PLANNING OF EV CHARGING INFRASTRUCTURE IN DISTRIBUTION GRIDS: A COMPARISON OF OPTIONS

VERSION 1.0

Fabrizio Sossan

Biswarup Mukherjee

May 2022

INTERNAL REFERENCE

Deliverable No.:	D 4.2 (2022)
Deliverable Name:	Planning of EV charging infrastructure in distribution grids: a comparison of options
Lead Participant:	MINES ParisTech (Former ETHZ)
Work Package No.:	WP4
Task No. & Name:	T4.2 Evaluation of the Hosting Capacity of Electrical Distribution Systems for EVs' Charging Demand and their Integrated Planning
Document (File):	EVA D4.2
Issue (Save) Date:	2022-05-31

DOCUMENT STATUS

	Date	Person(s)	Organisation
Author(s)	2022-05-30	Fabrizio Sossan	Mines ParisTech
	2022-05-30	Biswarup Mukherjee	Mines ParisTech
Verification by	2022-07-01	Albedo Bettini	SUPSI
Approval by	2022-07-04	Roman Rudel	SUPSI
Approval by			

DOCUMENT SENSITIVITY

☒	**Not Sensitive**	Contains only factual or background information; contains no new or additional analysis, recommendations or policy-relevant
☐	**Moderately Sensitive**	Contains some analysis or interpretation of results; contains no recommendations or policy-relevant statements
☐	**Sensitive**	Contains analysis or interpretation of results with policy-relevance and/or recommendations or policy-relevant statements
☐	**Highly Sensitive Confidential**	Contains significant analysis or interpretation of results with major policy-relevance or implications, contains extensive recommendations or policy-relevant statements, and/or contain policy-prescriptive statements. This sensitivity requires SB decision.

Executive Summary

The growing population of electric vehicles (EVs) requires the development of suitable charging infrastructure to enable EV owners to recharge their vehicles. The simultaneous charging process of many EVs results in increased power flows, possibly leading to violations of the operational constraints of distribution grids. In this context, the EV charging infrastructure should be planned while cognizant of the capability and limitations of the underlying power grid. Failing to do so might engender high grid reinforcement costs of recurrent use of smart charging to curtail the recharging actions of the EVs, ultimately under-utilizing the developed recharging infrastructure.

This report discusses cost-optimal planning of EV charging infrastructure in power distribution grids. It is considered the perspective of an integrated grid operator/urban planner wishing to attain minimum capital investments to roll out the EV charging infrastructure in a given grid. More specifically, the objective of the problem is to identify the location, rating (including fast and slow charging options), and the number of chargers in the grid to satisfy the charging demand of a given population of EVs at the minimum capital cost and while respecting the distribution grid's constraints.

The planning model developed as a part of this research is flexible and extensible, allowing a techno-economic comparison among different charging options and chargers' technologies. More specifically, the compared options are slow and fast chargers, single- and multi-port chargers (SPCs and MPCs, respectively), and flexibility of the EV owners in plugging and unplugging vehicles to and from chargers. Indeed, these options might result in different charging infrastructure requirements and configurations. For example, a fast charger costs more than a slow charger, but it shortens recharging time and, for the same operation time, might serve more vehicles, thus shortening payback times. MPCs (i.e., chargers with a centralized AC/DC power conversion stage and multiple ports allowing to arbitrage the charge among the connected vehicles) might lead to increasing flexibility. Finally, increased EV owners' flexibility (forgetful owners vs cooperative owners) could improve the utilization factor of the available charging infrastructure, improving cost efficiency.

Results show that MPCs and flexible EV owners can achieve significantly cheaper infrastructure costs than SPCs and forgetful owners. However, these differences tend to disappear with increasing values of the energy capacity of the EV batteries (from 16 kWh to 60 kWh). The reason for this result is that larger batteries require longer recharging times. These longer recharging times lead to saturating the utilization factor of the existing charging infrastructure, ultimately resulting in nearly optimal use of the chargers; in this context, the additional flexibility coming from MPCs and EVs' owners falls unused, bringing no additional benefit to the planning problem.

Within the context of this project (that tackles charging infrastructure for *autonomous* EVs), MPC chargers have been considered because they can be seen as as a first *autonomous* automation layer that achieves more flexibility than conventional chargers thanks to the possibility of arbitraging power flows locally. This represents a fundamental first step toward the development of more sophisticated planning algorithms for autonomous driving EVs, explaining the relevance to this project. The content of this report is based on two submitted (at the time of writing) papers of these same authors.

Table of Contents

Executive Summary 2

1 Introduction and problem statement 3

2 Summary of the proposed methods for the planning problem 4
2.1 General overview 4
2.2 Modeling the EV owners flexibility scenarios 5
2.3 Planning problem 6
2.4 Problem complexity and number of variables 7
2.5 Planning problem considering PV self-consumption 7

3 Case study (CIGRE benchmark grid for medium-voltage systems) 8

4 Results 8
4.1 Charging infrastructure requirements (without PV self-consumption) 8
4.2 Charging infrastructure requirements with PV self-consumption 10

5 Accuracy of the linearized grid models 13

List of publications 15

1 Introduction and problem statement

The massive adoption of electric vehicles (EVs) will play a central role in decarbonizing road transportation [1, 2, 3].Recharging EVs requires to develop an extended and pervasive charging infrastructure. Reference [4] estimates that, between 2019-2025, more than 2 billion Dollars will be necessary to improve the public and residential charging infrastructure across major U.S. metropolitan areas, whereas, in France, 2 billion Euros will be required to achieve the target of 7 million deployed public and private charger by 2030 [3, 5].

In addition to these investments, others will be necessary to adapt the electrical grid infrastructure, in particular distribution grids. Indeed, it is well known that the connection of many chargers in distribution grids might determine congestions at the level of substation transformer and lines, and violations of statutory voltage limits (e.g., [6, 7]).

