Probabilistic Energy Management Strategy for EV Charging Stations Using Randomized Algorithms

Peter Pflaum, Mazen Alamir, and Mohamed Yacine Lamoudi

***Abstract*— Electric vehicle charging stations (EVCSs) come along with great challenges for the power grid due to their highly uncertain load characteristic. This is particularly the case for charging stations located in nonresidential areas, such as commercial centers, company sites, or car-rental stations. For a safe and sustainable operation of the power grid, distribution system operators require reliable load forecasts of such charging stations. In this brief, a robust EVCS management strategy is proposed, which provides a day-ahead upper limit profile of the EVCS's power consumption. In real time, this upper limit profile is strictly respected while guaranteeing—at a configurable probability—the Quality of Service. The strategy is based on randomized algorithms and relies on a statistic occupancy model of the EVCS while not requiring any online forecasts of each EVs' arrival and departure schedules. In a case study based on statistic data, which has been provided by the Euref Campus in Berlin, the feasibility and relevance of the proposed approach are demonstrated.**

***Index Terms*— Electric vehicle charging station (EVCS), energy management, optimization, randomized algorithm, statistic EV behavior model.**

NOMENCLATURE

n_{CP}	Number of charging points.
n_{EV}	Number of vehicles in a scenario.
$t_{\text{arr}},, t_{\text{dep}}$	Arrival time and departure time of a vehicle.
t_{park}	Parking time of a vehicle.
E_{req}	Required energy to become fully charged.
S	Occupancy scenario of the charging station.
V	Set of vehicles in S ($V = \{1, \ldots, n_{\text{EV}}\}$).
H	Number of time intervals of length τ.
$P(n_{\text{arr}}\|i)$	Probability that n_{arr} EV's arrive during the ith time interval.
$E(t_{\text{dep}}\|i)$	Expected value of an EV's departure time which arrived during the ith time interval.
$\rho(t_{\text{dep}}\|i)$	Standard deviation of the EV's departure time.
$E(E_{\text{req}}\|i)$	Expected value of an EV's required energy.
$\rho(E_{\text{req}}\|i)$	Standard deviation of the EV's required energy.
E_{charged}	Energy supplied to a vehicle.
$t_{\text{connected}}$	Time a vehicle remains connected.
τ	Time step.
T_{th}	Time constant.
c_{satis}	Satisfaction threshold (in %).
$\mathbf{p}(\theta)$	Upper bound power profile parameterized by θ.
P_{max}	Maximal charging power of a charging point.
$\mathcal{W}$	Uncertainty set.
θ	Design parameter vector ($\theta \in \mathbb{R}^d$).
$\boldsymbol{\Theta}$	Finite set of design parameter vectors.
$J(\theta)$	Performance measure/cost function.
$g(\theta, S)$	Binary constraint satisfaction function.
$n_{\boldsymbol{\Theta}}$	Cardinality of the set $\boldsymbol{\Theta}$.
η, δ	Probabilistic parameters (precision and confidence).
m	Acceptable number of unsuccessful scenarios.

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I. INTRODUCTION

The foreseeable deployment of electric vehicles (EVs) will have an important impact on the existing power grid. The high amounts of energy required to charge the EV's batteries coupled with the uncertainty in their driving patterns may result in severe grid instabilities. Mainly, voltage fluctuations due to temporal imbalances between production and consumption as well as cable and transformer overloading in the low-voltage grid have been addressed in many recent studies concerning the integration of EVs into the existing power grid. The survey provided in [1] suggests that the impacts of EVs can be determined by the following aspects: driving patterns, charging characteristics, charge timing, and vehicle penetration. Reference [2] discusses chances and challenges arising with the integration of EVs into the power grid with an emphasis on potential impacts on the activities of current actors in the electricity systems. In [3], the impact of EVs on the Belgium distribution grid is assessed using a dynamic programming model.

While to this day, few real-life experiences regarding the EV integration at considerable scales have been conducted, and many numerical studies have addressed this issue and the general conclusion seems to be that the existing electricity grid is able to accommodate high amounts of EVs without having to reinforce its physical infrastructure, provided that intelligent charging strategies are applied. References [4] and [5] for instance show that using centralized control methods to manage the charging process allows to achieve EV shares in the range of 50%–100%

Unlike the so far mentioned papers, this brief does not focus on network-related aspects, but on the predictability of charging stations' power consumption profiles and the impact of the uncertain EV behavior. In this context, several authors propose control strategies where optimization problems over a certain prediction horizon are formulated, allowing to anticipate future events and to provide load predictions, which are very valuable for distribution system operators (DSOs). Reference [6] proposes a linear optimization problem formulation where an unbalanced distribution system is taken into account through a dc-equivalent model. In [7], a centralized controller for an EV aggregator is proposed, which computes charging schedules for the EVs such that the EV owners' charging costs are minimized while at the same time, the aggregator maximizes its revenue by selling regulation capacities to the DSO. Other related works where forecasts of the uncertain EV behavior are taken into account are for instance [8]–[10] where optimization problems for an aggregator agent acting as a commercial middle-man between the electricity market and the EV owners are proposed and validated through extensive simulations.

