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Optimization of Dynamic Prices for Electric Vehicle Charging Considering Fairness

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***Abstract*—For operators of public charging stations, it is economically reasonable to employ a dynamic pricing scheme in order to be able to react to varying operating conditions. However, dynamic prices may lead to the perception of price unfairness with negative consequences for the charging station operator's profit.**

In this work, the evolutionary optimization of the price offers with respect to the expected profit and the fairness is studied. With the help of numerical experiments, it is shown that a multi-objective optimization is able to increase the perceived fairness without impact on the profit compared to a single-objective optimization of the profit. Furthermore, it is shown that it is possible to achieve promising trade-off solutions by employing appropriate multi-criteria decision making approaches.

I. Introduction

In the literature, different approaches for the reduction of the costs of charging electric vehicles (EVs), like trading on the electricity market [1] or providing capacity to the regulation market [2], are described. Such approaches result in varying operating costs, which depend on the start and end time of charging. Thus, for public charging stations it is reasonable to employ a dynamic pricing scheme, which adapts the prices for charging EVs to the actual operating conditions. Gosh and Aggarwal [3] propose so called *menu-based pricing*, where customers can select from a menu of different energy-deadline-pairs with corresponding prices. Limmer and Rodemann [4] describe the multi-objective optimization of price offers for different charging deadlines with the objectives of maximizing the charging station operator's profit, minimizing the number of customers who decline charging due to too high prices and minimizing the number of customers who have to be rejected because all charging stations are occupied.

The varying prices arising from such a dynamic pricing scheme involve the risk of being perceived as unfair, which may lead to negative consequences for the operator of the public charging stations [5]. In the literature, various factors are expected to have an impact on the customer's perception on price fairness. Besides socio-ethical norms, the seller's reputation as well as technical and economic knowledge of individuals play a role [5]. Individual price comparisons in relation to others are the customer's rational base for price fairness estimation. What is discovered is that if people experience different prices for similar transactions this is most likely stated as unfair [5]. From an *objective* ethical standpoint a price can be considered as fair, when the price results from competition within a free market and is not caused e.g. by actors taking advantage of (temporary) monopoly [6]. When people experience unreasonable price differences, they may associate them with such unethical price practices. With dynamic pricing, prices can be easily misinterpreted as unreasonable what can be avoided by targeting the similarity of prices for similar transactions.

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The present paper investigates the optimization of dynamic prices for charging EVs at public charging stations under consideration of price fairness. Two formal definitions of unfairness of such prices are provided and the single-objective optimization of the charging station operator's profit with and without consideration of fairness is studied. Furthermore, the multi-objective optimization of the profit and the fairness with different approaches for multi-criteria decision making is investigated.

The rest of the paper is structured as follows: In the next section, the problem is described in more detail and formal definitions of price unfairness are provided. Section III discusses the price optimization with consideration of fairness on the basis of numerical experiments. Finally, Section IV gives a brief summary and provides possible directions for future work.

II. Problem Description

We consider a scenario similar to that described in [4]. Multiple public charging stations with a maximum power level of P_{max}, each, are operated by a charging station operator (CSO). The day is divided into T scheduling intervals of length Δt. Distributed throughout the day, N EVs arrive at the charging stations.

If the number N_i of EVs that arrive in interval $i-1$ is non-zero, then these N_i EVs $EV_{i,1},\dots,EV_{i,N_i}$ are considered for starting the battery charging in interval i. Each EV $EV_{i,n}$ of them has a certain energy requirement $E_{i,n}$ and a minimum deadline $D_{i,n}$. The minimum deadline is the earliest interval by which the energy requirement of the EV can be satisfied and it can be computed as $D_{i,n} = i + \lceil \frac{E_{i,n}}{P_{max}\cdot\Delta t} \rceil$.

At the end of interval $i-1$, the operator submits $K+1$ prices $p^0_{i,n},\dots,p^K_{i,n}$ to each $EV_{i,n}$, $n=1,\dots,N_i$, where $p^k_{i,n}$ is the price for charging $E_{i,n}$ energy by interval $D_{i,n}+k$.

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. The driver of $EV_{i,n}$ gets a certain utility $U_{i,n}^k$ for charging the required energy by deadline $D_{i,n}+k$, $k=0,\ldots,K$. The customer makes a "profit" of $U_{i,n}^k - p_{i,n}^k$ by selecting deadline extension k. If there is a k that results in a positive customer's profit, the customer selects the deadline extension $K_{i,n}$ that maximizes her/his profit: $K_{i,n} = \arg\max_k (U_{i,n}^k - p_{i,n}^k)$. Otherwise – if no price offer resulting in a positive customer's profit exists – the customer declines charging.

The drivers submit their decisions to the CSO and the EVs of drivers who did not decline charging, charge their required energy amounts starting from interval i up to the selected deadlines. The charging of $EV_{i,n}$ with a deadline extension of k results in certain charging costs $c_{i,n}^k$ for the CSO. The profit the operator achieves with respect to the EVs that are considered for starting battery charging in interval i is $profit_i = \sum_{n=1}^{N_i} profit_{i,n}$ with

$$profit_{i,n} = \begin{cases} 0 & \text{, if } EV_{i,n} \text{ declines} \\ p_{i,n}^{K_{i,n}} - c_{i,n}^{K_{i,n}} & \text{, otherwise} \end{cases}.$$

We assume that the utilities of the customers are realized as random variables and that the CSO does not know the exact utility values of arriving customers. 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 EVs arriving in future intervals.

