delta t \cdot \left(1 - \sigma_{j,t}^{\mathrm{EV,\ Pi}}\right) j \in \mathcal{J}, t \in \mathcal{T} \tag{27}$$

The binary variable $\sigma^{\mathrm{EV,\ Pi}}$ determines whether the EV of the tenant $j$ is plugged in at the time step $t$. Hence, it is necessary to implement the constraint 28 in the optimization framework that coerces the disconnection of the EVs ($\sigma_{j,t}^{\mathrm{EV,\ Pi}} = 0$) when the driving need ($p_{j,t}^{\mathrm{EV,C}}$) is greater than 0.

$$p_{j,t}^{\mathrm{EV,C}} = p_{j,t}^{\mathrm{EV,C}} \cdot \left(1 - \sigma_{j,t}^{\mathrm{EV,\ Pi}}\right) \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{28}$$

Furthermore, the terms $p_{j,t}^{\mathrm{EV,\ in}}$ and $p_{j,t}^{\mathrm{EV,\ out}}$ in 27 indicate the CS power input and output, respectively. One of the objectives of this model is to determine the optimal investment in CSs, which are described with two exogenous time-series: the possible installed nominal powers of the CSs ($\mathbf{\Phi}$) and their costs ($C_{\mathbf{\Phi}}$). For that reason, the input-output power are confined between 0 and the installed nominal power of the CS, as depicted below,

$$0 \leq p_{j,t}^{\mathrm{EV,\ in}} \leq \sum_{\varphi=\varphi_0}^{\varphi_\Phi} \varphi \cdot \sigma_{j,\varphi}^{\mathrm{EV,\ p}} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{29}$$

$$0 \leq p_{j,t}^{\mathrm{EV,\ out}} \leq \sum_{\varphi=\varphi_0}^{\varphi_\Phi} \varphi \cdot \sigma_{j,\varphi}^{\mathrm{EV,\ p}} \cdot \sigma_j^{\mathrm{EV,\ V2G}} \quad j \in \mathcal{J}, t \in \mathcal{T} \tag{30}$$

where the binary variable $\sigma_j^{\mathrm{EV,\ V2G}}$ indicates whether V2G operation is implemented and the binary variable $\sigma_{j,\varphi}^{\mathrm{EV,\ p}}$ determines the installed nominal power of the CS of tenant $j$. Moreover, it is necessary to employ constraint 31 to confine each tenant's CS to a constant nominal power $\varphi$.

$$\sum_{\varphi=\varphi_0}^{\varphi_\Phi} \sigma_{j,\varphi}^{\mathrm{EV,\ p}} = 1 \quad j \in \mathcal{J} \tag{31}$$

The EV costs of each tenant ($C_j^{\mathrm{EV}}$) are made up of three components: the investment costs ($C_j^{\mathrm{EV,\ I}}$), excluding the batteries of the EV, the battery costs ($C_j^{\mathrm{EV,\ LCOS}}$) and the CS costs ($C_j^{\mathrm{EV,\ CS}}$), as

described below.

$$C_j^{\mathrm{EV,\ I}} = C_j^{\mathrm{EV,\ I}} + C_j^{\mathrm{EV,\ LCOS}} + C_j^{\mathrm{EV,\ CS}} \quad j \in \mathcal{J} \tag{32}$$

The investment costs are given by the costs of the EV taken into account ($C^{\mathrm{EV,\ I}}$) without considering the battery costs, which are calculated separately, applying the levelized cost of storage (LCOS) method since they depend on the operation of the EV. Hence, the EV's battery costs within the optimized time range $\mathcal{T}$ can be described as the LCOS ($c^{\mathrm{EV,LCOS}}$) multiplied by the electricity supplied to the EV's batteries. Moreover, the CS costs are given by the investment costs ($C_\varphi$), which depend on the nominal power installed, and the costs of the bidirectional inverter ($C^{\mathrm{EV,V2G}}$) if V2G operation is implemented. The three EV's costs components considered in the optimization framework are depicted in 33, 34 and 35.

$$C_j^{\mathrm{EV,\ I}} = \frac{C^{\mathrm{EV,\ I}}}{A_{n^{EV},r}^{EV}} \quad j \in \mathcal{J} \tag{33}$$

$$C_j^{\mathrm{EV,\ LCOS}} = \Delta t \cdot \sum_{t=1}^{T} p_{j,t}^{\mathrm{EV,\ in}} \cdot c^{\mathrm{EV,LCOS}} \quad j \in \mathcal{J} \tag{34}$$

$$C_j^{\mathrm{EV,\ CS}} = \frac{\sum_{\varphi=\varphi_0}^{\varphi_\Phi} C_\varphi \cdot \sigma_{j,\varphi}^{\mathrm{EV,\ p}} + C^{\mathrm{EV,V2G}} \cdot \sigma_j^{\mathrm{EV,\ V2G}}}{A_{n^{CS},r}^{CS}} \quad j \in \mathcal{J} \tag{35}$$

According to the physical constraints and the costs, the optimization algorithm determines the operation of the CSs ($p_{j,t}^{\mathrm{EV,\ in}}$ and $p_{j,t}^{\mathrm{EV,\ out}}$) and the state of charge of the EVs ($soc_{j,t}^{\mathrm{EV}}$) in each time step in $\mathcal{T}$. In addition, the optimization determines the investment, defining the most financially convenient CS for each tenant $j$.

