35th International Electric Vehicle Symposium and Exhibition (EVS35)
Oslo, Norway, June 11-15, 2022

Vehicle-to-grid strategy for shared autonomous electric vehicles: A review of the charging infrastructure's impacts on energy and mobility

Ona Van den bergh[1], Cedric De Cauwer[1], Lieselot Vanhaverbeke[1]
[1]*Ona Van den bergh (corresponding author) MOBI Research Group,*
Vrije Universiteit Brussel, Pleinlaan 2, 1050 Brussels, Belgium, ona.van.den.bergh@vub.be

Executive Summary

This paper provides a systematic review of studies on charging stations for shared autonomous electric vehicles with implementation of vehicle-to-grid strategies. This review will focus on mobility and grid constraints for the optimization of the charging infrastructure. An evaluation of its impacts on mobility and on the electricity grid will be provided.

Keywords: EV (electric vehicle), autonomous vehicle, car-sharing, V2G (vehicle-to-grid), infrastructure

1 Introduction

Electric vehicles (EVs) and autonomous vehicles (AVs) have gained interest among researchers in the last years due to their potential to reduce oil dependence and greenhouse gas (GHG) emissions of the transportation sector and to increase safety, drivers' comfort and vehicle efficiency. However, large adoption of privately owned AVs may dramatically increase GHG emissions, which is why shared autonomous vehicles (SAVs) are studied [1].

Shared autonomous electric vehicles (SAEVs) are expected to accelerate transportation electrification. The lower operation costs of EVs compared to internal combustion engine (ICE) vehicles will outweigh their current higher purchase cost faster when used in a shared fleet, because of their many miles travelled (unlike privately owned vehicles which are idle 90% of the time). Furthermore, the fact that there is no need for a driver in SAEVs reduces the service cost even more [2], making SAEVs very attractive as a means of transport for customers.

Although the use of EVs might be beneficial in terms of emissions, it presents some challenges. The implementation of charging stations brings down the stability of the electrical grid, because EVs serve as extra load. Moreover, uncontrolled charging of EVs increases peak demand, causing an unbalance in energy demand and supply [3]. Therefore, the charging infrastructure (CI) must be studied and coordinated charging strategies are needed to safely introduce EVs into the grid. Bi-directional, i.e. vehicle-to-grid (V2G), charging is a promising charging technique [4]. With this technique, EVs do not only serve as an extra load, but also as a power source.

A clear overview of both the V2G charging strategy and location analysis for the CI for SAEVs from an energy and mobility point of view is currently missing in the literature. This study undertakes a systematic literature review to address the research question *What are the impacts of charging stations for SAEVs in a V2G context both from an energy and mobility point of view?* The goal of this study is vizualized in Figure 1.

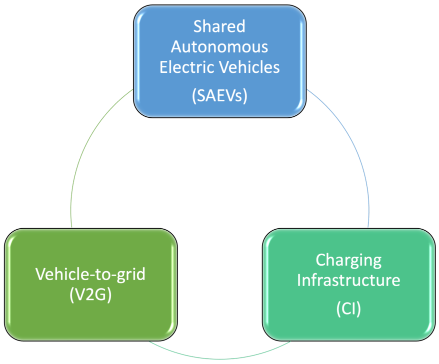


Figure 1: The goal of this systematic literature review is to bring together three coherent aspects that have not yet been jointly researched: SAEVs, the charging infrastructure, and the implementation of V2G.

2 Methodology

2.1 Search strategy

The methodology used for this review is based on the methodological framework from [5]. This study uses the three-stage procedure proposed by [6, p.3] : "(1) Planning stage: objectives; defining sources and procedures for article searches. (2) Review stage: descriptive and structural analysis. (3) Reporting and dissemination stage." In the planning stage, keywords are defined, inclusion and exclusion criteria are developed, and databases are chosen. For this study, we look at papers published after 2014 since the topic of this study is in a fast-evolving domain. Four databases are included: ISI Web of Science, ScienceDirect, Scopus and IEEE Xplore. Keywords that are used are among others "shared autonomous electric vehicles", "vehicle-to-grid" and "charging infrastructure".

First, a synonym search for every keyword is conducted. Looking at the first 50 results in Mendeley, synonyms are chosen (e.g. "bidirectional charging" as a synonym for "vehicle-to-grid charging").

After this, two search strings are built: one for the CI for SAEVs, and one for the CI with V2G. The resulting search strings are respectively *("auto* taxi" OR "auto* car" OR "auto* fleet" OR "auto* vehicle" OR "auto* mobility on demand" OR "driverless" OR "self-driving") AND ("charging infrastructure" OR "charging station* place*" OR "charging station* location*" OR "charging point* place*" OR "charging point* location*")* and *("charging infrastructure" OR "charging station* place*" OR "charging station* location*" OR "charging point* place*" OR "charging point* location*") AND ("vehicle-to-grid" OR "V2G" OR "bidirectional charging" OR "charging-discharging" OR "two-way energy" OR "bidirectional energy flow")*. We want to keep the papers that try to find an optimal CI for SAEVs and for V2G.

The search was conducted in January 2022.

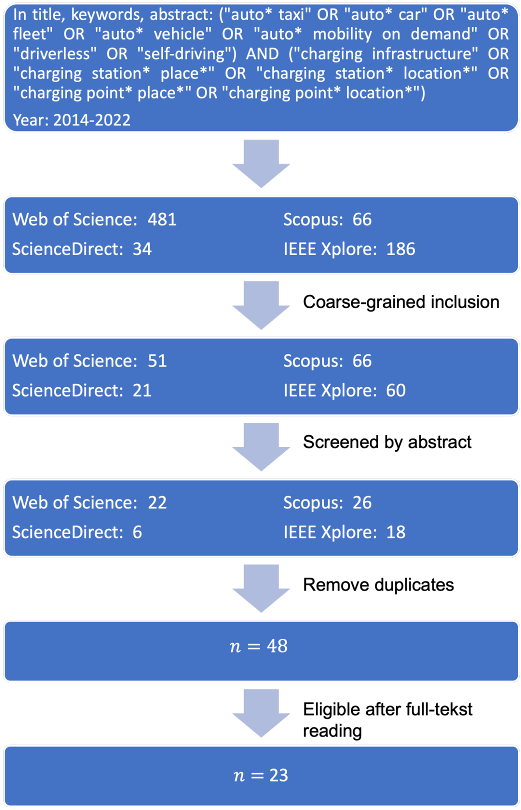
2.2 Results

An overview of the results is presented in Figure 2. The search string for CI for SAEVs delivered 481 results at Web of Science, 34 results at ScienceDirect, 66 results at Scopus, and 186 results at IEEE Xplore. The search string for CI with V2G delivered 237 results at Web of Science, 171 results at ScienceDirect, 290 results at Scopus, and 136 results at IEEE Xplore.

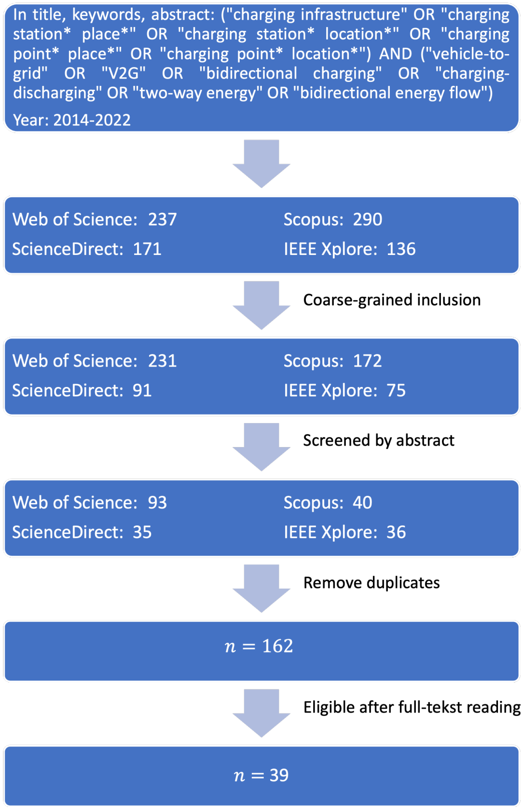
A coarse-grained inclusion is conducted, stopping the search after a sequence of 10 titles incoherent with the subject appeared. The results for the CI for SAEVs is now 51 at Web of Science, 21 at ScienceDirect, 66 at Scopus, and 60 at IEEE Xplore. For the CI with V2G, this is 231 at Web of Science, 91 at ScienceDirect, 172 at Scopus, and 75 at IEEE Xplore.

The remaining papers are screened by abstract, leaving for CI for SAEVs 22 results at Web ofScience, 6 results at ScienceDirect, 26 at Scopus, and 18 at IEEE Xplore. For CI with V2G, the screening of the abstracts leaves us with 93 results at Web of Science, 35 at ScienceDirect, 40 at Scopus, and 36 at IEEE Xplore.

After removing duplicate papers from the collection, there are 48 papers left about CI for SAEVs, and 162 papers about CI with V2G.



(a) Charging infrastructure for SAEVs



(b) Charging infrastructure with V2G

Figure 2: Overview of the search for papers about charging infrastructure for SAEVs and about charging infrastructure with implementation of V2G.

Finally a fine-grained-inclusion is conducted, leaving only the papers that are eligible after full-text-reading. There are 23 papers left discussing the optimal CI for SAEVs, and there are 39 papers left discussing (impacts of) the optimal CI with implementation of V2G.

The high reduction in number of V2G papers is due to the following reasons. In many cases, charge scheduling was optimized instead of CI. Those papers usually considered the grid constraints for charge scheduling, but CI was already fixed. Other papers only considered battery swap stations, which is also not the focus of this study. Another large part of the papers discussed many aspects of V2G, such as a safe communication between the EVs and the aggregator, a detailed construction of a V2G enabled charging station, ... but not the CI. Other papers considered separate energy storage systems, instead of using EVs as energy storage. We thus conclude that - to the best of our knowledge - there has not been many research conducted on optimal CI with V2G implementation or on the impact of the CI with respect to the V2G strategy.

3 Motivation for SAEVs and V2G

Due to climate change, the current goal for many countries is to reduce greenhouse gas (GHG) emissions. Therefore in the future, a shift in means of transport is important. In 2014 the transport sector was responsible for 23% of global energy-related CO2 emissions. For this reason, the mobility must be evaluated towards an electrically driven system. The autonomy of vehicles can also help reduce emissions, because AVs drive more efficiently. Furthermore it is important that these AVs are shared, because otherwise vehicle automation could lead to more congestion, more kilometers travelled, more energy consumption, and more emissions [7]. Finally, if a SAEV fleet is owned and operated by a central company instead of by individuals, the SAEV's charging scheme is more flexible. This enables charging to be more dispersed throughout the day and this makes it possible to take part in specific charging technologies, such as V2G charging, which is explained later in this section.

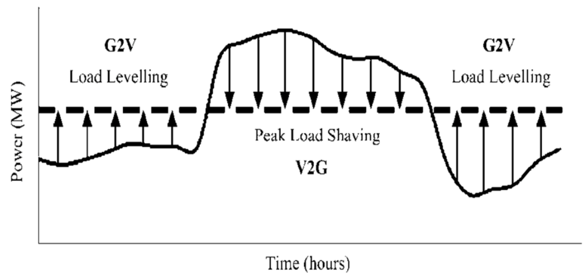


Figure 3: Peak-load shaving and load-levelling [10]

Shifting to an electrically driven transport system is not enough to reduce GHG emissions. At least as important is a transition to clean energy. To reach this goal, a larger share of the energy should come from renewable energy sources (RES). Next to RES's ability to reduce GHG emissions, another great advantage is that RES's can be placed anywhere near charging stations, reducing transmission losses, voltage fluctuations, and transmission cost [8]. However the problem with RES's is that it depends on nature conditions, thus it is not consistent and thereby not reliable [9]. In addition, the peak energy generated by renewable energy sources does not correspond to the peak in energy demand [8, 10]. This asymmetry of energy supply and energy demand may lead to an unbalanced grid.

