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Sizing of electric vehicle charging stations with smart charging capabilities and quality of service requirements☆

Alireza Khaksari[a], Georgios Tsaousoglou[b,*], Prodromos Makris[a,*], Konstantinos Steriotis[a], Nikolaos Efthymiopoulos[a], Emmanouel Varvarigos[a]

[a] National Technical University of Athens, Greece
[b] Eindhoven University of Technology, The Netherlands

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ABSTRACT

The increasing penetration of electric vehicles (EVs) inherently couples the transportation system with the electricity system through charging stations (CSs). Today's regulatory context highly incentivizes CS infrastructure investments that are expected to have a significant impact on reducing air pollution, cutting emissions and promoting environmentally sustainable cities. The Sizing problem of a CS typically concerns the minimization of the investment cost for charging facilities, subject to the CS being able to fulfill a certain level of charging requests. Several studies have shown the potential of Smart Charging technologies, towards controlling the charging profiles of EVs, so as to achieve a lower operational cost or a lower peak to average power consumption ratio for the CS, by shifting the charging of some EVs. By making more efficient use of charging facilities, Smart Charging can also help reducing the amount of chargers required in order to achieve a certain Quality of Service (QoS) for the CS's clients. In this paper we solve the CS's sizing problem (i.e. decisions on number and types of installed chargers) through an optimization framework that minimizes the investment cost of CS operators, subject to achieving a certain QoS for their clients (EV owners). In particular, we extend the existing CS sizing models by taking into account also the smart charging capabilities during operation. We present a novel formulation for the QoS level of the CS using chance-constraints and propose some relaxations that constitute the problem solvable. Finally, we present a methodology that enhances the scalability of the optimal sizing algorithm. The proposed methodology is able to offer valuable services to CS operators in competitive environments.

1. Introduction

The growth of urbanization generates important environmental and societal challenges, related to greenhouse gas emissions (GHG), air pollution, noise and dependence on fossil fuels (European Environment Agency, 2020). For this reason, one of the main challenges for environmentally sustainable cities is to decouple urban development from the deterioration of the quality of life of their citizens and environmental conditions. Towards promoting smart, clean and healthy transportation systems and infrastructure in cities, the electrification of urban transportation is increasingly accelerated in most developed countries (Ruggieri, Ruggeri, Vinci, & Poponi, 2021). According to recent technical reports, electric cars reached a 2.6% of global car sales and about 1% of global car stock in 2019, surpassing 7.2 million electric vehicles (EVs) in the roads (IEA, 2020). In order to facilitate this advancement, there is an increasingly high demand for investments in charging infrastructure. Indicatively, around 130 million private chargers and 13 million public chargers are estimated to be needed by 2030 to fulfill the EVs' charging energy demand (Chen et al., 2020) and, as a consequence, several policy measures are taken towards providing incentives for investments in charging facilities.

The largest potential reduction in GHG emissions in an EV compared to a conventional vehicle occurs in the use phase (i.e. charging) of the vehicle, especially when the EV is mostly charged with renewable energy and the respective EV charging infrastructure is developed in a smart manner. As a result, the need to create sustainable business models for charging station (CS) investments motivates extensive techno-economic analysis. One important aspect of CS investment

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* Corresponding author.

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decisions is the *sizing problem*, i.e. deciding the numbers and types of chargers to be installed. At the same time, advancements in information and communication technologies, improves data collection which will enhance the integration of EVs in the smart grid (Mahmud, Town, Morsalin, & Hossain, 2018). Gathered information and aggregation of data enables the optimization of the charging process (i.e. Smart Charging).

In smart charging, a management system schedules and controls the charging of EVs (Hu, Morais, Sousa, & Lind, 2018). A coordinating entity, operates the EV admission control system, makes the assignment of EVs to charging spots, and controls the charging power of each EV. The decisions are made based on the EVs' local objectives (i.e. preferences), as well as global objectives such as minimizing the CS's operational cost (Tang, Bis, & Jun Zhang, 2014), achieving a fair allocation of resources among users (Tsaousoglou, Pinson, & Paterakis, 2020), or complying with certain constraints that relate to the safe operation of the underlying electrical grid (Seklos et al., 2020; Tsaousoglou, Giraldo, Pinson, & Paterakis, 2020; Zheng, Nius, Shang, Shao, & Jian, 2019). Three separate families of studies can be identified in the literature, where the first addresses planning and sizing problems for CSs, the second designs scheduling algorithms for optimizing the CS's operation (with given charging infrastructure), and the third considers the sizing problem of a CS while taking into account also the resulting Quality of Service (QoS).

1.1. Charging station sizing

Various studies cope with the siting (determining the locations of CSs) and sizing (determining the installed charging capacity of a CS) problem of CS investment planning. Such studies either consider public CSs, where their objective is to compute the optimal location points for building or installing charging stations inside metropolitan cities or urban areas (Hea, Yin, & Zhou, 2015), or private CSs in competitive market environments (Guo, Deride, & Fan, 2016).

