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Investigating smart charging options for EVs in multi-family residential buildings

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Abstract

Electrification is currently perceived as one of the main solutions for decarbonizing the private transport sector. However, the rise in electricity consumption owing to EV charging can potentially stress the existing domestic electric infrastructure with peak demand, preventing the full exploitation of sustainable mobility in the residential sector. Alternatively, smart charging strategies can be adopted to mitigate this effect, promoting home charging also in multi-family residential buildings, where simultaneous charging events may occur. In this context, this paper intends to point out the benefits of implementing different smart charging strategies for EVs in a residential building, compared to unmanaged charging (or user-managed charging). The approach assumes the mobility habits of household members as an input to estimate EVs charging demand of the whole building. Then the optimal strategies, formulated as Mixed Integer Linear Programming problem integrated within a heuristic algorithm, are simulated with an increased level of flexibility to highlight how the EV charging sessions can be managed to reduce peak demand. The methodology is applied by investigating multiple scenarios with different users' mobility habits that may influence electricity demand. Results show that, according to the corresponding scenario, peak demand is halved or even reduced by a quarter thanks to the adoption of smart charging.

Keywords: MILP; private mobility; peak demand reduction; mobility habits; home charging.

1. Introduction

The European Union (EU) has set ambitious sustainability and decarbonization goals for its Member States in the future European Commission (2021). To achieve these targets, a significant shift is necessary in the way the energy is produced and consumed. This is particularly crucial in the residential sector, as it accounts for a significant portion of final energy consumption in the EU compared to other sectors Eurostat (2021).

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Nowadays, one of the most promising ways for carbon emission reduction is represented by the electrification of energy consumption Besagni et al. (2021); Wang et al. (2022). Although most of the research on residential buildings is focused on the electrification of space heating and cooling demand, the decarbonization of the mobility sector by promoting the Electric Vehicle (EV) diffusion is equally important Madurai Elavarasan et al. (2022) to foster sustainable cities and transport United Nation (2024).

However, the electrification of the transportation sector has also a relevant impact on building's power demand when EV adoption increases Gilleran et al. (2021). Since home charging availability seems to be the most influential factor in users' choice of EVs Brückmann and Bernauer (2023); Ramsebner et al. (2023); Patt et al. (2019), an increase on peak demand is usually expected with significant consequences also on the local distribution grid Macaluso et al. (2023). A good integration of e-mobility into the domestic energy system is possible with the coordination of charging power according to the electricity load of the home or the grid situation. Typically, long residential parking periods have a lot of potential in this context Ramsebner et al. (2023).

An optimal scheduling of EV charging could represent a valuable solution to limit peak effect and promote EV diffusion in residential sector. This approach, where EV charging process is controlled, is usually named as *smart charging* (SC), since it is in contrast with the so-called *uncontrolled* or *unmanaged* charging where EV is charged once it is simply plugged into the grid power supply Subashini and Vijayan (2023). Additionally, the SC process can be further subdivided into unidirectional (V1G), and bidirectional controlled charging for vehicle-to-grid, home, and building (V2G, V2H, V2B) applications. In any case, the EV-user mobility and charging behaviors strongly affect the impact of any SC algorithms Sadati et al. (2021). Knowing the mobility behavior of users which influences energy demand, particularly vehicle type, distance traveled, and parking habits, is much more relevant Hiesl et al. (2021) than mobility with traditional vehicles (internal combustion engine).

Current literature has already addressed the smart charging impact from the grid perspective also considering the integration of RES based generation Fachrizal et al. (2020). Differently, this study intends to evaluate smart charging in a smaller context of a residential building with home charging. Specifically, how charging and mobility behaviour of EV users may affect the capability of different SC options in reducing/limiting the peak demand of multi-family residential buildings with EVs is studied in this paper. Here three different charging options are considered with an increasing rate of flexibility. Consequently, the results point out which algorithms perform better according to different scenarios of EV user charging behavior.