A balanced power grid is important, because heavy energy waste can occur due to daily load demand fluctuations and regulation of voltage and frequency from the grid. An unbalanced grid can occur in two directions. Firstly, there can be too much electricity for a low power demand. In this case, the electrical frequency increases. Since power plants are designed to work within a certain frequency range, there is a risk that they will disconnect from the grid after a period of time. Secondly, there can be a too high power demand, with low energy availability. In this case, the frequency drops. If the frequency falls too low, the power plants switch off and a power blackout will occur [11, 12].

Controlled use of V2G charging strategy could enable EVs to help balancing the grid. V2G is a technology where energy flows from a vehicle back to the power grid. The EV acts as a movable storage of electrical energy, a battery on wheels one may say. Acting as storage systems, EVs can provide ancillary services to the grid to maintain voltage and frequency stability, such as power grid regulation and acting as spinning reserve (a quick response to the required needs) [10]. Power grid regulation can happen by providing regulation up/down to stabilize the frequency. When the grid experiences overvoltage, vehicles will start charging to keep the voltage within the acceptable limits. This is referred to as voltage down regulation. When vehicles give back energy to the grid, this is referred to as voltage up regulation and typically occurs during peak load hours [13]. Using the V2G technology, EVs can absorb the energy in periods of high electricity penetration and feed electricity back into the grid in situations of insufficient electricity generation [10]. Thereby, EVs can deliver active power support by flattening the grid load profile. This is done by peak-load shaving (sending power back to the grid when demand is high) and valley-filling/load-levelling (charging when demand is low), see Figure 3 [11, 14]. According to Guo et al. [15], the current electricity grid of California would need no update to be capable to serve power demand of 2 million PEVs, given that V2G integration is enabled and fully practiced. Kontic et al. [16] showed that is is possible to reduce peak power by more than 12% by utilizing EVs. All of the above enables EVs to balance the grid, and thus making a larger integration of RES's possible. Next to bringing advantage to the grid, V2G also gives rise to an economical benefit for EV owners. During off-peak demand hours, the EV can purchase energy at a lower price from the grid and store this energy. During peak-demand hours, the EV can sell its electrical energy to the grid at a higher price. Savings up to 227$ per year per vehicle in power network cost can be achieved with smart charging as compared with simple uncontrolled charging [17]. An overview of the values of V2G, which have been discussed in this section, is shown in Figure 6b.

EVs are the perfect tool to serve auxiliary services to the grid, because they are used by their owner for only a small amount of time during the day. Individually owned vehicles are idle 83% [11] or even 90-95% [9] of the time. That means they are free the rest of the time to serve in the V2G system. However, V2G also brings challenges. When participating in V2G, the constant charging and discharging increases the cycles the battery makes, resulting in a shorter battery life [10, 18].

Despite all the contributions EVs might have to the grid via V2G, the large-scale implementation of EVs could have adverse effects, such as voltage drops, frequency variations, non-desired load peaks, an increase in energy losses, overload on grid components, load factor reduction, and power quality issues [10, 19, 20, 8, 17]. According to Deb et al. [21], many problems (such as the degradation of voltage

stability and reliability indices and increased power losses) are actually a result of poor allocation of EV charging stations (CS) in the distribution network. Therefore it is important to take the power grid network into account when positioning CSs, which is usually neglected.
Up to now, optimization of CI for SAEVs is mostly done out of a mobility point of view, minimizing waiting times for passengers and maximizing service quality. Yet grid constraints or impacts are seldom checked [22]. Deb et al. [23] optimize the location for charging stations for individually owned EVs both looking at mobility and at grid constraints and impacts. However, research on CI for privately owned EVs is not always helpful since infrastructure needed for SAEVs may be substantially different from private individual EVs [2]. In the following section, an overview is presented of the point of view the reviewed papers take finding an optimal location for the CI.

4 Optimal charging infrastructure for SAEVs

Some papers that are reviewed in this literature review will solve the allocation problem using simulation (section 4.1), other papers use heuristics (section 4.2), and others will solve an optimization problem (section 4.3). A classification is shown in Figure 4a. (When one paper performs two separate strategies, both strategies are included as input for this bar chart. This is why the total considered in the bar chart is higher than 23.) When solving an optimization problem, different objective functions can be defined (section 4.3.1) and different constraints can be taken into account (section 4.3.2). All of them are discussed and summarized in appendix A.

4.1 Simulation

Some researchers place their charging stations using an agent-based model. Whenever a charging demand pops up, and there is no CS for the SAEV to reach with its remaining battery range, a new CS is generated at the location of the charging demand. This type of CS siting mimics the objective of a coverage model. [24, 25].

4.2 Heuristic placement

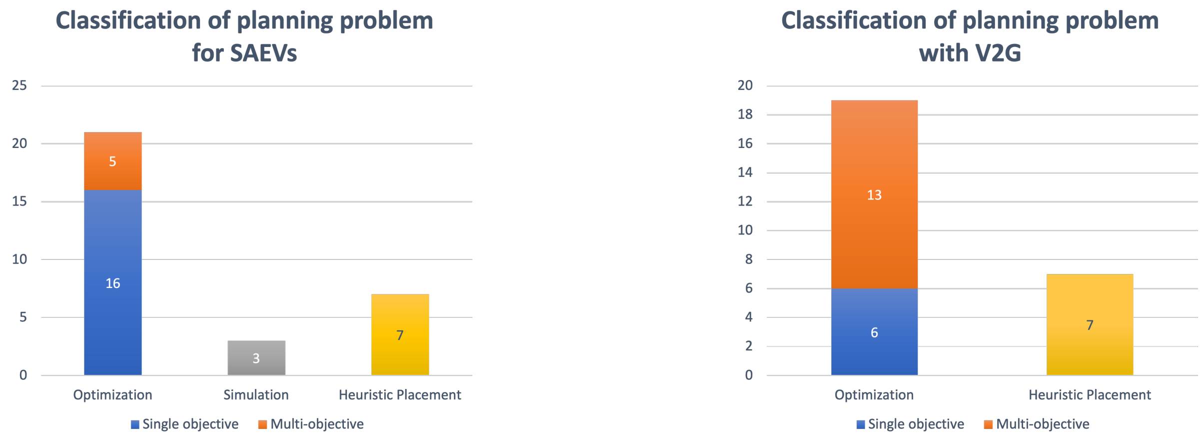
A heuristic placement is also a method used by some researchers to find optimal locations for CS's. Cocca et al. [26] compare the heuristic placement with a likelihood based on three different definitions: average parking time, total number of parking events, and random placement. They find that placing CSs at the parkings with the largest average parking time performed the worst of the three heuristics, followed by the random placement. Placing CSs at those parkings with the highest number of parking events, even for low duration, performed the best in terms of customers' comfort and system installation cost.
Funke et al. [27] investigate the economic profitability of an optimal CI exclusively built for e-taxi's in Karlsruhe, Germany. They rank the charging sites by taxi arrival rate and place a CS at the taxi stand with the highest rate and find that only half of the taxi stands need to be equipped with chargers to reach an electrification rate of 40%.
Cai et al. [28] use heuristics to expand some gas stations as charging stations. The likelihood of the gas stations is based on three heuristics: number of parking events within 1 mile of the gas station, the average vehicle-hour per day, and the average vehicle-hour per vehicle. They conclude that gas stations with the most parking events and daily vehicle-hours are concentrated in the center of the city while gas stations with the highest vehicle-hour per vehicle are located in the suburb. Their CI rollout located at gas stations with maximum total number of parking events can reach an electrification rate that is 37% higher than with the existing charging stations.

4.3 Optimization problem

In contrast to authors that opt for simulation or heuristic placement as a method to optimally locate charging stations, most of the researchers choose to solve a mathematical optimization problem.When solving an optimization problem, an objective function is minimized/maximized, subject to a series of constraints. Most of the time, the cost or customer convenience is respectively minimized or maximized. In very few cases, the power grid is also considered. This can happen in the objective function or in the constraints or both. The different objective functions and constraints, both from a mobility and energy point of view, are discussed in the following paragraphs.

4.3.1 Objective function

The objective functions that are used can be divided into three large groups. The first group of objective functions is the cost. In this group belong the papers that minimize infrastructure cost [29, 30, 31], fleet



(a) SAEV papers

(b) V2G papers

Figure 4: A classification of the methodologies used for the charging infrastructure allocation problem.

cost [32], or a combination of infrastructure and fleet cost [33, 34]. Infrastructure costs can include the construction cost to build CSs, but also the maintenance cost, and the cost that needs to be payed to use the space. Fleet cost can include purchase cost, operation cost, and mainenance cost of the vehicle.

The second group is customer convenience. In this group belong the papers that minimize the distance between CSs and customers [29, 35], maximize the number of satisfied requests [36], or minimize waiting time or total charging time [37].

The third group is all about coverage. Here belong the papers that solve a maximal coverage problem, where they try to cover a certain area with CSs as well as possible. This area can be geographical, in that case mobility is not considered. But this area can also be a series of pick-up and drop-off points based on mobility demand [38]. In that case, mobility is considered.

4.3.2 Constraints

Most constraints that are included are there to make sure that the model works. Some constraints are vehicle routing constraints, among which flow conservation is an important constraint [36, 33, 31, 39]. Constraints considering the vehicle's battery must also be involved, for example charging of the battery cannot exceed battery capacity, and a vehicle cannot continue serving trips when the State of Charge (SOC) is 0% [40, 30]. Other constraints considering the battery, can be that the vehicle's battery needs to be charged again to a certain level at the end of the the day. Some want a full battery, with a SOC of 100%, like [40, 31]. Others want the SOC in the final time to be identical to the SOC in the initial time, to ensure periodicity, like [32, 30]. Mohamed et al. [30] use the just appointed constraint to ensure charge-sustaining operation. A series of constraints can be bundled to control the energy level of vehicles [33].

Another sort of constraints are the ones considering mobility demand. Usually, one insists that all mobility demand must be served [32, 31, 34, 40]. Or one puts a maximum [41] or penalty [33] on rejection.

In very few cases, grid constraints are considered. Network flow models minimize fleet travel and electricity cost subject to among others charging constraints imposed by congestion on the power grid. Luke et al. [32] enforce consistency and flow conservation in the network flow problem. Although this is not a detailed look on the constraints of the grid, it is one of the very few papers that cares to consider the grid.

When the cost is not minimized in the objective function, there's a need to consider budget restrictions. If not, then the optimal CI from a mobility point of view would be to place a charging station at every corner of every street. Budget restrictions can be in the form of enforcing the total cost to be under a maximal imposed budget [37], or by fixing the number of CSs in advance [36, 35, 38].

5 Optimal charging infrastructure with V2G

Some papers that are reviewed in this literature review will solve the allocation problem using heuristics (section 5.1), and others will solve an optimization problem (section 5.2). A classification is shown in Figure 4b. Not all V2G papers included in this review optimized the CI. Some papers only discussed relevant impacts. Therefore, the total amount of papers in the bar charts (= 26) is less than the number of papers included in this review (= 39). When solving an optimization problem, different objective function can be defined (section 5.2.1) and different constraints can be taken into account (section 5.2.2). All of them are discussed and summarized in appendix B.

5.1 Heuristic placement

Some papers use heuristics to place CSs. These heuristics can be clearly divided into three groups. The first group focuses on mobility. CSs can be placed at locations with high vehicle density [42], based on the likelihood of being at a certain location [43], at locations with the highest dwelling time [44], or at locations with high energy demand [45]. The second group focuses on energy aspects, where CSs are located at strong buses, defined as buses with a high voltage stability index [46], or as buses with a high bus reliability index [47]. Finally, one reviewed paper considers both mobility and energy aspects, added with a social aspect, placing CSs at the geographic overlap of area's with solar excess generation, high convenience and accessibility for EV drivers, and a low crime index [48].