In Simorgh, Doagou-Mojarrad, Razmi, and Gharehpetian (2018), the optimal siting and sizing problem of CSs was modeled as an integer optimization problem in which the objective is to minimize: the investment cost, the connection cost, the total cost of power losses, and the cost of demand response actions. The solution was obtained using particle swarm optimization. In Yang, Dong, and Hu (2017), the authors propose a data-driven method for the sizing problem of taxi-CSs. In Hea et al. (2015), the authors also presented simulations that investigate the influence of the budget on the types of installed chargers and on the average charging time. In Luo et al. (2018), multiple types of chargers (slow, medium, fast) are considered. The objective was to find the optimal number of chargers to install for each particular charger type. A two-step scenario-based optimization model was proposed and transformed into a mixed-integer second-order cone program through the SOCP relaxation. A two stage optimization was formulated in Hayajneh, Naser Bani Salim, Bashetty, and Zhang (2019) for the sizing of CSs powered by batteries. In the first stage, a genetic algorithm is used to minimize the total transportation energy losses for all the EVs, by assigning each EV to a certain CS. In the second stage, the cumulative energy demand of each CS's assigned EVs is calculated based on the state of charge of EVs' batteries. Then, the optimal number of fast and slow chargers required to satisfy demands in each station is found through a linear optimization problem. In Zhang, Hu, Xu, and Song (2016), the social cost of the EV charging system in an urban area is optimized through planning the locations of public charging stations. A framework for optimal CS planning, considering location, size and charging strategies is presented in Zheng et al. (2014).

Other studies consider the problem of placing and sizing CSs in highways to serve EVs that travel for long distances. In such studies (e.g. Huang & Kockelman, 2020; Napoli et al., 2020Napoli, Polimeni, Micari, Andaloro, & Antonucci, 2020), only fast chargers are typically considered.

1.2. Scheduling algorithms for smart charging

There are various economic and technical benefits that smart charging offers to customers and power network operators. In particular, smart charging technology can be configured with scheduling algorithms in order to increase the social welfare by prioritizing the charging tasks that are more urgent (Tsaousoglou, Steriotis, Efthymiopoulos, Smpoukis, & Varvarigos, 2019), while it also allows the CS to offer demand response services to the system operator (Tsaousoglou, Steriotis, Efthymiopoulos, Makris, & Varvarigos, 2020). In Sachan, Deb, and Singh (2020a), the authors study the impact of different heuristic smart charging methods on the underlying electricity grid.

In Şükrü Kuran et al. (2015), the revenue-maximizing problem of a CS is considered. The authors propose a two-layer scheduling method and compare it with two heuristic algorithms: first come first serve (FCFS) and earliest deadline first (EDF). In Tsaousoglou, Steriotis, and Varvarigos (2019), scheduling of EV charging was used as a tool to minimize the operational electricity costs of CSs. In Li, Xie, Huang, Lin, and Liu (2020), the authors considered the scheduling problem of the EVs in a working place parking lot, with the objective of maximizing the average user satisfaction. Huang and Zhou (2015) also considers a workplace parking lot and leverages smart charging in order to minimize costs. A real-time EV charging strategy with preemption is proposed in Jiang and Zhen (2019), for a setting with an energy storage system and renewable generation. In Vandael, Claessens, Hommelberg, Holvoet, and Deconinck (2013), the authors developed a method for deciding the aggregate charging energy of a station, and prioritizing the station's EVs based on their urgency. In Tang et al. (2014), an online algorithm was developed for deciding the charging rate of EVs in a CS, so that the CS's energy cost is minimized under uncertain future arrivals. Finally, Tsaousoglou, Pinson, and Paterakis (2021) proposes a mechanism for allocating the available RES generation to EVs, using algorithmic game theory.

1.3. QoS-aware charging station sizing

Quality of Service is a major key performance indicator as it implicitly quantifies the acceptance rate of the proposed CS services from the end users' perspective. Xiao, An, Cai, Wang, and Cai (2020) jointly considers the QoS satisfaction of end users and the planning cost budget by deciding the optimal CS locations, the optimal quantities of chargers installed at each CS, the optimal allowable maximum queue length and maximum capacity of each CS. Their results show that the total CS infrastructure planning cost can be effectively reduced by appropriately increasing the quantity of chargers at each CS and the distribution density of CS.

Chen et al. (2017) emphasizes the need to conduct adequate congestion analysis when designing CS in order to guarantee acceptable QoS for end users in the future. It also adopts queuing theory to model and analyze the charging congestion phenomenon in CS planning results. This work is based on a data-driven methodology. Choi and Lim (2020) proposes a queuing model and two congestion control policies based on EV queue length thresholds. A thorough CS planning cost analysis is performed to investigate situations in which the application of each proposed QoS-aware congestion control policy is advantageous. However, the proposed QoS-aware schemes are not modelled jointly with the CS planning problem, but rather numerical results are provided for specific case studies. In Yang, Sun, Deng, Zhao, and Zhou (2018), the optimal number of chargers and waiting spaces in the fast charging stations are jointly optimized by considering the cost-benefit performance from both CS operator and EV users' perspectives. Works similar to Yang et al. (2018), such as Zhu et al. (2017) and Su, Li, and Gao (2017), have also used queuing theory to build EV charging station planning models and determined the optimal CS sites and their optimal scale (i.e. quantity of chargers and waiting spaces).

In this family of studies, QoS is predominantly modelled based on waiting times that result from queuing models, and the effect of smart charging capability (as this is proposed by studies in 1.2) is not considered. On the other hand, in Zenginis, Vardakas, Zorba, and Verikoukis (2017), Zenginis, Vardakas, Zorba, and Verikoukis (2016) and several references therein, the performance of a single CS in terms of the trade-off between the EV owners' QoS and CS operator's profits is evaluated. A QoS-aware scheduling model is proposed for multiple EV classes, but the authors do not deal with the CS sizing problem. They rather refer to the need to jointly consider CS planning and scheduling taking into consideration QoS constraints as a future work, which is this paper's main contribution.