2. Modeling Smart Charging

The Mixed Integer Linear Programming (MILP) formulation has already proven to be an useful approach within the optimal management of complex multi-energy systems Mancò et al. (2024); Lazzeroni et al.. For this reason, the modeling of SC processes adopted in this study follows this methodology. Specifically, both equations and constraints representing the charging system and its operation are linear or alternatively should be linearized. Binary (i.e., integer) variables are also introduced to describe the on/off status of the charging points within the infrastructure and to consider their operational limits. Finally, the time horizon of the simulation is assumed here on a daily basis subdivided into $N_i = 24$ hourly time steps and the SC is supposed to be unidirectional (i.e. as V1G).

2.1. EV battery

The modeling of EV battery adopted here is based on the one already introduced in Lazzeroni et al. (2019). Under this assumption, the electric power input to the BESS has a positive sign (during EV charge) while the output one (during EV travelling) has a negative sign. Consequently, the energy content E_j for the battery of each j-th EV is defined, in a given i-th time interval, as follows:

$$E_j(t_{i+1}) = \eta_{sd} E_i(t_i) + \left[\eta_c P_{c,j}(t_i) + \alpha_j(t_i) P_{d,j}(t_i)\right]\Delta t \quad (1)$$

where η_{sd} is the self-discharge efficiency, η_c is the charging efficiency, and P_c and P_d are the battery power respectively during charge (i.e., when the EV is connected to the charging infrastructure) and discharge (i.e., during EV traveling), respectively. The parameter α is introduced for describing the connections of the EV to the charging infrastructure. Essentially, $\alpha = 1$ if the j-th EV is not connected, otherwise α is zeroed. Clearly, electric power during charge is typically limited by the rated power of the charging point, while each EV can not be charged when not connected to the charging infrastructure. Thus, two additional constraints need to be introduced, to take into account these conditions, as follows:

$$0 \leq P_{c,j} \leq \delta_{c,j}(t_i) P_{c,max} \tag{2}$$

$$0 \leq \delta_{c,j}(t_i) \leq \alpha_j(t_i) \tag{3}$$

where $P_{c,max}$ is the rated power of the charging point, while $\delta_{c,j}$ is introduced in equation 2 as a binary variable to enable/disable the charging stage for each EV.

2.2. EV charging

The EV charging stage is how EV batteries are filled to reach the desired State of Charge (SOC) according to the users' requests. In this view, each EV coming back home at T_{in} have a battery level equal SOC_{in} and should be charged at SOC_{out} before leaving the building at T_{out}. From the MILP point of view, assuming $E_{b,j}$ as the size of the EV battery, this is equivalent to set:

$$SOC_j(t_i = T_{in,j}) = \frac{E_j(t_i = T_{in,j})}{E_{b,j}} = SOC_{in,j} \tag{4}$$

$$SOC_j(t_i = T_{out,j}) = \frac{E_j(t_i = T_{out,j})}{E_{b,j}} = SOC_{out,j} \tag{5}$$

where E_b is the size of EV battery. However, different EV charging modes have been considered here for the users living in multi-family residential buildings. First of all, a simplest but unoptimal one is related to an unmanaged process that charges EVs as soon as they are connected to the charging points. Alternatively, two SC options are available with increasing flexibility. A brief description of these processes is provided below.

2.2.1. Unmanaged Charging

As mentioned, in this unoptimal process EVs start charging as soon as they are connected to the charging infrastructure, and the charging power P_c remains fixed throughout the process. Once the charging process has started, it cannot be stopped until the EV battery is charged at the required level. However, only in the last time step of the charging process the power can be adjusted to fill the remaining capacity of the battery and prevent infeasibility in the optimization problem. This can be obtained by setting the charging time of an EV, as follows:

$$T_{ch,j} = \left\lfloor \frac{SOC_{out,j} - SOC_{in,j}}{100 \cdot \eta_c \cdot P_{c,max}} \, E_{b,j} \right\rfloor \tag{6}$$

and adding the following constraint:

$$\sum_{k=T_{in,j}}^{T_{in,j}+T_{ch,j}-1} P_{c,j}(t_k) = P_{c,max} \qquad \forall j = 1, \cdots, N_{EV} \tag{7}$$

