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Steffen Limmer, Tobias Rodemann

2017

Preprint:

This is an accepted article published in Proceedings IEEE SSCI 2017. The final authenticated version is available online at: https://doi.org/[DOI not available]

Multi-objective Optimization of Plug-in Electric Vehicle Charging Prices

Steffen Limmer
Honda Research Institute Europe GmbH
63073 Offenbach am Main, Germany
Email: steffen.limmer@honda-ri.de

Tobias Rodemann
Honda Research Institute Europe GmbH
63073 Offenbach am Main, Germany
Email: tobias.rodemann@honda-ri.de

***Abstract*—With the increasing penetration of plug-in electric vehicles (PEVs), the operation of public charging stations becomes a more and more interesting business case. For such a public charging station a dynamic pricing scheme can help to react to varying operation costs and to encourage customers to extend their charging deadlines.**

We propose a framework for the selection of dynamic prices with respect to the following three objectives: maximizing the charging station operator's profit, minimizing the number of customers that decline charging due to too high prices and minimizing the number of PEVs that have to be rejected because of missing charging capacities.

Two variants of the framework are proposed. In the first variant, the objectives are reduced to a single objective and CMA-ES is used for the optimization. In the second variant, the problem is solved with multi-objective optimization over NSGA-II in conjunction with desirability functions.

Numerical experiments show that the proposed approach is able to yield a tradeoff between short-term profit and the number of declining and rejected PEVs. In this way the social welfare can be increased in comparison to choosing prices solely with the objective of maximizing the profit. It can be expected that this has a positive effect on the long-term profit of the public charging station.

I. Introduction

The growing concerns about carbon emissions, the ongoing decrease of battery costs and the expansion of charging infrastructure results in an increasing popularity of plug-in electric vehicles (PEVs). According to a Bloomberg study [1], it is expected that in 2040 about 35 % of all new cars are PEVs.

In the literature, different ways for reducing the costs of charging PEVs based on an intelligent scheduling of the charging process are proposed. One of these ways is to take advantage of variable electricity prices, for example by trading on the day-head or intraday electricity market [2], [3], [4], [5]. Another approach is to make use of the batteries of the plugged-in PEVs in order to participate in the frequency regulation market [6], [3], [7]. This approach is particularly promising, if vehicle-to-grid (V2G) technology is employed, which allows to feed energy from a PEV's battery back to the main grid.

The employment of such an approach for cost reduction causes the charging costs to depend on the time of charging. For example, the electricity costs might be lower in the morning than in the evening. Additionally, the more time the charging of a PEV is allowed to take, the more options are available for the optimization of the charging process, leading probably to a reduction of the costs.

Thus, for operators of commercial public charging stations it seems natural to employ a dynamic pricing strategy, which adapts prices to the actual charging costs and which awards customers for extending the charging deadline. This raises the question of how to select the prices. Up to now, there exists only a small number of scientific publications dealing with the problem of PEV charging pricing.

Yuan *et al*. [8] investigate the pricing of two competing charging stations from a game theoretical point of view. The two charging stations periodically update their charging prices by considering each others pricing choices. Xiong *et al*. [9] deal with dynamic pricing for multiple charging stations in order to achieve a proper distribution of customers over the available charging stations. Bitar and Xu [10] propose a pricing strategy called *deadline differentiated pricing*. It is based on an offline computation of charging prices for different total amounts of energy required by different deadlines. Customers select their desired amounts of energy and deadlines. Based on the sum of the selected amounts of energy over all customers and the selected deadlines, the actual prices are determined. Hence, customers have to make choices without knowing the corresponding prices. Gosh and Aggarwal [11] propose so called *menu-based pricing*. That means, that customers can select from a menu of different energy-deadline-pairs with corresponding prices. Gosh and Aggarwal discuss different strategies for selecting the prices in order to maximize the charging station operator's (CSO's) or the customer's profit on an abstract level.

In the present paper, we follow a very similar approach of pricing. Customers can choose from pairs (d_i, p_i) of deadlines and prices. Alternatively, they can decline charging if they consider the offered prices as too high. In contrast to [11], we propose a framework for the practical optimization of the prices. Furthermore, we assume the optimization problem to be multi-objective. Optimizing the prices solely for a maximized CSO's profit will result in a comparatively high number of customers declining charging. These unsatisfied customers are likely to change the charging provider in future. Thus, the CSO should be concerned about keeping the number of declining customers low in order to increase the profit in a long-term perspective. In the same way, the operator should avoid to

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reject customers due to missing free charging stations in order to maximize the number of served customers. In sum, this requires a selection of the prices with respect to the following three partly conflicting objectives:

- maximizing the profit
- minimizing the number of customers declining the charging offers
- minimizing the number of customers that have to be rejected due to missing charging capacities.

In the present work, we propose a framework for the computation of such prices. At its core, it employs evolutionary optimization. We propose two variants of this optimization: In the first variant, the multi-objective problem is reduced to a single-objective one and is solved with CMA-ES (Covariance Matrix Adaptation Evolution Strategy) [12]. In the second variant the multi-objective algorithm NSGA-II (Non-dominated Sorting Genetic Algorithm II) [13] is used in conjunction with *desirability functions* [14] in order to solve the problem. In numerical experiments these two variants are compared and the overall framework is evaluated.

The rest of the paper is organized as follows: In the next section, the problem at hand and the assumed scenario is described in more detail. Section III outlines the proposed framework for the dynamic selection of charging prices. In Section IV, the setup and results of the numerical experiments are discussed and finally, Section V summarizes the work and its findings and provides possible directions for future research.

