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Sizing charging infrastructure for mobility electrification for large sites under smart charging conditions

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Executive Summary

This paper presents a methodology to guide the electrification process from traditional ICE-based carparks or fleets in large sites in terms of the required size charging infrastructure and local renewable solar electricity production, taking into account mobility needs and cost effectiveness. The models allow moreover to compare the difference with and without applying smart charging on site. The methodology is executed on two distinct use cases. The results show the number of chargers does not need to match the number of drivers without reducing the level of service. The type of mobility profiles on site are of great influence to the sizing results.

Keywords: Charging infrastructure, Modeling, Sizing, Simulation, Smart charging

1 Introduction

With new regulations in Europe for the faze out of ICE vehicles, such as a total ban on sales of fossil fuel-based ICE vehicles by 2035 [1], EV penetration is expected to rise rapidly the coming years. With the electrification of fleets, companies and sites with carparks are often under pressure from drivers to provide charging infrastructure. With this, fleet or carpark managers are faced with the question of how many chargers to install in order to satisfy the mobility demand of EV users, as well as the costs linked to the provision of this infrastructure and service. This study has developed a methodology to right size the charging infrastructure for a particular site in transition from ICE vehicles to EV which satisfies its mobility demand in a cost-effective way by combining it, where possible, with a right sized solar installation. This paper presents the methodology and applies it to two distinct sites to explain the dynamics and potential of the method.

2 Methodology

This work continues the work presented in [2], where a method has been presented to characterize the mobility demand for a particular site or carpark and transform it into a charging session-based electricity demand and [3], where an algorithm for uni- and bidirectional smart charging is presented. The work in [2] highlights that this “charging session generator” can be used to simulate the charging behavior and electricity demand for certain sites. The method presented in this paper will use the charging session generator in combination with simulation of smart charging behavior as components of a full extended method.

The method has the following steps to run through as depicted in Figure 1:

1. Building the EV mobility profiles: analysing charging session data to define clusters of drivers with a similar behavior in terms of arrival time, parking time, and energy need. Within these clusters, subclusters can be made based on the frequency/occurrence of a charging session. Clusters are then characterized by distributions for their arrival time, parking time, and energy need. More detailed information on this step can be found in [2].

2. Fleet constitution/driver allocation: defining an EV transition scenario to determine the number of EVs and allocating them to the different clusters from step 1. By allocating numbers of drivers to a cluster, charging sessions (defined as an arrival time, parking time, and energy) can be generated per day according to the cluster's characteristic probability functions and occurrence probability. If a site does not have representative charging data to build up the site-specific driver profiles, pre-defined clusters from other sites can be used as standard profiles. Qualitative classification (e.g. visitors, personnel, …) and metadata for arrival time, parking time, and energy need can be used to select and calibrate standard clusters.

3. Configure the electrical lay-out of the carpark or site and its buildings: data on yearly energy consumption, energy cost, grid connection limits, current installed solar and remaining surface for solar are to be assembled.

4. Calculating the required number of chargers and optimal PV size: a simulator calculates energy balances on site based on the EV mobility energy demand (from step 2) and other energy demand and production present on site (from step 3) for a full year. The simulator includes a model for smart charging, which allows to also calculate the energy balance under smart charging conditions. By evaluating pre-defined key-performance indicators (KPIs) for and tuning design variables (e.g. different sizes of the solar installation) which allow to select the "optimal size" of the solar installation.