While in most works—amongst which the above-cited ones—the robustness of the control strategies against uncertainties is validated through simulations, quite few works can be found where the uncertainty is explicitly considered in the computation of the control strategy. In [11], for instance a chance-constrained optimization problem is formulated, which minimizes the charging costs while providing probabilistic guarantees of network loading limits and constraints related to the batteries. An interesting control approach is proposed in [12] where a stochastic dynamic programming model is used to optimally charge an EV and where the user's individual risk-aversion is taken into account. Several contributions addressing EV charging at parking lots are [13]–[16]. Reference [13] for instance proposes a two-stage approximate dynamic programming framework to deal with the high uncertainty while aiming to reduce the energy cost of the charging station. In [14], a centralized recharge scheduling system for parking-lots is proposed. The authors distinguish between regular EVs whose behavior is repetitive and can be predicted and irregular ones whose individual behavior is unpredictable. Bayram *et al.* [15] propose a mechanism based on game theory, which allows to coordinate a population of EVs in such a way that existing network capacities are used more efficiently. In [16], a method to compute the necessary network resources such that the quality of service (QoS) can be guaranteed at a configurable probability is described.

In this brief, we present a centralized charging strategy for an EVCS located at places such as commercial centers with relatively high uncertainties in the EVs' behavior. The motivation for the proposed strategy comes from the fact that reliable load forecasts of large consumers such as EVCSs are of great value for DSOs and other entities that are in charge of managing the grid in a reliable and economically profitable way. For instance in distributed optimization frameworks such as the one presented in [17] and [18], a reliable load forecast of an EVCS is crucial to be able to coordinate the different grid actors (producers, consumers, and storage systems) in a globally optimal way. To the extent of our knowledge, this aspect is not tackled in the previously cited references.

The main characteristics of the proposed EVCS management strategy are the following.

- A day-ahead upper bound profile of the EVCS's power consumption is provided to the DSO, which is then strictly respected in real time.
- At the same time, the QoS for the EV customers is guaranteed at a configurable probability despite the potentially high uncertainties in the EV behavior. Note that a high probability for the guaranteed QoS leads to a higher overestimation of the required energy, which is reserved through the upper bound power profile for the EVCS.
- In real time, the control strategy does not require any forecast information from the EV customers such as arrival and departure times. It only relies on the measured state-of-charge (SOC) of the EVs' batteries.

The underlying technique used in the proposed EVCS management strategy is a randomized algorithm whose theoretic foundations are detailed in [19] and [20]. The main idea is to recast an NP-hard robust optimization problem in probabilistic terms and then to solve the probabilistic problem by means of randomized algorithms.

This brief is organized as follows. In Section II, the problem context is described. Section III provides a brief overview of the proposed approach, which is then detailed in Sections IV and V. In Section VI, we provide simulation results on a real-life EVCS and a discussion of the algorithm's performances. Finally, Section VII concludes this brief.

II. Problem Context

The objective of the proposed control strategy is to determine an upper bound profile on an EVCS's power consumption while guaranteeing the QoS with a configurable probability despite the uncertain EVCS occupancy. The underlying robust control problem can be represented as follows:

$$\min_{\theta} J(\theta) = \int_{t=0}^{24} \mathbf{p}(\theta)dt \quad \text{s.t.} \quad g(\theta, S) = 0 \quad \forall S \in \mathcal{W} \tag{1}$$

where $\theta \in \mathbf{\Theta}$ is a design parameter vector, $J(\theta)$ represents the objective function, more precisely the minimization of the preallocated energy for the day, $\mathcal{W}$ is the uncertainty set, and the binary constraint satisfaction function $g(\theta, S)$ being defined by

$$g(\theta, S) := \begin{cases} 0, & \text{if } \theta \text{ satisfies the QoS for scenario } S \\ 1, & \text{otherwise.} \end{cases} \tag{2}$$

To realize this objective by means of algorithms, it is important to define a mathematical representation of the QoS as well as a statistic model of the uncertain EVCS occupancy based on which the algorithms can be built. These two topics are addressed in this section.

A. Statistic Model of the EVCS Occupancy

One crucial characteristic of the proposed control strategy is that the uncertain EV behavior is explicitly taken into account

Algorithm 1 Scenario Generator Function

Inputs: $P(n_{\text{arr}}|i)$, $E(t_{\text{dep}}|i)$, $\sigma(t_{\text{dep}}|i)$, $E(E_{\text{req}}|i)$, $\sigma(E_{\text{req}}|i)$, H, τ, n_{CP} ;
Init: $n_{occ} = 0$;
for $i \leftarrow 1$ **to** H **do**
    Count number n_{occ} of occupied charging points ;
    Generate a sample n_{arr} from $P(n_{\text{arr}}|i)$;
    for $l \leftarrow 1$ **to** n_{arr} **do**
        Compute $t_{\text{arr}} = i \cdot \tau$;
        if $n_{occ} < n_{CP}$ **then**
            Generate t_{dep} from $E(t_{\text{dep}}|i)$, $\sigma(t_{\text{dep}}|i)$;
            Generate E_{req} from $E(E_{\text{req}}|i)$, $\sigma(E_{\text{req}}|i)$;
            $n_{occ} = n_{occ} + 1$;
            Add EV $\{t_{\text{arr}}, t_{\text{dep}}, E_{\text{req}}\}$ to scenario S ;
Outputs: S ;

through a certain number N of EVCS occupancy scenarios. In this brief, the term "scenario" describes a realization of 24-h occupancy schedules for all n_{CP} charging points of the EVCS. A scenario realization is obtained from a scenario generator function, which implements the statistic laws describing the uncertain EV arrival and departure times as well as the EVs' SOC at arrival.