II. Problem Description

We consider an operator of C public charging stations with a maximum power level of P_{max}, each. The day is divided into H intervals $i = 0, \ldots, H-1$ of length l. Distributed throughout the day, N PEVs arrive at the charging facility and request charging. If the number M_i of PEVs that arrive in interval $i-1$ and thus might start charging in interval i, exceeds the number F_i of free charging stations in interval i, then $M_i - F_i$ PEVs are rejected by the operator. A charging station is assumed to be free if it is not occupied by a PEV that arrived before interval $i-1$.

If the number N_i of PEVs that arrive in interval $i-1$ and that are not rejected is non-zero, then these N_i PEVs $n = 1, \ldots, N_i$ are considered for starting the battery charging in interval i. Each PEV n of them has a certain energy requirement E_n and a minimum deadline D_n. The minimum deadline is the earliest interval by which the energy requirement of PEV n can be satisfied and it can be computed as $D_n = i + \lceil \frac{E_n}{P_{max} \cdot l} \rceil$.

At the end of interval $i-1$ the operator submits $K+1$ prices $p_0^n, \ldots, p_K^n$ to each PEV $n = 1, \ldots, N_i$, where p_k^n is the price for charging E_n energy by interval $D_n + k$. Thus, customers can decide to charge the required energy by their minimum deadline or to extend the charging time for up to K intervals. The decisions are made based on the offered prices and the customers' utilities. A driver of a PEV n gets a certain utility $U_{n,k}$ for charging the required energy by deadline $D_n + k$, $k = 0, \ldots, K$. It can be assumed that $U_{n,k_1} \geq U_{n,k_2}$ holds for $k_1 < k_2$, since customers prefer smaller deadlines over longer ones. The customer makes a "profit" of $U_{n,k} - p_k^n$ by selecting deadline extension k. If there is a k that results in a positive customer's profit, the customer selects the deadline extension K_n that maximizes her/his profit:

$$K_n = \arg\max_k (U_{n,k} - p_k^n). \tag{1}$$

Otherwise, the customer declines charging.

The drivers submit their decisions to the CSO and the PEVs of drivers who did not decline charging, charge their required energy amounts starting from interval i up to the selected deadlines. The charging of a PEV n with a deadline extension of k results in certain charging costs c_k^n for the CSO. We assume, that the charging costs for a PEV are independent of the number and the deadlines of other PEVs served by the operator. The profit the operator achieves with respect to the PEVs that are considered for starting battery charging in interval i is $profit_i = \sum_{n=1}^{N_i} profit(n)$ with

$$profit(n) = \begin{cases} 0 & \text{, if } PEVn \text{ declines} \\ p_{K_n}^n - c_k^n & \text{, otherwise} \end{cases}.$$

The operator wants to compute the prices in each interval i with $N_i > 0$ so that the profit $profit_i$ is maximized. Additionally, the number of PEVs declining charging in interval i and the number of rejected customers in intervals $j > i$ should be minimized.

We assume that the utilities of PEV drivers are realized as random variables and that the CSO does not know the exact utility values of arriving PEVs. However, the probability distribution of the utilities is known by the operator. Furthermore, it is assumed that the operator does not know the number and energy requirements of PEVs arriving in future intervals. But again, the distributions of the arrival times and of the energy requirements as well as the total number of customers arriving during the day are known to the operator.

III. The Price Selection Approach

Our approach for computing the prices for the N_i PEVs considered for starting battery charging in interval i consists of three steps:

1) **Step 1**: Compute the costs for charging the N_i PEVs
2) **Step 2**: Optimize the prices with CMA-ES or NSGA-II
3) **Step 3**: Heuristically update the prices.

After step 2, the prices resulting from the optimization are submitted to the drivers, who make their decisions based on these prices and their utility values. In the 3rd step, the prices for PEVs that did not decline charging after step 2 are updated with a simple heuristic with the goal of increasing the number of free charging stations. The updated prices are submitted to the customers, who update their decisions and then start charging according to their selected deadlines. The update of the prices in step 3 does not increase the costs for the customers compared to their previously selected prices/deadlines.

A. Step 1 – Cost Computation

The computation of the charging costs in the first step is done according to Algorithm 1.

Algorithm 1 Computation of the charging costs.

1: **for** $n = 1, \ldots, N_i$ and $k = 0, \ldots, K$ **do**
2: $c(n,k) \leftarrow \min \text{costs}(P_i, \ldots, P_{D_n+k-1})$

$$\text{s.t.} \sum_{j=i}^{D_n+k-1} P_j = E_n$$
$$0 \leq P_j \leq P_{max}, \text{ for } j = i, ..., D_n + k - 1$$

For each PEV n and each possible deadline extension k the charging power levels $P_i, \ldots, P_{D_n+k-1}$ for the intervals from i to $D_n + k - 1$ are optimized with respect to the charging costs and $c(n,k)$ is set to the resulting costs. The constraints ensure that the energy requirement of the PEV is fulfilled and that the maximum charging power is not exceeded. If the cost function is linear, this optimization can be done over linear programming or mixed-integer linear programming.

B. Step 2 – Price Optimization

In the 2nd step, the prices of the PEVs that may start charging in interval i are optimized with respect to the three objectives (maximizing profit and minimizing the number of declines as well as the number of rejects). We propose two variants: Optimization with CMA-ES and optimization with NSGA-II. CMA-ES [12] is an evolution strategy and has been proven to be very efficient for single-objective continuous black-box optimization. NSGA-II [13] is a popular multi-objective genetic algorithm. It computes a complete set of non-dominated solutions. Since both algorithms are evolutionary algorithms, they both work on a population of individuals. For the price optimization, an individual $\mathfrak{I}$ has to represent the prices. Thus, an individual consists of $N_i \cdot (K+1)$ real values, reflecting all the prices to be optimized.