1.4. Contributions and organization

The literature review presented above reveals studies that deal with the sizing problem of a CS under forecasted charging demand (and possibly QoS considerations via queuing models), as well as a distinct family of studies that propose smart charging solutions that optimize the CS's operational objective with the CS's infrastructure (chargers) being fixed. However, by using smart charging, a CS can significantly alter its daily power demand profile (e.g. shave demand peaks), which in turn greatly interacts with the sizing decisions for the number and types of chargers to install. For example, if the charging demand of the CS is very flexible towards temporal shifting, then the CS can accommodate it with fewer chargers by optimizing the charging times of EVs during operation. Nevertheless, to the best of the authors' knowledge, optimizing the sizing decisions of a CS (in terms of cost and QoS) while also considering the effect of smart charging during operation, has not been addressed in the literature.

In this paper, we consider a CS with smart charging capabilities and formulate the objective of minimizing its investment cost (Capital Expenditures) while ensuring a certain level of QoS for its clients, using chance-constraints. We model the QoS based on the probability that an EV suffers a certain level of waiting time beyond its requested departure time. We also model and analyze the effect of smart scheduling and smart charging CS capabilities. We approximate through analytic probability distributions the parameters of the arriving charging tasks and solve the sizing problem using mixed-integer optimization. Finally, we perform extensive simulations for a particular case study to analyze the relation between the QoS and the investment cost under smart charging capabilities. The most important contributions of this paper can be summarized as follows:

- The sizing problem of a CS is extended, so that the CS's smart charging capabilities during operation are also taken into account.
- A novel formulation for the QoS level of the CS is presented, where the QoS is defined based on the probabilities that a charging task will suffer various levels of delay with respect to the satisfaction of its charging demand.
- The sizing problem is brought to a solvable form after certain constraint relaxations.
- The scalability of the optimal sizing algorithm is enhanced through a methodology based on Monte Carlo simulations.
- Simulation results are presented, that show the relation between the QoS and the cost of the chargers installed as well as the impact of smart charging towards reducing the infrastructure cost during the sizing phase.

The rest of the paper is organized as follows. Section 2 presents the system model and problem formulation. The evaluation setup and simulation results are presented in Section 3. Finally, Section 4, concludes the paper.

2. System model and problem formulation

We consider the sizing problem of a CS, which can install chargers of different types. Let J denote the set of candidate chargers to be installed. Each candidate charger $j \in J$ is characterized by a maximum charging power P_j that it can support and by a cost u_j. A candidate charger $j \in J$ can be selected to be installed or not, depending on the (binary) decision variable

$$q_j \in \{0, 1\}. \tag{1}$$

In an operational horizon, the CS admits a set N of arriving EVs. Within the horizon, continuous time is divided into a set T of time slots of equal duration. An EV $i \in N$, arrives to the CS at an arrival time $a_i \in T$, and features a certain charging task that it needs to satisfy, which is characterized by a departure time $d_i \in T$, where $a_i < d_i$, and a certain charging energy requirement E_i. The battery of EV i bears a maximum charging rate η_i.

Regarding the level of control that the CS has over the charging profile of its EVs, different cases are relevant. In the next three subsections, we formulate three different Charging Control models, i.e. "Smart Scheduling", "Smart Charging", and "First Come First Serve policy", that we later compare with respect to their effects on the CS's sizing problem.

2.1. Smart Scheduling model

In the Smart Scheduling model the EV can start charging at some timeslot (later than its arrival time a_i). The CS can decide the time that the EV begins to charge, but once the charging starts it cannot be interrupted. We say that the CS faces a non-preemptive scheduling problem. Let binary variable $x_{i,j,t}$ denote whether EV $i \in N$ starts charging at charger $j \in J$ at time slot $t \in T$. The EV can only be assigned to a charger that is selected to be installed, i.e.

$$x_{i,j,t} \leq q_j, \quad \forall i \in N, \ \ j \in J, \ \ t \in T. \tag{2}$$

If i is assigned to charger j, then, depending on the charging power P_j of charger j and the battery charging rate η_i of EV i, the EV will need $s_{i,j}$ timeslots to complete its charging task. It is

$$s_{i,j} = \left\lceil \frac{E_i}{min\{\eta_i, p_j\}} \right\rceil,$$

where $\lceil \cdot \rceil$ denotes the rounding to the nearest integer above.

Each EV is assigned to exactly one charger $j \in J$ and starts charging at exactly one particular time slot $t \in T$, that is,

$$\sum_{j\in J} \sum_{t=a_i}^{|T|-s_{i,j}+1} x_{i,j,t} = 1, \quad \forall i \in N. \tag{3}$$

Constraint (3) also makes sure that the EV is not assigned to a charger that cannot start charging the EV by timeslot $|T| - s_{i,j}$, so as to be able to complete the charging task within the horizon T.

The timeslot c_i where EV i completes its charging task is calculated by adding the EV's uninterrupted charging duration $s_{i,j}$ to the timeslot in which the EV starts charging. The latter is equal to $\sum_{j\in J}\sum_{t=0}^{|T|-s_{i,j}} x_{i,j,t}t$, since, by Eq. (3), variable $x_{i,j,t}$ will be non-zero for only one timeslot. Thus, we have

$$c_i = \sum_{j\in J} \sum_{t=0}^{|T|} x_{i,j,t} \cdot (t + s_{i,j}), \quad \forall i \in N. \tag{4}$$

The task of each EV must be completed within the time horizon T, that is,

$$c_i \leq |T|, \quad \forall i \in N, \tag{5}$$

while at most one EV may be charging on each charger at any given time slot:

$$\sum_{i\in N}\sum_{\tau=max\{a_i,t-s_{i,j}+1\}}^{t} x_{i,j,\tau} \le 1, \quad \forall j\in J, \quad t\in T \tag{6}$$

Depending on the CS's assignment decision, EV i will suffer a delay of ζ_i timeslots on the completion of its task, where

$$\zeta_i = max\{c_i - d_i, 0\}, \quad \forall i\in N. \tag{7}$$

2.2. Smart Charging model

The Smart Charging model differs from Smart Scheduling in the sense that it also allows for fully controlling the EV's charging power, while allowing also for charging interruption. Fig. 1 presents this difference graphically.