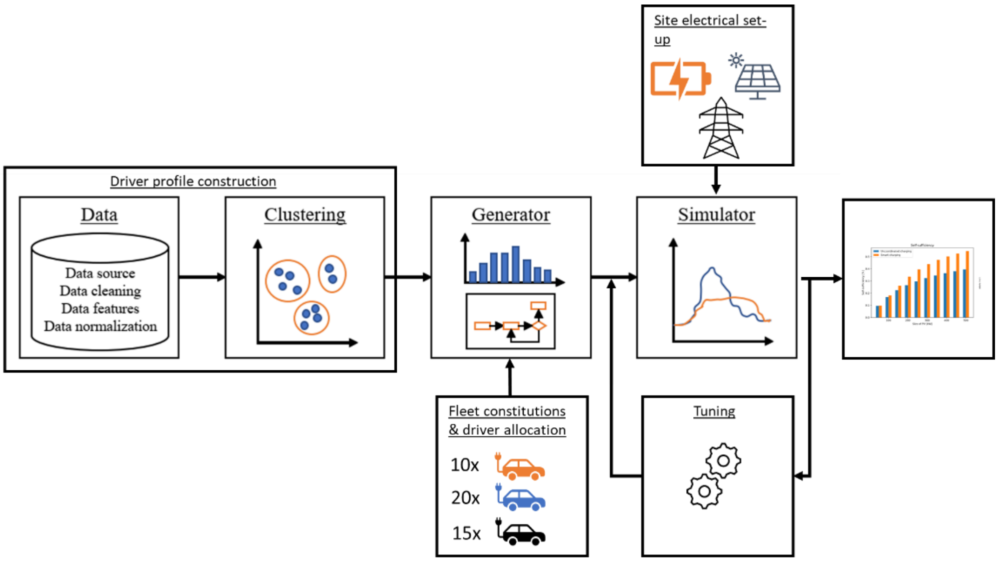


Figure 1 Diagram of the methodology steps

3 Case study

The methodology is applied to two specific sites. University hospital and a medium enterprise. These two cases were selected because they cover a different scope in terms of size and purpose. This means they are subject to different grid tariffs, to different electricity take-off volumes, and to different driver profiles. While the case of the hospital will be calculated based on the actual situation, the case for the medium enterprise will be hypothetical and based on assumptions. For the case of the hospital, charging data is available for a limited number of charging stations already installed for multiple years which can serve for the construction of the driver profiles. For the medium enterprise, profiles for visitors and employees have been selected based on the same dataset of the hospital. The university hospital is located in the Brussels Capital Region (BCR), while the small enterprise is located in the Flanders region. For the BCR, EV penetration scenarios have been researched in [4] and estimated at 51% by 2030. For the medium enterprise, similar transition is assumed with 32% coming by other mode of transport than a car, leading to 70 EVs for 203 employees. An overview of the two cases can be found in Table 1.

Table 1 Overview of two case study subject description

	Types of visitors	Number of Estimated EV drivers (by 2030)	Yearly total consumption (excl. EV)	Electricity price (Euro/kWh)	On-peak (Euro/kWh)	Off-Peak (Euro/kWh)
University Hospital	Personel	637 387	21 GWh	0.13065	0.1476	0.1111
Medium enterprise	Employees (office) Employees (other) Visitors	50 20 10	189 MWh	0.20235	0.2286	0.1722

Electricity prices are based on average values for non-households according to yearly volume as collected by Eurostat [5], with a common ratio on-peak and off-peak prices applied. For comparison reasons, the Flemish power-based tariffs are applied for both cases. The cost components for the PV and chargers are based on commercial offers from suppliers dating 2022. The discount rate is set to 5% and project lifetime set to 10 years.

Table 2 Costs used for the PV and charger

Asset	Capex	Opex	Lifetime
PV	1000 euros/kWp for medium entreprise 750 euros/kWp for university hospital	10 euros/kWp/year	25 years
Charger (11kW)	4000 euros	120 euros/year/charger	7 years

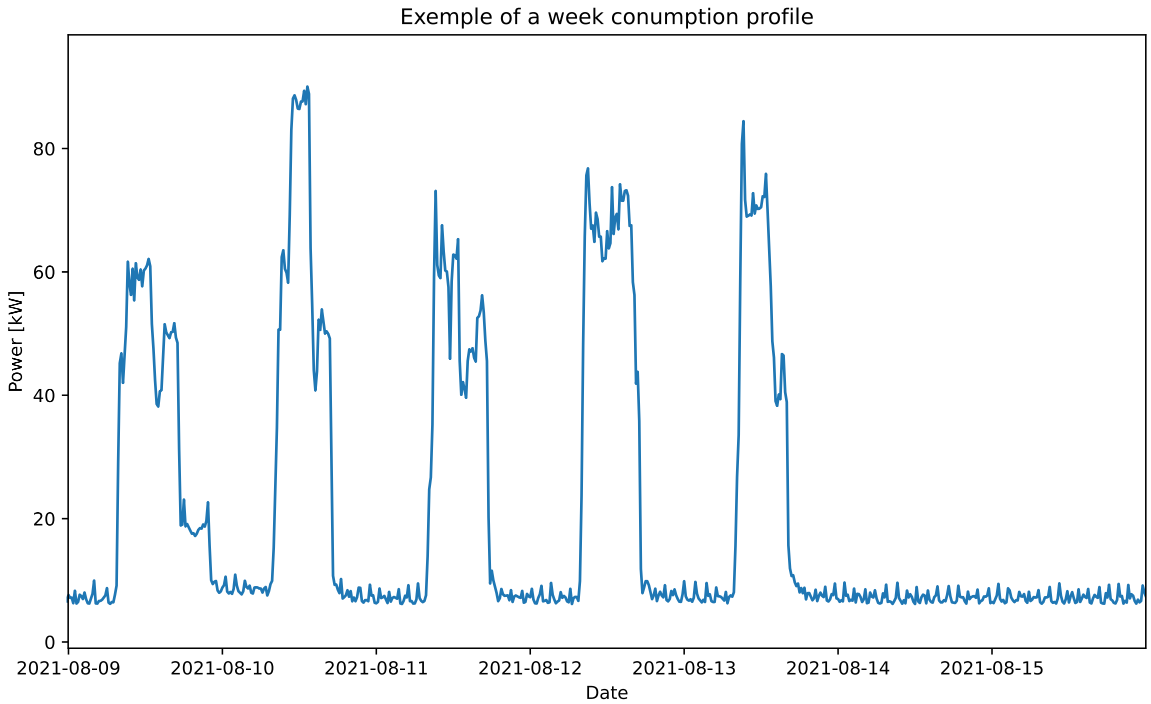
3.1 Dataset charging

The parking lot with the chargers is an open-access charging location, with paid parking fee located at the university hospital. The dataset of charging consists of a four-year dataset of charging sessions of six charge points containing two Type 2 (IEC 618511) connectors of 22kW each. The dataset contains plug-in time, plug-out time, energy charged, and a unique driver identification. After data cleaning, the total dataset contains 12350 charging sessions spread over 595 unique driver IDs. This dataset will be used to build up the driver profiles for both the university hospital and medium enterprise.