Since the utility functions are unknown to the charging station operator, the exact profit resulting from a certain choice of prices is also unknown and cannot be used for the evaluation of an individual. Instead, the expected value $\mathbb{E}(profit_i|\mathfrak{I})$ of the profit given the prices encoded in individual $\mathfrak{I}$ is used for the evaluation of $\mathfrak{I}$. We employ the Monte Carlo method to compute an approximation of the expected value: S samples of utility functions of the N_i PEVs are randomly drawn from the utility distribution known to the CSO. For each sample s the profit $profit_s$ is computed assuming the utility functions of s, the prices encoded in $\mathfrak{I}$ and the charging costs computed in step 1. Then the expected value is approximated as $\hat{\mathbb{E}}(profit_i|\mathfrak{I}) = \frac{\sum_{s=1}^{S} profit_s}{S}$. Analogously an approximation of the expected value $\hat{\mathbb{E}}(decl_i|\mathfrak{I})$ for the number of declining PEVs given the prices in $\mathfrak{I}$, is computed.

For the number of rejected vehicles, it is not possible to approximate an expected value in the same way. In order to evaluate individuals regarding the number of rejected PEVs, we propose the following approach:

As mentioned in Section II, the CSO is aware of the distributions of the arrival times and energy requirements of the PEVs as well as of the total number of PEVs arriving during a day. This allows to compute the expected value of the number of occupied charging stations for all intervals $j = 0, \ldots, H-1$, given that the PEVs are not allowed to extend their minimum deadlines. We again use the Monte Carlo method to compute an approximation of these expected values. This can be done offline, for example, at the beginning of the day. Let $\hat{\mathbb{E}}(o_j)$ denote the resulting approximation of the expected value for the number of occupied charging stations in interval j. Furthermore, let O_j denote the number of charging stations that are occupied in interval j by PEVs that were scheduled in an interval previous to interval i. For each sample s of the Monte Carlo method used in the fitness evaluation of an individual $\mathfrak{I}$ a penalty is computed, that penalizes a high number of deadline extensions resulting from prices in $\mathfrak{I}$ in intervals with a low number of free charging stations as follows:

$$rej_costs_i(\mathfrak{I}, s) = \sum_{j=i}^{H-1} 2^{-free(j,\mathfrak{I},s)} \cdot ext(j, \mathfrak{I}, s), \quad (2)$$

where $ext(j, \mathfrak{I}, s)$ is the number of deadline extensions in interval j given the prices encoded in $\mathfrak{I}$ and the utilities in s. It is computed as $ext(j, \mathfrak{I}, s) = \sum_{n=1}^{N_i} g(n, j, \mathfrak{I}, s)$ with

$$g(n, j, \mathfrak{I}, s) = \begin{cases} 1 & \text{, if } K_n^s > 0 \text{ and } D_n \leq j < D_n + K_n^s \\ 0 & \text{, otherwise} \end{cases},$$

where K_n^s is the deadline extension selected by PEV n given the prices in $\mathfrak{I}$ and the utilities in s. The value $free(j, \mathfrak{I}, s)$ in Equation (2) is an estimation of the number of free slots in interval j and is computed as

$$free(j, \mathfrak{I}, s) = \max(0, C - (\hat{\mathbb{E}}(o_j) + O_j + ext(j, \mathfrak{I}, s)).$$

An approximation of the expected value for the penalty costs is computed as

$$\hat{\mathbb{E}}(rej_costs_i|\mathfrak{I}) = \frac{\sum_{s=1}^{S} rej_costs_i(\mathfrak{I}, s)}{S}.$$

The approximations of the expected values for the number of declines and the rejection costs for an individual $\mathfrak{I}$ are normalized to the interval $[0, 1]$ as follows:

$$decl_i(\mathfrak{I}) = \frac{\hat{\mathbb{E}}(decl_i|\mathfrak{I})}{N_i}$$
$$rej_i(\mathfrak{I}) = \frac{\hat{\mathbb{E}}(rej_costs_i|\mathfrak{I})}{(N_i - \hat{\mathbb{E}}(decl|\mathfrak{I})) \cdot K}.$$

The approximation of the expected value for the charging stations profit is in the following denoted as

$$prof_i(\mathfrak{I}) = \hat{\mathbb{E}}(profit_i|\mathfrak{I}).$$

Now we are able to define the three objectives formally as follows:

(i) $\max_{\mathfrak{I}} prof_i(\mathfrak{I})$
(ii) $\min_{\mathfrak{I}} decl_i(\mathfrak{I})$
(iii) $\min_{\mathfrak{I}} rej_i(\mathfrak{I})$

For the optimization with CMA-ES, these objectives are combined to a single objective by defining the fitness function as follows:

$$fit_{CMA}(\mathfrak{I}) = \begin{cases} -10.000 \cdot prof_i(\mathfrak{I}) & \text{, if } prof_i(\mathfrak{I}) < 0 \\ 100 \cdot decl_i(\mathfrak{I}) & \text{, if } prof_i(\mathfrak{I}) \geq 0 \\ & \quad \& \; decl_i(\mathfrak{I}) > \alpha_{decl} \\ rej_i(\mathfrak{I}) & \text{, if } prof_i(\mathfrak{I}) \geq 0 \\ & \quad \& \; decl_i(\mathfrak{I}) \leq \alpha_{decl} \\ & \quad \& \; decl_i(\mathfrak{I}) > \alpha_{rej} \\ -prof_i(\mathfrak{I}) & \text{, otherwise} \end{cases}$$

CMA-ES minimizes this fitness. Since we want the expected profit to be positive in any case, the fitness is set to $-10.000 \cdot prof_i(\mathfrak{I})$ if the expected profit is negative. Over the external parameters α_{decl} and α_{rej}, it can be controlled, how important the minimization of the number of declining and rejected PEVs is. The optimization will try to maximize the expected profit while keeping $decl_i$ and rej_i below α_{decl} and α_{rej}, respectively.