2.2.2. Smart Charging 1

Each EV is charged within the time interval in which is connected to the charging infrastructure and the charging power P_c is still fixed (i.e., it can not be modulated). Once the charging process has started, it can not be stopped until the EV battery is charged at the required level. Only the last time step of the charging process can be modulated to fill the residual capacity of the EV battery and to avoid infeasibility in the optimization problem. This can be obtained by introducing Minimum On Time (MOT) and Minimum Shootdown Time (MST) constraints . Specifically, the MOT and MST are fixed, as follows:

$$MOT_j = T_{ch,j} - 1 \tag{8}$$

$$MST_j = N_i - MOT_j - 1 \tag{9}$$

where, $SOC_{out,j}$ and $SOC_{in,j}$ are the state of charge of the battery when EV is leaving and coming back to the building, respectively. Essentially, equations 8 and 9 set the number of time steps needed to charge the EV battery. Later, the following constraints have been added to ensure that each EV is charged consecutively at the rated power of the charging point, as follows:

$$\sum_{k=i}^{i+MOT_j-1} P_{c,j}(t_k) \geq MOT_j \cdot P_{c,max} \cdot \left[\delta_{c,j}(t_i) - \delta_{c,j}(t_{i-1})\right] \qquad \forall i = 1, \cdots, N_i \quad \text{and} \quad \forall j = 1, \cdots, N_{EV} \tag{10}$$

$$\sum_{k=i}^{i+MST_j-1} \delta_{c,j}(t_k) \leq MST_j \cdot \left[1 + \delta_{c,j}(t_i) - \delta_{c,j}(t_{i-1})\right] \qquad \forall i = 1, \cdots, N_i \quad \text{and} \quad \forall j = 1, \cdots, N_{EV} \tag{11}$$

where δ_c is the binary variable to enable/disable the EV charging in a given time step. Clearly, equations from 8 to 11 ensure that in the last time step the charging power can be opportunely modulated for filling the residual capacity of the EV battery.

2.2.3. Smart Charging 2

The EVs are charged within the time interval in which are connected to the charging infrastructure and the charging power can be also modulated. Once the charging process is started, it can be also stopped and restarted later, until the EV battery is charged at the required level. Differently from *Smart Charging 1*, MOT and MST are unessential, while P_c can be modulated up to the rated value of the charging point. Finally, since no additional constraints on binary variables δ_c are included, the charging stage can also be repeatedly interrupted and resumed.

2.3. Energy Balance

The EVs are charged when connected to the charging points of the residential building. Of course, this infrastructure withdraws electricity from the distribution grid to fill the EV battery, so that its SOC compels the requirements from the users and their mobility needs. Then, the corresponding energy balance for the EV fleet can be defined in each time step, as follow:

$$P_p(t_i) = \sum_{j=1}^{N_{EV}} P_{c,j}(t_i) \qquad \forall i = 1, \cdots, N_i \tag{12}$$

where P_p is the electricity bought from the grid. Essentialy, the left-hand side of Equation 12 represents the *source* for the charging infrastructure, while the right-hand side identifies the *loads*.

2.4. Objective Function

The goal of the MILP approach, in each possible charging option, is the charging of all the EVs according to their specific energy needs. Thus, the objective function of the optimization can be just expressed as the minimization of energy bought from the grid while keeping the constraints on the required SOC (i.e., eq. 4 and 5) always active, as follows:

$$OF = \min \sum_{i=1}^{N_i} P_p(t_i)\, \Delta t \tag{13}$$

2.5. Peak demand minimization

The MILP formulation described here is adopted for achieving EV charging with different strategies offering increasing flexibility. Starting from unmanaged charging with a limited degree of freedom, the other options reflect more flexible management in regulating the charging process. Nevertheless, to reduce the peak of the aggregated demand, an heuristic technique needs to be be additionally implemented. Specifically, the heuristic is used to minimize the peak demand calculated by means of the MILP approach. The heuristic assumed in this study is a population-based method named Teaching–Learning-Based Optimization (TLBO) developed by Rao et al. (2011) where the design variable is the maximum power withdraws from the grid.