3.2 Dataset consumption

The consumption for the use case hospital is based on the measurement of the main connection to the distribution grid in a 15 min resolution. The hospital has an average consumption of 2,5MW and ranges between 1MW and 5MW. Cycles are day-based and seasonal-based also largely due to variations in consumption and in production (solar installation of over 2MWp). No injection of energy occurs in the power profile. Due to reasons of confidentiality, the exact power profile is not disclosed. Since no exact measurement of the solar production is available, this study works with the net consumption and specifies any other value for solar installation as additional to the current setup.

The consumption for the medium enterprise is based on a measured consumption of a gas-heated medium enterprise in Flanders, Belgium and scaled to an office building hosting offices for 203 people at 12,5 m^2 per capita and 74,5 kWh/m^2, as per [6], leading to 189Mh yearly consumption. The consumption profile shows typical behavior of daytime consumption with peaks in the morning. An example of a week is shown in Figure 2.



3.3 Key performance indicators

To evaluate the technical and economic performance of the configurations the following key performance indicators are used:

- Total cost-of-ownership (TCO): calculates the total cost over the full project lifetime. Includes CAPEX and OPEX cost of the charging infrastructure and solar installations, as well as the energy costs of the full site. Allows to compare configurations on a cost base.
- Annualized return-on-investment (aROI): gains in total cost relative to the investment costs expressed over the full project lifetime and reconverted to a yearly return value. Allows to compare configurations on from an investment viewpoint.
- Self-consumption: relative amount of the own produced (solar) energy which is consumed by the local consumers and thus not injected into the distribution grid.
- Self-sufficiency: amount of the consumed energy which is supplied by own production to the total amount of consumed energy. The self-sufficiency indicates how reliant you are to energy supply from the grid.

4 Results

4.1.1 Driver profiles, fleet constitution & driver allocation

The driver profiles obtained from step 1 of the methodology for the dataset can be found in Table 3. The table gives the values for the behavioral parameters that define the profile and indicates an inferred hospital user group. The probability Week and probability Weekend indicate the probability of a charging session ocuring in respectively the week days and weekend days. The probability is based on behavior of individual drivers. This leads to very low probabilities for the visitor types as they have very low recurrent behavior and do not well represent the probability of charging of any visitor on any given day. Therefore, the probabilities for the visitor profiles have been artificially increased to 20% on weekdays and 5% on weekend days. This means that out of the total pool of daily visitors, 1 out of 5 will charge its vehicle. Since during weekdays the population of visitors is about 4 times smaller, this probability is set to 5% for weekend days to compensate for the decrease in population. In Plug-in, Parking, and Energy an indication is given of the values which have highest concentration of charging sessions. When a range is given, it indicates very high concentration within that range, when a single value is given, it is a high concentration around that value. The reason for describing the behavioral parameters in this way is because the Kernel distributions have irregular, asymmetric shapes which cannot easily be represented by typical statistical parameters. To illustrate this Figure 3 shows the distributions of plug-in time and parking time and Figure 4 the energy for profile 6, 9, and 12.

Table 3 Overview of driver profiles for the university hospital with the behavioral parameters and descriptive assumed category.

Profile	Probability Week	Probability Weekend	Plug-in	Parking	Energy	Inferred User group
1	14.87%	8.89%	6:30pm-7pm	13h	10kWh - 20kWh	Night shift employee
2	60.00%	0.00%	6:30pm-7pm	13h	20kWh	Night shift employee
3	17.88%	1.93%	7am-8am	8-12h	<20kWh	Day employee
4	60.82%	6.25%	7am-8am	8-12h	<20kWh	Day employee
5	2.61%	1.00%	7am-8am	8-12h	<20kWh	Day employee
6	30.38%	6.70%	7am-8am	8-12h	<20kWh	Day employee
7	2.25%	1.13%	12am-6pm	2h	<10kWh	Visitor
8	80.70%	56.94%	12am-12:30 6:30pm-7pm	12h	<10kWh	Day and Night shift employee
9	1.64%	0.66%	8am-6pm	1h	<10kWh	Consultation patient
10	31.41%	0.46%	8am	5h	<10kWh	Recurrent patient
11	3.65%	2.20%	7am-8am	4h & 10h	0-80kWh	Day employee
12	21.60%	5.42%	7am-8am	4h & 10h	0-80kWh	Day employee