For the multi-objective optimization with NSGA-II, we do not use all three objectives directly in the evaluation of an individual, because this will cause the optimization to search for a widespread approximation of the Pareto front, although we are interested only in a certain part (the part belonging to individuals $\mathfrak{I}$ with $decl_i(\mathfrak{I}) \leq \alpha_{decl}$ and $rej_i(\mathfrak{I}) \leq \alpha_{rej}$). Instead, we use the concept of *desirability functions* (DFs) [14] in order to concentrate the search on individuals $\mathfrak{I}$ with values of $decl_i(\mathfrak{I})$ and $rej_i(\mathfrak{I})$ under the desired bounds.

DFs are a way to express a preference for a certain objective value. A DF maps a value Y of an objective to a desirability value between 0 and 1, where a higher value means a higher desirability. Wagner and Trautmann [14] propose to use Harringtons one-sided DF. It is defined as

$$D(Y) = \exp(-\exp(-(b_0 + b_1 Y)))$$

with

$$\begin{aligned} b_0 &= -\log(-\log(d^{(1)})) - b_1 Y^{(1)}, \\ b_1 &= \frac{-\log(-\log(d^{(2)})) + \log(-\log(d^{(1)}))}{Y^{(2)} - Y^{(1)}} \end{aligned}$$

and certain parameters $d^{(1)}$, $d^{(2)}$, $Y^{(1)}$ and $Y^{(2)}$.

We use DFs to map the values of $decl_i(\mathfrak{I})$ and $rej_i(\mathfrak{I})$ to desirabilities. In initial experiments, it turned out that it is beneficial for the maximization of the profit to set the DF so that it has a very steep slope around α_{decl} and α_{rej}, respectively, like the function $D1$ in Figure 1 for an $\alpha \in \{\alpha_{decl}, \alpha_{rej}\}$ of 0.1. The function is nearly a step function. This imposes the problem, that the function value is exactly 0 for a large range of values in $[0, 1]$ due to a limited floating-point precision. On this range, the optimization algorithm has no gradient information – it does not know, in which direction the desirability increases/decreases. If α_{decl} and/or α_{rej} are small, this makes it hard for the optimization to find a feasible solution (a solution $\mathfrak{I}$ with $decl_i(\mathfrak{I}) \leq \alpha_{decl}$ and $rej_i(\mathfrak{I}) \leq \alpha_{rej}$). As a countermeasure, we propose to use another DF $D2$, which is also shown in Figure 1, to evaluate

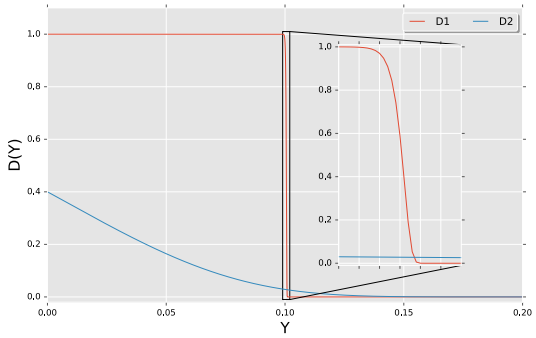


Fig. 1. The two desirability functions $D1$ and $D2$ used in the multi-objective optimization with NSGA-II with zoom in a range around 0.1. The functions are shown for a desired value (either α_{decl} or α_{rej}, depending on the objective) of 0.1.

individuals in the case that no feasible solution was found in the optimization so far. The slope of $D2$ is not as steep as that of $D1$, guiding the optimization more efficiently in the direction of the feasible region. When a first feasible solution is found, the DF is switched from $D2$ to $D1$ in order to maximize the profit inside the feasible region. In our experiments, we used the parameters shown in Table I for $D1$ and $D2$

TABLE I
PARAMETERS USED FOR THE DESIRABILITY FUNCTIONS $D1$ AND $D2$.

DF	$d^{(1)}$	$d^{(2)}$	$Y^{(1)}$	$Y^{(2)}$
$D1$	0.9999	0.0001	$\max(0, \alpha - 0.001)$	$\min(1, \alpha + 0.001)$
$D2$	0.4	0.000001	0	$\min(1, 2\alpha)$

The objectives for the evaluation of an individual $\mathfrak{I}$ in NSGA-II are set as follows:

$$\begin{aligned} f_1(\mathfrak{I}) &= -D(decl_i(\mathfrak{I})) \\ f_2(\mathfrak{I}) &= -D(rej_i(\mathfrak{I})) \\ f_3(\mathfrak{I}) &= -prof_i(\mathfrak{I}), \end{aligned}$$

where D is either $D1$ or $D2$, as described before.

If at least one feasible solution is found by the optimization, the feasible solution with the largest expected profit is returned as final result. Otherwise, the solution with the smallest distance to the feasible region[1] is returned.

C. Step 3 – Heuristical Update of the Prices

After the customers selected deadlines or declined charging based on prices resulting from step 2, the prices are updated with a simple heuristic with the goal to decrease the number of rejected PEVs in future intervals. Let $K_n > 0$ be the deadline extension chosen by a customer n after step 2. This deadline extension results in a profit of $profit(n) = p^n_{K_n} - c^n_{K_n}$ for the CSO. The heuristic sets the prices for the customer to $p^n_k = c^n_k + profit(n)$ for all $k = 0, \ldots, K_n - 1$. This is done for all customers $n \in \{1, \ldots, N_i\}$, who did not decline charging after step 2. Afterwards, these customers update their

[1]We compute the distance of an individual $\mathfrak{I}$ to the feasible region as $dist(\mathfrak{I}) = \max(0, decl_i(\mathfrak{I}) - \alpha_{decl}) + \max(0, rej_i(\mathfrak{I}) - \alpha_{rej})$.

decisions based on the updated prices. This will not increase or decrease the charging station operator's profit compared to the prices set in step 2, but it may increase the profit of the customers while decreasing the chosen deadlines. The latter will potentially reduce the number of rejected PEVs in future intervals (potentially affecting the profit in future intervals).