This is because distribution grids were designed to host prescribed amounts of demand and with predefined voltage gradients along the feeders, which are typically violated when massively recharging EVs. The large investments required to both install suitable charging infrastructure for EVs and upgrade existing distribution networks motivate the need to research formal methods to locate and size EV chargers effectively accounting for realistic driving demand patterns, technical limits of existing distribution grids, and cost of the chargers. In other workds, the EV charging infrastructure should be planned while cognizant of the capability and limitations of the underlying power grid. Failing to do so might engender large grid reinforcement costs of recurrent use of smart charging to curtail the recharging actions of the EVs, ultimately under-utilizing the developed recharging infrastructure.

This report discusses cost-optimal EV charging infrastructure planning in distribution grids and summarizes the main findings of the publications [8, 9]. It is considered the perspective of an integrated grid operator/urban planner wishing to attain minimum capital investments to roll out the EV charging infrastructure in a power distribution grid. The objective of the problem is to identify the location, rating (i.e., fast and slow charging), and the number of chargers in the grid to satisfy the charging demand of a given population of EVs at the minimum capital cost and while respecting the distribution grid's constraints.

Both single-port chargers (SPCs) and multi-port chargers (MPCs) are considered in the problem to evaluate the techno-economical benefits of one or the other configuration, or a mixed one. The distinction between these two charger typologies is that SPCs have a plug for each charging column, whereas MPCs have a centralized AC/DC power conversion stage and multiple ports (each with a DC/DC converter to enable power flow control to each EV) to enable the connection of multiple EVs (Fig. 1). From an operational perspective, the differences between them are as follows: since an MPC can have a smaller AC/DC converter than a group of SPCs with the same number of plugs, it can be cheaper to purchase and install. MPCs, thanks to interfacing multiple EVs, enable arbitraging the charge among multiple vehicles, offering increased flexibility for congestion management; finally, connecting a large number of EVs to the same charger without requiring the EV owners to plug in and plug out vehicles manually might improve the utilization factor of the chargers.

Although the proposed methodology is general and can be adapted to model arbitrary power rating of the charging stations, we specifically consider two charger ratings for SPCs, i.e., fast and slow chargers.

The existing literature has investigated planning methods for the EV recharging infrastructure extensively. The work in [10] proposes joint planning of EVs charging stations and distribution capacity expansion, without modeling, however, MPCs and EV owners flexibility. Authors of [11] proposed a method for the cost-optimal planning of EV charging stations in a distribution grid considering grid

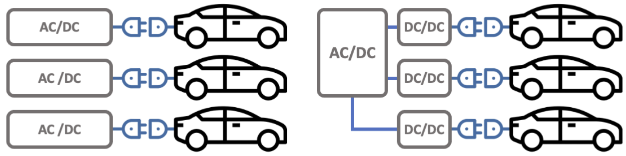


Figure 1: Single-port chargers (SPCs) on the left, and multi-port chargers (MPCs) on the right.

constraints; however, this work did not consider MPCs that, as shown in this report, can achieve significant cost savings. Methods for optimal planning of charging stations were also developed in [12, 13], without however including grid constraints. The work in [14] proposes a planning method to design multiple-charger multiple-port charging systems for EVs that features the capability of sharing a limited number of chargers to more EVs. However, this method extends to a parking slot and not to entire distribution grids. In [15], and similarly in [16], both distribution network and traffic flows were used to identify appropriate nodes to locate and size the EV charging stations. This work uses genetic algorithm to solve nonconvex AC load flows, a formulation which could not scale well to a large number of EVs, and do not consider voltage and line ampacities constraints, only the rated power of the nodes. The work in [17] proposes a data-driven approach for identifying driving demand and, based on this information, advises system planners on suitable locations for the charging infrastructure without considering, however, grid constraints. More recently, in [18, 19], a two-stage optimization framework was proposed, in combination with an efficient resolution method, to co-optimize the charging infrastructure in combination with the operations of the power grid and gas network. This work however, does not specifically address multi-port chargers and EV owners' flexibility.

The main contribution of this research compared to the existing state of the art is a planning method to site and size chargers of EVs in distribution grids accounting for grid constraints, multiple charger typologies, and EV owners' flexibility in plugging and unplugging their EVs. In addition, the impact of promoting PV self-consumption on the obtained planning results is investigated.

2 Summary of the proposed methods for the planning problem

2.1 General overview

Figure 2 depicts and introduces all the modeling elements involved in the planning problem. The figure is now explained, from top to bottom. At the top of the figure (black and dark yellow boxes), the evolution in time of the vehicles' SOCs is computed as a function of the battery discharging power due to driving. In order to keep the EVs in a functional state and satisfy the driving demand, the SOCs should be within the physical limits (e.g., between 10% and 100%, or any other configurable range). To this end, the problem computes when recharging the EVs (red box): a prerequisite for an EV to be charged is being plugged into a charger (first blue box from the top), which is in turn possible only when a vehicle is parked (this information is available from input variables). The EV plugged-in state does not depend on its parking state only but also on i) a charger availability and ii) EV owners' availability to unplug a charged EV and plug in an EV that needs to be recharged. For example, it is unlikely that an EV is plugged into a charger in the early morning hours as its owner might sleep: this flexibility of the driEV owners is specifically modeled with a dedicated set of constraints, as explained later.

An additional constraint of the charging problem is that charging an EV should not engender violations of the grid operational constraints (green box); the parking location of the EVs (known from p_{nvt})

establishes the link between the EVs' recharging demand and the power demand at the grid's nodes, allowing to model grid quantities.

Once all the charging schedules are determined (grey boxes), they are used to evaluate how many chargers are needed to meet the recharging demand. The total number of chargers is finally used to assess the total cost of the infrastructure, which is the objective function that the problem minimizes. An additional set of constraints (denoted by the last blue box) models whether SPCs or MPCs are allowed in the problem.

The problem is an economical cost minimization formulated as a mixed-integer linear program (MILP). The need for integer variables stems from the requirement of modeling connection and disconnection events to and from chargers, which are inherently discrete.

It is worth remarking that a byproduct of the planning problem illustrated in Fig. 2 is the optimal recharging policy that EV owners should adopt to recharge their EVs. In this respect, the proposed model assumes that EV owners follow these recharging policies and that the operator can reliably estimate their recharging needs.