Upon arrival, the EV is assigned to a certain charger. Let binary variable $y_{i,j}$ denote whether EV i is assigned to charger j. The EV is assigned to exactly one charger, i.e.

$$\sum_{j\in J} y_{i,j} = 1, \quad \forall i\in N, \tag{8}$$

and it can be assigned only to a charger that has been installed, i.e.

$$y_{i,j} \le q_j, \quad \forall i\in N, \quad j\in J. \tag{9}$$

An EV i can charge at charger j and timeslot t, at a power rate $p_{i,j,t}\ge 0$ which is a continuous variable chosen by the charging station, representing smart charging. The EV can receive charging only from the charger to which it is assigned:

$$p_{i,j,t} \le y_{i,j}\cdot min\{P_j,\eta_i\}, \quad \forall i\in N, \quad j\in J, \quad t\in T, \tag{10}$$

where η_i is the EV's maximum charging rate. Moreover, the EV cannot charge before its arrival time

$$p_{i,j,t} = 0, \quad \forall t < a_i, \quad i\in N, \quad j\in J. \tag{11}$$

Multiple EVs can be assigned to the same charger, but they would have to share the charger's output power:

$$\sum_{i\in N} p_{i,j,t} \le q_j\cdot P_j, \quad \forall j\in J, \quad t\in T. \tag{12}$$

We define a binary variable $c_{i,t}$ to denote whether EV i completes its charging task at timeslot t. In order for that to happen, i needs to have received a charging equal or higher than its charging demand E_i, up until timeslot t. This is expressed as

$$\sum_{j\in J}\sum_{\tau=1}^{\tau=t} p_{i,j,\tau} \ge c_{i,t}\cdot E_i, \quad \forall i\in N, \quad t\in T, \tag{13}$$

while it is required that i receives its charging demand within the horizon T:

$$\sum_{t\in T} c_{i,t} = 1. \tag{14}$$

Depending on the timeslot $t\cdot c_{i,t}$, in which EV i completes its charging task, the EV suffers a delay of ζ_i timeslots, where

$$\zeta_i = max\left\{0, \sum_{t\in T} t\cdot c_{i,t} - d_i\right\} \tag{15}$$

2.3. First Come First Serve policy

In order to have a benchmark for comparison, we consider the first-come-first-serve (FCFS) policy, as a scheduling policy that represents the absence of smart charging/scheduling. In FCFS, the tasks are prioritized based on their arrival time, i.e. for two tasks m, n where task m has an earlier arrival time ($a_m < a_n$), then task m should start charging earlier than n. This is implemented by considering the Smart Scheduling model as described, but adding the following constraint

$$\sum_{j\in J}\sum_{t\in T} x_{m,j,t} t \le x_{n,j,t} t, \quad \forall m,n \in \{N_k : a_m < a_n\}. \tag{16}$$

2.4. Formulation of sizing problem with QoS constraints

It is assumed that the parameters a_i, d_i, E_i of the EVs that request charging services from the CS are not known beforehand for future operational days but they can be approximated by known probability distributions. Thus, the QoS of the CS is defined by a tuple (Γ,ε,D), where Γ is the upper bound on the probability that an EV suffers any amount of delay, and ε is an upper bound on the probability that an EV suffers a delay higher than D. In order to secure a certain level (Γ,ε,D) of QoS, the CS needs to install enough chargers, so that

$$\Pr\{\zeta_i > 0\} \le \Gamma, \tag{17}$$

and

$$\Pr\{\zeta_i > D\} \le \varepsilon. \tag{18}$$

Notice that the CS's level of QoS, depends on the CS's sizing decisions q_j through Eqs. (1)–(18). The sizing problem of the CS is to find the optimal configuration of chargers such that the selected level of QoS is ensured, with the minimum possible cost. Considering a monetary cost of u_j for each charger $j\in J$, the CS's cost is comprised by the investment cost of chargers $\sum_{j\in J} q_j u_j$. Under these considerations, the CS's sizing optimization problem with chance constraints for QoS, is formulated as

$$\begin{aligned} \min_{q_j,\mathcal{V}} \quad & \sum_{j\in J} q_j u_j \\ \text{s.t.} \quad & \text{model constraints of a Charging Control model,} \\ & (1), (17), (18), \end{aligned} \tag{19}$$

where set $\mathcal{V}$ contains the decision variables of the relevant Charging Control model used.

Chance constraints (17), (18) of problem (19) cannot be handled analytically. We tackle problem (19) by a Monte Carlo simulation method, where we sample different problem instances from the probability distributions of parameters a_i, d_i, E_i and obtain an estimation of $\Pr\{\zeta_i > 0\}$ and $\Pr\{\zeta_i > D\}$. In particular, we create a set K of problem

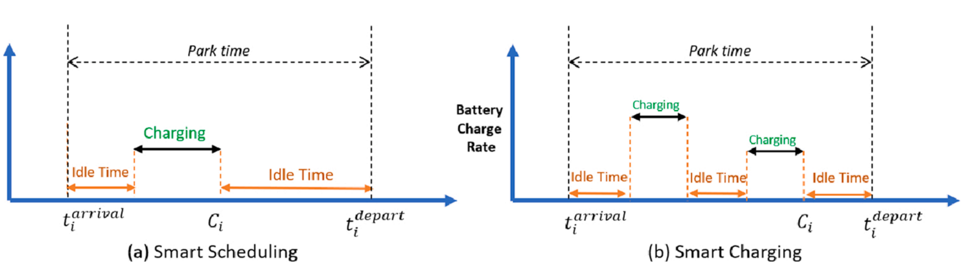

Fig. 1. Difference between Smart Scheduling and Smart Charging.