IV. Numerical Experiments

A. Use Case and General Experimental Setup

The numerical experiments are executed with the following use case: A fixed number N of PEVs, each with a capacity of 120 kWh, arrive during the day at $C = 20$ charging stations with a maximum power level of $P_{max} = 50$ kW, each. The length of a scheduling interval is 15 min. The arrival times of the PEVs are normally distributed with a mean of 12 p.m. and a standard deviation of 2 hours. The initial states of charge (SoCs) of the PEVs are chosen uniformly random distributed between 10 % and 80 % and it is assumed, that the target SoC of all PEVs is 100 %. The maximum allowed deadline extension K is set to 5 intervals and the following utility function is used for a PEV n:

$$U_n(k) = E_n \cdot (\alpha + \delta_n) - \beta \cdot k - \gamma_{n,k}$$

with $\alpha = 0.2$ and $\beta = 0.4$. The value of δ_n is normally distributed with a mean of 0 and a standard deviation of 0.01. The values $\gamma_{n,k}$ are drawn from a truncated normal distribution with $\mu = 0$ and $\sigma = 0.1$, truncated left at $-\frac{\beta}{2}$ and right at $\frac{\beta}{2}$. Thus, on average a PEV driver is willing to pay up to α units of money per charged kWh if the PEV is charged by the minimum deadline and for each interval the charging takes longer, she/he expects a discount of β units of money.

We assume that the electricity price varies over the day and that the CSO participates in the frequency regulation market. Thus, she/he is payed by the main grid operator for the provided frequency regulation capacity. Like Mehta *et al.* [6], we assume that only idle PEVs (i.e. PEVs with a charging power of 0 kW) contribute to the frequency regulation capacity and that the total capacity provided in an interval is the product of the number of idle PEVs in that interval, the maximum charging power P_{max} and the interval length. Further, it is assumed that the frequency regulation has no impact on the SoC of an involved PEV.

The electricity prices are assumed to be composed of a fixed constant fee of 15 euro cent per kWh and a time varying amount. For the latter one, we use data from the German intraday electricity market of EPEX SPOT SE [15]. More precisely, we use the quarter-hourly intraday market prices averaged over all days in June 2017. While this might change in the future, there is no German market that allows trading of frequency regulation capacity on a 15 minute basis, to date. According to a study of Just [16], in the time between 2001 and 2015, the prices on the German primary regulation market ranged between €12 and €30 per MWh. Based on this study, we assume a quarter-hourly regulation market price uniformly random distributed between 2.4 and 2.9 euro cent per kWh. The used electricity and regulation market prices are shown in Figure 2. It is assumed that the prices are known to the CSO beforehand. The costs of charging a PEV are computed as the

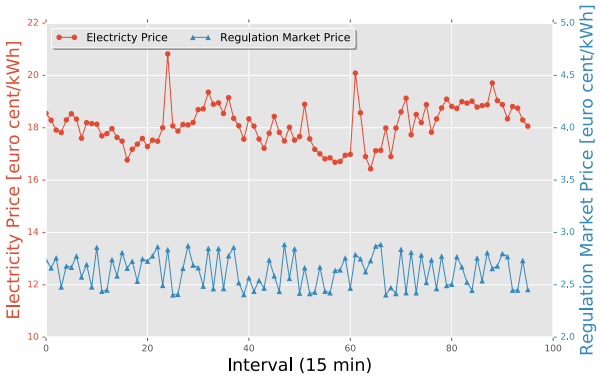


Fig. 2. Electricity and regulation market prices used in the experiments.

electricity costs for the charging minus the regulation market credit earned due to idle intervals of the PEV. The problem of optimizing the charging schedule of a PEV with respect to the charging costs can be formulated as a mixed integer programming (MIP) problem.

In the experiments, described in the following subsections, we used the open-source MIP solver Cbc (Coin-or branch and cut) [17] for the optimizations of the charging schedules of the PEVs in order to compute the corresponding charging costs for the PEVs in step 1 according to Algorithm 1. For CMA-ES, the C implementation mainly written by Nikolaus Hansen [18] is used. For the optimizations with NSGA-II, version 1.1.6 of the C implementation provided by Kanpur Genetic Algorithms Laboratory [19] is employed. The approximations of the expected values for the number of occupied charging stations in the different intervals of the day without considering deadline extensions are computed with 10,000 samples for the Monte Carlo method like described in Subsection III-B. In all experiments, CMA-ES is run with default parameters of the implementation. These are the parameters recommended by Hansen and Kern [20]. This means in particular, that the number λ of offspring per generation is set to $\lambda = 4 + \lfloor 3 \ln(dim) \rfloor$, where dim is the number of parameters to optimize ($N_i \cdot (K+1)$ in our case). For NSGA-II, a population size of 60, a mutation rate of $\frac{1}{dim}$ and a crossover rate of 0.9 is used. The parameters η_c and η_m of the real-valued crossover and mutation operators of NSGA-II are set to 20 and 5, respectively.

B. Comparison of Optimization Results

In a first experiment, we compared the pure optimization results of CMA-ES and NSGA-II without considering the impact of the optimizations on the deadlines chosen by the PEV drivers. For that purpose we simulated the charging throughout a day with $N = 80$ PEVs arriving during the day and with charging prices set to the corresponding costs plus €0.25 ($p_j^n = c_j^n + 0.25$ for $n = 1, \ldots, N_i$ and $j = 0, \ldots, K$).