2.2 Modeling the EV owners flexibility scenarios

A vehicle can charge only when it is parked and it is plugged into a charger. However, because plugging an EV into a charging column is an operation performed by the vehicle owner, their availability to plug and unplug an EV should also be modeled. For example, a person driving home in the evening and

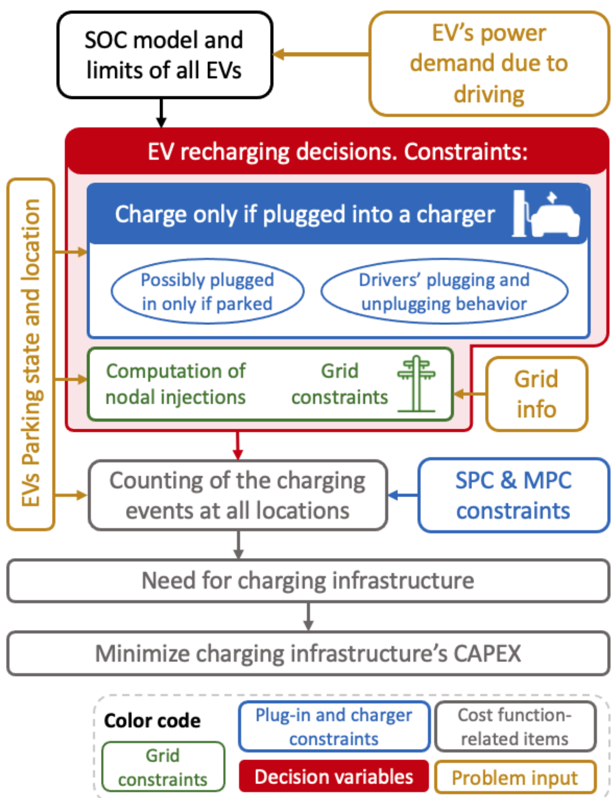


Figure 2: The main elements used in the planning problem.

using a public charging column might prefer to plug their EV at the arrival rather than queuing for a charger to become available. In order to model this key aspect, we introduce additional constraints to represent EV owners' flexibility for plugging and unplugging their EVs.

To explain these constraints, we refer to the case study analyzed in this study, which is a home-work commute where EVs are used in the morning, parked in the central part of the day, used again in the afternoon, and finally parked overnight. Two EV owners' flexibility scenarios are considered and are defined as follows:

- **Forgetful EV owners**: in both parking intervals, vehicle owners plug their EVs to a charger only at the arrival time, and unplug them only at the departure time. We implement this by enforcing no connection outside the initial parking time interval (for both fast and slow chargers).
- **Flexible EV owners**: for overnight parking, vehicle owners plug their EVs to a charger only at the arrival time, and unplug them only at the departure time; when parking in the central part of the day, EV owners allow one disconnection. We implement this by enforcing no connection outside the initial parking time for the overnight time interval.

We impose the EV owners' flexibility scenarios in the planning problem as additional constraints. The analysis of these flexibility scenarios is presented in the results section to evaluate their impact on the problem solution.

2.3 Planning problem

We propose here a summarized pseudo-formulation of the planning problem. Mathematical details are omitted for simplicity. The interested reader can find the fully detailed formulation in the papers associated with this report (available in the dedicated section at the end of this report).

The problem reads as the following mathematical optimization problem:

$$\min \{\text{Total cost of the chargers and plugs}\} \tag{1a}$$

subject to the following constraints:

EV charging power (fast or slow)	(1b)
EV state-of-charge evolution of all vehicles	(1c)
Nodal injections (EV charging power + other loads + distributed renewables)	(1d)
Linearized grid models and constraints	(1e)
Plugged-in only if parked constraints	(1f)
Charge only if plugged-in constraints	(1g)
EVs' owners flexibility model for EV plugging and unplugging	(1h)
Model to compute the number of chargers and plugs as a function of the recharging patterns	(1i)

The resulting model is a MILP program.

2.4 Problem complexity and number of variables

The number of variables in the proposed optimization problem increases linearly with the number of temporal samples and of vehicles. As know, MILP problems are NP-hard and have computationally complexity that increases exponentially with the number of variables. Thus, it is therefore necessary to limit the temporal samples and number of vehicles in order to retain problem's tractability. The case study has been performed for two set of samples: firstly, for the 16 kWh battery (i.e., low capacity EV battery) with set to 24 samples (i.e., 1 day optimization horizon with samples of each hour), and secondly, for the 60 kWh battery (i.e., higher capacity of EV battery) with 120 samples (i.e., 5 days optimization horizon) under the assumption that this interval is either a worst-case scenario of the driving demand or a pattern that occurs often during the service life of the charging infrastructure.

The reason for the longer optimization horizon for the larger batteries is that EVs with larger energy capacity can make multiple trips on a single charge and might not require to charge each day, possibly staggering the charging process and contributing to avoiding grid overloading. The 1-day-long demand profiles are replicated five times to attain the input time series for the 5-day planning period.

2.5 Planning problem considering PV self-consumption

One possible solution to mitigate the adverse effects of PV generation on distribution grids, as well as reduce grid losses, is consuming PV generation locally. This paradigm is known as PV self-consumption and has been widely advocated in the literature as a way to integrate more PV electricity into distribution grids [20, 21].

This section discusses how the planning method described above is modified to implement PV self-consumption with EVs, and the impact of this on the charging infrastructure needs. The objective is to understand whether charging EVs with locally produced PV generation requires having a charging infrastructure that is fundamentally different compared to the case where PV self-consumption is not explicitly sought, or whether this has no impact on the resulting optimized charging infrastructure.