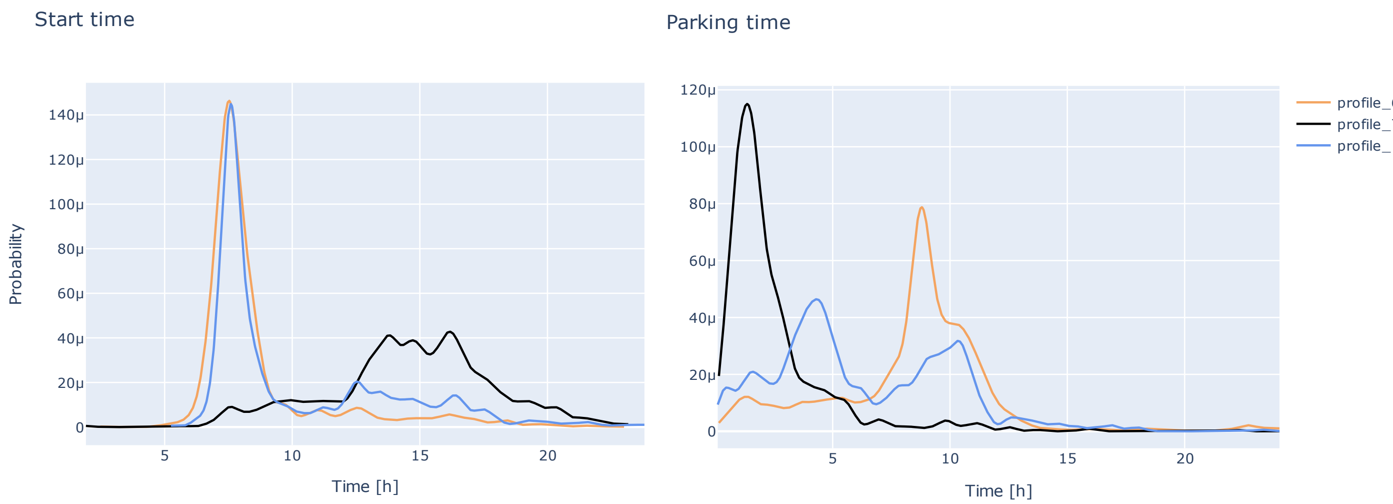


Figure 3: Kernel Distributions for the Plug-in time (left) and parking time (right) of driver profile 6, 7 and 12

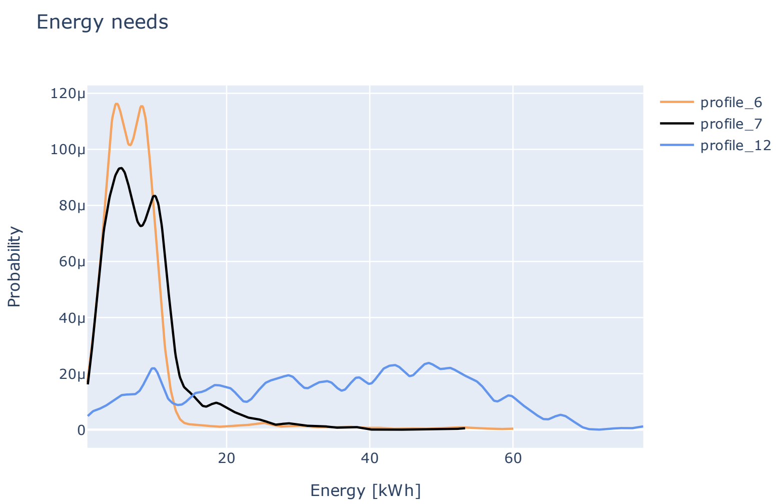


Figure 4: Kernel Distribution for the energy needs of driver profile 6, 7 and 12

The plug-in time distributions in Figure 3 (left) show a very similar behavior for profile 6 and profile 12 with concentration of plug-in times in the morning around 8am, but a completely different behavior for profile 7 which has plug-in time spread across office hours, with a skew towards the afternoon. The parking times depicted in Figure 3 (right) show three different behaviors for the driver profiles: profile 7 has a high concentration of short parking times consistent with visitor behavior, profile 6 has a high concentration of parking times around 8-12 hours consistent with regular office hours or hospital day shifts, and profile 12 has parking time spread with concentrations around a half and full working day which we associate here with more irregular office hours consistent with e.g people that have appointments outside of the office regularly. The energy distribution depicted in Figure 4 shows very similar behavior between profile 6 and 7 with high concentration of session below 20kWh, but a completely different behavior for profile 12 with a wide range of energy charged per session up to 80kWh. The latter is consistent with the hypothesis for the parking time behaviour as linked to a more irregular behavior of people being more on the road for work.

Table 4 shows an overview of constitution of the driver population with the number of users and charging sessions per driver profiles and relative share of the driver profile within the user group based on number of users. To build up the transition scenario for the hospital use case, it is assumed the constitution of the driver profiles within a user group (employee or visitors) will remain the same.

Table 4 Overview of driver profiles for the university hospital their number of users and sessions and relative share of the profile within the user group based on number of users.

Profile	**Number of users**	**Number of sessions**	**Inferred user group**	**Share of total**	**Share within user group**
1	10	344	Personel	1.7%	5.9%
2	1	3	Personel	0.2%	0.6%
3	17	1218	Personel	2.9%	10.0%
4	7	3041	Personel	1.2%	4.1%
5	50	903	Personel	8.4%	29.4%
6	17	2980	Personel	2.9%	10.0%
7	225	790	Visitor	37.9%	54.6%
8	4	635	Personel	0.7%	2.4%
9	187	774	Visitor	31.5%	45.4%
11	53	283	Personel	8.9%	31.2%
12	11	677	Personel	1.9%	6.5%

To build up the scenario of the medium enterprise, a selection of driver profiles 6, 7 and 12 of Table 4 for the employee (office), the employee (other), and the visitor respectively, as their specific behaviors explained with Figure 3 and Figure 4 is appropriate for the use case presented here.