Remark: It is not in the scope of this brief to provide advanced and validated stochastic models of the EVCS occupancy. In fact, the very nice feature of the randomized algorithm approach, which is applied in our proposed control strategy, is its independence from the type of underlying statistic occupancy model. The only requirement is that the statistic model allows generating independent and identically distributed (i.i.d.) scenario realizations.

In the literature, numerous suitable statistic models of the uncertain EV behavior can be found. In [11], for instance a traffic model is proposed where different states (driving, parked at work, at home, for leisure, or at a shopping location) are defined and driving patterns are modeled using a continuous time non-Markov chain. In [9], a linear model with lagged variables and covariates is chosen and fitted from historical data, aiming to forecast the arrival and departure times of EVs at residential charging points. In Section VI, we follow a similar approach in order to fit a statistic model to the historical data of an e-Car sharing station, which is located at the Euref Campus in Berlin [21].

In the sequel, the uncertainty model, which is used to generate scenario realizations of the EVCS occupancy in this brief, is detailed. A scenario S is defined as follows:

$$S := \{t_{\text{arr},\upsilon}, t_{\text{dep},\upsilon}, E_{\text{req},\upsilon}\} \quad \text{with} \quad \upsilon = 1, \ldots, n_{\text{EV}} \tag{3}$$

where $t_{\text{arr},\upsilon}$ and $t_{\text{dep},\upsilon}$ are the arrival and departure times of the υth EV, and $E_{\text{req},\upsilon}$ is its required energy to become fully charged. n_{EV} is the number of vehicles, which are charged in scenario S. In order to generate a scenario realization as described in algorithm 1, the following stochastic parameters have to be determined (e.g., by identification from historic data).

Fig. 1. e-Car sharing station located at the Euref Campus in Berlin.

1) $P(n_{\text{arr}}|i)$ is the probability that n_{arr} EVs arrive during the ith time interval with $i = 1, \ldots, H$. Note that the 24-h horizon is discretized into H time intervals of equal length τ (e.g., $\tau = 1$ h).
2) $E(t_{\text{dep}}|i)$ is the expected value of an EV's departure time, which arrived during the ith time interval.
3) $\sigma(t_{\text{dep}}|i)$ is standard deviation of the EV's departure time.
4) $E(E_{\text{req}}|i)$ is the expected value of an EV's required energy to become fully charged.
5) $\sigma(E_{\text{req}}|i)$ is the standard deviation of the EV's required energy to become fully charged.

In Section VI, a case study based on statistic data from an e-Car sharing station located at the Euref Campus in Berlin (see Fig. 1) is provided.

B. Definition of Customer Satisfaction

Since the proposed control strategy aims at providing probabilistic guarantees for the QoS, this term needs to be defined precisely. In [5], a metric to quantify customer satisfaction is proposed, which is based on the ratio between the time it takes to fully charge an EV's battery and the time it would have taken if the battery had been charged constantly at nominal power. However, for the purpose of this brief, this kind of measure is not appropriate for the following reasons. First, not every EV remains connected long enough to become fully charged, but the customer may still be satisfied with a partial charge. Second, a binary satisfaction indicator is required for our proposed strategy. For these reasons, we propose a new metric to evaluate an EV owner's satisfaction. However, any other metric providing a binary indicator whether a customer is satisfied or not can be applied.

The basic idea of the proposed metric is that a customer is considered to be satisfied if he has obtained more than a certain percentage of the energy he would have required to become fully charged. Moreover, this percentage depends on the connection time of the EV, since a customer, who remains connected for a short time interval only, will not expect his battery to be fully charged. The metric is implemented by

Generate n_Θ candidate upper bound profiles $\mathbf{p}(\theta^{(1)}), \ldots, \mathbf{p}(\theta^{(n_\Theta)})$ of the EVCS's power consumption using a suitable parametrization (sec. IV-A)

↓

Use the probabilistic certification framework to compute the necessary number of scenarios N (sec. V-A). For each candidate profile $\mathbf{p}(\theta^{(i)})$, simulate a real-time controller to distribute the available power to N random occupancy scenarios $S^{(1)}, \ldots, S^{(N)}$ (sec. IV-B)

↓

Use randomized algorithms to determine the feasible $\theta^{(i)}$ that guarantee the QoS and amongst them the θ^{opt} that pre-allocates the least energy for the day (sec. V-B).

Fig. 2. Overview of the proposed approach.

inequality (4). If it is true, then the customer is considered to be satisfied

$$\frac{E_{\text{charged}}}{E_{\text{req}}} \geq c_{\text{satis}} \times \min\left(1, \frac{t_{\text{connected}}}{T_{\text{th}}}\right) \tag{4}$$

where E_{charged} is the charged amount of energy, E_{req} is the amount of energy, which would have been required to become fully charged, $t_{\text{connected}}$ is the time the EV was connected, and T_{th} is a time constant (e.g., $T_{\text{th}} = 3$ h). It represents the maximal acceptable waiting time for a customer to have his EV's battery fully charged. The right-hand side of (4) represents the satisfaction threshold (in %), which decreases linearly if an EV is connected less than T_{th}. c_{satis} is the percentage from which on a battery is considered to be "fully charged" (e.g., $c_{\text{satis}} := 90\%$). For a real-life application, T_{th} and c_{satis} should be determined through sociological studies in order to properly reflect the customers' expectations.