### 3.1.7. Shared electric vehicles

The employment of a residential e-car-sharing system can lead the residential building's tenants to invest in a reduced number of EVs to cover their driving needs. Hence, a new player is implemented in the optimization algorithm: the e-car-sharing company $J^*$. The e-car-sharing company must cover the driving need of the tenants in $\mathcal{J}$, which can be resumed as follows,

$$p_{\gamma,t}^{\mathrm{EV,C}} = \sum_{j=1}^{J} p_{j,\gamma_j,t}^{\mathrm{EV,C}} \quad \gamma \in \mathbf{\Gamma}, t \in \mathcal{T} \tag{36}$$

where $\mathbf{\Gamma}$ indicates the travel cycles of the tenants in $\mathcal{J}$. The optimization framework determines the optimal number of EVs ($m^{\mathrm{EV}}$) and the type of CSs. To achieve this in mixed-integer linear optimization, the use of binary variables is necessary. The state of charge of a shared EV ($\theta$) is bounded at its maximal capacity multiplied by the binary variable $\sigma_\theta^{\mathrm{EV,\ I}}$ as described in 37, and the optimal number of EVs is defined in 38.

$$0 \le soc_{\theta,t}^{\mathrm{EV}} \le E^{\mathrm{EV}} \cdot \sigma_\theta^{\mathrm{EV,\ I}} \quad \theta \in \mathcal{J}, t \in \mathcal{T} \tag{37}$$

$$m^{\mathrm{EV}} = \sum_{\theta=1}^{J} \sigma_\theta^{\mathrm{EV,\ I}} \tag{38}$$

Thus, if the capacity of an EV ($\theta$) is not required to cover the driving needs of the residential building's tenants, the binary variable $\sigma_\theta^{\mathrm{EV,\ I}}$ is equal to zero, and the number of EVs results lower than the number of tenants ($m^{\mathrm{EV}} \le J$). Furthermore, the state of charge of the EVs is defined as depicted below,

$$soc_{\theta,0}^{\mathrm{EV}} = soc_{\theta,Start}^{\mathrm{EV}} \quad \theta \in \mathcal{J} \tag{39}$$

$$soc_{\theta,t}^{\mathrm{EV}} = soc_{\theta,t-1}^{\mathrm{EV}} \cdot \left(1 - p^{\mathrm{EV,L\%}}\right) + \left(p_{\theta,t}^{\mathrm{EV,\ in}} \cdot \eta^{\mathrm{EV,in}} - \frac{p_{\theta,t}^{\mathrm{EV,\ out}}}{\eta^{\mathrm{EV,out}}}\right) \cdot \Delta t \cdot \sigma_{\theta,t}^{\mathrm{EV,\ Pi}} - \sum_{\gamma=1}^{\Gamma} p_{\gamma,t}^{\mathrm{EV,C}} \cdot \sigma_{\theta,\gamma}^{\mathrm{EV,\ c}} \cdot \Delta t \cdot \left(1 - \sigma_{\theta,t}^{\mathrm{EV,\ Pi}}\right) \theta \in \mathcal{J}, t \in \mathcal{T} \tag{40}$$

where the binary variable $\sigma_{\theta,\gamma}^{\mathrm{EV,\ c}}$ assigns each travel cycle ($\gamma$) to an EV ($\theta$). Also, the following constraints are defined, respectively, to ensure that each travel cycle is realized once and to ensure that an EV ($\theta$) does not operate more than one travel cycle simultaneously.

$$\sum_{\theta=1}^{J} \sigma_{\theta,\gamma}^{\mathrm{EV,\ c}} = 1 \quad \gamma \in \mathbf{\Gamma} \tag{41}$$

$$\sum_{\gamma=1}^{\Gamma} \mathrm{sgn}\left(p_{\gamma,t}^{\mathrm{EV,C}}\right) \cdot \sigma_{\theta,\gamma}^{\mathrm{EV,\ c}} \le 1 \quad \theta \in \mathcal{J}, t \in \mathcal{T} \tag{42}$$

Similar to the case of private EVs, it is necessary to implement constraint 43 to coerce the disconnection of the EV ($\theta$) when the driving need assigned by the binary variable $\sigma_{\theta,\gamma}^{\mathrm{EV,\ c}}$ is greater than 0.

$$\sum_{\gamma=1}^{\Gamma} p_{\gamma,t}^{\mathrm{EV,C}} = \sum_{\theta=1}^{J} \sum_{\gamma=1}^{\Gamma} p_{\gamma,t}^{\mathrm{EV,C}} \cdot \sigma_{\theta,\gamma}^{\mathrm{EV,\ c}} \cdot \left(1 - \sigma_{\theta,t}^{\mathrm{EV,\ Pi}}\right) \quad t \in \mathcal{T} \tag{43}$$

The equations concerning the nominal installed power and the charging-discharging power of the CSs for the shared EVs system are analogous to 29, 30, 31, described in the previous section. The three costs components (44–46) and the EVs total costs (47) for the e-car-sharing company $J^*$ are resumed below.

$$C_{J^*}^{\mathrm{EV,\ I}} = m^{\mathrm{EV}} \cdot \frac{C^{\mathrm{EV,\ I}}}{A_{n^{EV},r}^{EV}} \tag{44}$$

$$C_{J^*}^{\mathrm{EV,\ LCOS}} = \Delta t \cdot \sum_{\theta=1}^{J} \sum_{t=1}^{T} p_{\theta,t}^{\mathrm{EV,\ in}} \cdot c^{\mathrm{EV,LCOS}} \tag{45}$$

$$C_{J^*}^{\mathrm{EV,\ CS}} = \frac{\sum_{\theta=1}^{J} \left( \sum_{\varphi=\varphi_0}^{\varphi_\Phi} C_\varphi \cdot \sigma_{\theta,\varphi}^{\mathrm{EV,\ p}} + C^{\mathrm{EV,V2G}} \cdot \sigma_\theta^{\mathrm{EV,\ V2G}} \right)}{A_{n^{CS},r}^{CS}} \tag{46}$$

$$C_{J^*}^{\mathrm{EV}} = C_{J^*}^{\mathrm{EV,\ I}} + C_{J^*}^{\mathrm{EV,\ LCOS}} + C_{J^*}^{\mathrm{EV,\ CS}} \tag{47}$$

In accordance with the constraints, the mixed-integer linear optimization framework determines the operation and the optimal investment of the CSs, and the number of required EVs.