4.1.2 Number of charging stations

Based on the fleet composition, the charging session can now generate the total charging demand for both use cases. To determine the number of required charging sessions, we look at the number of charging sessions happening simultaneously. Figure 5 and Figure 6 show the cumulative percentage of demand, expressed as the percentage of time, covered in function of the number of charging sessions for the hospital and medium enterprise scenarios respectively. In the figures the threshold for 90%, 95%, 99% coverage is also indicated. The first observation is that the required number of chargers for 100% demand coverage is only a small percentage of the considered fleet. 221 charge points for 2007 EV drivers in the population of the hospital and 25 charge points for the 80 drivers in the population of the medium enterprise, respectively a ratio of 11% and 31%. The second observation is the rate of coverage decreases with increasing number of chargers. This makes that increasing 99% coverage by the last percentage point to 100% coverage leads to relatively high number of chargers needed: an increase of 24% and 32% for the hospital and medium enterprise respectively. Therefore, the coverage rate is a design variable that can take into account the criticality which is given to the service level of charging with respect to the additional cost.

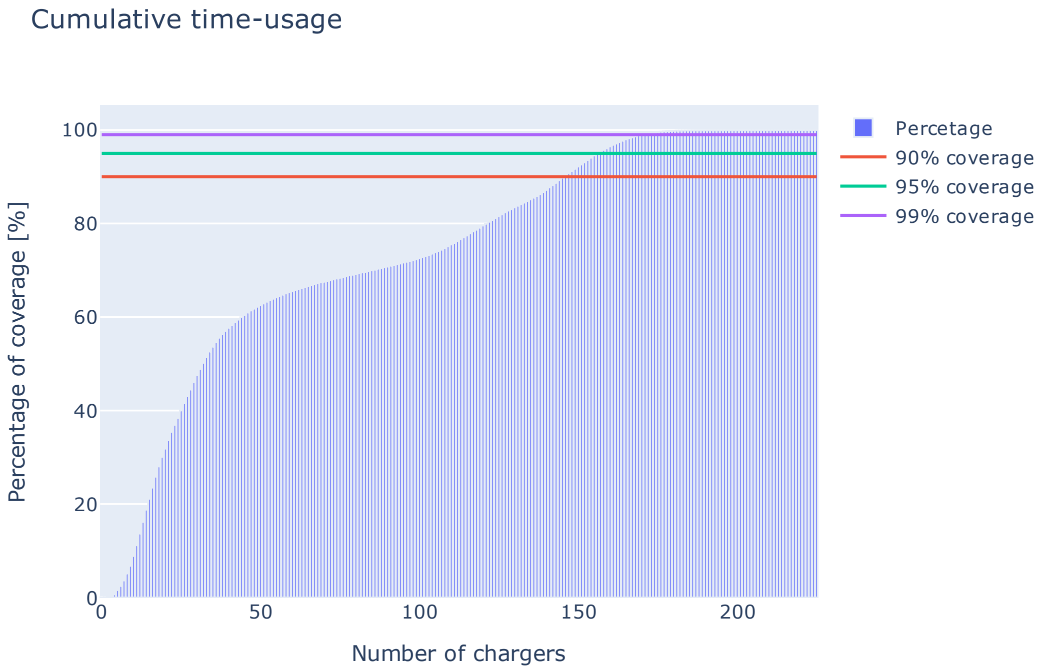


Figure 5: Coverage for the charging demand for the hospital use case

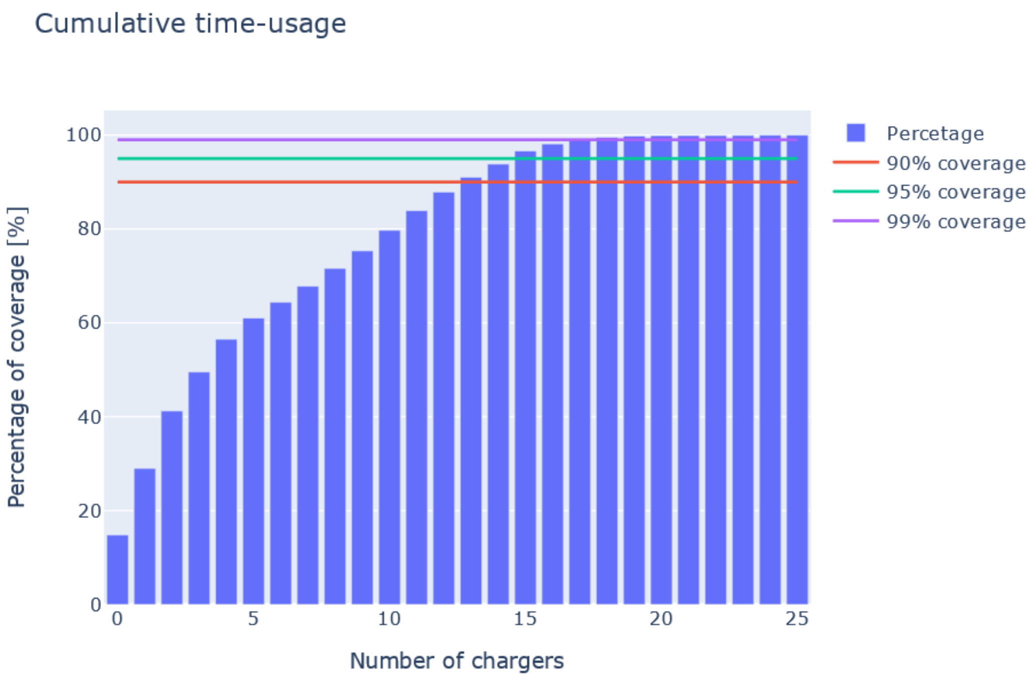


Figure 6: Coverage for the charging demand for the medium enterprise use case

4.1.3 Technical and economic indicators