Definition 1: The QoS of a 24-h-charging strategy for an EVCS scenario is considered to be fulfilled if 95% of all EV customers are satisfied in the sense of (4).

III. Brief Outline of the Proposed Approach

Before going into the details of our proposed approach, a brief overview is provided in this section with the objective to facilitate the readability of this brief.

The objective of the control strategy proposed in this brief is to determine an allowed day-ahead power consumption profile for an EVCS such that—despite the strongly uncertain EV behavior—the QoS is guaranteed with a preconfigured probability. The method applied to achieve this objective is a randomized algorithm. The key steps of the proposed approach are summarized in the flowchart in Fig. 2.

IV. Parametrization and Controller Heuristic

In this section, the parameterization method for the upper bound power profile $\mathbf{p}(\theta)$ to be transmitted to the DSO is illustrated. Moreover, the real-time controller heuristic for distributing $\mathbf{p}(\theta)$ to the EVs is explained.

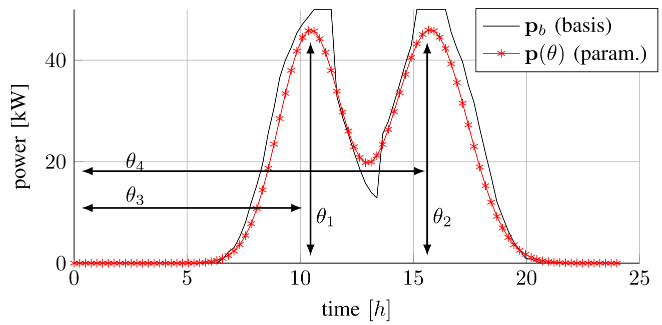

Fig. 3. Illustration of the parameterization of the upper bound power profile $\mathbf{p}(\theta)$. The base profile $\mathbf{p}_b$ is obtained by simulating a simple direct charging strategy for 100 scenarios and by building their mean profile.

A. Parameterization of $\mathbf{p}(\theta)$

The objective of the parametrization method for the allowed upper bound power profile $\mathbf{p}(\theta)$ is to be able to modify the shape of $\mathbf{p}(\theta)$ in a sufficiently rich way. Furthermore, this should be achieved by means of a relatively low-dimensional design parameter vector $\theta \in \mathbb{R}^d$.

In this section, a generic parameterization based on two superposed Gaussian distributions is proposed. Note that this very general parameterization has proven to work well for several problems, but it may also be replaced by a more customized parametrization when addressing a specific problem. Fig. 3 shows how the design parameter vector $\theta = (\theta_1, \theta_2, \theta_3, \theta_4)^T$ is used to parameterize the upper bound power profile $\mathbf{p}(\theta)$. θ_1 and θ_2 are scaling factors allowing to modulate the amplitude of the two superposed Gaussians, and θ_3 and θ_4 allow to shift the two Gaussians horizontally. The initial value for the design parameter vector θ is obtained by some curve fitting technique, such that $\mathbf{p}(\theta)$ fits the base profile $\mathbf{p}_b$ as well as possible. The base profile $\mathbf{p}_b$ is computed by simulating a simple direct charging strategy for a large number of scenarios (e.g., 100) and by building the mean profile of the resulting power consumption profiles of the simulated scenarios. In this brief, the term "direct charging strategy" refers to a charging heuristic where each vehicle is charged at its nominal power as soon as it arrives at the EVCS, and until it is fully charged or until it leaves the station.

B. Real-Time Controller Heuristic

For a given parametrized upper bound power profile $\mathbf{p}(\theta)$ for the EVCS's power consumption, the real-time controller is simulated for the N scenarios in order to distribute the allowed power profile $\mathbf{p}(\theta)$ to the EVs. The relatively simple heuristic implemented in the real-time controller is as follows.

- At each sampling instant of the 24-h horizon (e.g., every minute), check the number of connected EVs and try to equally distribute the available total power $\mathbf{p}(\theta)$ to the EVs.
- If there is still some power left, because one or more vehicles were already fully charged in the previous time step, revisit each car starting from the one with the lowest SOC and affect the remaining power to them.

Note that the main characteristic of the real-time controller is that the upper bound profile on the EVCS's power consumption $\mathbf{p}(\theta)$ is strictly respected.

V. Randomized Algorithm Approach

This section explains how randomized algorithms are used to compute the optimal design parameter vector θ^{opt}. The corresponding allowed day-ahead power profile $\mathbf{p}(\theta^{\text{opt}})$ for the EVCS can then be declared to the DSO or to any other entity, which is in charge of managing the distribution grid.

Although an exhaustive explanation of randomized algorithms is beyond the scope of this brief, the main result, which is applied in this brief, is recalled in a first step before being applied to the considered EVCS problem. The interested reader is referred to [19] for more detailed information on the theory of randomized algorithms.