3. Case study and scenarios description

An artificial but realistic case study of a multi-family residential building of 30 apartments Canova et al. (2022) has been selected as use case in this study, assuming an EV available for each household. The chosen case study is supposed to be located in an Italian urban context and it is intentionally defined with many EVs (100%) to stress the proposed model toward widespread private electric mobility Ramsebner et al. (2023). In this context, a fully deployed charging infrastructure is supposed to be available within the residential building, so that each EV can be independently charged in its private parking lot (i.e., 30 charging points). In addition, EV drivers are supposed to be capable of sharing their mobility habits in advance to the charging infrastructure for planning and scheduling the EV charging according to the strategies presented in section 2. The EV drivers' habits and the energy demand during charging sessions have been randomly selected according to existing probability distribution functions defined in previous studies concerning e-mobility as Brancaccio and Deflorio (2023).

Four scenarios are proposed to investigate multi-family building's possible typical and extreme situations on a working day. The elements that differentiate the scenarios concern the state of vehicle charge on arrival in the parking lot (SOC_{in}), exit (SOC_{out}) and the dwell time described with the variables T_{in} and T_{out}. The baseline scenario is generated with the distributions from literature, in detail, Quirós-Tortós et al. (2018) for the SOC, the charging start time with the starting home parking from Corchero et al. (2014). and with the distributions of the home parking duration from Brancaccio and Deflorio (2023) the exit time is derived. Scenario 1 simulates a typical pattern of mobility habits but an extreme situation from the point of view of energy demand with SOC at 15% for all 30 incoming vehicles. Scenarios 2 and 3 try to model possible stressed situations from the mobility point of view: the former simulates evening arrivals and overnight stops for all cars whereas the latter combines evening flow with random exits also at night.

Figure 1 shows the resulting hourly profiles for the different scenarios in terms of EVs parked. Practically, as they were previously defined, Scenario 0 and 1 have the same profile, EV trips are more spread out throughout the day, but no more than 25 EVs are parked at the same time. Differently, Scenario 2 and 3 where EVs driving habits follow a systematic mobility trend (i.e., leaving and backing home of EV occur mainly in the mooring and late afternoon, respectively), can instead reach 30 EVs parked at the same time. The aggregated daily energy demand for Scenario 0, 2, and 3 is quite similar to each other since SOC_{in} and SOC_{out} are randomly selected according to the same probability distribution Quirós-Tortós et al. (2018). As a consequence, the overall energy demand ranges between 502 and 507 kWh/day for these scenarios corresponding to around 16 kWh/day/EV on average. In contrast, Scenario 1 is the most critical from the energy point of view, since all EVs have the same maximum charging demand. Then, in this case, the aggregated demand is expected to reach 1020 kWh/day corresponding to around 34 kWh/day/EV on average.

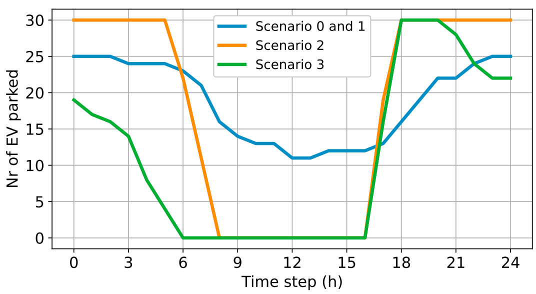


Fig. 1: Number of EVs parked for the different Scenarios

Finally, battery size and the corresponding efficiency during the charging stage have been assumed for all EVs equal to 40 kWh and 97.5%, respectively , while battery self-discharge has been neglected Lazzeroni et al. (2019).