The simulator now simulates the energy balance for a full year for different configurations (i.e. different PV sizes here) and calculates some technical and economic indicators mentioned in section 3.3. Figure 7 - Figure 12 present the KPIs for the hospital and the medium enterprise. Figure 7 and Figure 8 show the TCO for the university hospital and medium enterprise respectively. Both cases have a decrease in TCO with increasing PV sizes and a reduction of costs with smart charging and reach a minimum for a specific PV size, after which the costs increase again. This point of minimum cost is shifted to higher sizes of PV installation when performing smart charging (from 5.5MW to 6MW or 9% increase, and 100kW to 150kW or 50% increase for the hospital and medium enterprise respectively). The relative cost differences and associated shift in cost-optimal PV size are much smaller for the university hospital because the consumption of EV charging is small compared to the baseload. To highlight the cost differences for the university better, a zoom-in is also depicted in Figure 7. Looking at it from the investment perspective, Figure 9 shows that at the minimum cost point of the TCO, both case show aROI of around 10%. Although the relative cost savings by smart charging are small in comparison to the total cost for the hospital, in absolute values they still present substantial savings of just over 355.327 Euro over the project lifetime, as can be seen in Figure 10. In the medium enterprise, relative cost savings of smart charging are significant (6.4%) at the smart charging cost-optimal PV size, as can be seen in Figure 8 (right).

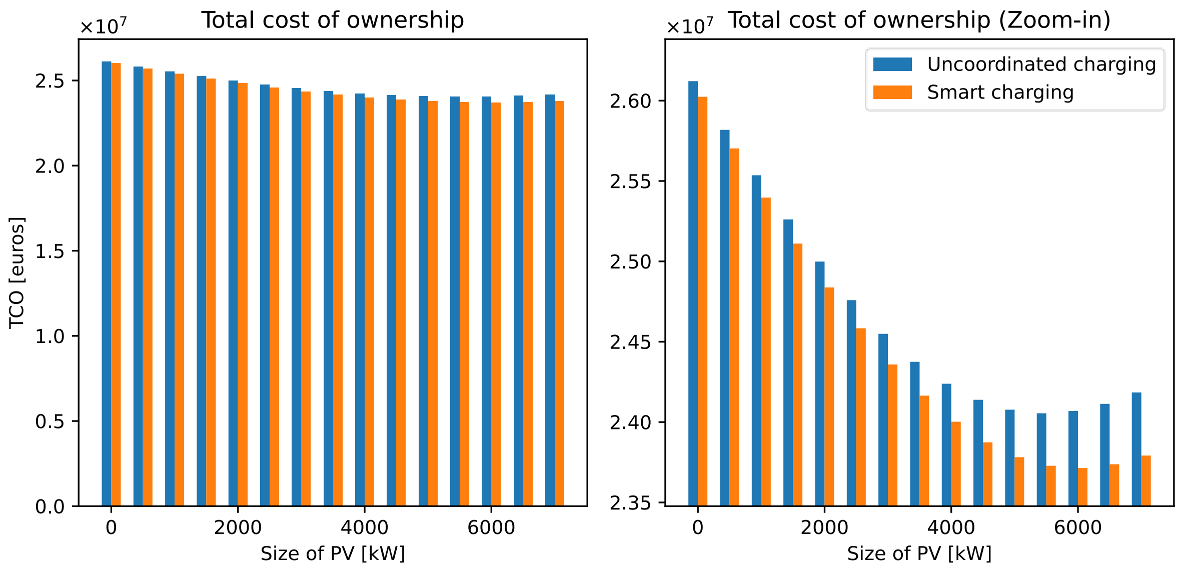


Figure 7: Total-cost-of ownership (left) in function of PV size for the hospital case with zoom in (right) for readability purpose, with and without smart charging