instances, where in each instance $k \in K$ a different set N_k of EVs is generated. We extend the variable set $\mathcal{V}$ to $\mathcal{W} = \{q_j, \mathcal{V}^{(k)}, \xi_i^{(k)}, \mu_i^{(k)}\}$, where $k \in K$. Binary variable $\xi_i^{(k)}$ denotes whether EV i of instance k suffers any delay, and binary variable $\mu_i^{(k)}$ denotes whether it suffers a delay larger than D, i.e.:

$$\xi_i^{(k)} = \begin{cases} 1, & \zeta_i^{(k)} \geq 0, \\ 0, & \text{otherwise}, \end{cases} \tag{20}$$

$$\mu_i^{(k)} = \begin{cases} 1, & \zeta_i^{(k)} \geq D, \\ 0, & \text{otherwise}, \end{cases} \tag{21}$$

Using these auxiliary variables, chance constraint (17) is replaced by

$$\frac{\sum_{k\in K}\sum_{i\in N_k}\xi_i^{(k)}}{|N_k||K|} \leq \Gamma, \tag{22}$$

and chance constraint (18) is replaced by

$$\frac{\sum_{k\in K}\sum_{i\in N_k}\mu_i^{(k)}}{|N_k||K|} \leq \varepsilon, \tag{23}$$

where $\sum_{k\in K}\sum_{i\in N_k}\xi_i^{(k)}/|N_k||K|$ is an estimation of $\Pr\{\zeta_i > 0\}$ and $\sum_{k\in K}\sum_{i\in N_k}\mu_i^{(k)}/|N_k||K|$ is an estimation of $\Pr\{\zeta_i > D\}$. Finally, the constraints of the Charging Control model of choice need to hold for all instances in K. Therefore, with a slight abuse of notation, we reformulate problem (19), as

$$\begin{aligned} &\min_{\mathcal{W}} \sum_{k\in K}\left(\sum_{j\in J} q_j^{(k)} u_j\right) \\ &\text{s.t. model constraints of a Charging Control model, } \forall k \in K, \\ &(1), (20)\text{–}(23). \end{aligned} \tag{24}$$

Problem (24) can now be brought to a solvable form, by relaxing constraints (20) and (21), using the big-M method, i.e.

$$(1 - \xi_i^{(k)})M + \zeta_i^{(k)} > 0, \tag{25}$$

$$\xi_i^{(k)}M - \zeta_i^{(k)} \geq 0, \tag{26}$$

$$(1 - \mu_i^{(k)})M + \zeta_i^{(k)} - D > 0, \tag{27}$$

$$\mu_i^{(k)}M - \zeta_i^{(k)} + D \geq 0, \tag{28}$$

where M is a constant large number.

The last remaining issue is that in order to have a decent estimation of the chance-constraint probabilities, a large number of sample instances $|K|$ needs to be considered. However, the computational time of problem (24) becomes a burden for large values of $|K|$, due to the increase in the number of decision variables. In order to tackle this issue, we design an algorithm, in which instead of constraints (22), (23), we consider the following constraints:

$$\frac{\sum_{i\in N_k}\xi_i^{(k)}}{|N_k|} \leq \Gamma, \quad \forall k \in K, \tag{29}$$

and

$$\frac{\sum_{i\in N_k}\mu_i^{(k)}}{|N_k|} \leq \varepsilon, \quad \forall k \in K. \tag{30}$$

Notice that, in contrast to (22), (23), constraints (29), (30) are required to hold for every instance $k \in K$. Therefore, (29) and (30) can be thought as the more conservative counterparts of (22) and (23) respectively. Indeed, notice that if (29), (30) hold, then so do (22), (23). Therefore, the CS will provide a QoS that is at least as good as the selected one. By using (29), (30), however, each instance is decoupled from the rest of the instances, which allows us to formulate the problem as

$$\begin{aligned} &\min_{\mathcal{W}^*} \sum_{k\in K}\left(\sum_{j\in J} q_j^{(k)} u_j\right) \\ &\text{s.t. model constraints of a Charging Control model,} \\ &(20)\text{–}(21), \\ &(29)\text{–}(30), \end{aligned} \tag{31}$$

where $\mathcal{W}^* = \{q_j^{(k)}, \mathcal{V}^{(k)}, \xi_i^{(k)}, \mu_i^{(k)}\}$. The motivation for the above reformulation is that problem (31), is directly separable to $|K|$ subproblems, i.e. a separate problem for each instance $k \in K$, since there are no coupling constraints between different scenarios k. By leveraging this formulation, we can solve $|K|$ instances of problem (31) (possibly in parallel), where in each subproblem the order of the number of variables is $\mathcal{O}(|N||J||T| + |N||J| + |N||T| + |J|)$, instead of one problem (i.e. (24)) with a number of variables in the order of $\mathcal{O}(|N||J||T||K| + |N||J||K| + |N||T||K| + |J|)$. After solving (31) in a distributed manner, the decisions for variables q_j are taken as

$$q_j = \max_{k\in K}\{q_j^{(k)}\}, \quad \forall j \in J. \tag{32}$$

In the next section we present a case study and respective simulation results of the proposed methodology.