A. Randomized Algorithm Principle

Given the deterministic robust control problem (1), which is NP-hard due to the infinite number of possible scenarios $S \in \mathcal{W}$, and thus basically impossible to be solved efficiently. It can, however, be recast as a probabilistic problem, which can then be solved by randomized algorithms in reasonable time.

Assume that a probability measure $\text{Pr}_{\mathcal{W}}$ over the sample space $\mathcal{W}$ is given. Each element of $\mathcal{W}$ is a possible realization of the uncertainty and i.i.d. samples from $\mathcal{W}$ can be generated. The probability of violation associated with θ is defined as

$$E(\theta) := \text{Pr}_{\mathcal{W}}\{S \in \mathcal{W} \ : \ g(\theta, S) = 1\}. \tag{5}$$

The idea underlying randomized algorithms is to provide, with high probability, $\theta \in \mathbf{\Theta}$ in such a way that $E(\theta) \leq \eta$. The key result making randomized algorithms interesting is that if one draws N i.i.d. samples $\{S^{(1)}, \dots, S^{(N)}\}$ from $\mathcal{W}$ according to probability $\text{Pr}_{\mathcal{W}}$ where N obeys the inequality

$$N \geq \frac{1}{\eta}\left(\frac{e}{e-1}\right)\left(ln\frac{n_{\mathbf{\Theta}}}{\delta} + m\right) \tag{6}$$

and then solves the m-level randomized strategy given by

$$\min_{\theta \in \mathbf{\Theta}} J(\theta) \quad \text{subject to} \sum_{l=1}^{N} g(\theta, S^{(l)}) \leq m \tag{7}$$

then the probability of violation $E(\theta)$ is smaller than η with probability larger than $1 - \delta$. $n_{\mathbf{\Theta}}$ is the cardinality of the finite set $\mathbf{\Theta}$. The precision η and the confidence δ are the probabilities defining the robustness of the solution (as stated previously). They should not be chosen unnecessarily small, since otherwise the necessary number of samples N becomes very large, which may result in high computation times. The parameter m represents the acceptable number of unsuccessful scenarios and needs to be chosen in advance (typically in the range 5–20 in the works presented in this brief).

B. Robust EVCS Strategy Based on Randomized Algorithms

Having briefly introduced the randomized algorithm principle in Section V-A, it is now applied to the considered EVCS case. The precise steps to be performed are provided by algorithm 2.

Note that the choice of the set of design parameter vectors $\mathbf{\Theta}$ needs to be done in a conservative way, such that the existence of feasible solutions is enhanced. Finally, the objective function $J(\theta)$, i.e., the criterion based on which the best solution θ^{opt} amongst the feasible ones (the set $\mathcal{A}$) is chosen is defined in problem (1). This objective function reflects that we aim to find the upper bound power profile $\mathbf{p}(\theta)$ that results in the lowest overestimation of the required energy for the EVCS over the considered time horizon (typically 24 h). The design parameter vector θ that minimizes $J(\theta)$ is denoted θ^{opt} in the sequel.

Remark: While the proposed method allows to provide a guaranteed upper bound profile of the EVCS's power consumption to the DSO, the DSO may also be interested in a guaranteed resource utilization. In our proposed approach, this issue could be addressed by adding an additional parameterizable lower bound power profile $\mathbf{p}_{\text{lower}}(\theta)$. Such an extension would mainly require to find a suitable parametrization of both, the upper and lower bound profiles $\mathbf{p}(\theta)$ and $\mathbf{p}_{\text{lower}}(\theta)$ and to extend the real-time controller.