5.2 Optimization problem

As in the papers on SAEVs, also in the V2G papers is the location of CSs found by solving an optimization problem.

5.2.1 Objective function

The objective functions used for optimally locating V2G enabled CSs can be divided into three groups. The first and largest group takes an economical look at the problem. Some papers maximize the total revenue or income from the aggregator [49, 50, 51, 52], other papers minimize cost such as investment, operational, and maintenance costs [53, 54, 55, 51, 56], and other papers maximize benefit [57, 58, 59]. Many benefits are included, such as the benefit of daytime charging, benefit from discharging, benefit from reduced cost of purchased energy, benefit from reducing active power loss, ... But also costs are subtracted from this benefit, such as investment costs, operational costs, and maintenance costs. It can be seen that maximizing revenue, minimizing cost, and maximizing benefits all mean more or less the same.

Another group of papers looks at grid aspects when optimizing the locations of CSs. They minimize the negative impacts on the grid, such as power losses, voltage deviation, and thermal line loading [53, 60, 61, 55, 62, 63].

A third small group, in this literature review only one paper, takes a mobility point of view in their objective function, by maximizing traffic flow captured [55].

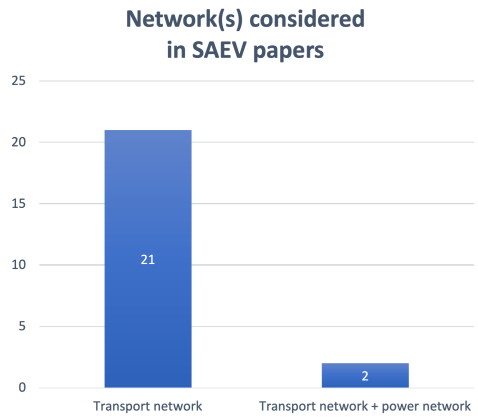
5.2.2 Constraints

The constraints that are taken into account in the optimization problems are almost in all papers the same. The most important and most frequently used constraints are grid constraints. One that always returns is the limited range of the voltage profile, which is usually between 0.95 ppu and 1.05 ppu [53, 60, 61, 64, 54, 57, 55, 47, 51, 58, 65, 52, 62, 66, 56, 67, 63]. Other grid related constraints are imposing a maximum capacity on distribution lines by imposing power flow constraints or thermal constraints [53, 60, 61, 57, 58, 65, 66, 64, 55, 49, 51, 52, 62, 56, 63], and CS capacity constraints [64, 57, 55, 47, 49, 50, 51, 58, 56, 63].

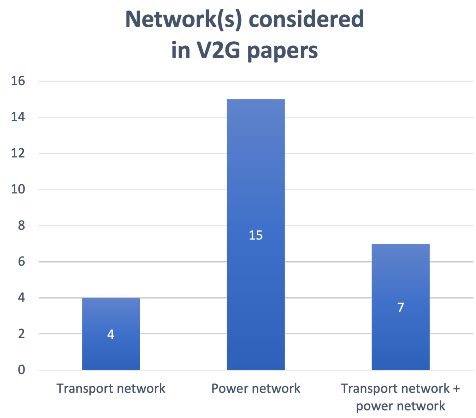
Another type of constraints are the ones to make sure the model works, such as power flow equations and demand-supply balance [53, 61, 55, 65, 52, 66, 56, 63],

As explained in section 3, V2G is mainly introduced to enable a larger integration of renewable energy. There are also constraints imposed on RESs, such as limited capacity and generation of RES [61, 57, 49, 58, 65, 66]

A final type of constraints focus on the EVs, such as limits on EV battery storage systems [61, 54, 59, 63], and limited input/output power of EVs [54, 59, 52, 66].



(a) SAEV papers



(b) V2G papers

Figure 5: Partition of papers based on the network(s) they consider.

6 Point of view

In optimization problems, when the grid is included in either the objective function or the constraints, we will say that an energy point of view is taken. When mobility is included in either the objective function or the constraints, we say that a mobility point of view is taken. It is possible that both points of view are taken, when both the grid and mobility are included in the objective function and/or the constraints. In simulations, none of the papers reviewed in this study take an energy point of view, and the mobility point of view is taken when the simulation is based on mobility demand/driver's behaviour. For heuristic placement, the mobility point of view is taken when driver's behaviour is taken into account. The energy point of view is taken when the grid is taken into account. None of those points of view is taken when the heuristic placement is purely based on geographical features. The partition of networks considered is shown in Figure 5. We see that for the allocation of CSs for SAEVs, almost all papers solve the allocation problem from an exclusively mobility perspective. Only 2 papers out of 23 consider the grid along with mobility constraints. For allocating CI with V2G, we see the opposite appear. The majority of the papers only consider the power network. Some papers consider both the transport and power network, and there are only few papers that do not consider the grid.

7 Results

In this section, the results and findings of the reviewed papers will be discussed. First we will take a look at the impact of SAEVs and at some CI effects. Then we will look at the impact of V2G and some CI effects that might affect the V2G potential.

7.1 Impact of SAEVs

A SAEV fleet has an impact on many levels. Some of the impacts represent values of a SAEV fleet, some impacts represent challenges. An overview of the values of a SAEV fleet is presented in Figure 6a.

7.1.1 Travel behaviour

An aspect that SAEVs have a major impact on is travel behaviour. The first in this category is vehicle replacement. The literature mentions a replacement of conventional vehicles by 67% to 91%, depending on vehicle range and level of charging [7, 24, 40]. Lokhandwala et al. [37] compared autonomous taxi's without ride-sharing with autonomous shared taxi's in New York City. They found that ride-sharing reduces the taxi fleet with 59%, going from 13,500 conventional taxi cabs without sharing to 5500 autonomous shared taxis serving the same amount of travellers.
Another aspect in the category of travel behaviour is vehicle kilometer/miles travelled (VKT/VMT). In general when private vehicles are replaced by SAEVs, an increase in VKT is expected. This is because SAEVs will spend some time travelling empty, e.g. when they are finding a charging station or when they are relocating [24, 38]. An additional 7.1% to 14% of travel miles is generated due to this empty travelling [24]. Longer-range vehicles spend more of their empty VMT for passenger pick-up while shorter-range vehicles spend more of their empty VMT for relocation [24]. Loeb et al. [68] found that

empty travel accounted for 19.8% of VKT, where 23% of all empty travelling is for driving to CSs. Luke et al. [32] found that their optimal station siting could reduce VMT by 11.20% compared to a scale-up of the present day station siting. This means that the increase in VMT can be partly countered by optimal charging station siting in San Francisco. Besides, also the in-vehicle passenger kilometer travelled (PKT) decreases when deploying SAEVs instead of SAVs, indicating a reduction in service performance [38]. However, next to these negative aspects, ride-sharing reduces the total travel distance [37].

7.1.2 Fleet cost

SAEVs also have an economical impact. A SAEV fleet is associated with a great reduction in the total cost of ownership. The first reason for this reduction is the lower operation costs for electric vehicles compared to gasoline vehicles. The second reason for this reduction is that there is no need for a chauffeur that needs to be payed. Sheppard et al. [7] found a reduction in total fleet cost of 74% compared to gasoline vehicles. Bauer et al. [25] found that the operation cost for a SAEV fleet is about 10 times lower than for present-day Manhattan taxis. When comparing to an automated fleet of conventional vehicles, they found a cost reduction of $0.05-0.08 per mile. Luke et al. [32] propose a framework for an electric autonomous mobility-on-demand fleet, which can reduce the total cost (incured by the E-AMoD operator, the peak charging load, and the empty-vehicle distance travelled) by 10%. Their framework can also lower the charging station procurement by more than 30%. These two number are savings compared to a baseline station siting based on a scale-up of the present station siting.

7.1.3 Environment

Another great impact of SAEVs, is the one on the environment. There is less energy consumption and lower emissions with an electric fleet. A SAEV fleet would reduce GHG emissions by 70-73% and energy consumption by 58% compared privately owned conventional vehicles [7, 25]. Bauer et al. [25] are convinced that by 2030 a SAEV fleet could reduce emission per mile with more than 90% compared to privately owned conventional vehicles. Zhang et al. [69] find that AEVs reduce CO2 emissions by more than 75%. Lokhandwala et al. [37] agree to this high percentage, finding that AVs can reduce CO2 emissions by 9% because of efficient driving. EV adoption further reduces CO2 emissions by 74%. Miao et al. [70] however find a much smaller percentage, saying AEVs only reduce CO2 emissions by 42% compared to fuel vehicles. Cai et al. [28] present an even worse result. They perform a case study in Beijing and find an increase in electrification rate accompanied with an increase in CO2 emissions. The reason for this is that Beijing's electricity is for 98% generated by coal. Luke et al. [32] found that with their optimal CI, energy consumption was reduced by 4.08% due to the lower VMT compared to with a scale-up of the present day station siting in San Francisco.

7.1.4 Charging infrastructure

The use of SAEVs has some effects on the needed CI. The first aspect is the size of the CI. Ride-sharing reduces the number of chargers needed [40]. The second aspect is the level of charging. Sheppard et al. [40] found that urban regions can be satisfied by lower-power chargers, while rural regions often require fast chargers. Funke et al. [27] found that fast-charging infrastructure is necessary for electric taxi driving, due to their high daily VKT.

7.1.5 The power grid

Due to their flexibility in terms of charging scheme, SAEVs can have a great positive impact on the power grid. For example Luke et al. [32] model an electric mobility-on-demand fleet such that charging during the highest price period from 4pm to 9pm can be completely avoided. The fleet's peak charging occurs during the lowest price period from 9am to 2pm. Sheppard et al. [7] find that SAEV fleet can provide a reduction in peak load by 47% compared to a private fleet with uncontrolled charging. According to Chen et al. [24] longe range SAEVs (with a 200-mile range) equipped with a fast-charging scheme is the best scenario for spreading out charging demand across the day, with a maximum of 7.46% of vehicles in the fleet concurrently charging during any time step, compared to as many as 52.6% of the vehicle fleet concurrently charging in the base SAEV scenario (80-mile range SAEVs with a level II charging scheme). However, Cai et all. [28] find that fast public charging results in a more significant load shock (160 MW) comparing to slow public charging (40 MW) for 40 charging stations. This indicates that charging time management is needed when deploying fast public charging stations. Luke et al. [32] proof that CI can have an impact on the power grid. The compare their optimal CI to a scale-up of the present day station siting in San Francisco and find a reduction of peak charging load by 10.07%, a result of the lower VMT and thereby lower energy consumption.

7.2 Effects explored in SAEV papers

7.2.1 Battery range

Zhao et al. [71] find that increasing the battery range from 100km to 400km leads to less CSs needed. Also Loeb et al. [68] find that the number of stations is highly dependent on vehicle range, calling for 222 stations for a 409-vehicle fleet with 100-km ranges, but just 5 to 6 stations needed for the same size fleet with 325-km ranges. Zhang et al. [69] find a higher utilization level of CSs as a result of higher battery range. However, according to Chen et al. [24] the number of charging sites does not change with the vehicle's electric range, but is more determined by the city's geographical area. Though the total number of charging ports is highly sensitive to charge time and vehicle range. Increasing vehicle range from 80 miles to 200 miles, the number of chargers needed decreases with 45.0% (using level II chargers) and with 85.6% (using level III chargers). Battery range also has an effect on fleet size. Increasing the range from 80 miles to 200 miles reduces the fleet size by 28.1% and 19.5% for level II and level III charging schemes respectively. Funke et all. [27] investigate the electrifiable part of the taxi fleet to be economically profitable with the accompanying optimal CI rollout. They find that the combination of very high vehicle ranges and a medium to high availability of CI is necessary for high electrification shares above 40%. E-taxi's with ranges below 300 km might only be interesting if operated very locally.