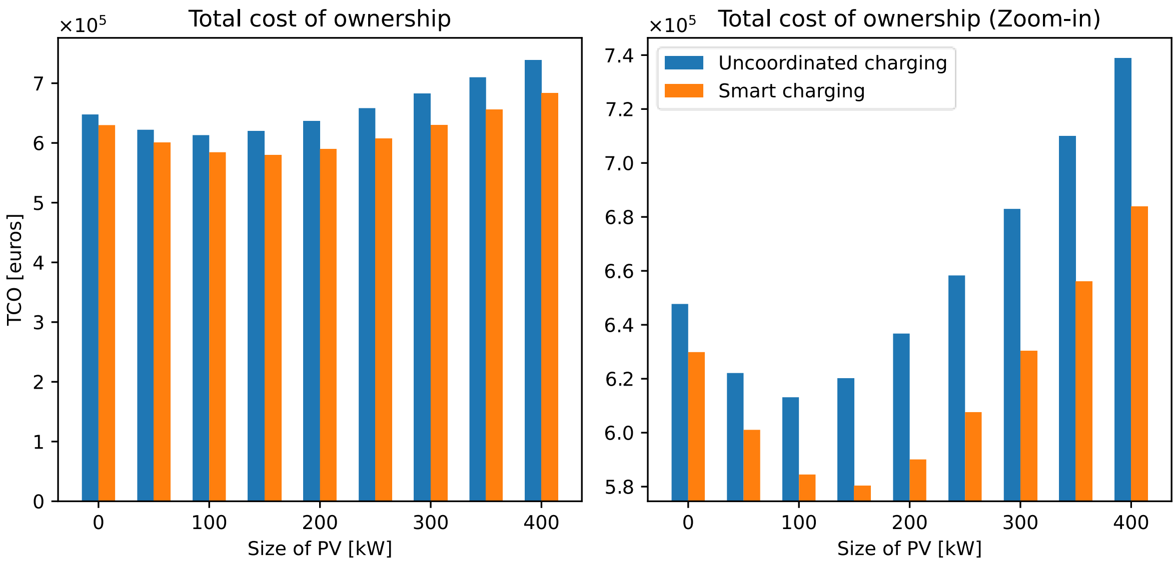


Figure 8: Total cost-of-ownsership (left) in function of PV size for the medium enterprise with zoom in (right) for readability purpose, with and without smart charging

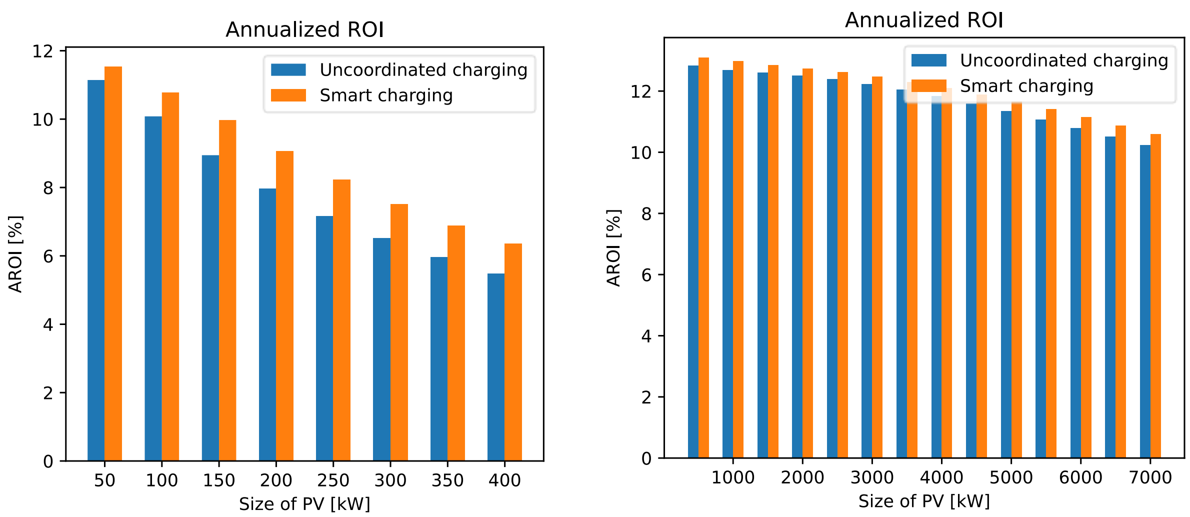


Figure 9: Annualized return on investment in function of PV size for the medium enterprise (left) and for the hospital case (right), with and without smart charging

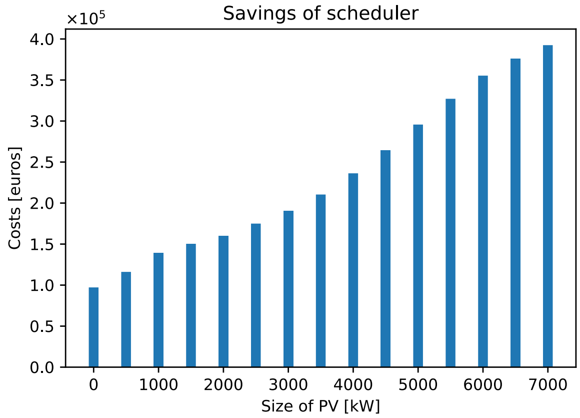


Figure 10: Savings by adopting smart charging in the hospital use case

The self-consumption for the hospital and medium enterprise are shown in Figure 11. Both cases show decreasing percentages of self-consumption with increasing PV size, but the hospital has significantly higher self-consumption (80%) than the medium enterprise (73%) at the smart charging cost-optimal PV size. The further decrease in self-consumption is also the explanation for the increasing cost and decreasing aROI after the cost optimal point. The increase in self-consumption by smart charging is an important component in its cost reductions. The self-sufficiency for the hospital and medium enterprise are shown in Figure 12. The self-sufficiency ranges from close to 20% in the hospital case to 35% in the medium enterprise at the cost-optimal PV size with smart charging. The significant difference in these percentages for self-consumption and self-sufficiency at cost optimal PV size are related to how the cost components contribute to the total cost in both cases. The hospital has a lower electricity commodity price, reducing the cost benefits of PV. This is partly compensated by the lower CAPEX cost per kWp installed because of the size PV being order of magnitude bigger for the hospital than for the medium enterprise.