PV self-consumption can be promoted by incentivizing EVs to recharge when PV generation is available. Say P_{nt}^{PV} is the PV power production at grid node n at time interval t and P_{nt}^{EV} the total charging demand of EVs connected at node n at time interval t, a suitable target function to minimize in order to foster the recharging of EVs with local PV generation is the following:

$$J^{\mathsf{PV}} = \sum_{n=1}^{N} \sum_{t=1}^{T} \frac{1}{P_{nt}^{\mathsf{PV}} + \epsilon} P_{nt}^{\mathsf{EV}}, \tag{2}$$

where ϵ is an arbitrary small coefficient to avoid a zero denominator with no PV generation. The expression (2) is used to extend the cost function of problem (1), called $J^{\mathsf{chargers}}(\cdot)$ for compactness, as:

$$J^{\mathsf{total}} = J^{\mathsf{chargers}}(\cdot) + k \cdot J^{\mathsf{PV}} \tag{3}$$

where k is an input coefficient that determines how one wants to weight one or the other term. A sensitivity analysis of the impact of the value of k on the planning problem is proposed in the results. In summary, by way of the new cost function (3), the charging infrastructure planning problem now consists in jointly minimizing the total investment and maximizing the PV self-consumption.

Power grid constraints are the same as in (1). Several options (charger power ratings, technologies, and EV owners' flexibility) can be modeled in the problem by inserting the suitable constraints. Results are only shown for the case of slow chargers and SPCs because other options show similar behavior in terms of the impact of PV self-consumption on the planning results.

3 Case study (CIGRE benchmark grid for medium-voltage systems)

The CIGRE benchmark grid for medium-voltage (MV) systems is a three-phase 14-bus system with a nominal voltage of 20 kV [22]. It is connected to the upper-grid level with two transformers, each serving a radial feeder, for a total power of 50 kVA. The system is modeled with a single-phase equivalent model under the assumptions of balanced loads and lines with transposed conductors. Table 1 shows the PV generation capacity installed at the various nodes of the grid. A total PV generation of 400 kWp is installed in the network and connected to nodes 6, 10, and 11. These nodes correspond to where EVs are parked during the daytime. PV generation is simulated with first-principles models starting from irradiance time series as described in [23], considering clear-sky conditions and PV panels with tilt and azimuth optimized to guarantee the largest yield over the year. A population of 800 EVs was considered, inline with the number of EVs reported in [24, 25] for grids of a similar size.

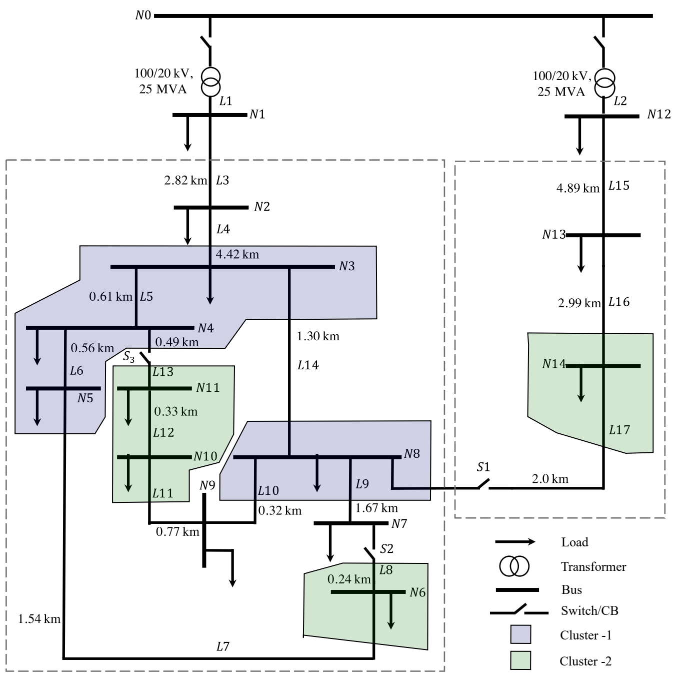


Figure 3: Topology of the CIGRE European benchmark grid for MV systems [22, 26].

4 Results

4.1 Charging infrastructure requirements (without PV self-consumption)

The results presented here refer to applying method (1) to the case study discussed in the former section. Results are first shown for EVs with 16 kWh batteries and then for EVs with 60 kWh batteries.

The MILP optimization problem was implemented in MATLAB and solved using Gurobi. The optimization problem with a 1-day-long optimization horizon was solved in about 90 minutes on an Intel i7 machine with a MIP gap setting of 10%; the problem with a 5-day-long optimization horizon (for larger batteries) was solved with a MIP gap of 15% to reduce the computation time. In these settings, the optimization problem was solved in around 5 hours.

Node	Apparent Power [kVA]	Power factor	Cluster	PV Gen [kW]
3	285	0.97	1	0
4	445	0.97	1	0
5	750	0.97	1	0
6	565	0.97	2	150
8	605	0.97	1	0
10	490	0.97	2	200
11	340	0.97	2	50
14	215	0.97	2	0

Table 1: Nodal nominal demand and power factors

The number of required chargers and plugs for SPCs, MPCs, and the two scenarios for EV owners' flexibility scenarios A and B are reported in Table 2 for the 1-day horizon. Table 3 reports the numbers for the 5-day optimization horizon. It can be observed that in both these cases, fast chargers are not required; slow chargers are enough to satisfy the charging demand of EVs and economically more optimal.

Table 3 shows that the number of installed chargers/plugs are the same for MPCs and SPCs, differently than Table 2 where the use of MPCs was conducive to lower installation costs. This is because EVs with larger batteries can accommodate multiple trips on a single charge and might ultimately take longer to recharge. Due to longer recharging times, the feature of swapping among several EVs (thanks to MPCs or increased vehicle owner flexibility) falls unused, without leading to more optimal use of the charging infrastructure. The total number of chargers (or plugs) required for the 60 kWh EVs is smaller than for the 16 kWh EVs. This is because smaller batteries EVs need to be recharged more often, possibly at different nodes, thus requiring a pervasive charging infrastructure and the installation of more chargers. Instead, EVs with larger batteries and more driving autonomy can perform multiple travels on a single charge and stagger the recharging process.