Algorithm 2 Randomized Algorithm Implementation

```
Define the set of candidate design parameter vectors
  Θ = {θ^(1), ..., θ^(n_Θ)} ;
Choose η, δ, and m, and compute the necessary number
  of scenarios N according to (6) ;
Generate N scenarios S^(1), ..., S^(N) according to algo 1 ;
Initialize J ∈ R^(n_Θ), g ∈ R^(n_Θ × N), feasible set A = {} ;
for i = 1 : n_Θ do
    Compute the param. profile p(θ^(i)) (sec. IV-A) ;
    Compute the cost fc. J^(i) = J(θ^(i)) (sec. V-B) ;
    for k = 1 : N do
        Simulate the real-time controller (sec. IV-B) ;
        if QoS is achieved according to definition 1 then
            g^(i,k) = 0 ;
        else
            g^(i,k) = 1
    if Σ_{k=1}^{N} g^(i,k) ≤ m then
        Add index i to feasible set A ;
Compute index of best feasible point: i* = argmin_{i∈A} J^(i) ;
Outputs: θ^opt = θ^(i*) ;
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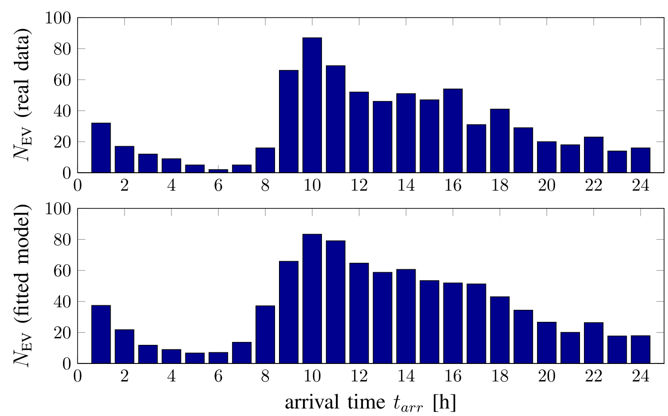

Fig. 4. Validation of the statistic model for the arrival time t_{arr}.

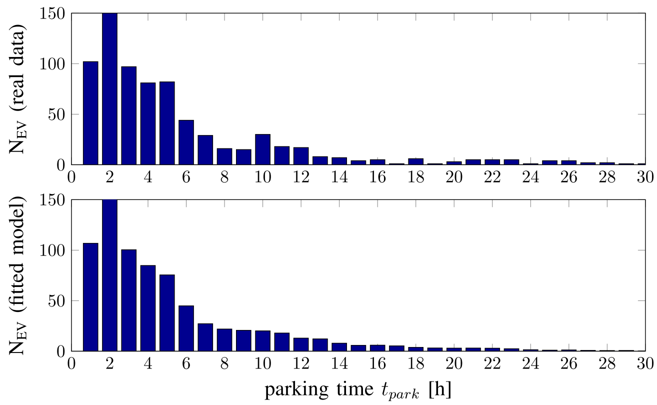

Fig. 5. Validation of the statistic model for the parking time t_{park}.

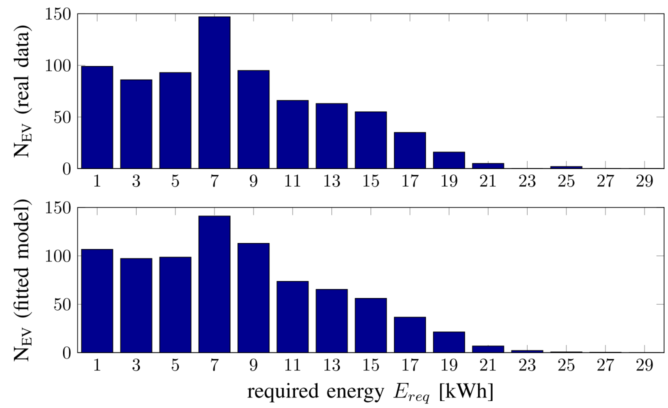

Fig. 6. Validation of the statistic model for the required energy E_{req}.

VI. Simulations and Sensitivity Analysis

In this section, simulation results based on real data from the Euref Campus in Berlin [21] are provided in order to demonstrate the feasibility and the relevance of the proposed approach. Moreover a comparison with a simple nonrobust charging strategy where each EV is directly charged at its nominal power as soon as it connects to the EVCS is performed and the sensitivity of the approach to certain key parameters (n_{CP}, η, and c_{satis}), involved in Algorithm 1, (6), and (4) is analyzed.

A. Statistic Data From the Euref Campus

In the following, the statistic model, derived from the historical data from the Euref Campus, is described.

The Euref Campus EVCS is particular in the sense that it is an e-Car sharing station. For this reason, the parking time of the vehicles and their required energy are not linked to the behavior of a particular car owner, and the statistic dispersion of the data is relatively high. For instance, the required energy of a vehicle can lie in the range of 0–15 kWh with almost equally high probability as it can be seen from Fig. 6.

In total, the data set contains 780 effective charging events. For each charging event, the arrival and parking time of the vehicle as well as the peak and the mean charging power are available. From the mean charging power and from the parking time, the required energy $E_{\text{req}} = t_{\text{park}} \cdot P_{ch,mean}$ can be computed. Moreover, from the arrival time t_{arr} and form the parking time t_{park}, the departure time $t_{\text{dep}} = t_{\text{arr}} + t_{\text{park}}$ of a vehicle can directly be obtained. This means that the necessary information to describe a scenario [see (3)] is available.

In order to build a statistic model of the EV behavior, nonparametric probability distributions have been fitted to the stochastic variables t_{arr}, t_{park} and E_{req}. In Figs. 4–6, the fitted probability distributions for t_{arr}, t_{park}, and E_{req} are validated. On the top graphs, the samples from the data set are plotted, and bottom graphs, a set of randomly drawn samples from the fitted probability distributions are provided for comparison. For instance, the first bar in Fig. 6 reads as the number of vehicles in the data set whose required energy lies in the range 0–2 kWh. One can see that the similarity between the real data and the data drawn from the fitted probability distributions is relatively high, meaning that the fit of the statistic model with the historical data is satisfying.

Note that the data does not show any correlation between the arrival time and the parking time, and between the arrival time and the required energy. For this reason, a random EV realization consisting of the set $\{t_{\text{arr}}, t_{\text{dep}}, E_{\text{req}}\}$ can be generated by drawing the three variables independently from their fitted probability distributions.

B. Demonstration of the Approach's Feasibility

In this section, an EVCS consisting of $n_{\text{CP}} = 50$ charging points is considered. The uncertain EV behavior follows the statistic model from the Euref Campus in Berlin, described previously.

In order to parametrize the upper bound power profile $\mathbf{p}(\theta)$, the method described in Section IV-A is applied, but with a small extension. More precisely, a fifth parameter θ_5 serving as a saturation on the amplitude of the profile $\mathbf{p}(\theta)$ is added. This customization of the parameterization method, which was initially proposed in Section IV-A, has been chosen in this case study, because it results in slightly better performances. Nevertheless, the original parametrization would have worked as well.