Next to the number of CSs, battery range also influences the waiting times for customers to be picked up by a vehicle, and thus the service performance. A higher battery range results in lower waiting times [71] and a higher service performance [38]. However according to Loeb et al. [68] this would only be the case when charging time is very long (4 hours). Moreover for ranges higher than 175km, an increase in battery range no longer improves response times, even when the number of CSs is fixed. Besides, as vehicle ranges rise, CSs become scarce, resulting in higher VKT/VMT, which is a negative effect. Miao et al. [70] also find the similar results that a higher battery range means a longer vehicle travel distance.

Finally, a higher battery range could also save costs. First of all, with higher battery ranges, a lower fleet size is needed [71, 33, 70]. Next to that, the cost will drop due to reduced vehicle usage [33] and less recharging activities [70]. Ma et al. [33] find a battery capacity of 35 kWh to be the most economical, which incurs the least cost. However Zhang et al. [69] find a 60 kWh battery capacity to lead to the lowest cost. They include passengers' time cost, which lowers with higher battery capacity because AEVs will charge less on the road.

7.2.2 Fleet size

Increasing the fleet size improves service performance by lowering waiting times [71, 68] and increasing the number of satisfied requests [36, 69]. Loeb et al. [68] find that a fleet (150-km range with 30-min charge times) with 10 travellers per vehicle resulted in an average response time of 41.6 min, while a fleet of 7 or 3 travellers per vehicle resulted in an average response time of only 6.52 min and 2.16 min respectively.

Zhang et al. [69] find that with a higher fleet size, less CSs are needed. However, according to Loeb et al. [68] fleet size does not appear to correlate with number of CSs generated. Finally Zhang et al. [69] find that when fleet size increases, AEVs utilization level reduces and with a low fleet size, there are more empty VMT.

7.2.3 Charge power of charging stations

Many papers find as a results that a higher power level means that there are less CSs needed [24, 41, 71, 69]. Chen et al. [24] find that the total number of charging ports is highly sensitive to charge time. Using level III chargers cuts the charge times by 87.5% and thus the number of chargers needed by 45.2% for SAEVs with a range of 80 miles and by 85.6% for SAEVs with a range of 200 miles. However Loeb et al. [68] do not find charging time to influence the number of CSs generated.

Moreover, charge power also has an impact on fleet size. Switching from level II chargers to level III chargers reduced the fleet size by 30.9% for 80-mile range SAEVs and by 23.3% for 200-mile range SAEVs [24].

Also, when the power increases, a same charger can satisfy more demands and the average charging time will be lowered. Faster charging thus results in lower waiting times and thus higher service performance [31, 71, 70, 68]. Loeb et al. [68] find that response times increase approximately exponentially for charging times longer than 90 minutes. Reducing charge time (and thus increasing charge power) from 4 hours to 90 minutes for a fleet with 150-km range and 5 travellers per vehicle, resulted in an average response time of 4.25 min instead of 9.40 min. Miao et al. [70] find that faster charging results in lower charging waiting delay and lower charging waiting events. They conclude that charging speed does not influence charging behaviour frequency, but it can make the occurrence of daily charging behaviours more stable. A higher charging power can impose extra load on the power grid. Higher power means that AEVs drive and charge more and this results in a higher charging demand [69].

Vosooghi et al. [38] finally find that with increasing the charge power from 22kW to 43kW, the empty distance ratio increases. This is because the vehicle drives and charges more, and thus spends more time relocating and driving to CSs.

7.2.4 Number of CSs

In some papers, the number of CSs is fixed on beforehand instead of serving as a decision variable. In that case, this number can have an impact as well. [38] looks at the impact of the variation of units at each charging station. They conclude that by increasing the number of outlets per CS, the charging waiting times decrease.

7.3 Impact of V2G

The V2G charging strategy has various positive impacts. An overview of the values of V2G is shown in Figure 6b.

7.3.1 Ancillary services

The first main contribution of V2G is enabling EVs to provide ancillary services to the grid. Under these services, we understand voltage and frequency regulation, and peak-shaving. One of the results of these ancillary services is an improved voltage profile, found by [72, 53, 64, 54, 57, 46, 58, 59, 65, 62, 66, 56, 63]. The improved voltage profile is a result of V2G, but also a results of optimally locating charging stations. Ma et al. [72] found that nodal voltage deviation is related to EV permeability, node location and node type. The nodal voltage deviation increases when EV permeability increases. Nodes further away from power supply are more easily affected by EV charging load, as there is a bigger difference between rated voltage and actual voltage. Next to the voltage profile, also the net power flow stays within acceptable range with coordinated charging [49].
Another result of ancillary services is a flattened load profile. V2G enables a reduction in net peak demand [73, 57, 74, 67, 75], because a portion of the load is provided by EV discharging. Bibak et al. [76] find that V2G has the ability of peak-shaving and valley-filling and thus assuring a better reliability of the grid. However, according to Tarroja et al. [44], V2G is unable to level the load profile to the same extent as stationary energy storages (SESs). This is because the V2G strategy is still constrained by consumer travel patterns. The vehicles cannot completely discharge to respond to a grid event, because they always need to save enough battery for their next scheduled trip. Also, the variability of the number of vehicles available for V2G is another constraint that SESs don't have.

7.3.2 Power loss reduction

Aljanad et al. [60] say that in general, the injected phase current in the V2G mode brings thermal effects in the distribution lines, which results as losses. Bilal et al. [53] also find that the even optimal CS placement increases power loss and disturbs the voltage profile in electrical power networks, even though EVCS are positioned near to the substation bus. The optimal placement of capacitors after CSs improves power loss and voltage profile. EV participation in V2G further decreases active power loss and improves the voltage profile. The reduction in power losses is confirmed by [64, 57, 46, 59, 65, 62, 66, 56, 67, 63]. The reduction in power loss is not only a result of V2G, but also of optimally locating the CSs.

7.3.3 Renewable share

Tarroja et al. [44] investigated the possible share of renewable energy with the use of the V2G strategy and compared this to other charging strategies. Depending on vehicle penetration, renewable penetrations between 60% and 75% are reached. With higher vehicle penetration goes a lower renewable penetration, because in this study renewable capacity is fixed and higher penetration of vehicles indicates a larger electric load. V2G achieves the highest renewable energy utilization, followed by SES, then followed by smart charging without energy storage (ES). V2G reaches renewable energy utilization very close to the ideal ES case. The ideal ES case refers to a SES system with no losses, 100% round trip efficiency. Such a system is impossible in reality, but serves as an upper bound check to evaluate the performance of V2G. V2G charging achieves 73% renewable penetration, less than 1% lower than the ideal ES case. With achieving the highest renewable energy utilization, goes producing the lowest GHG emissions. Also Aunedi et al [73] find that V2G reduces carbon emissions due to better integration of renewable generation.

7.3.4 Cost

V2G can lead to a reduction in costs thanks to charging during off-peak hours, when energy prices are low, and discharging during peak hours, when energy prices are high. Next to that, discharging actions also reduce net peak demand and thereby reduce the energy generation cost. Finally, operational costs are reduced because the EV fleet displaces 50% of frequency regulation that would otherwise be served by less efficient thermal generators [66, 73]. Rajamand et al. [54] agree with these findings and find a reduction of 10.54% in energy costs compared to no existance of EV charging parks (EVCP) in the microgrid. However non-optimal location of the EVCP leads to energy cost increasing. Hajidavallo et al. [74] find cost savings of 52% with V2G compared to uncontrolled charging. And finally also Fahmy et al. [77] find that the profit for a parking owner is highest when the parking rooftop is equipped with solar panels and when V2G feature is allowed. The parking owner's profit is the lowest when the parking is only connected to the grid.

7.4 Effects explored in V2G papers

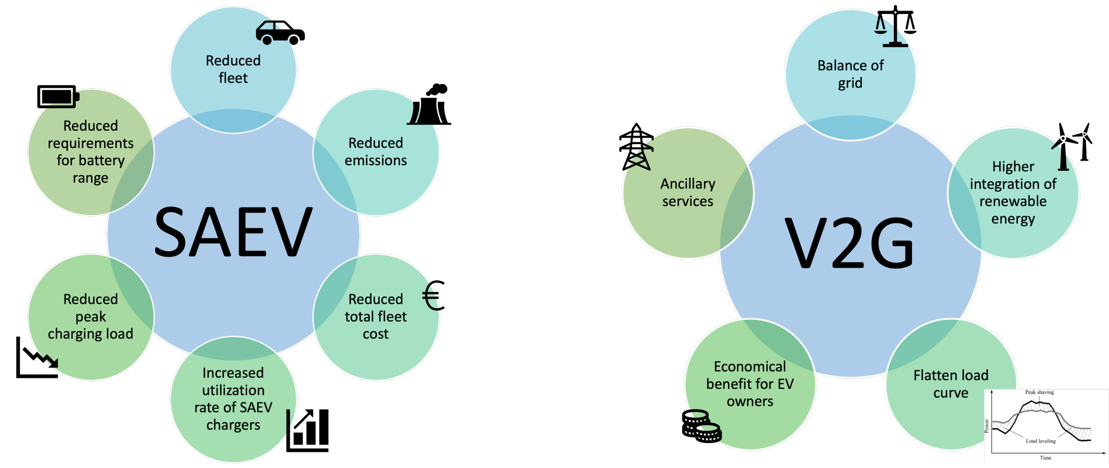
There are some aspects explored in the papers reviewed in this study that have an effect on the efficiency of V2G. The first aspect is when there is a limitation on CI (in number of charging ports or in location), and the second aspect is when CI occurs as a central charging hub or in distributed CSs.

7.4.1 Charging infrastructure availability

Kong et al. [78] find that V2G can only be feasible in the case that there is sufficient CI to meet the primary charging needs of EVs, which is their transportation function. Once this critical point is met, higher availability of CI enables more flexibility for V2G purposes. Fewer charging ports reduce the ESS capacity and the potential power flow from V2G. Next to that, power flow constraints can also limit V2G potential, because low power flow capabilities limit the rate at witch power is injected by EVs into the grid. There is a an interaction between available charging ports and power flow constraints, as higher power flow reduces the time a ESS needs to be connected to the grid and thereby reduces the number of charging ports needed. The feasibility of V2G is thus highly dependent on the rate of power injection from EVs.
Tarroja et al. [44] investigated the location where CSs are build, being residential area's or workplace area's. They find that restricting the V2G charging to residences has a negative impact on the potential of V2G. For example this would reduce the renewable penetration with 12.4%, because removing the workplace chargers limits the possibility for EVs to absorb solar power during the day. With this, also GHG emissions increase when CSs are limited to residences only. The feasibility of V2G is thus dependent on the locations where CSs are built. Moreover, Taljegard et al. [79] find that the V2G potential is overestimated when CSs are restricted to home-charging only, when using aggregated (AGG) vehicle profiles ("AGG uses the values averaged from the measured individual vehicles" [79, p. 4]). They say that this results for example in an overestimation of approximately a 10 percentage point in renewable energy share. With this, they confirm the finding in [44] that restricting CSs to home locations would negatively impact the V2G potential. Contradictory to this, Bibak et al. [76] find that charging at home with V2G charging flattens the demand profile, having a positive impact on the reliability of the system, more than charging everywhere else. This is because EVs are available at home during the night until the morning.
Mills et al. [80] find that, with respect to transport energy requirement (TER), the availability of V2G CSs is far more important than the charging rate. They find that implementation of off-street CI reduces the peak TER by more than half compared to only residential CI. Also in terms of distributed energy resources (DER) is CI more influential than charging rate. The benefit of extra CI is the strongest during the middle of the day, when the battery capacity available for discharge is 30% higher. They conclude that non-residential CI is necessary for enabling EV flexibility and DER potential during the day.