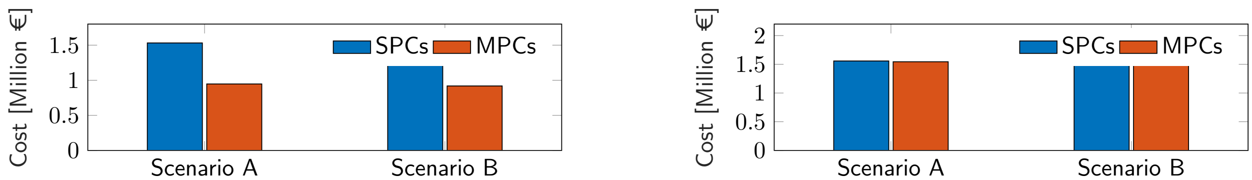
Node	Scenario A			Scenario B		
	MPCs		SPCs	MPCs		SPCs
	Chargers	Plugs	Chargers	Chargers	Plugs	Chargers
Cluster1	329	842	519	250	767	526
Cluster2	133	288	502	210	251	360
Total	462	1130	1021	460	1018	886

Table 2: Number of slow chargers and plugs with 1 day horizon (1'000 EVs, 16 kWh battery)

Fig. 4 summarizes the charging infrastructure costs in the various cases. Fig. 4a shows the result for 1000 16 kWh EVs. MPCs achieve significant cost savings compared to flexible EV owners. In particular, choosing MPCs over SPCs attains a cost reduction of 38% and 30% in Scenario A and B; whereas implementing flexible EV owners (Scenario B) achieves a cost reduction of 13% and 3% for SPCs and MPCs, respectively. This has the interesting implication that a technological solution obtains a better effect than a change in consumer behavior. Fig. 4b shows the result for 1000 60 kWh EVs. We now observe that the costs are nearly the same for all four cases, denoting that different options can achieve the same recharging performance at a similar costs.

Node	Scenario A			Scenario B		
	MPCs		SPCs	MPCs		SPCs
	Chargers	Plugs	Chargers	Chargers	Plugs	Chargers
Cluster 1	583	584	588	586	589	595
Cluster 2	312	313	315	309	309	309
Total	895	897	903	895	898	904

Table 3: Number of slow chargers and plugs with 5 days horizon (1'000 EVs, 60 kWh battery)



(a) 16 kWh EVs and 1-day optimization horizon

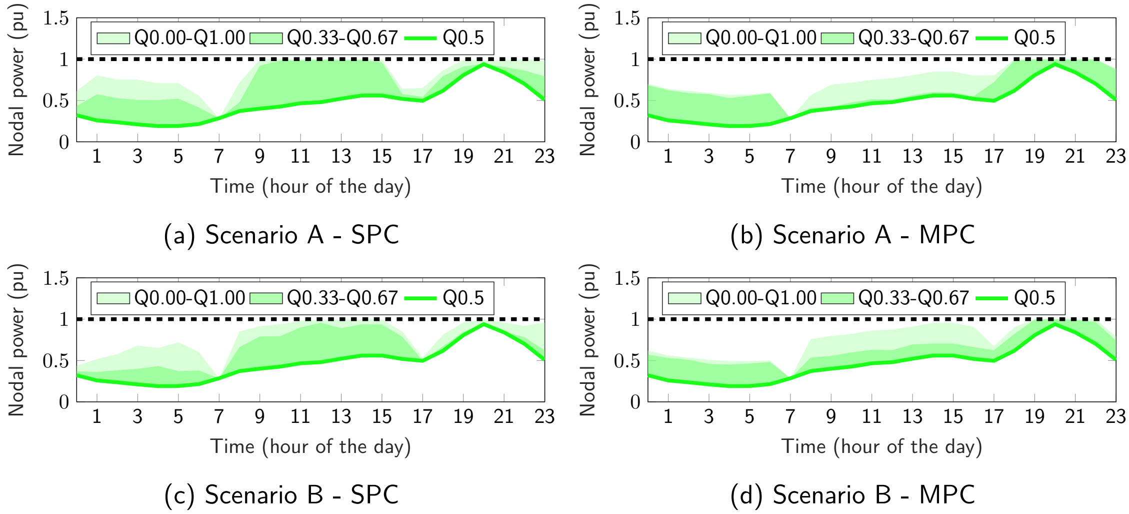
(b) 60 kWh EVs and 5-day optimization horizon

Figure 4: Cost of optimal charging infrastructure for 16 kWh and 60 kWh electric vehicles.

Figures 5 and 6 shows the nodal power injections over time in terms of quantiles (shades of green) and the median value (thicker green line) across the nodes. Nodal injections consist of conventional demand, total EV charging power at that node and PV generation. They are scaled by the rated power of the respective node so that the value of one per unit (denoted by the horizontal dashed lines in the figure) corresponds to the maximum power flow at that node. Nodal injections and power transformer limits in (1e) were found to be the active constraints of the planning problem, thus those determining the spatial configuration of the charging infrastructure. In all the cases, the nodal injections hit the limit value in the evening hours. This is due to the combination of the evening's conventional demand and the EVs' charging demand. With SPCs, the grid is mostly loaded in the day's central hours, whereas with MPCs, the grid is mostly loaded in the afternoon and evening hours. This denotes that MPCs tend to shift the charging demand from the central part of the day to the afternoon and evening hours. Fig. 6 shows the distribution quantiles of the nodal injections over the 5-day planning horizon. Compared to the case with smaller batteries which featured significant differences among the nodal injections for different chargers and EV owners' flexibility, nodal injections in the various cases are now similar.