4. Results

Figure 2 shows the results of the reduction of peak demand for different scenarios, considering a working day and a charging infrastructure with $P_{c,max}$ = 7 kW. As expected, unmanaged charging is always the worst condition: peak demand is higher than the ones observed when SC is adopted. Moreover, if all EVs tend to back home at the same time, as for Scenario 2 and 3, the corresponding peaks are inevitably relevant with a value close to 190 kW, even if the aggregated energy demand is lower than the Scenario 1, since all EVs would be essentially charged starting at the same time step. On the other hand, the flexibility offered by *Smart Charging 1* ($SC1$) and *Smart Charging 2* ($SC2$) is always capable of reducing peak demand, since each of the EV charging session is rescheduled to flatten the aggregated demand. Both smart charging options can almost halve the peak demand in Scenario 0 and 1, passing from 48.2 and 92.7 kW down to around 23.7-23 kW and 49.7-45 kW, respectively. Clearly, since the charging time is influenced by the energy demanded by EVs, Scenario 1 requires longer charging sessions, i.e. approximately 6 hours on average, than Scenario 0 which requires 3 hours on average. Moreover, the higher flexibility of $SC2$ compared to $SC1$, offers a bit longer charging session with lower average power demanded during charging. In Scenario 2 and 3, where all EVs have similar habits of leaving and coming home, the benefits of $SC1$ and $SC2$ are more remarkable. Peak demand can be reduced by more than 4 folds, passing from 180-190 kW down to 37.7 and 43-46 kW, respectively. Indeed, while $SC1$ has a similar behavior in both scenarios, $SC2$ shows different behavior due to different mobility users' habits. In particular, during Scenario 2 with longer EV stops at home, the power modulation is more effective increasing the duration of charging sessions up to 9 hours with around 2.5 kW of charging power on average. Consequently, the charging infrastructure as well as the distribution grid can be less stressed (i.e. investment in grid reinforcement could be eventually postponed) and the residential building can benefit from a lower contracted power with significant savings in terms of grid access costs.

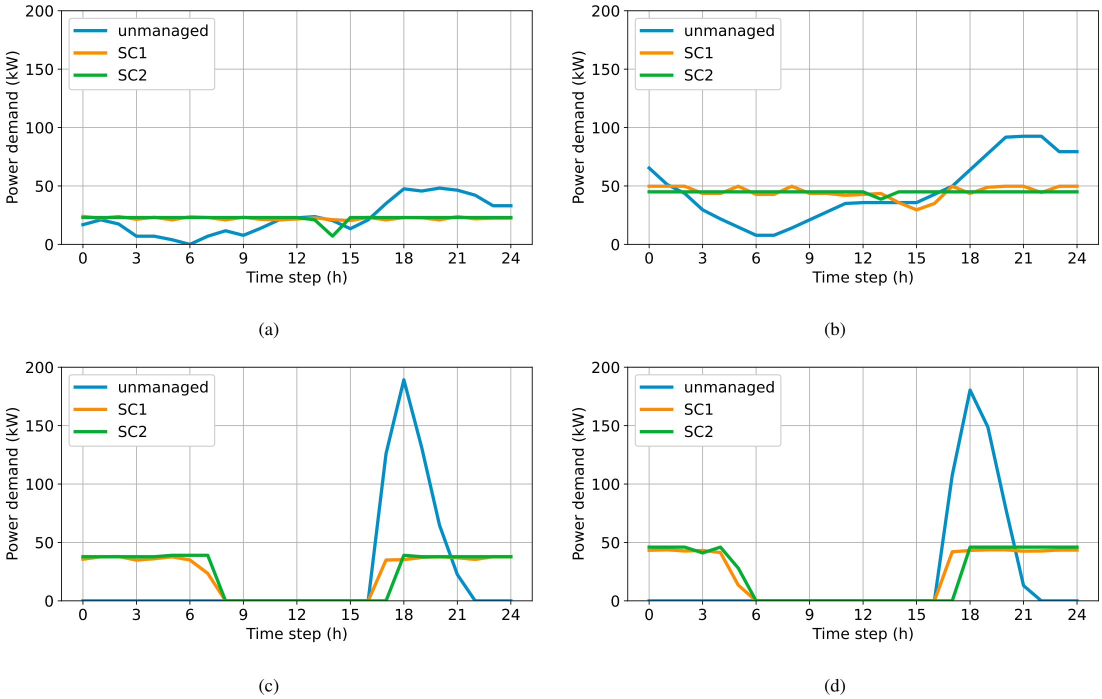
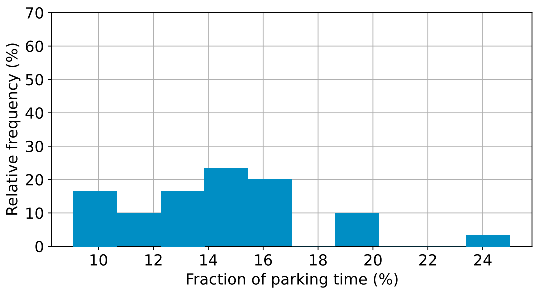
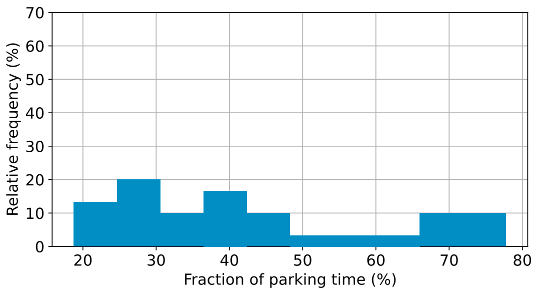