### 3.2. Scenarios and objective functions

This section presents the scenarios investigated to evaluate the economic potential of residential on-site e-car-sharing. Each scenario is distinguished by different objective functions and, therefore, by different investment decisions. Fig. 2 shows the set-up of the five investigated scenarios, and further details are given in the following subsections. It is important to note that the scenarios are characterized by different local optimums, with the only exception of the *Fully Integrated E-Car-Sharing Company*, which represents the global optimum and thus allows the lowest total costs.

#### 3.2.1. Baseline

In the *baseline* scenario, as shown in Fig. 2, the residential building tenants are characterized by a residential load and a driving need. They don't have the opportunity to invest in PVs or BSs, but only in optimal CSs. Furthermore, the tenants optimize their electricity consumption and their investment individually. Thus, the objective function in the *baseline* scenario and the total cost of the tenants are defined as below.

$$\min_{\mathcal{T}} \quad C_j^{\mathrm{DA}} + C_j^{\mathrm{Gr}} + C_j^{\mathrm{EV}} \quad j \in \mathcal{J} \tag{48}$$

$$C_j^{\mathrm{Tot}} = C_j^{\mathrm{DA}} + C_j^{\mathrm{Gr}} + C_j^{\mathrm{EV}} \quad j \in \mathcal{J} \tag{49}$$

#### 3.2.2. Individual

In the *individual* scenario, the residential building tenants have the opportunity to invest in PVs and BSs to reduce their yearly costs. In this scenario, again the tenants optimize their electricity consumption and investment individually, as illustrated in Fig. 2. The total costs are described in 4 and the objective function is as follows.

$$\min_{\mathcal{T}} \quad C_j^{\mathrm{DA}} + C_j^{\mathrm{Gr}} + C_j^{\mathrm{PV}} + C_j^{\mathrm{BS}} + C_j^{\mathrm{EV}} \quad j \in \mathcal{J} \tag{50}$$

#### 3.2.3. External E-car-sharing company

This scenario is characterized by an external e-car-sharing company $J*$, which covers the driving need of the tenants $\mathcal{J}$, as depicted in Fig. 2. The tenants have the opportunity to invest in PVs and BSs without taking into account their driving needs. At the same time, the external e-car-sharing company optimizes the EVs' and CSs' operation and investment, and the tenants share the EVs made available by the e-car-sharing company. The non-simultaneous tenants' need for EVs allows, possibly, the e-car-sharing company to cover their driving needs with fewer cars. Hence, the tenants and the e-car-sharing company optimize their electricity consumption and investment individually, as described in the following objective functions.

$$\min_{\mathcal{T}} \quad C_j^{\mathrm{DA}} + C_j^{\mathrm{Gr}} + C_j^{\mathrm{PV}} + C_j^{\mathrm{BS}} \quad j \in \mathcal{J} \tag{51}$$

$$\min_{\mathcal{T}} \quad C_{J^*}^{\mathrm{DA}} + C_{J^*}^{\mathrm{Gr}} + C_{J^*}^{\mathrm{EV}} \tag{52}$$

Furthermore, in this study, the costs incurred by the e-car-sharing company $C_{J^*}^{\mathrm{Tot}}$ are distributed among the tenants on the basis of their driving needs $(p_{j,\mathcal{T}}^{\mathrm{EV,C}})$, as described in 53. Hence, the total costs of the tenants $C_j^{\mathrm{Tot}}$ are defined as depicted below.

$$C_j^{\mathrm{Fee}} = \frac{\sum_{t=1}^{T} p_{j,t}^{\mathrm{EV,C}}}{\sum_{j=1}^{J} \sum_{t=1}^{T} p_{j,t}^{\mathrm{EV,C}}} \cdot C_{J^*}^{\mathrm{Tot}} \quad j \in \mathcal{J} \tag{53}$$

$$C_j^{\mathrm{Tot}} = C_j^{\mathrm{DA}} + C_j^{\mathrm{Gr}} + C_j^{\mathrm{PV}} + C_j^{\mathrm{BS}} + C_j^{\mathrm{Fee}} \quad j \in \mathcal{J} \tag{54}$$

#### 3.2.4. Partially integrated E-car-sharing company

In this scenario, the e-car-sharing company $J*$ can also invest in PVs and BSs to reduce its costs $(C_{J^*}^{\mathrm{Tot}})$, as shown in Fig. 2. Since the rooftop area of a residential building is generally limited, the e-car-sharing company $J*$ has the opportunity to use the part of the rooftop area, which is not used by the tenants $J$, as depicted below.

$$p_{J^*,max}^{\mathrm{PV,\,I}} = p_{max}^{\mathrm{PV,\,I}} - \sum_{j=1}^{J} p_j^{\mathrm{PV,\,I}} \quad j \in \mathcal{J} \tag{55}$$