4.2 Charging infrastructure requirements with PV self-consumption

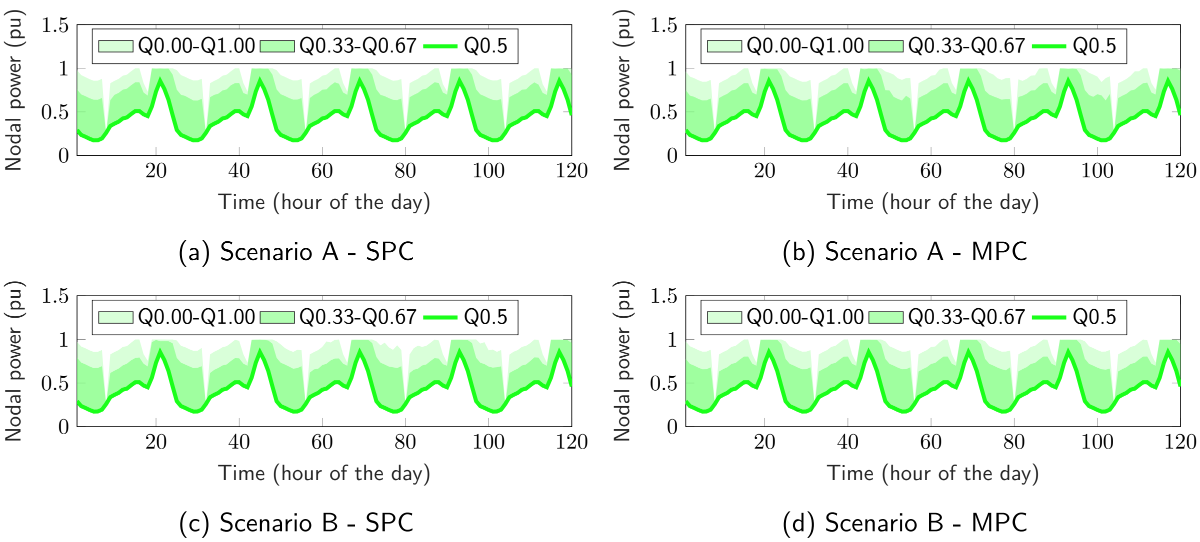
This section shows the charging infrastructure planning results when specifically fostering PV generation. Fig. 7 shows the values of the two components of the planning problem's cost function in (3): J^{chargers} (capital investments required for the resulting charging infrastructure) and J^{PV} (achieved PV self-consumption, where lower values denoted improved PV self-consumption, and viceversa) for different values of k and base case/extended parking intervals. Subpanels (a), (b), (c), and (d) respectively show a base case scenario with forgetful EV owners, cooperative EV owners, forgetful EV owners with extended parking intervals in the central part of the day, and cooperative EV owners with extended parking intervals. Extended parking intervals in the central part of the day is implicitly beneficial for PV self-consumption because EVs have higher chance to recharge when PV production is available. Fig. 7 is now discussed in details.



(a) Scenario A - SPC (b) Scenario A - MPC

(c) Scenario B - SPC (d) Scenario B - MPC

Figure 5: Distribution quantiles and median values of the active power injections across the various nodes of the grid over time for the EVs with 16 kWh batteries.



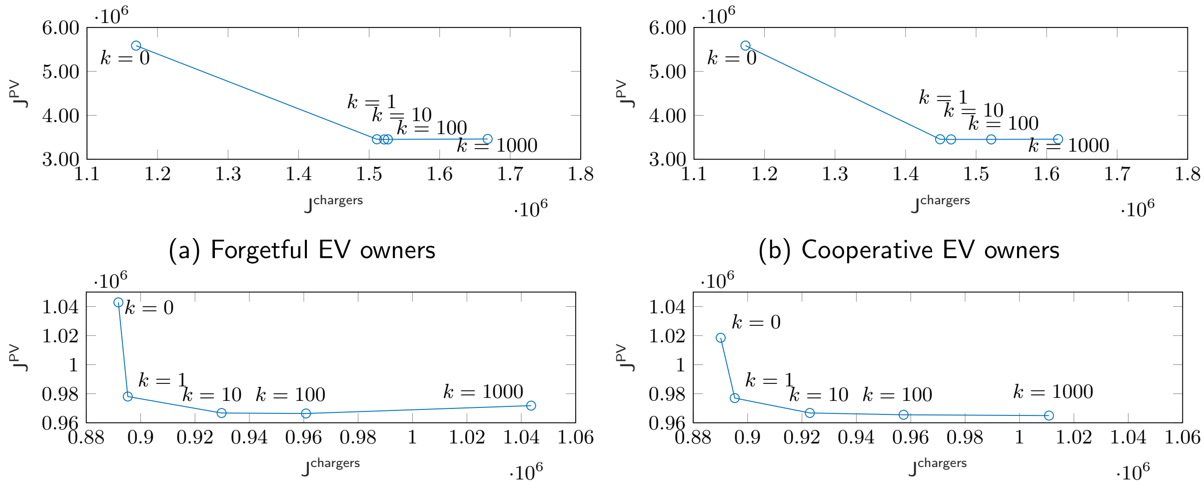
(a) Scenario A - SPC (b) Scenario A - MPC

(c) Scenario B - SPC (d) Scenario B - MPC

Figure 6: Distribution quantiles and median values of the active power injections across the various nodes of the grid over time for the EVs with 60 kWh batteries.

Fig. 7(a) shows that higher values of k attains lower values of J^{PV} (i.e., improved PV self-consumption) but higher infrastructure costs J^{chargers}. This trend can be traced also in the remaining plots of Fig. 7. It is to be expected because larger values of k in the cost function (3) gives more weight to PV self-consumption, and less to decreasing infrastructure costs. Fig. 7(c) shows the evolution of the costs with extended duration of the daytime parking intervals. By comparing this against Fig. 7(a), it can be seen that:

- extending the daytime parking intervals results in improving PV self-consumption J^{PV}, as visible by comparing the scale of the y-axis of the two plots;



(a) Forgetful EV owners

(b) Cooperative EV owners

(c) Forgetful EV owners with extended parking intervals

(d) Cooperative EV owners with extended parking intervals

Figure 7: PV self-consumption J^{PV} (lower values denote better PV self-consumption) versus the cost of the charging infrastructure J^{PV} for increasing values of k (from left to right: 0, 1, 10, 100, and 1000) in four different cases.

- the value of the costs components in Fig. 7(c) is not as sensitive to variations of k as in Fig. 7(a), as visible by comparing the axes' range of these two cases.

Finally, Fig. 7(b) and (d) show the impact of cooperative owners. It can be seen that increased flexibility of the EV owners leads to better infrastructure costs and PV self-consumption compared to the respective cases with forgetful EV owners. However, the benefit compared to extended parking intervals appears marginal.