The domain $\boldsymbol{\Theta}$ for the design parameters $\theta_1, \ldots, \theta_5$ is chosen in a conservative way such that the existence of feasible solutions is enhanced: $\theta_1 \in \{0.9, 1.0, 1.1\}$, $\theta_2 \in \{0.9, 1.0, 1.1\}$, $\theta_3 \in \{0.9, 1.0, 1.1\}$, $\theta_4 \in \{0.9, 1.0, 1.1, 1.2\}$, and $\theta_5 \in \{0.9, 0.95, 1, 1.05\}$. The cardinality $n_{\boldsymbol{\Theta}}$ of the set $\boldsymbol{\Theta}$ is then $n_{\boldsymbol{\Theta}} = 3^3 \cdot 4^2 = 432$. The parameters of the randomized algorithm are chosen as $\eta = 0.05$, $\delta = 0.05$ and $m = 20$. According to (6), the necessary number of scenarios is then $N = 920$.

Running the randomized algorithm [Algorithm 2], the optimal feasible solution $\theta^{\text{opt}} = \{0.9, 1.0, 1.0, 1.2, 0.95\}$ is obtained. The result is shown in Fig. 7 (left), where the black dashed profile is the optimal upper bound power profile $\mathbf{p}(\theta^{\text{opt}})$. The colored profiles show three random scenarios to whom this allowed power profile has been affected following the real-time controller heuristic described in Section IV-B. Note that in the three scenarios—though quite different from each other—the QoS is achieved for all scenarios according to the satisfaction metric defined in Section II-B. Moreover, the upper bound power profile is respected in all three scenarios, which is the reason why our robust charging strategy is very valuable from a DSO's perspective.

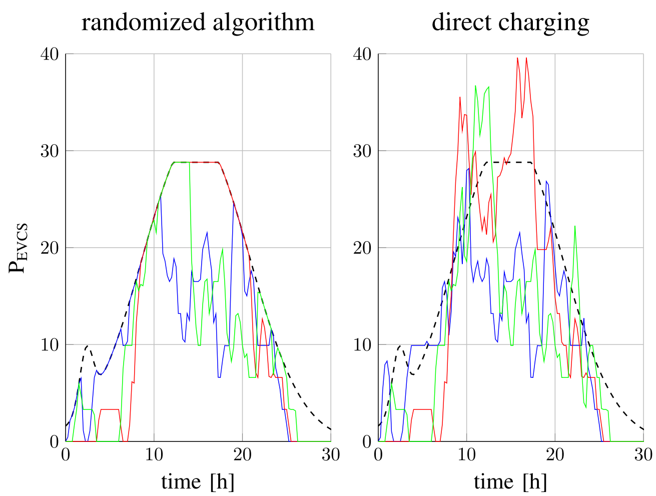

Fig. 7. Left: robust upper bound power profile $\mathbf{p}(\theta^{\text{opt}})$ (black) and the actual power consumption profiles for three different scenarios resulting from the proposed randomized algorithm strategy. Right: power consumption profiles for the same three scenarios when applying a direct charging strategy.

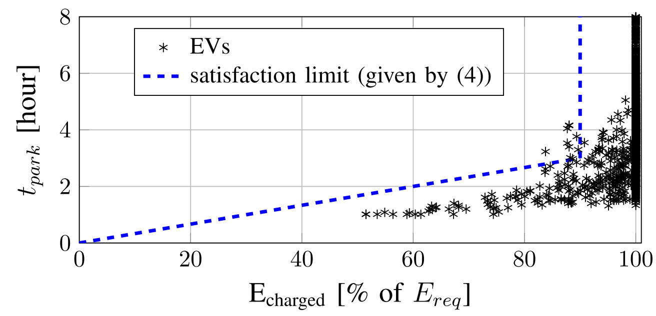

Fig. 8. Relation of each EV's charging time with its actually charged energy being expressed as the percentage of its initially demanded energy at arrival.

In order to underline the relevance of our proposed approach, Fig. 7 (right) shows the power consumption profiles, which would have been obtained from a direct charging strategy for the same three scenarios. Recall that with the direct charging strategy, each vehicle is directly charged at its nominal power of 3.3 kW as soon as it connects to the charging station. One can see that the fluctuations in the power consumption profile from one scenario to another are significantly higher with the direct charging strategy. Moreover, important power peaks may occur which might cause congestion problems in the distribution grid.

1) Customer Satisfaction: In order to provide a more precise idea of the QoS at EV customer level, the scatter plot in Fig. 8 relates the charging time of all EVs from 20 different scenarios with their charged energy, represented as the percentage of their initially demanded energy at arrival. It shows that most EVs actually leave the station being fully charged. Among those which stay connected for less than 5 h, some leave the station partially charged, but still almost all of them are above the customer satisfaction threshold, which is visualized by the blue dashed line.

2) Validation of the Robustness on a Large Set of Scenarios: In order to verify whether the desired robustness configured by the probabilities η and δ is actually achieved, the optimal solution $\mathbf{p}(\theta^{\text{opt}})$ is validated on a large number of scenarios ($\gg N$). Having done so for 5000 scenarios, the percentage of unsuccessful scenarios was found to be 1.1%. This result being clearly less than the desired limit on the probability of violation $\eta = 5\%$ confirms that the desired robustness is achieved. For the 5000 scenarios, the mean overestimation of the allowed energy consumption through the upper bound power profile $\mathbf{p}(\theta^{\text{opt}})$ for one day was in average 34% with a standard deviation of 6%. It is important to note that the mean overestimation highly depends on the statistic dispersion in the statistic model of the EV behavior. As mentioned before, the dispersion in the data from the Euref Campus is particularly high, which is the reason for the relatively high overestimation of the allowed energy consumption of 34%. It is likely that for an EVCS located at a commercial center or at a company site and which is not an e-Car sharing station, a lower statistic dispersion and consequently a lower overestimation in the allowed energy may be expected. In order to prove this hypothesis, a similar study as the one provided for the Euref Campus would have to be performed based on historical data from such a commercial center or company site. Since to the present day, the authors do not have access to a suitable data set, this study still needs to be done.