Hence, the objective function of the e-car-sharing company $J*$ is defined as follows, while the objective function and the total costs of the tenants are calculated as in 51 and 54, respectively.

$$\min_{\mathcal{T}} \quad C_{J^*}^{\mathrm{DA}} + C_{J^*}^{\mathrm{Gr}} + C_{J^*}^{\mathrm{PV}} + C_{J^*}^{\mathrm{BS}} + C_{J^*}^{\mathrm{EV}} \tag{56}$$

#### 3.2.5. Fully integrated E-car-sharing company

The scenario with the full integrated e-car-sharing company is the most ideal one. In this case, the tenants build up an energy community with an e-car-sharing company to make joint investments in BSs, PVs, EVs and CSs, as illustrated in Fig. 2. Consequently, the total costs $(C^{\mathrm{Tot}})$ are given by the objective function in 57. Furthermore, the costs are distributed among the tenants on the basis of their residential loads $(p_{j,\mathcal{T}}^{\mathrm{RL}})$ and driving needs $(p_{j,\mathcal{T}}^{\mathrm{EV,C}})$, as depicted in 58.

$$\min_{\mathcal{T}} \quad \sum_{j=1}^{J^*} \left( C_j^{\mathrm{DA}} + C_j^{\mathrm{Gr}} + C_j^{\mathrm{PV}} + C_j^{\mathrm{BS}} + C_j^{\mathrm{EV}} \right) \tag{57}$$

$$C_j^{\mathrm{Tot}} = \frac{\sum_{t=1}^{T} \left( p_{j,t}^{\mathrm{RL}} + p_{j,t}^{\mathrm{EV,C}} \right)}{\sum_{j=1}^{J} \sum_{t=1}^{T} \left( p_{j,t}^{\mathrm{RL}} + p_{j,t}^{\mathrm{EV,C}} \right)} \cdot C^{\mathrm{Tot}} \quad j \in \mathcal{J} \tag{58}$$

## 4. Description of the case study

In this work, we consider an Austrian residential building with eight tenants. The simulated period covers one year: from January 01, 2019 to December 31, 2019. The residential load $(p_{\mathcal{J},\mathcal{T}}^{\mathrm{RL}})$ of the tenants is modeled with the *LoadprofileGenerator* software [35] and the driving need $(p_{\mathcal{J},\Gamma,\mathcal{T}}^{\mathrm{EV,C}})$ with the *Python* toolbox *emobpy* [36]. The *emobpy* toolbox considers empirical mobility statistics of different types of drivers to deliver EVs' consumption profiles. The tenants' annual consumption and driven kilometers are resumed in Fig. 3.

The grid tariffs considered ($P^{\mathrm{Gr,\,P}}$, $P^{\mathrm{Gr,\,E}}$ and $C^{\mathrm{Gr,\,FR}}$) are given by the Austrian electricity regulator [37]. The DA prices (of the European Power Exchange) and the PV time-series of specific generation $(p_{\mathcal{T}}^{\mathrm{PV,\,p}})$ considered are those of the ENTSO-E Transparency Platform [38]. The rooftop of the investigated residential building is limited to 30 kW$_p$ of installed PV and is equally distributed among the tenants $\mathcal{J}$. The tenants also have the opportunity to invest in a lithium-ion BS to reduce their total costs. Besides, the EV