Table 4 shows the total number of chargers installed in the grid and their distribution in clusters 1 and 2 for the base case daytime parking intervals, forgetful EV owners, and increasing values of k. It can be seen that the total number of chargers increases for larger k, in line with what was observed for the infrastructure costs in Fig. 7. It is worth noting that the distribution of the chargers among clusters changes for increasing values of k. In particular, for $k = 0$, chargers are mostly installed in Cluster 1 (where EVs are parked overnight), whereas the case with $k > 0$ features a larger number of chargers in Cluster 2 (where EVs are parked during the daytime and where PV generation is available). This denotes that promoting PV self-consumption from EVs requires developing a more pervasive charging infrastructure in those nodes where EVs are parked during the daytime. This is to be expected because the proposed formulation tend to promote PV self-consumption at the level of a node. As an alternative, one could consider to promote PV self-consumption at the grid level.

Tables 5 and 6 show the total number of chargers and distribution between clusters 1 and 2 under extended parking intervals, and forgetful and cooperative EV owners, respectively, for increasing values of k. It can be seen that, in both these cases, the charging infrastructure is nearly entirely developed in Cluster 2, where EVs are parked during the daytime. Compared to the case of Table 4, it can be seen that increasing the value of k, first, does not significantly impact the distribution of the chargers among the clusters, and second, it does not significantly impact the total number of chargers to install. The fact that the properties of the charging infrastructure are similar for different values of k denotes

Node	k = 0	k = 1	k = 10	k = 100	k = 1000
Total	678	876	882	885	967
Cluster 1	64%	36%	36%	36%	40%
Cluster 2	36%	64%	64%	64%	60%

Table 4: Total number of chargers and distribution among clusters for different values of k, base case daytime parking intervals, and forgetful EV owners.

that an EV charging infrastructure that is optimized for minimizing the investment cost is also capable of delivering good performance in terms of PV self-consumption.

Node	k = 0	k = 1	k = 10	k = 100	k = 1000
Total	516	519	535	555	586
Cluster 1	6%	4%	4%	4%	4%
Cluster 2	94%	96%	96%	96%	96%

Table 5: Total number of chargers and distribution among clusters for different values of k, extended parking intervals, and forgetful EV owners.

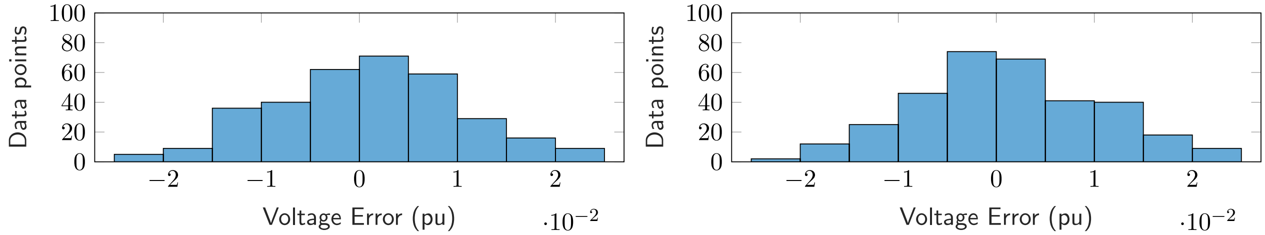
Node	k = 0	k = 1	k = 10	k = 100	k = 1000
Total	517	519	539	557	605
Cluster 1	5%	4%	4%	4%	3%
Cluster 2	95%	96%	96%	96%	97%

Table 6: Total number of chargers and distribution among clusters for different values of k, extended parking intervals, and cooperative EV owners.

5 Accuracy of the linearized grid models

The accuracy of the linearized grid model is evaluated by comparing the linear estimates against the results of a nonlinear load flow executed by playing back the nodal injections determined by the optimization problem. The histograms of the errors of the linear voltage and current estimations are shown in figures 8 and 9, respectively.

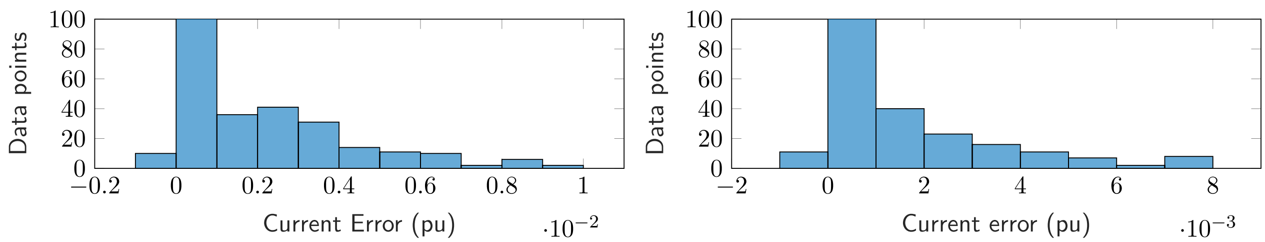
It the proposed case study, the active constraints of the problem were the nodal injections. It was verified that grid's voltage and current constraints would not have been violated even when accounting for the estimation errors of the linear model. However, in order to (conservatively) hedge against these modeling errors, one could add back-off terms to voltage and current constraints considering, for example, worst-case modelling errors from these histograms.



(a) Scenario A - SPC

(b) Scenario A - MPC

Figure 8: Errors of the linear estimates of the nodal voltage magnitudes (in per unit of the base voltage).



(a) Scenario A - SPC

(b) Scenario A - MPC

Figure 9: Errors of the linear estimates of the lines' current magnitudes (per unit obtained by rescaling by the larger current observed in the grid).

List of publications

Journal papers:

- Mukherjee, B., & Sossan, F. (2021). Optimal Planning of Single-Port and Multi-Port Charging Stations for Electric Vehicles in Medium Voltage Distribution Networks. IEEE Transactions on Smart Grid (In preparation, revision 2) Preprint.
- Mukherjee, B., & Sossan, F. (2022). Optimized Planning of Chargers for Electric Vehicles in Distribution Grids Including PV Self-Consumption and Cooperative Vehicle Owners. IET Energy Conversion and Economics (Submitted, revision 0).

References

[1] "EU 2030 climate & energy framework." Accessed: 2020-07.