7.4.2 Charging hubs or distributed CSs

Strickland et al. [81] take as starting point a car-park as a base for V2G services. They do not search optimal scattered locations for CS, but they take a central hub to investigate its feasibility to serve as an ES and grid balancing solution. They conclude that it would take 20 years for investment costs of the infrastructure to be payed back by the income from a large-scale V2G scheme. Thus charging in a central hub would not be economically beneficial.
Sachan et al. [82] compared distributed CI (with V2G) with fast-charging infrastructure (gathered together like a gas station) and with battery swapping (also gathered together). They find that distributed CSs have the highest potential to provide regulating power. The consumption of distributed CSs is higher at night, while the consumption of the other two strategies is higher during the day. The average consumption of fast charging is the highest. A distributed CI has the highest capacity and connection to the grid, and thus has the most potential to provide peak power and system services like V2G.



(a) Values of SAEVs

(b) Values of V2G

Figure 6: Overview of the values for SAEVs and for V2G.

8 Challenges

To the best of our knowledge, no research has yet been done on optimizing a CI for SAEVs with the implementation of V2G, taking into account both the constraints from mobility and from the electricity grid.

The biggest challenges to filling this research gap are twofold. First, it is difficult to implement the link between the transport network and the power network. The transport network influences the routes of the SAEVs, which influences the locations where demand for charging will occur. This affects the placement of charging stations, which affects the power grid. The power grid is experiencing increased demand for electricity in certain places, which affects prices. As a result, SAEVs may choose a different place to load, which in turn changes the routes of the SAEVs.

In addition, it is also a challenge to reflect reality. In the papers reviewed, a simplified version is usually used, where all SAEVs have the same battery capacity and where all charging stations offer the same level of charging and/or have the same amount of charging ports per CS. Implementing a heterogeneous fleet and CI is therefore still a challenge.

9 Conclusion

This paper reviews the literature on CI for SAEVs and CI with V2G. First, we conclude that many papers on V2G optimize the charge schedules in order to minimize negative grid impacts, but they rarely optimize the locations of the CI. Thereby many papers were not useful for this review. When looking at the point of perspective of the papers, being a focus on the transport network and/or on the power network, we notice a difference between the papers about SAEVs and the papers on V2G. Papers that discuss optimal CI for SAEVs usually take a mobility point of view, while papers on the optimal CI focus more on grid constraints and impacts, ans thus take an energy point of view. Also the objective functions in the optimization problems are discussed and compared. We can conclude that minimization of cost is an objective function that occurs as a similarity between both groups of reviewed papers. However, maximization of customer convenience (expressed in any form, like minimal distance travelled, or minimal waiting times) is typical for optimization problems for the CI for SAEVs. On the other hand minimization of negative grid impact (such as voltage deviation or power losses) is a typical objective function for the optimization problem of CI with V2G implementation.
In this review, the impact of CI on the feasibility of SAEVs and V2G, and the impacts of SAEVs and V2G are discussed. In terms of CI, we can conclude that V2G has the most potential in a distributed CI which is not restricted to residences. For mobility and customer convenience purposes, also SAEVs would benefit from a distributed CI. SAEVs and V2G both have many values, and some of their values are similar, such as the reduction of GHG emissions, the reduction of peak load, and a reduction in cost. To the knowledge of the authors, a study where CI is optimized for SAEVs with implementation of V2G, looking both at mobility and grid constraints, is still missing from the literature. Such a study could give an impression of the values we might expect to be promising when SAEVs and V2G are joint together. Looking at our findings in this review, a potential way for this study to find the optimal CI would be by solving an optimization problem where cost is minimized, and grid and mobility constraints are added.

References

References

[1] J. M. Greenwald and A. Kornhauser, "It's up to us: Policies to improve climate outcomes from automated vehicles," *Energy Policy*, vol. 127, pp. 445–451, 4 2019.

[2] J. Weiss, R. Hledik, R. Lueken, T. Lee, and W. Gorman, "The electrification accelerator: Understanding the implications of autonomous vehicles for electric utilities," *Electricity Journal*, vol. 30, no. 10, pp. 50–57, 2017.

[3] M. R. Khalid, M. S. Alam, A. Sarwar, and M. S. Jamil Asghar, "A Comprehensive review on electric vehicles charging infrastructures and their impacts on power-quality of the utility grid," *eTransportation*, vol. 1, p. 100006, 2019. [Online]. Available: https://doi.org/10.1016/j.etran.2019.100006

[4] B. Bibak and H. Tekiner-Mogulkoc, "Influences of vehicle to grid (V2G) on power grid: An analysis by considering associated stochastic parameters explicitly," *Sustainable Energy, Grids and Networks*, vol. 26, p. 100429, 2021. [Online]. Available: https://doi.org/10.1016/j.segan.2020.100429

[5] J. Li, E. Rombaut, and L. Vanhaverbeke, "A systematic review of agent-based models for autonomous vehicles in urban mobility and logistics: Possibilities for integrated simulation models," *Computers, Environment and Urban Systems*, vol. 89, no. May, p. 101686, 2021. [Online]. Available: https://doi.org/10.1016/j.compenvurbsys.2021.101686

[6] A. Bask and M. Rajahonka, "The role of environmental sustainability in the freight transport mode choice: A systematic literature review with focus on the EU," *International Journal of Physical Distribution and Logistics Management*, vol. 47, no. 7, pp. 560–602, 2017.

[7] C. J. Sheppard, A. T. Jenn, J. B. Greenblatt, G. S. Bauer, and B. F. Gerke, "Private versus shared, automated electric vehicles for U.S. personal mobility: Energy use, greenhouse gas emissions, grid integration, and cost impacts," *Environmental Science and Technology*, vol. 55, no. 5, pp. 3229–3239, 2021.

[8] R. S. Gupta, A. Tyagi, and S. Anand, "Optimal allocation of electric vehicles charging infrastructure, policies and future trends," *Journal of Energy Storage*, vol. 43, p. 103291, 11 2021. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2352152X2100983X

[9] T. U. Solanke, V. K. Ramachandaramurthy, J. Y. Yong, J. Pasupuleti, P. Kasinathan, and A. Rajagopalan, "A review of strategic charging–discharging control of grid-connected electric vehicles," *Journal of Energy Storage*, vol. 28, no. September 2019, p. 101193, 2020. [Online]. Available: https://doi.org/10.1016/j.est.2020.101193

[10] R. Garruto, M. Longo, W. Yaïci, and F. Foiadelli, "Connecting parking facilities to the electric grid: A vehicle-to-grid feasibility study in a railway station's car park," *Energies*, vol. 13, no. 12, 2020.

[11] Y. Zhou and X. Li, "Vehicle to grid technology: A review," *Chinese Control Conference, CCC*, vol. 2015-Septe, pp. 9031–9036, 2015.

[12] "Why does the electricity grid have to stay in balance? – Energuide." [Online]. Available: https://www.energuide.be/en/questions-answers/why-does-the-electricity-grid-have-to-stay-in-balance/2136/

[13] A. Alobaidi, H. DesRoches, and M. Mehrtash, "Impact of Vehicle to Grid Technology on Distribution Grid with Two Power Line Filter Approaches," in *2021 IEEE Green Technologies Conference (GreenTech)*, vol. 2021-April. IEEE, 4 2021, pp. 163–168. [Online]. Available: https://ieeexplore.ieee.org/document/9458513/

[14] S. M. Shariff, D. Iqbal, M. Saad Alam, and F. Ahmad, "A State of the Art Review of Electric Vehicle to Grid (V2G) technology," *IOP Conference Series: Materials Science and Engineering*, vol. 561, no. 1, 11 2019.

[15] Y. Guo and S. Bashash, "Analyzing the impacts of Plug-in EVs on the California power grid using quadratic programming and fixed-point iteration," *Proceedings of the American Control Conference*, vol. 1, no. 408, pp. 2060–2065, 2017.

[16] M. Kontic, S. Mujovic, and M. Calasan, "Electric vehicles as a mean for peak power curtailment in micro grids," *2019 20th International Symposium on Power Electronics, Ee 2019*, pp. 19–23, 2019.

[17] S. Habib, M. M. Khan, F. Abbas, and H. Tang, "Assessment of electric vehicles concerning impacts, charging infrastructure with unidirectional and bidirectional chargers, and power flow comparisons," *International Journal of Energy Research*, vol. 42, no. 11, pp. 3416–3441, 9 2018. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1002/er.4033

[18] J. D. Arango Castellanos, H. Dhanasekaran Velayutha Rajan, A. K. Rohde, D. Denhof, and M. Freitag, "Design and simulation of a control algorithm for peak-load shaving using vehicle to grid technology," *SN Applied Sciences*, vol. 1, no. 9, pp. 1–12, 2019. [Online]. Available: https://doi.org/10.1007/s42452-019-0999-x

[19] J. Hu, H. Morais, T. Sousa, and M. Lind, "Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 1207–1226, 2016.

[20] A. Arias-Londoño, O. D. Montoya, and L. F. Grisales-Noreña, "A chronological literature review of electric vehicle interactions with power distribution systems," *Energies*, vol. 13, no. 11, pp. 1–23, 2020.

[21] S. Deb, K. Tammi, X. Z. Gao, K. Kalita, and P. Mahanta, "A Hybrid Multi-Objective Chicken Swarm Optimization and Teaching Learning Based Algorithm for Charging Station Placement Problem," *IEEE Access*, vol. 8, pp. 92 573–92 590, 2020.

[22] A. R. Kizhakkan, A. K. Rathore, and A. Awasthi, "Review of Electric Vehicle Charging Station Location Planning," *2019 IEEE Transportation Electrification Conference, ITEC-India 2019*, pp. 24–28, 2019.

[23] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Charging Station Placement for Electric Vehicles: A Case Study of Guwahati City, India," *IEEE Access*, vol. 7, pp. 100 270–100 282, 2019.

[24] T. D. Chen, K. M. Kockelman, and J. P. Hanna, "Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions," *Transportation Research Part A: Policy and Practice*, vol. 94, pp. 243–254, 2016. [Online]. Available: http://dx.doi.org/10.1016/j.tra.2016.08.020

[25] G. S. Bauer, J. B. Greenblatt, and B. F. Gerke, "Cost, energy and environmental impact of automated electric taxi fleets in Manhattan," *Angewandte Chemie International Edition, 6(11), 951–952.*, 2018.

[26] M. Cocca, D. Giordano, M. Mellia, and L. Vassio, "Free floating electric car sharing design: Data driven optimisation," *Pervasive and Mobile Computing*, vol. 55, pp. 59–75, 2019. [Online]. Available: https://doi.org/10.1016/j.pmcj.2019.02.007

[27] S. A. Funke and T. Burgert, "Can charging infrastructure used only by electric taxis be profitable? A case study from Karlsruhe, Germany," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 6, pp. 5933–5944, 2020.

[28] H. Cai, X. Jia, A. S. Chiu, X. Hu, and M. Xu, "Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet," *Transportation Research Part D: Transport and Environment*, vol. 33, pp. 39–46, 2014. [Online]. Available: http://dx.doi.org/10.1016/j.trd.2014.09.003

[29] B. Gacias and F. Meunier, "Design and operation for an electric taxi fleet," *OR Spectrum*, vol. 37, no. 1, pp. 171–194, 2015.

[30] A. A. Mohamed, L. Zhu, A. Meintz, and E. Wood, "Planning Optimization for Inductively Charged On-Demand Automated Electric Shuttles Project at Greenville, South Carolina," *IEEE Transactions on Industry Applications*, vol. 56, no. 2, pp. 1010–1020, 2020.