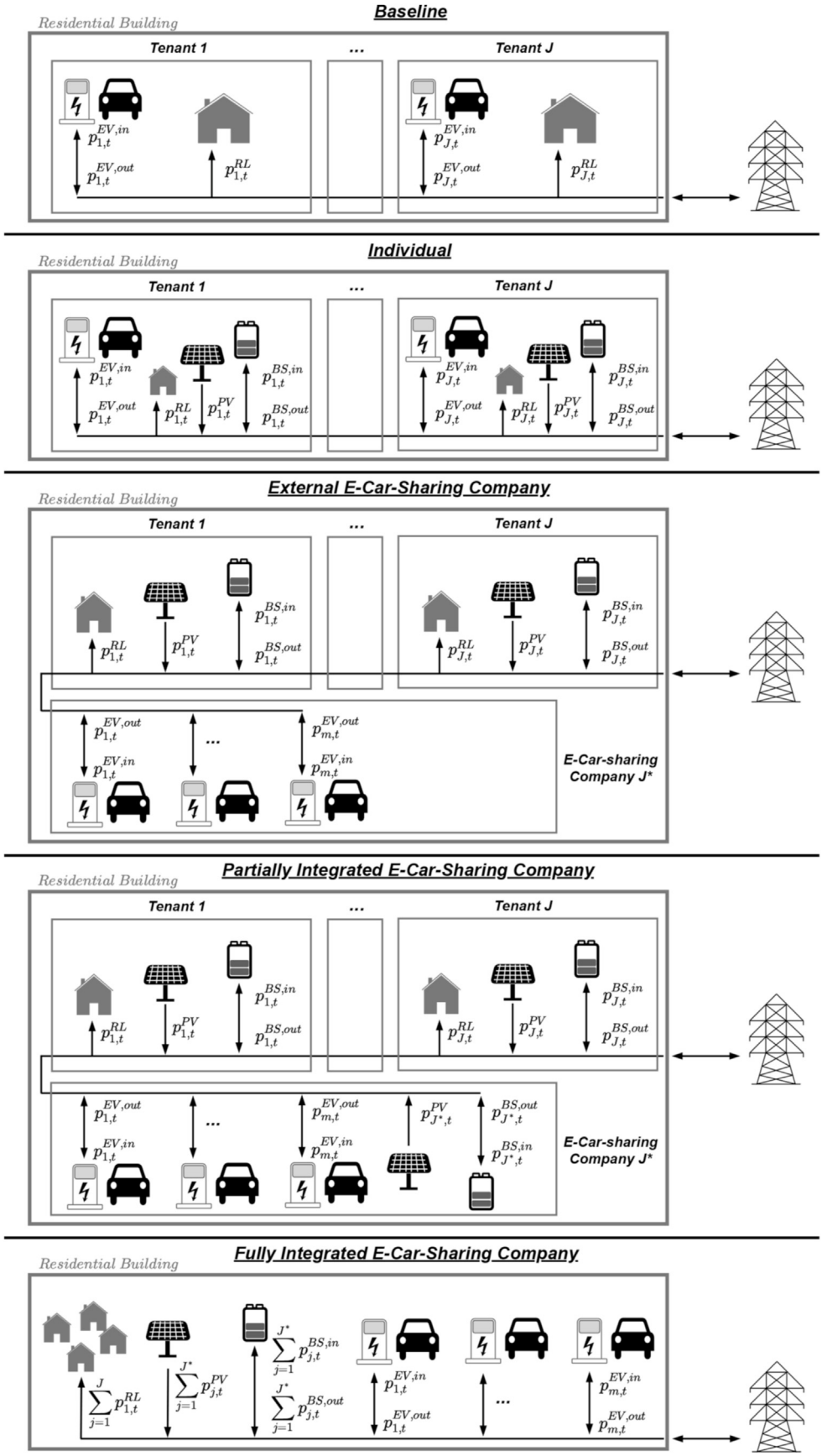


**Fig. 2.** Set-ups of the investigated scenarios.

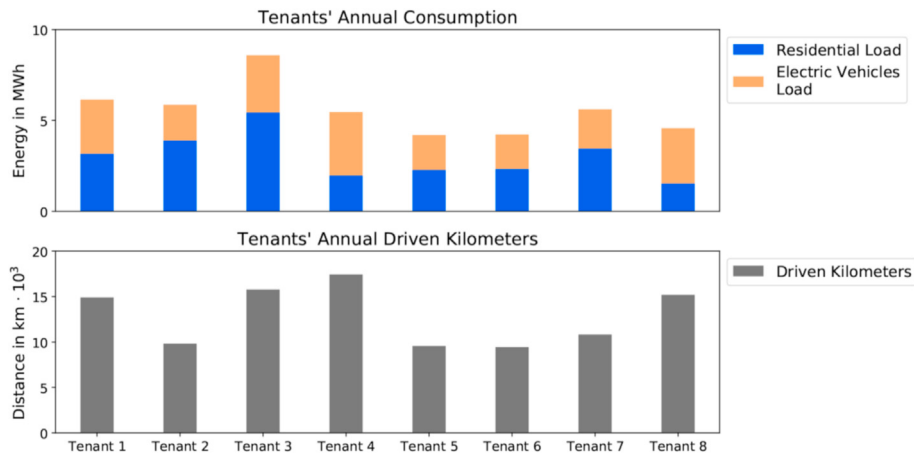


**Fig. 3.** Tenants' annual consumption and driven kilometers.

considered is the model *"Nissan Leaf"* with a capacity of 40 kWh and a consumption rate of 0.2 $\frac{\text{kWh}}{\text{km}}$. The tenants and the e-car-sharing company can invest in one of 8 different CSs with different nominal power: 3.7 kW, 7.4 kW, 11 kW, 22 kW, bidirectional, or not. The complete list of the input parameters used in this analysis and their origin is provided in appendix A. Moreover, the time-series data of residential load, EVs consumption and driven kilometers, and specific PV generation considered in the simulations can be found in the *Mendeley Data Repository* [39].

In the investigated case study, it has been assumed that the tenants invest in EVs and not in other conventional vehicles to cover their driving needs. Furthermore, perfect forecast for the residential load, the driving need and PV generation are assumed.

## 5. Results

This section presents the results of the simulations performed in order to evaluate the economic potential of residential on-site e-car-sharing. The operational strategy of the technologies, which are implemented in the mixed-integer linear optimization framework using the *Python* toolbox *Pyomo*, is defined by the *Gurobi* solver. The annual total costs for the residential building tenants $\mathcal{J}$ in the five different scenarios are resumed in Fig. 4.

In the *baseline* scenario, the tenants optimize their electricity consumption and investment in CSs to cover their residential and driving needs. Hence, in this simulation, no investment in PVs, BSs, or e-car-sharing system is considered. The availability of the EV batteries allows the tenants to flexibilize their consumption patterns to optimize their electricity withdrawals and minimize their total costs. In this case, 47.2 MWh were bought at the DA for an average price of 40 $\frac{€}{\text{MWh}}$. The grid costs ($\sum_{j=1}^{J} C_j^{\text{Gr}}$) represent 18% of the total costs, of which 37% are energy-related, 44% power-related and 19% are the fixed rate. The EVs' costs ($\sum_{j=1}^{J} C_j^{\text{EV}}$) make up 73% of the total costs, as shown in Fig. 4. The optimal investment for the tenants is for each a 3.7 kW CS without implementing a bidirectional inverter.