This pricing strategy results in a utilization of the charging stations as shown in Figure 3. Additionally, Figure 3 shows the resulting numbers N_i of PEVs to schedule for each interval i.

For 5 of the 96 intervals of the day (highlighted with orange background in Figure 3), the charging prices of the PEVs that arrive in the corresponding interval and that are not rejected, are optimized with CMA-ES and NSGA-II (but as already mentioned, the results are not used to set the prices). The optimizations are done with different settings for α_{decl} and α_{rej} and with different numbers f_{max} of maximally allowed fitness evaluations per PEV. For an optimization in interval i, the maximum number of executed fitness evaluations is $N_i \cdot f_{max}$. The samples used in the Monte Carlo method for the fitness evaluation are the same for CMA-ES and NSGA-II. For each setup, we executed 30 optimization trials.

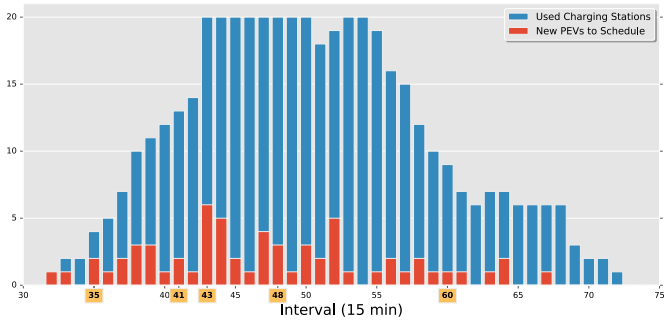


Fig. 3. The numbers of PEVs to schedule and the numbers of occupied charging stations in the different intervals of the day resulting from setting the charging prices to the corresponding charging costs plus €0.25. The numbers are zero for all intervals not shown. Numbers of intervals used for the comparison of CMA-ES and NSGA-II are highlighted with orange background.

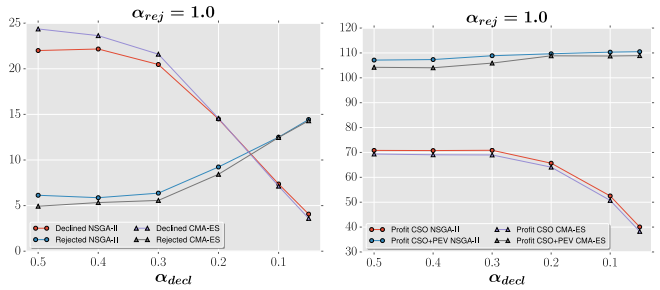
Table II shows the results of the optimizations. For each setup, the expected profit is averaged over all trials that yielded a feasible solution (a solution $\mathfrak{I}$ with $decl_i(\mathfrak{I}) \leq \alpha_{decl}$ and $rej_i(\mathfrak{I}) \leq \alpha_{rej}$). The values N_{uf} in Table II indicate for each setup, how many of the 30 trials did not yield a feasible solution.

For $\alpha_{decl} = \alpha_{rej} = 1.0$, NSGA-II yielded significantly better results than CMA-ES for all intervals and all values of f_{max}. For lower values of α_{decl} and α_{rej} the picture slightly changes. There, for lower numbers of f_{max}, the results of CMA-ES are better than that of NSGA-II for several setups. But with $f_{max} = 5000$, the results of NSGA-II are always better than that of CMA-ES. Except for interval 43 with $\alpha_{decl} = \alpha_{rej} = 0.05$, the differences are statistically significant. In some trials of the optimizations for the intervals 41 and 48, CMA-ES yielded no feasible solution, while all of the executed trials with NSGA-II yielded feasible solutions. From the experiment, it can be concluded that the multi-objective optimization with NSGA-II performs better than the single-objective one with CMA-ES, as long as enough fitness evaluations are permitted. However, if only a small number of fitness evaluations can be executed, for example because the optimization has to run on embedded hardware with low performance, it is advisable to use the single-objective optimization instead of the multi-objective one.

C. Complete Simulation

So far, only the pure optimization results were compared. Now we want to evaluate the complete framework. In order to do this, we simulated the charging during 30 different days (with different arrival times, SoCs and utilities of the PEVs), where in step 2 the prices are optimized with CMA-ES and with NSGA-II and no heuristic update of the prices is employed in order to make the results with the two optimization algorithms better comparable. Again, the total number N of PEVs arriving during a day is set to 80. The optimizations are done with $f_{max} = 5000$.

Figure 4a shows the resulting numbers of declining and rejected PEVs averaged over the 30 days for a fixed α_{rej} of 1.0 and decreasing values of α_{decl} between 0.5 and 0.05. Figure 4b shows the corresponding values of the CSO's profit and of the social welfare in terms of the sum of the profit of the CSO and the profit of the PEVs. It can be seen,



(a) (b)

Fig. 4. Results with CMA-ES and with NSGA-II averaged over 30 days for $\alpha_{rej} = 1.0$ and different values of α_{decl}. Step 3 (the heuristical update of the prices) is not used. (a) The average number of PEVs that decline charging and the average number of rejected PEVs. (b) The average profit of the charging station operator (Profit CSO) and the average social welfare (Profit CSO+PEV).

that the number of PEVs that decline charging is very high for $\alpha_{decl} = 0.5$. More than 25 % of the PEVs decline the price offers. With a decreasing value of α_{decl}, the number of declines also decrease, as intended. However, the number of rejected PEVs increases, since the utilization of the charging stations increases. Additionally, it can be seen that decreasing values of α_{decl} result in a decreasing profit of the CSO, because the prices have to be set lower in order to decrease the number of expected declines. By contrast, the social welfare slightly increases.