Fig. 2: Aggregated demand of EVs charging calculated by TLBO and MILP considering different charging options with N_{EV} = 30 and $P_{c,max}$ = 7kW for a) *Scenario 0*, b) *Scenario 1*, c) *Scenario 2* and d) *Scenario 3*.

However, although the results of $SC1$ and $SC2$ are similar, some differences exist. As depicted in section 2, $SC1$ offers lower flexibility as the charging power can not be modulated and each charging session can not be stopped once started. In other words, $SC1$ just reallocates "slots" of charging sessions with a fixed duration. Otherwise, $SC2$ can extend the duration of the charging sessions by modulating charging power and stopping and restarting each charging "slot". Thus, if an integrated platform should be used to enable SC, by acquiring information on end users' mobility habits, deviation from the programmed individual mobility plan could have an impact on the available SOC. For example, if an unexpected event requires the EV to be moved earlier than planned, the desired SOC_{out} may not be reached. Therefore, a check was performed to determine the level of SOC reached by the EV batteries in half the parking time for Scenario 1. Figure 3a shows how $SC1$ can effectively reach 50% of SOC within half of the parking time for all the charging sessions. In comparison, Figure 3b shows how some of the charging sessions with $SC2$ required more than 50% of the parking time to reach the same SOC level. Then, $SC1$ seems, in this case study, to potentially offer better performance in case of deviations from planned mobility habits. This result may be even more interesting when EV users have higher range anxiety because $SC1$ provides the possibility to reach a higher level of SOC in a shorter time.



(a)



(b)

Fig. 3: Relative frequency describing the fraction of the parking time at which SOC=50% for Scenario 1 with a) $SC1$ and b) $SC2$.

5. Conclusion

In this study the evaluation on how mobility behaviour of EV users may affect the performances of different smart charging options was performed in a residential use case with an internal charging infrastructure. Three different charging options are considered with increasing flexibility. Simulations have been performed by means of a MILP approach integrated within a heuristic algorithm, by using mobility habits as inputs for the model. Results highlight how a smart charging option should be preferred than unmanaged or uncontrolled one, because of its capacity in significantly reducing peak demand bringing to higher economic benefits for the residential building and the distribution grid. Nevertheless, some smart charging options could be more attractive than others on EV users when deviations from the planned mobility habits may occur.

The knowledge of users' mobility habits is a critical data, limiting the potentiality of the proposed approach, to optimize home charging even in highly stressed residential settings such as the case study presented. For example, work contexts with defined entry and exit times and several charging points suitable to the demand, similar to Scenario 2, may be appropriate for smart charging strategies applications. On the other hand, for the management of dynamic situations from the point of view of mobility and energy demand, the use of platforms or applications with user interfaces to collect requests and manage suitable charging strategies may be a solution. Future work will extend the methodology by considering spatial constraints (limited number of parking spaces) and variations in mobility habits in other contexts. Integration of renewable energy sources such as in the case of Renewable Energy Communities and the implementation of Vehicle-to-Grid or Vehicle-to-Building operation, for instance, will be also considered in the future to empower local distributed generation, greener e-mobility and sustainable cities.

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