[31] H. Zhang, C. J. Sheppard, T. E. Lipman, and S. J. Moura, "Joint Fleet Sizing and Charging System Planning for Autonomous Electric Vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 11, pp. 4725–4738, 2020.

[32] J. Luke, M. Salazar, R. Rajagopal, and M. Pavone, "Joint Optimization of Autonomous Electric Vehicle Fleet Operations and Charging Station Siting," *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, vol. 2021-Septe, pp. 3340–3347, 2021.

[33] B. Ma, D. Hu, and X. Wu, "The Location Routing Problem of the Car-Sharing System with Autonomous Electric Vehicles," *KSCE Journal of Civil Engineering*, vol. 25, no. 8, pp. 3107–3120, 2021.

[34] C. Ran, Y. Zhang, and Y. Yin, "Demand response to improve the shared electric vehicle planning: Managerial insights, sustainable benefits," *Applied Energy*, vol. 292, no. April, p. 116823, 2021. [Online]. Available: https://doi.org/10.1016/j.apenergy.2021.116823

[35] N. Kang, F. M. Feinberg, and P. Y. Papalambros, "Autonomous electric vehicle sharing system design," *Journal of Mechanical Design, Transactions of the ASME*, vol. 139, no. 1, 2017.

[36] X. Liang and G. H. D. A. Correia, "An optimal charging location model of an automated electric taxi system considering two types of charging," *2020 Forum on Integrated and Sustainable Transportation Systems, FISTS 2020*, pp. 264–271, 2020.

[37] M. Lokhandwala and H. Cai, "Siting charging stations for electric vehicle adoption in shared autonomous fleets," *Transportation Research Part D: Transport and Environment*, vol. 80, no. April 2019, p. 102231, 2020. [Online]. Available: https://doi.org/10.1016/j.trd.2020.102231

[38] R. Vosooghi, J. Puchinger, J. Bischoff, M. Jankovic, and A. Vouillon, “Shared autonomous electric vehicle service performance: Assessing the impact of charging infrastructure,” *Transportation Research Part D: Transport and Environment*, vol. 81, no. May 2019, 2020.

[39] L. Yan, “Optimal layout and scale of charging stations for electric vehicles,” *China International Conference on Electricity Distribution, CICED*, vol. 2016-Septe, no. Ciced, pp. 10–13, 2016.

[40] C. J. Sheppard, G. S. Bauer, B. F. Gerke, J. B. Greenblatt, A. T. Jenn, and A. R. Gopal, “Joint Optimization Scheme for the Planning and Operations of Shared Autonomous Electric Vehicle Fleets Serving Mobility on Demand,” *Transportation Research Record*, vol. 2673, no. 6, pp. 579–597, 2019.

[41] J. Yang, J. Dong, and L. Hu, “A data-driven optimization-based approach for siting and sizing of electric taxi charging stations,” *Transportation Research Part C: Emerging Technologies*, vol. 77, no. 2, pp. 462–477, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.trc.2017.02.014

[42] B. Sah, P. Kumar, R. Rayudu, S. K. Bose, and K. P. Inala, “Impact of Sampling in the Operation of Vehicle to Grid and Its Mitigation,” *IEEE Transactions on Industrial Informatics*, vol. 15, no. 7, 2019.

[43] J. Waldron, L. Rodrigues, M. Gillott, S. Naylor, and R. Shipman, “Decarbonising Our Transport System: User Behaviour Analysis to Assess the Transition to Electric Mobility,” *35th PLEA conference sustainable architecture and urban design (to appear)*, pp. 1–6, 2020.

[44] B. Tarroja, L. Zhang, V. Wifvat, B. Shaffer, and S. Samuelsen, “Assessing the stationary energy storage equivalency of vehicle-to-grid charging battery electric vehicles,” *Energy*, vol. 106, pp. 673–690, 7 2016.

[45] M. De Gennaro, E. Paffumi, and M. Giogrgio, “Customer-driven design of the recharge infrastructure and Vehicle-to-Grid in urban areas: A large-scale application for electric vehicles deployment,” *Energy*, vol. 82, pp. 294–311, 2015.

[46] S. Velamuri, S. H. C. Cherukuri, S. K. Sudabattula, N. Prabaharan, and E. Hossain, “Combined Approach for Power Loss Minimization in Distribution Networks in the Presence of Gridable Electric Vehicles and Dispersed Generation,” *IEEE Systems Journal*, 2021.

[47] A. N. Archana and T. Rajeev, “A Novel Reliability Index Based Approach for EV Charging Station Allocation in Distribution System,” *IEEE Transactions on Industry Applications*, vol. 57, no. 6, pp. 6385–6394, 2021.

[48] V. Sultan, H. Bitar, A. Alzahrani, and B. Hilton, “Electric Vehicles Charging Infrastructure Integration Into The Electric Grid Considering The Net Benefits To Consumers,” *7th International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies (ENERGY)*, no. c, pp. 21–26, 2017.

[49] O. M. Abdelwahab and M. F. Shaaban, “PV and EV charger allocation with V2G capabilities,” *Proceedings - 2019 IEEE 13th International Conference on Compatibility, Power Electronics and Power Engineering, CPE-POWERENG 2019*, 2019.

[50] F. Amarena, G. Chicco, N. Neyestani, M. Y. Damavandi, and J. P. Catalao, “Location of parking lots for plug-in electric vehicles considering traffic model and market participation,” *2017 IEEE Manchester PowerTech, Powertech 2017*, 2017.

[51] M. Mozaffari, H. A. Abyaneh, M. Jooshaki, and M. Moeini-Aghtaie, “Joint Expansion Planning Studies of EV Parking Lots Placement and Distribution Network,” *IEEE Transactions on Industrial Informatics*, vol. 16, no. 10, pp. 6455–6465, 2020.

[52] M. Rahmani-Andebili and G. K. Venayagamoorthy, “SmartPark placement and operation for improving system reliability and market participation,” *Electric Power Systems Research*, vol. 123, pp. 21–30, 2015.

[53] M. Bilal and M. Rizwan, “Integration of electric vehicle charging stations and capacitors in distribution systems with vehicle-to-grid facility,” *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, 2021.

[54] S. Rajamand, “Optimal electrical vehicle charging park in residential-commercial microgrid based on probability of vehicles routing and cost minimization approach,” *International Journal of Energy Research*, vol. 45, no. 6, pp. 8593–8605, 5 2021.

[55] S. Wang, Z. Y. Dong, F. Luo, K. Meng, and Y. Zhang, “Stochastic Collaborative Planning of Electric Vehicle Charging Stations and Power Distribution System,” *IEEE Transactions on Industrial Informatics*, vol. 14, no. 1, pp. 321–331, 2018.

[56] S. Gao, H. Jia, J. Liu, and C. Liu, “Integrated configuration and charging optimization of aggregated electric vehicles with renewable energy sources,” *Energy Procedia*, vol. 158, pp. 2986–2993, 2019.

[57] S. Shojaabadi, S. Abapour, M. Abapour, and A. Nahavandi, "Simultaneous planning of plug-in hybrid electric vehicle charging stations and wind power generation in distribution networks considering uncertainties," *Renewable Energy*, vol. 99, pp. 237–252, 12 2016.

[58] S. M. A. Masoumian, A. Alfi, and A. R. Jordehi, "Using not-dominated sorting backtracking search algorithm for optimal power system planning in the vicinity of the electric vehicle charging station and scattered generation sources under uncertainty conditions," *International Journal of Nonlinear Analysis and Applications*, vol. 12, no. Special Issue, pp. 161–172, 2021.

[59] B. Y. Khanghah, A. Anvari-Moghaddam, J. M. Guerrero, and J. C. Vasquez, "Combined solar charging stations and energy storage units allocation for electric vehicles by considering uncertainties," *Conference Proceedings - 2017 17th IEEE International Conference on Environment and Electrical Engineering and 2017 1st IEEE Industrial and Commercial Power Systems Europe, EEEIC / I and CPS Europe 2017*, no. 1, 2017.

[60] A. Aljanad, A. Mohamed, H. Shareef, and T. Khatib, "A novel method for optimal placement of vehicle-to-grid charging stations in distribution power system using a quantum binary lightning search algorithm," *Sustainable Cities and Society*, vol. 38, no. December 2017, pp. 174–183, 2018.

[61] K. Gupta, R. Achathuparambil Narayanankutty, K. Sundaramoorthy, and A. Sankar, "Optimal location identification for aggregated charging of electric vehicles in solar photovoltaic powered microgrids with reduced distribution losses," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, pp. 1–16, 3 2020.

[62] O. Rahbari, M. Vafaeipour, N. Omar, M. A. Rosen, O. Hegazy, J. M. Timmermans, S. Heibati, and P. V. D. Bossche, "An optimal versatile control approach for plug-in electric vehicles to integrate renewable energy sources and smart grids," *Energy*, vol. 134, pp. 1053–1067, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.energy.2017.06.007

[63] F. Ahmad, M. Khalid, and B. K. Panigrahi, "An enhanced approach to optimally place the solar powered electric vehicle charging station in distribution network," *Journal of Energy Storage*, vol. 42, no. August, p. 103090, 2021. [Online]. Available: https://doi.org/10.1016/j.est.2021.103090

[64] J. Prasomthong, W. Ongsakul, and J. Meyer, "Optimal placement of vehicle-to-grid charging station in distribution system using Particle Swarm Optimization with time varying acceleration coefficient," in *Proceedings of the 2014 International Conference and Utility Exhibition on Green Energy for Sustainable Development, ICUE 2014*, 2014.

[65] M. H. Moradi, M. Abedini, and S. M. Hosseinian, "Improving operation constraints of microgrid using PHEVs and renewable energy sources," *Renewable Energy*, vol. 83, pp. 543–552, 2015.

[66] M. R. Mozafar, M. H. Moradi, and M. H. Amini, "A simultaneous approach for optimal allocation of renewable energy sources and electric vehicle charging stations in smart grids based on improved GA-PSO algorithm," *Sustainable Cities and Society*, vol. 32, no. November 2016, pp. 627–637, 2017.

[67] C. Raja S, V. Kumar N M, S. k. J, and J. D. Nesamalar J, "Enhancing system reliability by optimally integrating PHEV charging station and renewable distributed generators: A Bi-Level programming approach," *Energy*, vol. 229, p. 120746, 2021.

[68] B. Loeb, K. M. Kockelman, and J. Liu, "Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions," *Transportation Research Part C: Emerging Technologies*, vol. 89, no. May 2017, pp. 222–233, 2018. [Online]. Available: https://doi.org/10.1016/j.trc.2018.01.019

[69] H. Zhang, C. J. Sheppard, T. E. Lipman, T. Zeng, and S. J. Moura, "Charging infrastructure demands of shared-use autonomous electric vehicles in urban areas," *Transportation Research Part D: Transport and Environment*, vol. 78, p. 102210, 2020. [Online]. Available: https://doi.org/10.1016/j.trd.2019.102210

[70] H. Miao, H. Jia, J. Li, and T. Z. Qiu, "Autonomous connected electric vehicle (ACEV)-based car-sharing system modeling and optimal planning: A unified two-stage multi-objective optimization methodology," *Energy*, vol. 169, pp. 797–818, 2019. [Online]. Available: https://doi.org/10.1016/j.energy.2018.12.066

[71] D. Zhao, X. Li, and J. Cui, "A simulation-based optimization model for infrastructure planning for electric autonomous vehicle sharing," *Computer-Aided Civil and Infrastructure Engineering*, vol. 36, no. 7, pp. 858–876, 2021.

[72] G. Ma, L. Jiang, Y. Chen, C. Dai, and R. Ju, "Study on the impact of electric vehicle charging load on nodal voltage deviation," *Archives of Electrical Engineering*, vol. 66, no. 3, pp. 495–505, 2017.