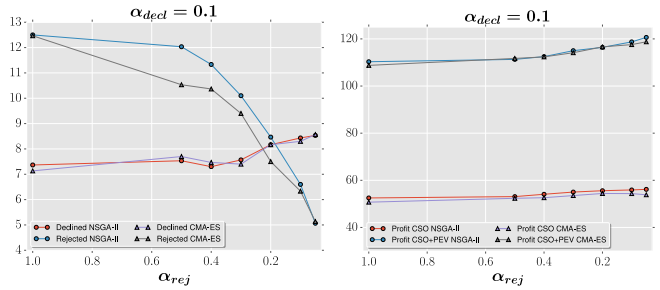
For higher values of α_{decl}, the number of declines is smaller with NSGA-II than with CMA-ES, while for lower values of α_{decl}, the number of declines is almost identical with both optimization algorithms. But for all values of α_{decl}, NSGA-II yields a higher profit than CMA-ES. This is in line with the findings of the previous subsection.

Figure 5 shows the results analogously to Figure 4 for a fixed α_{decl} of 0.1 and decreasing values for α_{rej}. As desired,

TABLE II

RESULTS OF THE PRICE OPTIMIZATIONS FOR INTERVALS 35, 41, 43, 48 AND 50 WITH CMA-ES AND NSGA-II WITH DIFFERENT NUMBERS f_{max} OF MAXIMALLY ALLOWED FITNESS EVALUATIONS PER PEV AND DIFFERENT VALUES FOR α_{decl} AND α_{rej}. FOR EACH SETUP 30 TRIALS WERE EXECUTED. THE VALUE N_{uf} INDICATES HOW MANY OF THE TRIALS DID NOT YIELD A FEASIBLE SOLUTION. THE EXPECTED PROFIT IS AVERAGED OVER ALL TRIALS THAT YIELDED A FEASIBLE SOLUTION. A $*$ INDICATES, WHETHER A RESULT OF ONE OF THE TWO OPTIMIZATION ALGORITHMS IS SIGNIFICANTLY BETTER THAN THE CORRESPONDING RESULT OF THE OTHER OPTIMIZATION ALGORITHM (ACCORDING TO TWO-SIDED WILCOXON RANK SUM TEST WITH A SIGNIFICANCE LEVEL OF 0.05).

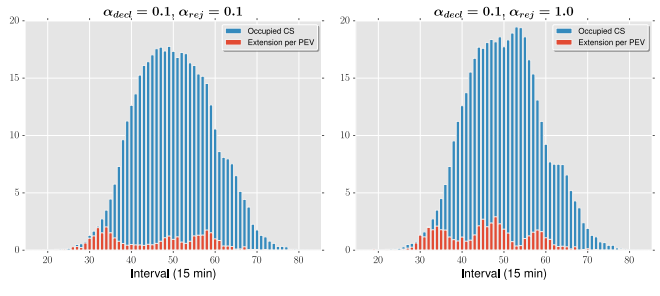
		$\alpha_{decl}=1.0, \alpha_{rej}=1.0$				$\alpha_{decl}=0.2, \alpha_{rej}=0.2$				$\alpha_{decl}=0.1, \alpha_{rej}=0.1$				$\alpha_{decl}=0.05, \alpha_{rej}=0.05$			
		CMA-ES		NSGA-II		CMA-ES		NSGA-II		CMA-ES		NSGA-II		CMA-ES		NSGA-II	
Interval	f_{max}	Profit	N_{uf}	Profit	N_{uf}	Profit	N_{uf}	Profit	N_{uf}	Profit	N_{uf}	Profit	N_{uf}	Profit	N_{uf}	Profit	N_{uf}
35	1000	1.319	0	**1.363***	0	**1.168**	0	1.163	0	**0.836***	0	0.813	0	**0.450***	0	0.435	0
	2000	1.321	0	**1.379***	0	1.172	0	**1.190***	0	0.840	0	**0.861**	0	0.458	0	**0.471**	0
	5000	1.321	0	**1.384***	0	1.172	0	**1.214***	0	0.840	0	**0.910***	0	0.458	0	**0.512***	0
41	1000	1.734	0	**1.762***	0	**1.600**	0	1.591	0	**1.246**	0	1.243	0	**0.884**	1	0.874	0
	2000	1.736	0	**1.774***	0	1.604	0	**1.632***	0	1.251	0	**1.269**	0	0.894	1	**0.908**	0
	5000	1.736	0	**1.779***	0	1.604	0	**1.661***	0	1.252	0	**1.286***	0	0.876	0	**0.931***	0
43	1000	6.488	0	**6.629***	0	**6.140**	0	6.138	0	**5.041***	0	4.985	0	**3.560***	0	3.501	0
	2000	6.497	0	**6.682***	0	6.165	0	**6.227***	0	5.073	0	**5.091**	0	**3.604**	0	3.598	0
	5000	6.497	0	**6.706***	0	6.165	0	**6.286***	0	5.074	0	**5.153***	0	3.607	0	**3.659**	0
48	1000	1.237	0	**1.275***	0	1.168	0	**1.182**	0	0.926	0	**0.941**	0	**0.657***	3	0.644	0
	2000	1.239	0	**1.291***	0	1.172	0	**1.209***	0	0.932	0	**0.971***	0	0.665	3	**0.672**	0
	5000	1.239	0	**1.297***	0	1.172	0	**1.228***	0	0.932	0	**0.989***	0	0.666	3	**0.694***	0
50	1000	0.589	0	**0.602***	0	0.583	0	**0.597**	0	0.522	0	**0.523**	0	**0.453***	0	0.447	0
	2000	0.589	0	**0.605***	0	0.585	0	**0.602***	0	0.523	0	**0.538**	0	0.454	0	**0.466**	0
	5000	0.589	0	**0.606***	0	0.585	0	**0.604***	0	0.523	0	**0.545***	0	0.454	0	**0.477***	0



(a) (b)

Fig. 5. Results with CMA-ES and with NSGA-II averaged over 30 days for $\alpha_{decl} = 0.1$ and different values of α_{rej} analogous to Figure 4.