In the *individual* scenario the tenants have the opportunity to invest in PVs and BSs. Fig. 5 presents the overall installed BS capacity ($\sum_{j=1}^{J^*} p_j^{\text{BS, I}} \cdot d^{\text{BS}}$), the total installed PV power ($\sum_{j=1}^{J^*} p_j^{\text{PV,I}}$) and the autarky and self-consumption rates. The self-consumption rate describes the relationship between the energy used, which is produced from the photovoltaic plant, and the total energy produced by the photovoltaic plant itself. The autarky rate is the relationship between the energy used generated by the photovoltaic plant and the total amount of electricity required by the tenants. It is observable that in the *individual* scenario, the residential building's tenants utilize almost the entire rooftop area installing 28.6 $\text{kW}_p$ PV power. Also, the further investment in 18.7 kWh BS

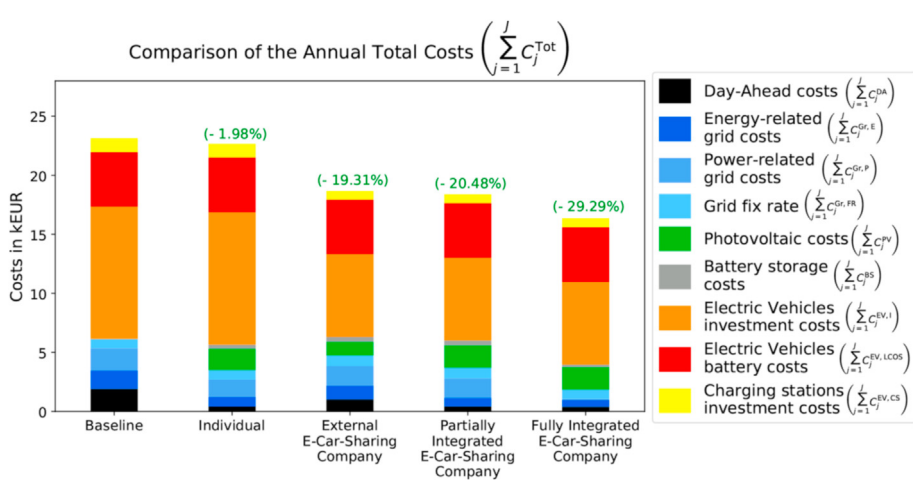


**Fig. 4.** Comparison of the annual total costs.

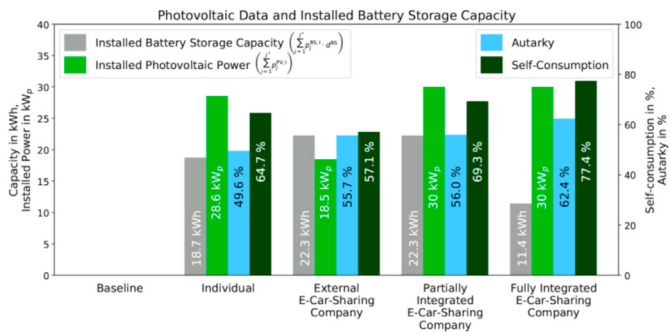


**Fig. 5.** Photovoltaic data and installed battery storage capacity.

capacity leads the tenants to a total costs reduction of 1.98%, as shown in Fig. 4. In this case, the DA costs represent only 2% of the total costs. In total, 37.8 MWh were negotiated at the DA, of which 25 MWh bought and 12.8 MWh sold. The operation of the BSs allows the tenants to purchase energy when the DA prices are low and to sell it again when prices are high. The self-production of energy through PV leads to a significant reduction of energy-related grid costs. In fact, the grid costs ($\sum_{j=1}^{J} C_j^{\mathrm{Gr}}$) are 27% lower in comparison to the *baseline* scenario. On the other hand, the PV and BS costs represent 10% of the total costs. The opportunity to invest in PV and BS does not affect the investment in CSs. In fact, as in the *baseline* scenario, each tenant invest in a not bidirectional 3.7 kW CS. However, it should be noted that the availability of the EV batteries allows the tenants to achieve a noteworthy self-consumption rate (65%), as shown in Fig. 5.

In the *external e-car-sharing company* scenario, an external e-car-sharing company covers the driving needs of the tenants, which invest in PVs and BSs, taking into account only their residential load. In this scenario, the e-car-sharing company does not have the opportunity to invest in PVs and BSs. As shown in Fig. 4, the total costs drop by over 19%. The non-simultaneous use of EVs allows the e-car-sharing company to cover the tenants' driving needs with five cars ($m^{\mathrm{EV}} = 5$). This leads to a significant reduction of the EVs' costs ($\sum_{j=1}^{J} C_j^{\mathrm{EV}}$) of 26%. Also in this case, the CSs are not bidirectional, but have different nominal charging powers. In fact, the e-car-sharing company invest in 1 CS with 3.7 kW nominal power, 3 with 7.4 kW and 1 with 11 kW. The reduced number of EVs causes a lower amount of flexibility, leading to higher DA and grid costs. As a result, the DA and the grid costs are, respectively, 148% and 20% higher in comparison to the *individual* scenario. It is important to note that, since the residential building tenants no longer have to cover their driving needs, they optimally invest in less PV power (only 18.5 kW$_p$), as illustrated in Fig. 5. Nevertheless, the non-availability of the EV batteries makes it more convenient for the tenants to invest in batteries, which are installed for more than 22 kWh. These facts lead the tenants to have an autarky rate of 56% and a self-consumption rate of 57%.