3. Evaluation setup and results

We consider a time horizon T which consists of 24 timeslots of equal duration, and a number of 50 EVs unless stated otherwise. In order to evaluate the proposed methodology, we used an evaluation setup where the parameters of the charging demands (EVs) were generated randomly, using realistic probability distributions,[1] as the ones presented in Ma and Mohammed (2014) and Sachan, Deb, and Singh (2020b). In particular, the arrival time a_i of an EV is randomly generated by a truncated Gaussian distribution with mean $\mu = 8.5$ and standard deviation $\sigma = 2.7$ (rounded to the nearest integer below). Each EV, before reaching the CS is assumed to have driven a distance ρ_i, where ρ_i follows another truncated Gaussian distribution with mean $\mu = 40$ miles and standard deviation $\sigma = 15$.

The departure time d_i of an EV, is also sampled from a truncated Gaussian distribution with mean $\mu = 18.5$ and standard deviation $\sigma = 3.2$ (rounded to the nearest integer above). We considered four types of EVs with different specifications of energy consumption rate when driving θ_i, battery capacity b_i and battery charging rate η_i. The type distribution of EVs was generated randomly with a probability weight $(0.4, 0.3, 0.2, 0.1)$ for the EV types "Small", "Sedan", "SUV", and "Truck" respectively. The EV types and their characteristics are summarized in

Table 1
Types and specifications of EVs.

	Small	Sedan	SUV	Truck
Consumption rate θ_i	0.38	0.43	0.57	0.82
Battery Capacity b_i	16	24	54	70
Max Charging Rate η_i	8	24	50	50

[1] Note that the proposed methodology is not tailored to any particular model for the characteristics of the charging demands. Moreover, this paper does not discuss which model performs best towards accurate simulation of real EV arrivals. Rather, a probabilistic model for the arrival and departure distributions is taken from the literature and used as a testbed in order to evaluate the proposed methodology.

Table 1. The energy demand of each EV i depends on its distance ρ_i, covered before reaching the CS, and its energy consumption rate θ_i

$$E_i = min\{b_i, \rho_i\theta_i\}. \tag{33}$$

For the CS's choices for charging facilities, we considered three types of chargers where each type features a different level of charging rate. Level 1 charging uses a standard home (garage) 120 or 230 V, AC charger. The second option (Level 2) uses a 240/400 V outlet. Charging Level 1 and Level 2 are used mainly in single phase. Level 3, also known as fast charging, is a third option. The output power and the price of each charger are presented in Table 2. With respect to the QoS level chosen by the CS, we considered three different cases.

1. "No-Delay": QoS-(0,0,0):
   This QoS level means that $\Gamma = \varepsilon = D = 0$, which means that each one of all the arriving EVs should receive its whole energy demand E_i until its deadline d_i, and no delay is allowed. In practice, this would correspond to an expensive CS, whose business model is to guarantee that its clients never suffer any delay.
2. "One-Slot-Delay": QoS-(0.2, 0, 1):
   This level of QoS means that an arriving EV has a maximum of 20% chance of being delayed for one timeslot, but no delay higher than 1 timeslot is allowed. This business model would correspond to a medium QoS in practice.
3. "Free-Delay": QoS-(1,0,$|T| - d_i$):
   In this QoS-level the EVs have no guarantee with respect to when their charging will finish. The only guarantee is that their energy demand will be satisfied within the horizon T.

For each of the above cases, the sizing problem was solved for different numbers $|N|$ of arriving EVs and for a number of $|K| = 200$ instances (scenarios) for each choice of $|N|$. These scenarios are modeled in python 3.8 using Pyomo 5.7 (Hart et al., 2017), and solved by Gurobi 12.9 (Gurobi Optimization, 2020). The number of candidate chargers for each charger type is set to $\frac{\sum_{i\in N} E_i^{(k)}}{p_\omega |T|}$, where $p_\omega \in \{4, 8, 19.2\}$ is the output power of the corresponding charger type.

First, we evaluate the effect that the different Charging Control models have on the CS's investment cost. Fig. 2 depicts the results for the No-Delay case. As the figure suggests, the investment cost with Smart Charging can be significantly lower (more than 50%) compared to the FCFS case. Moreover, the difference increases with higher numbers of EVs, which suggests that it is indeed important to consider the smart charging (or smart scheduling) functionality of the CS in the CS sizing problem, especially as EV penetration increases.

In Fig. 3, the amount of investment cost, for the Smart Scheduling model, is compared for the three cases of QoS that were considered. It can be observed that, in comparison to the Free-Delay case (i.e. the one with the worst QoS), the CS can establish a medium level of QoS, i.e. One-Slot-Delay, with a relatively small extra cost.

For the case of One-Slot-Delay, the results of installed chargers (as a percentage of charger type) were obtained for different cases of the number of EVs $|N|$. Fig. 4 depicts the results for the Smart Scheduling model, while Fig. 5 depicts the results for the Smart Charging model. The results show that, in the case of Smart Scheduling, this particular CS would be mainly relying on Level 2 and Level 3 chargers. However, the results are vastly different in the case of the Smart Charging model: By allowing full controllability of the EVs, the Smart Charging model

Table 2
Charger types and costs.