[73] M. Aunedi and G. Strbac, "Whole-system Benefits of Vehicle-To-Grid Services from Electric Vehicle Fleets," *2020 15th International Conference on Ecological Vehicles and Renewable Energies, EVER 2020*, 2020.

[74] M. R. Hajidavalloo, F. A. Shirazi, and M. J. Mahjoob, "Performance of different optimal charging schemes in a solar charging station using dynamic programming," *Optimal Control Applications and Methods*, vol. 41, no. 5, pp. 1568–1583, 2020.

[75] B. Yagcitekin and M. Uzunoglu, "A double-layer smart charging strategy of electric vehicles taking routing and charge scheduling into account," *Applied Energy*, vol. 167, pp. 407–419, 2016.

[76] B. Bibak and H. Tekiner-Mogulkoc, "The parametric analysis of the electric vehicles and vehicle to grid system's role in flattening the power demand," *Sustainable Energy, Grids and Networks*, vol. 30, p. 100605, 2022.

[77] S. B. Fahmy, S. E. Guirguis, O. M. Shehata, and E. I. Morgan, "Investigation of an Optimal Charging/Discharging Policy for Electric Vehicles Parking Station in a Smart Grid Environment," *2020 8th International Conference on Control, Mechatronics and Automation, ICCMA 2020*, pp. 138–143, 2020.

[78] Q. Kong, M. Fowler, E. Entchev, H. Ribberink, and R. McCallum, "The role of charging infrastructure in electric vehicle implementation within smart grids," *Energies*, vol. 11, no. 12, pp. 1–20, 2018.

[79] M. Taljegard, L. Göransson, M. Odenberger, and F. Johnsson, "To Represent Electric Vehicles in Electricity Systems Modelling—Aggregated Vehicle Representation vs. Individual Driving Profiles," *Energies*, vol. 14, no. 3, p. 539, 1 2021. [Online]. Available: https://www.mdpi.com/1996-1073/14/3/539

[80] G. Mills and I. MacGill, "Assessing Electric Vehicle storage, flexibility, and Distributed Energy Resource potential," *Journal of Energy Storage*, vol. 17, pp. 357–366, 2018.

[81] D. Strickland, T. Embley, J. Osborne, J. Yang, Z. Qiao, A. Malhotra, A. Corliss, and K. Ashworth, "Feasibility study: investigation of car park-based V2G services in the UK central hub," *The Journal of Engineering*, vol. 2019, no. 17, pp. 3967–3971, 6 2019.

[82] S. Sachan, S. Deb, and S. N. Singh, "Different charging infrastructures along with smart charging strategies for electric vehicles," *Sustainable Cities and Society*, vol. 60, no. May, p. 102238, 2020.

[83] P. Zhou, C. Wang, and Y. Yang, "Design and Optimization of Electric Autonomous Vehicles with Renewable Energy Source for Smart Cities," *Proceedings - IEEE INFOCOM*, vol. 2020-July, pp. 1399–1408, 2020.

[84] B. Azin, X. T. Yang, N. Marković, and M. Liu, "Infrastructure enabled and electrified automation: Charging facility planning for cleaner smart mobility," *Transportation Research Part D: Transport and Environment*, vol. 101, no. October, p. 103079, 2021. [Online]. Available: https://doi.org/10.1016/j.trd.2021.103079

Presenter Biography

Ona Van den bergh graduated in June 2021 as a Master of Science in Mathematics at the University of Antwerp (UA). She has a strong interest in (statistical) data science and optimization methods. In September 2021 she started as a PhD researcher and teaching assistant at the Vrije Universiteit Brussel (VUB) at the BUTO (Business Technology and Operations) department in the MOBI (Mobility, Logistics and Automotive Technology) research group under supervision of prof. dr. Lieselot Vanhaverbeke. Her research activities are at the crossing between mobility and energy.

A SAEV

Table 1: How to find optimal charging infrastructure placement and what is considered. TN = Transport Network, PN = Power network, S = shared, A = autonomous

Paper	Vehicle/ Country	TN	PN	Problem formulation	Objective function	Methodology	Main findings
[83]	AEV in Yantai City, China	✓	-	Single objective Optimization Problem	Minimize maximum distance from any position to CS	NP-hard problem –> clustering algorithm, followed by stochastic online algorithm	Instead of being placed at the energy richest places, the stations tend to be more scattered to accommodate the charging requests from different locations.
[84]	AEV in Utah, USA	✓	✓	Multi-objective Optimization Problem	Maximize CS' demand coverage Minimize the network's power cost	Nondominated sorting genetic algorithm (NSGA-II)	Stations will be mostly located close to routes with high traffic and shorter distances and traffic nodes with high inner traffic demand. On the other hand, to minimize the charging demands power load cost by assigning stations to locations that will keep the voltage profile stable.
[25]	SAEV in Manhattan, USA	✓	-	Agent-based model	/	Elimination method, iteratively removing locations whose absence cause the least impact on the system	With an efficient charging algorithm, results for fleet size and battery range do not change appreciably until the number of locations falls below 50. Since only mobility demand is considered, the authors expect that the charging locations are scattered.
[24]	SAEV in Austin, Texas	✓	-	Agent-based model	/	Two-phase warm start. Phase 1: generate CS (mimics the objective of a coverage model). Phase 2: determine fleet size.	Charging station locations are a function of both the geography of the service geo-fence and travelers' trip-making patterns (spatial and temporal). Only 1.8% of the trip-active cells are equipped with a CS (equipped with 43 (level III) or 653 (level II) charging pads).
[26]	SEV in Turin, Italy	✓	-	Heuristic placement Heuristic placement Heuristic Placement	/	Likelihood based on Average parking time Likelihood based on Total number of parking events Likelihood based on Random placement	The best approach among these three heuristics is to place charging stations in the central areas, in which the parkings last less but are more frequent. Only 5% of the city area needs to be equipped with CSs, which corresponds to 13 CSs for Turin with 1 million habitants.
[26]	SEV in Turin, Italy	✓	-	Multi-objective Optimization Problem	Minimize percentage of infeasible trips Minimize walked distance from the desired destination	• Hill-climbing local search • Genetic algorithm	The Genetic Algorithm allows us to improve both the system performance, and customers' discomfort. GA leads to a more dispersed CI than Local Search or the Heuristic placement with a likelihood based on Number of Parking events.
[27]	E-taxi in Karlsruhe, Germany	✓	-	Heuristic placement	/	Likelihood based on taxi arrival rate	CI at half of all taxi stands (10 out of 20) is sufficient for an electrification rate of 40%. The cost of CI only for taxi's is high. However in 2025, 15 charging sites could be refinanced because of lower vehicle cost, allowing for over 50% of km to be electrified.

Table 2: How to find optimal charging infrastructure placement and what is considered. TN = Transport network, PN = Power network, S = shared, A = autonomous

Paper	Vehicle/ Country	TN	PN	Problem formulation	Objective function	Methodology	Findings
[40]	SAEV in USA	✓	-	Quadratic programming problem, quadratic constraints	Minimize daily cost of fleet, infrastructure, and fleet operations	Second-order cone programming solver	Fleet size and amount of CI is decided. Heterogeneous vehicle ranges and charger levels are allowed. If all U.S. mobility was satisfied by SAEVs with a sharing factor of 1.5, a fleet of only 12.5 million vehicles (instead of currently 276 million personally owned vehicles) and 2.4 million charge points would be required.
[28]	PHEV taxi's in Beijing	✓	-	Heuristic placement Heuristic placement Heuristic placement	/	Likelihood based on Number of parking events within 1 mile Average vehicle-hour per vehicle Average vehicle-hour per day	Goal is to maximize electrification rate. Gas stations with the most parking events and daily vehicle-hours are concentrated in the center of the city while gas stations with the highest vehicle-hour per vehicle located in the suburb. Gas-station-based charging stations identified with maximum total number of parking events provide the highest overall electrification rate.
[29]	E-Taxi in Paris, France	-	-	P-median Optimization Model	Minimize sum of the distances between clients and facilities	IBM-ILOG CPLEX Optimizer	Decides the locations of charging facility to obtain a convenient spread over the geographical area..
[29]	E-Taxi in Paris, France	✓		Demand-based Optimization model: Mixed Integer Linear Program	Maximize the pointwise demand covered by a charging terminal considering the distance	IBM-ILOG CPLEX Optimizer	Decides the number of facilities at a certain location. When the number of charging terminals is equal to five, the demand-based model outperforms the P-median model, for any criterion. More customers are satisfied, the operating time of taxis is higher, and the time waiting for an available charging terminal is drastically reduced. When the number of charging terminals is larger (20 and 40 charging terminals), there is no real difference between the two models.
[41]	E-Taxi in Ghangsha, China	✓	-	Single objective Optimization Model	Minimize overall infrastructure investment	666 candidate sites selected. After logarithmic transformation, the optimization model is reformulated as an ILP and solved by Gurobi solver.	The optimal charging sites are mostly located in the densely populated area of the inner city.
[36]	AEV taxi's in Delft, the Netherlands	✓	-	Mixed Integer Linear Program	Maximize the number of satisfied requests (for a limited fleet size)		With a higher fleet size, the AET system can serve more travel requests. With fewer charging stations, the average travel distance will increase when serving the same number of satisfied requests.

Table 3: How to find optimal charging infrastructure placement and what is considered. TN = Transport network, PN = Power network, S = shared, A = autonomous

Paper	Vehicle/ Country	TN	PN	Problem formulation	Objective function	Methodology	Findings
[71]	SAEV in Yantai City, China	✓	-	EAVSDP: (1) geographical service area planning (2) charging infrastructure allocation	Minimize the rebalancing cost (for given charging locations, fleet size, and user demand) Minimize the system cost	Simulation-based optimization approach Genetic Algorithm	Locations for the shared vehicles parking as candidates for building charging stations. Parking spaces are scattered, but individual charging stations are not scattered beyond the parking spaces
[70]	ACEV in Changchun, China	✓	-	Two-stage multi-objective optimization model: (1) optimize the geographical area (concentrates on system vehicle service) (2) optimize allocation of CI (focuses on system charging performance)	Maximize total served trip distance Maximize satisfied charging needs Minimize total cost (construction cost + charging cost)	Non-dominating sorting genetic algorithm II (NSGA-II), combining the population-based nature of Genetic Algorithm and Pareto-optimal front methods	Longer range improves system vehicle service and charging performance. Autonomous vehicle technology improves the system vehicle service. Connected vehicle technology improves the system charging performance.
[35]	AEV sharing in Ann Arbor, Michigan, USA	-	-	P-median Optimization Model	Minimize distance between AEVs and CSs (decision variable: number of CSs, CS locations)		15 candidate locations were selected among the existing public parking lots, assuming fast-charging stations with a single charger. AEV services are feasible.
[32]	E-AMoD in San Francisco, CA	✓	✓	Convex optimization framework	Minimize total fleet cost	Any general LP solver	Sufficient flexibility to completely avoid charging during highest price period. The station siting is more spatially distributed than present-day station siting for which the majority of capacity is concentrated in commercial zones.
[68]	SAEVS in Austin, Texas, USA	✓	-	Agent-based simulation	Minimize number of CSs	Generating a CS whenever a vehicle receives a request, has too low SOC to fulfill request and to travel to an existing CS.	A scattered distribution of CS locations, entirely decided based on mobility requests.
[38]	SAEVs in Rouen Normandie, France	✓	-	Maximal Covering Location Problem P-median P-Median while avoiding placing charging stations in areas with low parking availability	Maximize coverage of charging stations by considering the potential pick-up and drop-off locations Minimize distances between those locations and charging stations Minimize distances between those locations and charging stations		Charging stations are less scattered when MCLP optimization is employed. The charging stations are rather located in the areas with high potential demand close to each other. Within the third strategy, the charging stations are more dispersed and particularly the demands for charging are more balanced across the stations during peak demand.