The *partially integrated e-car-sharing company* scenario is characterized by an e-car-sharing company, which covers the driving needs of the tenants and has the opportunity to invest in PVs and BSs. As observable in Fig. 4, the total costs drop by over 20% in comparison to the *baseline* scenario. Also in this case, the non-simultaneous usage of EVs allows the e-car-sharing company to cover the tenants' driving needs with five cars ($m^{\mathrm{EV}} = 5$), investing in the same type of CSs used in the *external e-car-sharing company* scenario. The e-car-sharing company invests in the remaining 11.5 kW$_p$ of PV available on the rooftop without investing in BS. This investment involves the maximum exploitation of the available PV power on the rooftop (30 kW$_p$), reducing the DA and grid costs by 78% and 23%, respectively, in comparison to the *baseline* scenario. Since the e-car-sharing company can invest in PV, its consumption patterns are considered in the calculation of the autarky and self-consumption rates. Fig. 5 shows how the opportunity for the e-car-sharing company to invest in PV leads to an overall self-consumption rate of 69%.

In the *fully integrated e-car-sharing company* scenario, the tenants and the e-car-sharing company build up an energy community to make joint investments in BSs, PVs, EVs and CSs. This scenario represents the most ideal one and leads to a total costs reduction of 29%, as illustrated in Fig. 4. In this case, the optimization aims to minimize the total costs, as described in the objective function 57, and not to minimize the costs of each player in $\mathcal{J}^*$ individually. The tenants' driving needs are covered with five cars ($m^{\mathrm{EV}} = 5$) and 5 non-bidirectional CSs: 1 with 3.7 kW nominal power, 3 with 7.4 kW and 1 with 11 kW. The optimization considers all residential loads ($\sum_{j=1}^{J} p_{j,\mathcal{T}}^{\mathrm{RL}}$) and driving needs ($\sum_{j=1}^{J} p_{\mathcal{J},\Gamma,\mathcal{T}}^{\mathrm{EV,C}}$) simultaneously, which lead to optimal dispatching of the PV-generated electricity, optimal BS capacity usage, and optimal operation of the CSs. In fact, the DA costs ($\sum_{j=1}^{J} C_j^{\mathrm{DA}}$) fall by 80%, and the grid costs ($\sum_{j=1}^{J} C_j^{\mathrm{Gr}}$) fall by 66% compared to the *baseline* scenario. Moreover, the decrease of the installed BS (11.4 kWh) and the increase of the autarky and self-consumption rates are remarkable, which in this scenario are 62% and 77%, respectively.

Since the optimization framework optimizes the residential building as a single agent and the costs are distributed among the tenants based on their residential loads ($p_{j,\mathcal{T}}^{\mathrm{RL}}$) and driving needs ($p_{j,\mathcal{T}}^{\mathrm{EV,C}}$), the cost savings are not shared equally. Fig. 6 compares the tenants annual total costs ($C_j^{\mathrm{Tot}}$) in the five investigated scenarios.

It is observable that in the scenarios where the e-car-sharing company costs are distributed on the basis of the tenants' driving needs ($p_{j,\mathcal{T}}^{\mathrm{EV,C}}$), the tenants with the higher driving need (tenants 3, 4 and 8) have slighter cost reductions compared to the tenants with a low driving need. In particular, in the *fully integrated e-car-sharing company* scenario, where both the residential load ($p_{j,\mathcal{T}}^{\mathrm{RL}}$) and driving need ($p_{j,\mathcal{T}}^{\mathrm{EV,C}}$) are considered to share the cost savings (58), there are tenants for whom this set-up may not be economically advantageous. In fact, in this case study, tenants 2 and 3 minimize their costs in the *partially integrated e-car-sharing company* scenario, as illustrated in Fig. 6. This happens because of their high residential load ($p_{j,\mathcal{T}}^{\mathrm{RL}}$). A more sophisticated approach to share the total costs is required to make this scenario the most economically convenient for all the tenants, such as the Shapley value, the Nash bargaining solution, and different reinforcement learning-based mechanisms.

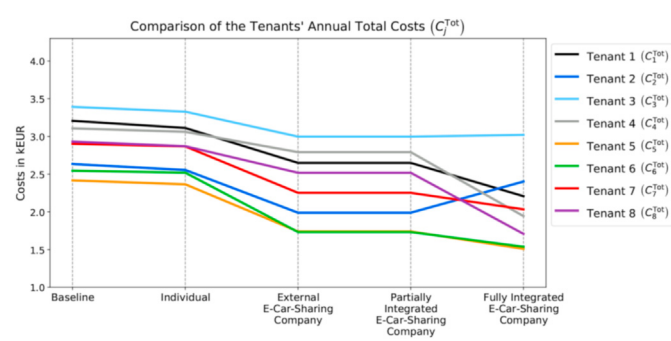


**Fig. 6.** Comparison of the tenants' annual total costs.

## 6. Conclusion and outlook

This paper presents a comprehensive overview of modeling and evaluating the economic potential of a residential on-site e-car-sharing concept. A mixed-integer linear optimization framework is developed to define the optimal investment and operation of multiple technologies such as BSs, PVs, EVs, and CSs. The flexibilities of the residential tenants are allocated in the DA, which is characterized by fluctuating prices, under consideration of the grid costs. The technologies of the tenants are described using linear relationships only in order to make the optimization framework scalable.

The method shows a novel approach to determine the optimal number of EVs and the optimal type of CSs for tenants of a residential building willing to switch from private cars to an e-car-sharing system. In the near future, new residential buildings can be expected to have an integrated e-car-sharing system in order to optimize parking space and the use of PV energy on-site. Therefore, this optimization-based approach can become a useful tool to determine the technical edges of residential on-site e-car-sharing systems.