Charger type	Charging rate p_j	Charger cost u_j
Level 1	4 kW	1000$
Level 2	8 kW	1500$
Level 3	19.2 kW	2200$

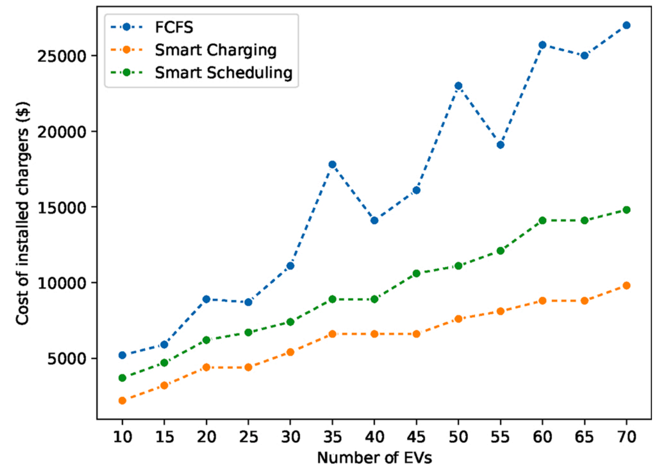

Fig. 2. Cost of installed chargers as a function of number of EVs for the three Charging Control models.

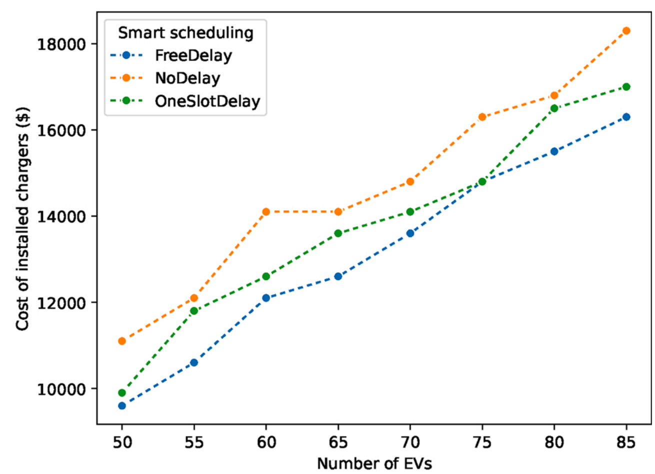

Fig. 3. Cost of installed chargers for different numbers of EVs.

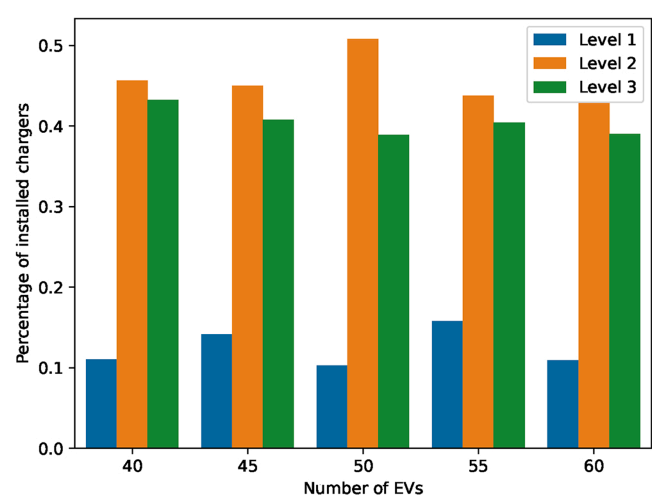

Fig. 4. Percentage of installed chargers of each charger type for different numbers of EVs for the Smart Scheduling model and for the One-Slot-Delay model.

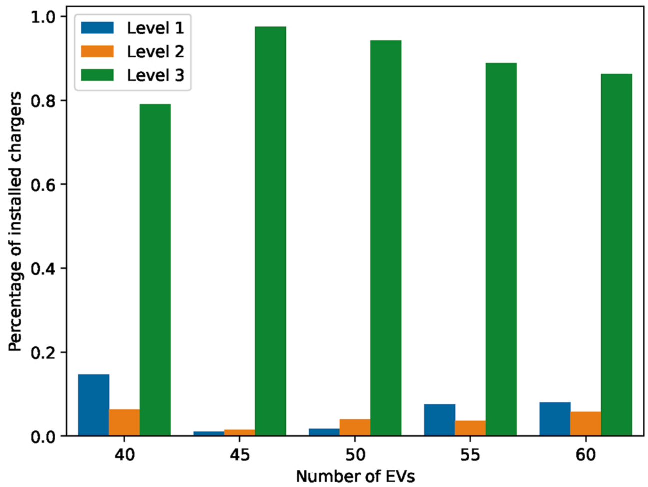

Fig. 5. Percentage of installed chargers of each charger type for different numbers of EVs for the Smart Charging model and for the One-Slot-Delay model.

enables higher adoption of Level 3 chargers, i.e. the ones that have the lowest cost per kW. In contrast, the Smart Scheduling model opts also for other types of chargers in order to have more chargers in total since it cannot charge EVs simultaneously. As a final observation, we note that even with the Smart Charging model the algorithm also chooses some Level 1 and Level 2 chargers in most cases, because having more chargers is still beneficial since it provides more choices for the initial assignment of EVs to chargers.

It is worth noting that we also included an extra charger type in the simulations, namely ultra-fast charging with a charging rate of 50 kW, and a cost of 50,000$. Notice that, by Tables 1 and 2, this type of chargers can charge the Sedans, SUVs and Trucks faster than the other charger types, and a naive approach might have also installed some of these chargers. Nevertheless, the simulation results show that this charger type was never needed to be installed, for the given level of QoS (for this reason, it is not included in the figures).

The results of Fig. 6, depict the respective percentages of installed charger types for all three cases of QoS and for both Smart Scheduling and Smart Charging models, for a fixed number of 70 EVs.

Next, we demonstrate the resulting matchings, i.e. in what charger type is each EV-type assigned to for the Smart Scheduling model. As shown in Fig. 7, the slower Level 1 and Level 2 chargers that are installed, are mainly used to charge small EVs. By increasing the battery capacity b_i and charging rate η_i, EVs are shifting to use faster chargers.