Table 4: How to find optimal charging infrastructure placement and what is considered. TN = Transport network, PN = Power network, CS = charging station, S = shared, A = autonomous

Paper	Vehicle/ Country	TN	PN	Problem formulation	Objective function	Methodology	Findings
[37]	SA taxi's in New York, USA	✓	-	Single objective Optimization problem	Minimize the total wasted time T (travel time to CS + waiting time at CS spent in queue)	Genetic Algorithm	Ride-sharing of autonomous taxi's reduces the taxi fleet by 59%.
[33]	SAEVs	✓	-	Mixed-integer non-linear Optimization Problem	Minimize total daily cost	Genetic Algorithm	Partial recharging induces cost-savings. Therefore, the government can for example install more charging piles in scattered places; support the implementation of other faster-charging technologies: battery swapping or wireless charging.
[30]	SAESs in Greenville, South Carolina, USA	✓	-	Mixed-integer single-objective non-linear Optimization Problem	Minimize total cost	Genetic Algorithm	Implementing high-power (100-kW) in-route wireless charging at the locations that are designated as stops for a fixed route of the SAESs can provide a charge-sustaining operation, and thus infinite driving range.
[31]	AEVs	✓	-	Mixed Integer Linear Program	Minimize total cost	Elimiate redundant paths to reduce cemplexity, as an alternative to column generation	for the system with 15,000 trips/day, a total of 2,500+ AEVs and 300+ chargers are required. The proposed strategy can reduce investment costs by at least 4.4% and 8.8% compared with benchmarks for passenger and goods transportation, respectively.
[34]	SEV in Amsterdam, the Netherlands	✓	-	Mixed Integer Linear Program	Minimize sum of yearly operation costs		Compared with non-demand response policies (i.e., load-based policy and general policy), a demand response policy (i.e., a price-based policy) reduces operating costs.
[69]	SAEVs in San Francisco Bay Area, USA	✓	-	Single-objective Optimization Problem for optimal siting of CSs Heuristic sizing of CSs	Minimize the overall distance between the charging requests to their corresponding nearest charging stations /	K-means clustering Hybrid algorithm	Most of the ride-hailing and charging requests happen in the densely-populated areas, and the charging request locations are strongly correlated with the trip destinations. The total number of charging stations is generally inversely proportional to fleet size.

B V2G

Table 5: Optimal charging infrastructure placement for V2G purposes. TN = Transport network, PN = Power network, DN = Distribution network

Paper	DN	TN	PN	Problem formulation	Objective function	Methodology	Findings
[53]	IEEE 33-bus and 34-bus	-	✓	Multi-objective Optimization Problem	Minimize active power loss Maximize net profit (energy loss reduction benefit + operating cost + installation cost of EVCS as well as capacitors)	Hybrid of Grey Wolf optimization and Particle Swarm Optimization	CSs are placed close to the substation bus. Capacitors are placed closer to CSs and end of feeders for enhancement of voltage profile and loss by contributing some reactive power.
[60]	IEEE 37-bus	-	✓	Multi-objective Optimization Problem	Minimize active power loss Minimize thermal line loading effect Minimize voltage deviation Minimize total circuit losses	Quantum binary lightning search algorithm (QBLSA) BPSO (Binary Particle Swarm Optimization) BLSA	Optimal placement and sizing of the CSs in the power system are crucial to utilize the ability of PHEV to supply power from V2G. Optimal CS placement improves the performance of the distribution network: improvement of line loading, improvement of voltage deviation. QBLSA outperforms BLSA and BPSO with the best fitness value and minimum number of iterations.
[61]	Unknown	-	✓	Single-objective Optimization Problem	Minimize distribution losses	PSO-based OPF (Optimal Power Flow) along with IPM (Integrated Power Management) algorithm	There is a reduction of 84% in the total daily distribution loss between un-optimized and PSO optimized power flows in the considered microgrid network. There is a further reduction of 8% using IPM in power flow optimization.
[64]	9 buses	-	✓	Multi-objective Optimization Problem	Maximize total benefit: Benefit of peak power providing (net revenue, capital cost, cost of V2G power purchasing, cost of purchased energy for driving) Benefit of reliability improvement (saved cost of not supplied energy) Benefit of power loss reduction (saved cost of power losses)	PSO-TVAC (PSO with time varying acceleration coefficients)	Voltage profile can be improved by V2G. The total maximum benefit by PSO-TVAC is higher than those of GA, BPSO (basic PSO) , and PSO-TVIW (PSO with time varying inertia weight)
[54]	Unknown	-	✓	Multi-objective Optimization problem	Minimize cost (repair cost, installation cost, performance cost, investment cost, annual loss cost, explotation cost of the system	GAMS (General Algebraic Modeling Language)	Voltage profile and power flow are improved due to V2G. There is a reduction in cost due to optimal locations.
[42]	DN of Guwahati, India	✓	-	Heuristic placement	/	Place CS at the node which is the commercial hub of Guwahati and has a high vehicle density	
[43]	48 EVs in University of Nottingham	✓	-	Heuristic placement	/	Average likelihood of being at a certain location (based on end location of each journey and dwell time)	Some locations were not feasible for installing a CS, because of high cost of groundworks or due to power supply limitations. Those locations were not used in the CI.
[57]	nine-bus system 33-node DN	✓	✓	Bi-objective Optimization Problem	Maximize benefits of DSM (distribution system manager) and WGO (wind generation owners)	NSGA-II	Proper placement of CSs reduces power losses and improves voltage profile. Also charging/discharging managing of EVs reduces the risk of electric demand during peak load times.

Table 6: Optimal charging infrastructure placement for V2G purposes. TN = Transport network, PN = Power network, DN = distribution network

Paper	DN	TN	PN	Problem formulation	Objective function	Methodology	Findings
[44]	California	✓	-	Heuristic placement	/	Place CSs at locations with highest dwelling time	CSs available at residences and workplaces which represent respectively 75% and 14% of vehicle dwelling time. The average dwell time spent at each location is 10 h at residences and 6 h at workplaces.
[46]	IEEE 33-bus	-	✓	Heuristic placement	/	VSI (voltage stability index): close to unity = strong node close to zero = weak node EV CSs are placed at strong buses	It is possible to reduce power loss and improve the voltage profile.
[55]	54-node DN and 25-node TS	✓	✓	Multi-objective Optimization Model	Minimize investment and operation costs Maximize captured traffic flow	MOEA/D algorithm (multi-objective evolutionary algorithm based on decomposition)	With the increase of traffic flow captured comes also an increase in investment cost and energy losses. A compromise between the two conflicting objectives needs to be made.
[47]	IEEE 33-bus	-	✓	Heuristic placement	/	CSs placed at buses with highest bus reliability index (BRI[1])	Slow and moderate CSs of 10 kW and 15 kW can be placed at weaker buses, but fast DC CSs at weak buses degrades the system reliability indices (SRI[2]). Appropriate locations need to be established for a reliable functioning of the network and to improve customer satisfaction.
[49]	Unknown	-	✓	Single-objective Mixed Integer Nonlinear Problem (MINLP)	Maximize the net annual revenue	Unknown	Coordinated charging keeps net power flow within acceptable range.
[50]	Italy	✓	✓	Single-objective optimisation problem	Maximize parking lot's owner profit	Unknown	Profit increases with PEV penetration. In the year 2030, the residential area has the highest number of charging points, followed by rural area, then commercial area and then industrial area with the lowest number of CPs. Starting from the year 2050, this distribution changes with the highest number of CPs in the commercial area, followed by the residential area, then the industrial area and finally the rural area. What mainly changed between 2030 and 2050 is the number of PEVs.
[51]	IEEE 33-bus	✓	✓	Multi-objective Optimisation Model	Maximize profit of parking lot's owners Minimize operational cost of distribution network	NSGA-II	V2G leads to higher profit for the PL's owner and lower DN costs. The higher the participation in V2G, the higher this benefit.
[58]	IEEE 33-bus	-	✓	Multi-objective Optimization Model	Maximize public sectors' profit rates Maximize private sectors' profit rates	Not-Dominated Sorting Backtracking Search Algorithm (NSBSA)	The presence of CSs, WG and PV in their optimal location enhanced the voltage profile. With the participation of both private and public sectors, benefits were gained.

[1] BRI identifies weak and strong buses. The higher the BRI, the stronger the bus.

[2] SRIs are indicators for the reliability of the whole network, among which are customer-oriented indices (such as Average failure rate) and energy-oriented indices (such as Average energy not supplied).

Table 7: Optimal charging infrastructure placement for V2G purposes. TN = Transport network, PN = Power network, DN = distribution network

Paper	DN	TN	PN	Problem formulation	Objective function	Methodology	Findings
[48]	LA County	✓	✓	Heuristic placement	/	Geographic Decision Support System (GDSS): Solar excess generation Crime Index layer Convenience and accessibility factors of EV drivers	”EV charging demand can be managed geographically to minimize potential increases to overall electric system costs while still meeting customer demands.”
[59]	IEEE 33-bus	-	✓	Multi-objective Optimization Problem	Maximize benefit of Distribution Company Maximize benefit of CS owner	GA combined with Monte Carlo simulation	Benefits for the DC and for the CS owner are increased as a result of load shifting and loss reduction during peak periods in systems with Energy Storage Systems.
[65]	69-bus	-	✓	Multi-objective Optimization Model	Minimize system losses Minimize voltage profile index Minimize cost of charging and load supplying	Differential Evolution algorithm	
[52]	28-bus	✓	✓	Single-objective Optimization Problem	Maximize aggregator’s income	Simulated Annealing algorithm	Optimally locating SmartParks can increase the aggregator’s income and improve system liability.
[62]	IEEE 26-bus	-	✓	Multi-objective Optimization Problem	Minimize voltage deviation Minimize power losses Minimize annual investments and operation cost	NSGA-II algorithm	Power losses and voltage deviation peak can be reduced by V2G.
[45]	province of Firenze	✓	-	Heuristic placement	/	Based on Average geographical key performance indicator Repetitiveness index Energy demand	Regardless the recharge behaviours, some POIs behave as hubs. Next to this, V2G can reduce the electric peak power load, and thereby the average daily load.
[66]	IEEE 33-bus	-	✓	Multi-objective Optimization Problem	Minimize power losses Minimize total voltage fluctuations index Minimize EV charging and demand supplying cost Minimize depreciation cost of battery	GA-PSO	Location and capacity of RES as well as CS is determined. Optimal siting and sizing of RES and CSs reduced power losses, and improves the voltage profile.
[56]	IEEE 123-bus	-	✓	Single-objective Mixed integer nonlinear programming problem (MINLP)	Minimize cost	Two-stage hybrid optimization allgorithm based on PSO and SQP	”Optimal solution can improve the reliable operation of the power system with EV charging load.”
[67]	IEEE 33-bus	-	✓	Non-linear single-objective problem	Minimize energy not supplied (ENS)	Hybrid Nelder-Mead Cuckoo Search (HNM-CS) algorithm	Goal is to optimally locate CSs and renewable energy distribution (RED) simultaneously. Doing this reduces the power loss and ENS by 45% and 6% respectively. The ENS of the system is improved by 74.67% with the integration of RDG units.
[63]	IEEE 33-bus	✓	✓	Multi-objective Optimization problem	Minimize voltage deviation Minimize power loss Minimize average voltage deviation index with respect to the nominal voltage Minimize voltage stability index	Jaya algorithm Teaching and learning based optimization (TLBO) Modified chicken swarm optimization (MCSO)	Optimally locating solar power CSs reduces power loss and voltage deviation. Also the economic losses (due to penalties of voltage deviation going beyond its permissible limit) are lower when the CSs are optimally placed in the DN. MCSO is the best performing algorithm in with the lowest objective value and the lowest number of iterations.