TABLE I

SENSITIVITY OF THE MEAN OVERESTIMATION OF THE TOTAL RESERVED ENERGY (IN %) TO THE PARAMETERS n_{CP} AND η

		η			
		0.05	0.1	0.15	0.2
n_{CP}	25	58.4	56.3	54.2	51.7
	50	37.5	34.1	32.9	31.2
	100	30.6	28.8	27.1	25.1

3) Computational Considerations: The computations were performed on an Intel Core i7-3540M at 3-GHz machine. For a given θ, i.e., for one iteration, the required computation time is around $t_{\text{iter}} = 5.8$ s. The total computation time is then obtained by multiplying with the cardinality $n_{\mathbf{\Theta}}$: $t_{\text{comp}} = t_{\text{iter}} \cdot n_{\mathbf{\Theta}} = 5.8\ s \cdot 432 = 42$ min for the case study configuration described in Section VI-B. Note that these computations are performed off-line and that more complex parameterizations θ or a set $\mathbf{\Theta}$ of higher cardinality could be handled, especially if the possiblity to parallelize the computations was used.

C. Sensitivity Analysis to Certain Key Parameters

In order to provide a quantitative idea of how certain parameters of the approach influence its performance, the sensitivity to these parameters is analyzed in the following. The studied parameters are the number of charging points n_{CP}, the robustness parameter η and finally the customer satisfaction threshold c_{satis}.

1) Impact of n_{CP} and η: Table I shows how the objective value $J(\theta^{\text{opt}})$, i.e., on the mean overestimation of the total energy consumption (in %), depends on the number of charging points n_{CP} and on the robustness parameter η. The first conclusion that can be drawn is that the larger the charging station is, the smaller is the mean overestimation. This result

TABLE II

SENSITIVITY OF THE MEAN OVERESTIMATION OF THE TOTAL RESERVED ENERGY TO c_{SATIS}

c_{satis}	mean over-estimation [%]
0.8	23.0
0.9	28.8
0.97	31.7

confirms that the approach is specifically well suited for charging stations of large size. The second conclusion is that for stronger robustness guarantees, i.e., for smaller values of η, the mean overestimation increases as it would be expected. However, this effect is less pronounced than the impact of n_{CP} in the performed case study.

2) Impact of c_{satis}: In Table II, the influence of the parameter c_{satis} on the objective value $J(\theta^{\text{opt}})$, i.e., on the mean overestimation of the daily energy consumption reserved through $\mathbf{p}(\theta^{\text{opt}})$, is shown. Recall that c_{satis} is the threshold which determines when a battery is considered to be fully charged in the individual customer satisfaction metric (4). The remaining parameters are fixed to $n_{\text{CP}} = 100$, $\eta = 0.05$, $\delta = 0.05$, and $m = 20$. Table II shows that the tighter this limit is chosen, the higher becomes the mean overestimation of the daily energy consumption.

VII. CONCLUSION AND FUTURE WORK

In this brief, a robust energy management strategy for electrical vehicle charging stations is proposed. The strategy is based on randomized algorithms and determines a day-ahead upper bound profile on the EVCS's power consumption, which is then strictly respected in real time. The method stands out, because it guarantees the QoS with a preconfigured probability. Moreover, it can be easily implemented, since the real-time controller is based on a computationally light heuristic, which does not require any online forecasts of the EV customer behavior.

The approach is very valuable from a DSO's perspective, since it permits to better anticipate the EVCS's power consumption and thus to guarantee the grid stability in a more efficient and less costly manner. Moreover, the fact that the method allows to strictly respect a certain peak power consumption of the EVCS, may help to avoid costly infrastructure reinforcements.

In future investigations the proposed method can be extended with the following features.

- The possibility to recompute an updated power allocation profile during the day itself, taking into consideration the previously realized charging tasks.
- The use of an additional storage unit which could be used to compensate EV uncertainties and consequently allow to further reduce the mean overestimation.
- Extension of the proposed framework by an additional lower bound power profile which would guarantee a certain resource utilization.

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