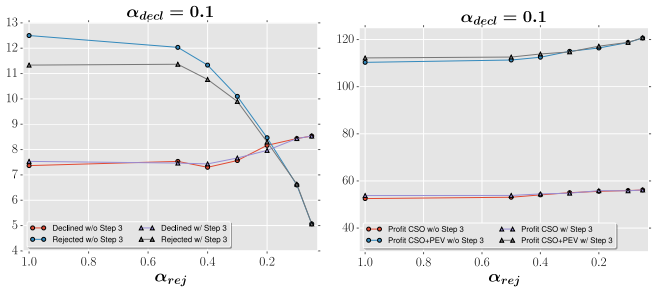
the number of rejected PEVs decreases with a decreasing α_{rej}. As it can be seen from Figure 5b, simultaneously the CSO's profit and the social welfare increase. Again, NSGA-II yields a higher profit than CMA-ES. The impact of α_{rej} on the deadline extension selected in average by a PEV can be seen in Figure 6. It shows the number of occupied charging stations and the average value of the selected deadline extension for different intervals averaged over the 30 days of the experiment with $\alpha_{decl} = 0.1$ and with values of 0.1 and 1.0 for α_{rej}. In Figure 6a it can be seen that with $\alpha_{rej} = 0.1$, the average extensions are comparatively small in the range of intervals before the maximum utilization of the charging stations (around intervals 35 to 50). With $\alpha_{rej} = 1.0$, considerably higher deadline extensions are chosen in this range of intervals, resulting in a higher maximum utilization of the charging stations, as it can be seen in Figure 6b.



(a) (b)

Fig. 6. The number of occupied charging stations and the deadline extension per PEV for different intervals averaged over 30 different days.

In order to investigate the effect of the heuristic update of the prices in step 3, we repeated the simulation of the 30 days with inclusion of step 3. Figure 7 shows the results for $\alpha_{decl} = 0.1$ and different values of α_{rej}.



(a) (b)

Fig. 7. Results with NSGA-II with and without price updates (step 3) analogous to Figure 5.

It can be seen, that the heuristic is able to decrease the number of rejected PEVs, especially for high values of α_{rej}. As expected, the effect on the CSO's profit is small. But nevertheless, the heuristical update of the prices slightly increases the profit. Simultaneously, the social welfare increases.

Table III shows the results with NSGA-II averaged over the

30 days with $\alpha_{decl} = \alpha_{rej} = 1.0$ (corresponding to selecting the prices for solely maximizing profit) without inclusion of step 3 and with $\alpha_{decl} = 0.1$, $\alpha_{rej} = 0.05$ with inclusion of step 3. With the latter setting the social welfare is increased by 12.9 % while the number of declining and rejected customers is decreased by 61.7 % and 17.5 %, respectively, compared to the first setting. This comes at the expense of a decrease of the CSO's profit by 20.4 %. Over the selection of α_{decl} and α_{rej}, the CSO can achieve a reasonable tradeoff between profit and social welfare.

TABLE III
COMPARISON OF RESULTS WITH NSGA-II AVERAGED OVER 30 DAYS WITH $\alpha_{decl} = \alpha_{rej} = 1.0$ WITHOUT STEP 3 AND WITH $\alpha_{decl} = 0.1$, $\alpha_{rej} = 0.05$ AND STEP 3.

	$\alpha_{decl} = 1.0$, $\alpha_{rej} = 1.0$, w/o step 3	$\alpha_{decl} = 0.1$, $\alpha_{rej} = 0.05$, w/ step 3	Difference
Profit CSO	70.61	56.18	-20.4 %
Profit CSO+PEV	106.92	120.74	+12.9 %
#declined	22.43	8.53	-61.7 %
#rejected	6.13	5.06	-17.5 %

V. SUMMARY AND OUTLOOK

We presented a framework for the optimization of charging prices regarding the three objectives of maximizing the charging station operator's profit, minimizing the number of declining customers and minimizing the number of customers that have to be rejected. Experiments have shown that the number of declining and rejected customers can be considerably reduced in this way, at the expense of an also reduced profit. On the other hand, the social welfare increases and since the number of satisfied customers increases, this might be beneficial for the profit in a long-term perspective. For the assumed use case, the daily average number of declining customers can be reduced from about 22 to 9 and the daily average number of rejected customers from 6 to 5 compared to choosing the prices solely for maximizing profit. This results in a decrease of the average daily profit from about €71 to €56 and an increase of the social welfare from 107 to 121. By adjusting the parameters α_{decl} and α_{rej}, other tradeoffs can be achieved.

Two approaches for the actual price optimization were compared: Reduction to a single-objective optimization with CMA-ES and multi-objective optimization with NSGA-II. Experiments indicate that the multi-objective optimization is superior as long as enough fitness evaluations are permitted. If only a small number of fitness evaluations can be executed, the single-objective optimization seems to be the better choice.

In this work it is assumed that the costs for charging PEVs do not depend on each other. This allows the fast computation of the charging costs of the PEVs before the actual price optimization. If the costs depend on the selected deadlines of other PEVs, the computation of the costs for all possible combinations of deadlines in order to use them in the Monte Carlo method for the evaluation of an individual becomes too time intensive. The investigation of approaches to deal with this issue might be the topic of future research.

Additionally, it might be of value to deeper investigate the choice of the desirability function for the multi-objective optimization. In the present paper it is proposed to switch between two functions, once a feasible solution is found. There might be ways to continuously adapt the desirability function in order to guide the optimization in the direction of the feasible region, more efficiently.

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