The simulations have shown that integrating an e-car-sharing system in a residential building allows for fewer cars and CSs with higher nominal power. A reduced number of EVs results in lower total annual costs and space gain in the residential building. From an economic point of view, it has been shown that the tenants' annual total costs can in fact be reduced by 29% in the ideal case in which the tenants build up an energy community with the e-car-sharing company. Furthermore, in all the scenarios investigated, the integration of bidirectional CSs is never cost-effective because of the high investment costs.

It is worth noting that, in the case of an external e-car-sharing company, the optimal installed PV capacity is reduced, and the optimal installed BS capacity grows, compared to the case in which the tenants optimize themselves individually. As a matter of fact, managing the charging of EVs reduces the optimal size of BSs and increases the self-consumption rate of PVs.

Nowadays, e-car-sharing seems one of the most sustainable means of transportation, in particular in urban areas. Hence, developing attractive business models and varied e-car-sharing offers can possibly play a key role in the energy transition. In fact, this model applies to all residential buildings, old, new, and still under construction. The reduction in the number of EVs from 8 to 5 and the increase in optimal installed PV power demonstrates how the impact of residential on-site e-car-sharing can be significant for the energy transition on a large scale.

It has to be noted that this study did not consider the investment and operational costs of a necessary communication infrastructure between the tenants and the e-car-sharing system. Finally, the optimizations are performed without taking into account any supplementary fee for the direct negotiations of energy in the DA and without considering any additional fee for the e-car-sharing company, which in these scenarios reaches the break-even. Directions for future research could include the analysis of other markets, such as the reserve markets, or the application of different grid tariff designs to investigate to what extent bidirectional CSs can become cost-effective.

## Credit author statement

**Carlo Corinaldesi:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – Original, Draft, Writing - Review & Editing, Visualization. **Georg Lettner**: Conceptualization, Writing - Review & Editing, Funding acquisition. **Hans Auer:** Conceptualization, Draft, Writing - Review & Editing, Visualization, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## A. List of the Input Parameters

List of the Input Parameters.

| Description | Parameter | Value | Origin |
|---|---|---|---|
| Number of tenants | $J$ | 8 | – |
| DA prices | $p^{\mathrm{DA}}_{\mathcal{T}}$ | Time-Series | [38] |
| Power-related grid price | $p^{\mathrm{Gr,P}}$ | $46.7\ \frac{€}{\mathrm{kW}}$ | [37] |
| Energy-related grid price | $p^{\mathrm{Gr,E}}$ | $33.3\ \frac{€}{\mathrm{kWh}}$ | [37] |
| Grid fix rate | $C^{\mathrm{Gr,\ FR}}_{j}$ | $99.3\ \frac{€}{\mathrm{y}}$ | [37] |
| Residential load | $p^{\mathrm{RL}}_{\mathcal{J},\mathcal{T}}$ | Time-Series | [35] |
| Interest rate (WACC) | $r$ | 3% | – |
| PV investment costs | $c^{\mathrm{PV}}$ | $1.25\ \frac{€}{\mathrm{kW}_p}$ | [40] |
| Maximal installed PV | $p^{\mathrm{PV,\ I}}_{max}$ | $30\ \mathrm{kW}_p$ | – |
| PV lifespan | $n^{\mathrm{PV}}$ | 25 y | [40] |
| PV generation profile | $p^{\mathrm{PV,\ p}}_{\mathcal{T}}$ | Time-Series | [38] |
| PV LCOE | $c^{\mathrm{PV,LCOE}}$ | $5.3\ \frac{€\mathrm{cent}}{\mathrm{kWh}}$ | – |
| BS & EV input eff. | $\eta^{\mathrm{BS,\ in}}, \eta^{\mathrm{EV,\ in}}$ | 0.94 | [34] |
| BS & EV output eff. | $\eta^{\mathrm{BS,\ out}}, \eta^{\mathrm{EV,\ out}}$ | 0.92 | [34] |
| BS & EV standby-losses | $p^{\mathrm{BS,L_{\%}}}$ | $0.255\ \frac{\%}{\mathrm{h}}$ | [41] |
| BS investment costs | $c^{\mathrm{BS}}$ | $230\ \frac{€}{\mathrm{kWh}}$ | [34] |
| BS duration (E/P) | $d^{\mathrm{BS}}$ | $4\ \frac{\mathrm{kWh}}{\mathrm{kW}}$ | [34] |
| BS lifespan | $n^{\mathrm{BS}}$ | 15 y | [42] |
| BS cycles limit | $N^{\mathrm{BS}}$ | $1\ \frac{\mathrm{cycle}}{\mathrm{d}}$ | [42] |
| CSs costs | $C_{\varphi}, C^{\mathrm{EV,V2G}}$ | Series | [43] |
| CS lifespan | $n^{\mathrm{CS}}$ | 10 y | [44] |
| EV capacity | $E^{\mathrm{EV}}$ | 40 kWh | [45] |
| EV lifespan | $n^{\mathrm{EV}}$ | 15 y | [45] |
| EV investment costs | $C^{\mathrm{EV,I}}$ | 18 k€ | [45] |
| EV batteries LCOS | $c^{\mathrm{EV,LCOS}}$ | $0.2\ \frac{€}{\mathrm{kWh}}$ | [34] |
| EV consumption profiles | $p^{\mathrm{EV,C}}_{\mathcal{J},\Gamma,\mathcal{T}}$ | Time-Series | [36] |

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