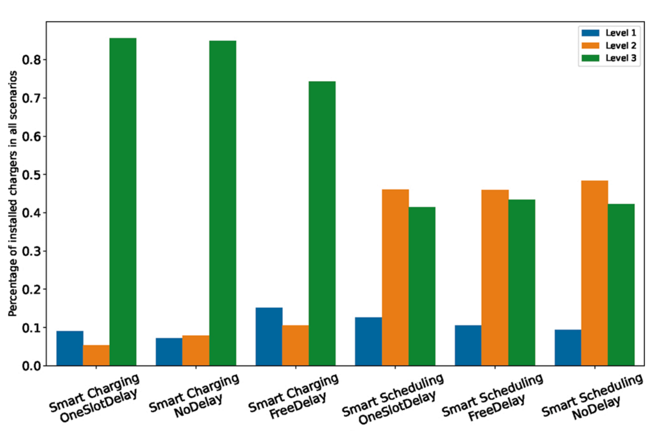

Fig. 6. Percentage of installed chargers of each charger type in each Charging Model and QoS case.

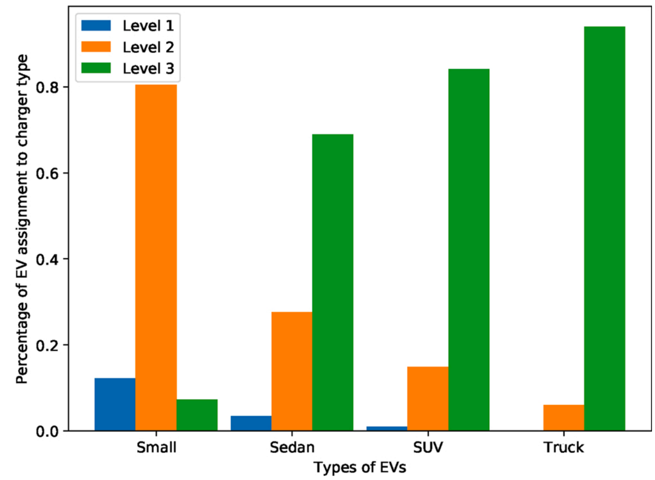

Fig. 7. Percentages of EV assignments to each charger type, for all EV types.

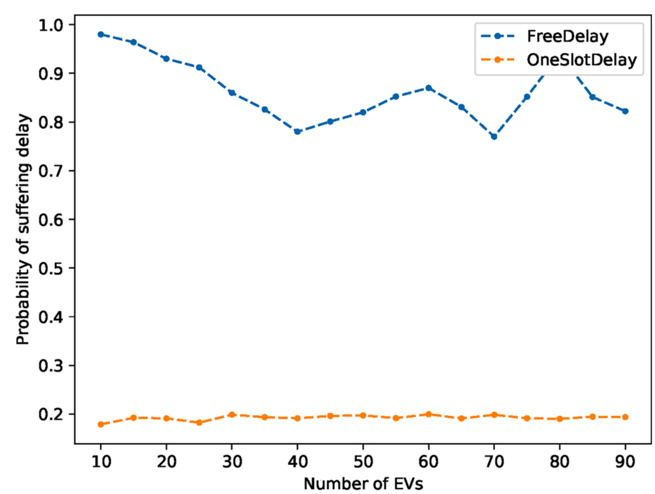

Fig. 8. Probability of suffering delay for different numbers of EVs.

In Fig. 8, we also compare the two QoS levels that allow delay (i.e. Free-Delay and One-Slot-Delay) with respect to the probability that an EV will suffer any amount of delay, as computed by $\frac{\sum_{k\in K}\sum_{i\in N_k}\xi_i^{(k)}}{|N_k||K|}$. Recall that the QoS level for One-Slot-Delay was (0.2, 0, 1) which means that we allow up to 20% of EVs to suffer any amount of delay. Note that, while the problem was solved using (29), in Fig. 8, the probability of delay is evaluated using the metric defined in (22). Thus, the figure provides insight into how good the proposed relaxation is. As can be observed by the figure, the delay probability for One-Slot Delay is always lower than 20%, which justifies the approach that we adopted by replacing (22) with (29). Moreover, the figure demonstrates that the proposed relaxation is not only conservative, but actually fairly tight as well, since the resulting probability is quite close to 20% in most cases.

4. Conclusions

In this paper we considered the sizing problem of a Charging Station (CS), i.e. deciding the amounts and types of chargers to be installed. We enhanced the sizing optimization models of the existing literature by taking into account the ability of the CS to control the charging of EVs during operational time, under different charging control models (i.e. Smart Scheduling, Smart Charging and First-Come-First-Serve policy). The sizing problem was formulated as a cost-minimization problem with chance constraints for Quality of Service (QoS). In particular, a CS's level of QoS was defined based on the probability that an EV will suffer a delay in the completion of its charging task, and the probability that this delay will be higher than a given threshold. We proposed a novel methodology based on optimization theory for bringing this problem to a solvable form, while we also proposed a conservative relaxation that highly reduces the computational time and increases the scalability of the proposed algorithm.

For the case study presented, our simulation results verified that this relaxation is indeed conservative (i.e. respects the CS's desired QoS) and even fairly tight (i.e. results in a QoS level which is very close to the one desired by the CS). Also, the results show substantial differences in the choice of charger types, depending on which charging control model is available to the CS. Finally, the motivation for considering the CS's smart charging capabilities into the CS's sizing problem was verified experimentally, since smart charging was shown to reduce the infrastructure cost more than by 50%, and the percentage increases for larger charging stations.

Conflict of interest

None declared.

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