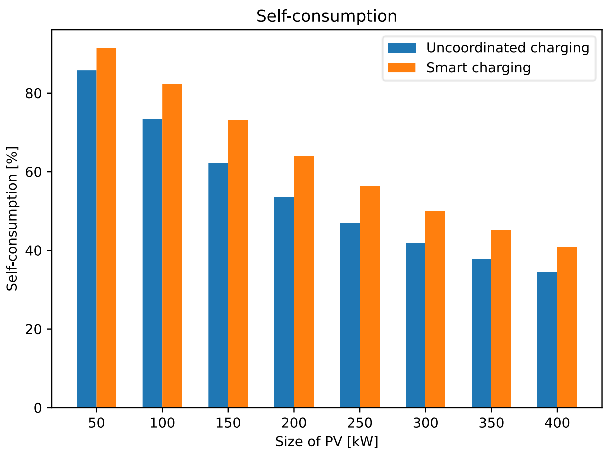


Figure 11: Self-consumption in function of PV size for the medium entreprise (left) and hospital (right) cases, with and without smart charging

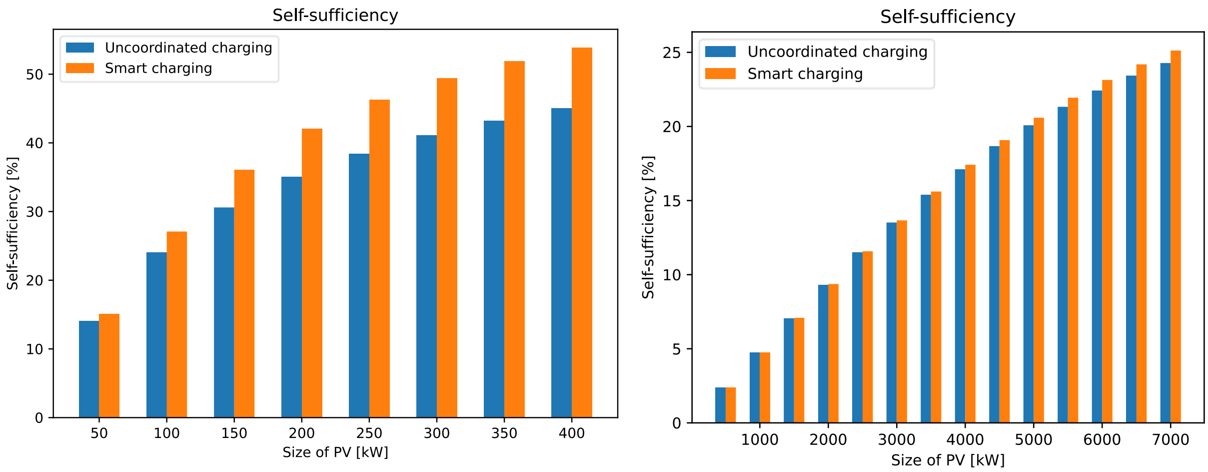


Figure 12: Self-consumption (left) and self-sufficiency (right) in function of PV size for the medium enterprise, with and without smart charging

4.2 Conclusions

A methodology to size charging infrastructure and PV installation for converting carparks in large sites has been proposed and applied to two distinct cases: a hospital and medium enterprise. Both sites differ in scope, (size and purpose) and thus have different electricity take-off volumes, and different charging behavior. The results show a versatile site like the hospital has large set of driver profiles (12) with distinctly different driver behavior. These differences can be linked to different user groups (visitors, personel) and differences within the user group linked to their specific behavior (night shifts, day shifts, …). All of these profiles were used to construct the hospital future fleet in assumed 51% EV transition scenario, while a selection of profiles was used in the hypothetical use case constructed for a medium enterprise. The required number of chargers to fully satisfy the charging demand in both cases was only a fraction of the total fleet size (11% for the hospital and 31% for the medium enterprise). Moreover, satisfying only 99% of demand leads to 24% further decrease of number of charge points for the hospital and 32% further decrease for the medium enterprise. It shows that the importance given to service semi-public charging is an important design parameter for the size of the charging infrastructure.

The TCO in relation to the PV size shows similar trends in both cases. Increasing the size of PV reduces the total cost-of-ownership until certain thresholds. This threshold is different in both cases due to the lower electricity price for PV CAPEX of the hospital are. This leads to a cost-optimal point at higher self-consumption for the hospital (80%) compared to the medium enterprise (72%). Smart charging increases the cost optimal size of PV by 9% for the hospital and 50% for the medium enterprise. The relative impact on the total cost by introducing EVs and on the cost-optimal size of the PV system by introducing smart charging are significantly smaller in the hospital case compared to the medium enterprise because of the smaller relative impact of the introduction of EVs on the local energy system.

Overall, the results show the design of a charging hub is case specific where the required number of chargers is linked to the mix of driver profiles linked to the site. Cost-optimal PV size will be dependent on the mix and complementarity of the consumers (charging inclusive) and smart charging increases the cost-effective size of PV. The impact of EV charging and mitigation by smart charging on the TCO depend on importance of other consumers take-off and peak consumption, on the energy prices, power-based tariffs, and CAPEX costs which are site specific and linked to its size and purpose.

Acknowledgments

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Presenter Biography

Dr. Cedric De Cauwer obtained his Master's Degree in Engineering at the Vrije Universiteit Brussel in 2011, with a specialization in vehicle and transport technology. He immediately joined the MOBI research group to work on electric and hybrid vehicle technology. Since 2013, Cedric's PhD research was funded by an IWT scholarship and focused on the prediction of energy consumption and driving range of electric vehicles, and energy-efficient routing. He obtained his PhD in 2017 and has since continued to apply his expertise in national and international projects. He is currently focused on the integration of mobility solutions (electric vehicles, autonomous vehicles) into the electricity grid (charging infrastructure, vehicle-to-grid).