[2] IRENA, "Innovation outlook: Smart charging for electric vehicles," Tech. Rep. MSU-CSE-06-2, International Renewable Energy Agency, Abu Dhabi, 2019.

[3] M.-O. Metais, O. Jouini, Y. Perez, J. Berrada, and E. Suomalainen, "Too much or not enough? Planning electric vehicle charging infrastructure: a review of modeling options.." working paper or preprint, Feb. 2021.

[4] "Estimating electric vehicle charging infrastructure costs across major U.S. metropolitan areas." Accessed: 2021-03.

[5] "Ministère de l'environnement de l'énergie et de lamer - La loi de transition Énergétique pour la croissance verte." Accessed: 2021-03.

[6] M. S. ElNozahy and M. M. A. Salama, "A comprehensive study of the impacts of PHEVs on residential distribution networks," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 1, pp. 332–342, 2014.

[7] S. Johansson, J. Persson, S. Lazarou, and A. Theocharis, "Investigation of the impact of large-scale integration of electric vehicles for a swedish distribution network," *Energies*, vol. 12, 2019.

[8] B. Mukherjee and F. Sossan, "Optimal planning of single-port and multi-port charging stations for electric vehicles in medium voltage distribution networks," *IEEE Transactions on Smart Grid (Submitted to, revision 2)*.

[9] B. Mukherjee and F. Sossan, "Optimized planning of chargers for electric vehicles in distribution grids including pv self-consumption and cooperative vehicle owners," *IET Energy Conversion and Economics (Submitted to, revision 0)*.

[10] Z. Hu and Y. Song, "Distribution network expansion planning with optimal siting and sizing of electric vehicle charging stations," in *2012 47th International Universities Power Engineering Conference (UPEC)*, pp. 1–6, 2012.

[11] Z. Liu, F. Wen, and G. Ledwich, "Optimal planning of electric-vehicle charging stations in distribution systems," *IEEE Transactions on Power Delivery*, vol. 28, no. 1, pp. 102–110, 2013.

[12] A. Y. S. Lam, Y.-W. Leung, and X. Chu, "Electric vehicle charging station placement: Formulation, complexity, and solutions," *IEEE Transactions on Smart Grid*, vol. 5, no. 6, pp. 2846–2856, 2014.

[13] C. Luo, Y.-F. Huang, and V. Gupta, "Placement of EV charging stations—balancing benefits among multiple entities," *IEEE Transactions on Smart Grid*, vol. 8, no. 2, pp. 759–768, 2017.

[14] H. Chen, Z. Hu, H. Luo, J. Qin, R. Rajagopal, and H. Zhang, "Design and planning of a multiple-charger multiple-port charging system for PEV charging station," *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 173–183, 2019.

[15] G. Liu, L. Kang, Z. Luan, J. Qiu, and F. Zheng, "Charging station and power network planning for integrated electric vehicles (EVs)," *Energies*, vol. 12, no. 13, 2019.

[16] Y. Xiang, J. Liu, R. Li, F. Li, C. Gu, and S. Tang, "Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates," *Applied Energy*, vol. 178, pp. 647–659, 2016.

[17] J. Li, X. Sun, Q. Liu, W. Zheng, H. Liu, and J. A. Stankovic, "Planning electric vehicle charging stations based on user charging behavior," in *2018 IEEE/ACM Third International Conference on Internet-of-Things Design and Implementation (IoTDI)*, pp. 225–236, 2018.

[18] W. Gan, M. Shahidehpour, J. Guo, W. Yao, A. Paaso, L. Zhang, and J. Wen, "Two-stage planning of network-constrained hybrid energy supply stations for electric and natural gas vehicles," *IEEE Transactions on Smart Grid*, vol. 12, no. 3, pp. 2013–2026, 2021.

[19] W. Gan, M. Shahidehpour, M. Yan, J. Guo, W. Yao, A. Paaso, L. Zhang, and J. Wen, "Coordinated planning of transportation and electric power networks with the proliferation of electric vehicles," *IEEE Transactions on Smart Grid*, vol. 11, no. 5, pp. 4005–4016, 2020.

[20] J. Widén, E. Wäckelgård, and P. D. Lund, "Options for improving the load matching capability of distributed photovoltaics: Methodology and application to high-latitude data," *Solar Energy*, vol. 83, no. 11, pp. 1953–1966, 2009.

[21] R. Luthander, J. Widén, D. Nilsson, and J. Palm, "Photovoltaic self-consumption in buildings: A review," *Applied Energy*, vol. 142, pp. 80–94, 2015.

[22] CIGRE' Task Force C6.04.02, "Benchmark systems for network integration of renewable and distributed energy resources," tech. rep., CIGRE International Council on large electric systems, July 2009.

[23] F. Sossan, E. Scolari, R. Gupta, and M. Paolone, "Solar irradiance estimations for modeling the variability of photovoltaic generation and assessing violations of grid constraints: A comparison between satellite and pyranometers measurements with load flow simulations," *Journal of Renewable and Sustainable Energy*, vol. 11, no. 5, p. 056103, 2019.

[24] B. Mukherjee, G. Kariniotakis, and F. Sossan, "Scheduling the charge of electric vehicles including reactive power support: Application to a medium-voltage grid," in *CIRED 2021 - The 26th International Conference and Exhibition on Electricity Distribution*, IET, 2021.

[25] B. Mukherjee, G. Kariniotakis, and F. Sossan, "Smart charging, vehicle-to-grid, and reactive power support from electric vehicles in distribution grids: A performance comparison," in *2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, pp. 1–6, IEEE, 10 2021.

[26] B. Mukherjee and F. Sossan, "Optimal planning of single-port and multi-port charging stations for electric vehicles in medium voltage distribution networks," *arXiv preprint arXiv:2111.07100*, 2021.

Funding

This research was developed in the context of the "Optimization of Regional Infrastructures For The Transition To Electric And Connected Autonomous Vehicles" (EVA) project (91188), supported by the Smart Energy Systems ERA-NET program and European Union's Horizon 2020 research and innovation programme under grant agreement no. 775970 (RegSys).