A goal is to optimize in each interval i with $N_i \geq 1$ the price offers with respect to the expected profit. In order to consider the price fairness in the optimization, a formal definition of price (un)fairness is required. As outlined in [5], the more similar different products are, the more is a discrepancy in prices of the products perceived as unfair. Thus, similar products should have similar prices in order to perceive the prices as fair. In the context of EV charging, one can say that two customers request a similar product, if they arrive in the same scheduling interval and request a similar amount of energy. Accordingly, we define the unfairness of price offers in an interval i with $N_i \geq 2$ as

$$unfair_0^i = \frac{\sum_{j=1}^{N_i}\sum_{k=j+1}^{N_i} \frac{\|\vec{p}_{i,j},\vec{p}_{i,k}\|}{|E_{i,j}-E_{i,k}|}}{\binom{N_i}{2}}, \tag{1}$$

with $\vec{p}_{i,j}$ being the vector of the K prices in money units per kWh offered to the j-th vehicle in interval i. The pairwise differences in the prices offered to the customers in interval i are divided by the pairwise differences in the energy requirements[1]. Thus, the more similar the energy requirements of two customers are, the more the difference in the prices offered to these two customers contributes to the unfairness $unfair_0^i$. The sum is divided by $\binom{N_i}{2}$ – the number of pairwise comparisons. For intervals i with $N_i < 2$, $unfair_0^i$ is set to 0.

The definition of unfairness according (1) only considers price differences between customers who arrive in the same interval. One might argue that two customers with similar energy requirements who arrive in different but nearby intervals request similar products and thus should get similar price offers. This is reflected by the following definition of unfairness of price offers in an interval i with $N_i \geq 1$:

$$unfair_M^i = unfair_0^i + \sum_{m=1}^{M} unfair^{i,m} \tag{2}$$

with

$$unfair^{i,m} = \frac{\sum_{j=1}^{N_i}\sum_{k=1}^{N_{i-m}} \frac{\|\vec{p}_{i,j},\vec{p}_{i-m,k}\|}{|E_{i,j}-E_{i-m,k}|\cdot m}}{N_i \cdot N_{i-m}}. \tag{3}$$

This definition of unfairness considers differences between prices in interval i and prices in M previous intervals. The differences in the energy requirements are multiplied with m in (3), to ensure that differences to more distant intervals contribute less to the unfairness than differences to closer intervals. For interval i with $N_i = 0$, $unfair_M^i$ is set to 0.

Given a certain day, one can define the unfairness of the prices offered on that day according (1) as

$$unfair_0^{day} = \frac{\sum_{i=0}^{T-1} unfair_0^i}{T^{>1}} \tag{4}$$

with $T^{>1}$ being the number of intervals with at least two customers who get price offers. Analogously, the unfairness of the prices over the day according (2) can be defined as

$$unfair_M^{day} = \frac{\sum_{i=0}^{T-1} unfair_M^i}{T^{>0}} \tag{5}$$

with $T^{>0}$ being the number of intervals with at least one customer.

III. Optimization Considering Fairness

A. Use Case

The price optimization with consideration of fairness is investigated based on the following use case: $N = 80$ EVs, each with a capacity of 120 kWh, arrive during the day at multiple charging stations with a maximum power level of $P_{max} = 50$ kW, each. It is assumed that the number of charging stations is sufficient to serve all arriving customers. The length of a scheduling interval is 15 min. The arrival times of the EVs are normally distributed with a mean of 12 p.m. and a standard deviation of two hours. The initial states of charge (SoCs) of the EVs are chosen uniformly distributed between 10 % and 80 % and it is assumed, that the target SoC of all EVs is 100 %. The maximum allowed deadline extension K is set to five intervals and the following utility function is used for $EV_{i,n}$: $U_{i,n}^k = E_{i,n}\cdot(\alpha+\delta_{i,n}) - \beta\cdot k - \gamma_{i,n,k}$, with $\alpha = 0.2$ and $\beta = 0.4$. The value of $\delta_{i,n}$ is normally distributed with a mean of 0 and a standard deviation of 0.01. The values $\gamma_{i,n,k}$ are drawn from a truncated normal distribution with $\mu = 0$

[1]To handle cases where pairwise differences in the energy requirements are zero or very small, the denominator can also be set to $\max(\epsilon, |E_{i,j}-E_{i,k}|)$ with a small $\epsilon > 0$.

and $\sigma = 0.1$, truncated left at $-\frac{\beta}{2}$ and right at $\frac{\beta}{2}$. The utility is stated in euro, meaning that on average an EV driver is willing to pay up to 0.2 euros per charged kWh if the EV is charged by the minimum deadline and for each interval the charging takes longer, she/he expects a discount of 0.4 euros on average.

We assume that the electricity price varies over the day and that the CSO participates in the frequency regulation market. Thus, the CSO is payed by the main grid operator for the capacity provided for frequency regulation. Like Mehta *et al.* [7], we compute the capacity provided in an interval i as $C_i = P_{max} \cdot \Delta t \cdot N_i^{idle}$ with N_i^{idle} being the number of idle EVs (i.e. EVs with a charging power of 0 kW) in interval i. Furthermore, it is assumed that the frequency regulation has no impact on the SoC of an involved EV.

The electricity prices are composed of a fixed fee of 10 euro cent per kWh and a time varying amount. For the latter one, we use the quarter-hourly prices from the German intraday market EPEX SPOT SE [8] averaged over all days in July 2017. The used quarter-hourly regulation market prices are normally distributed with a mean of 2.5 and a standard deviation of 0.5 euro cent per kWh. The used electricity and regulation market prices are shown in Figure 1. The costs of charging an EV

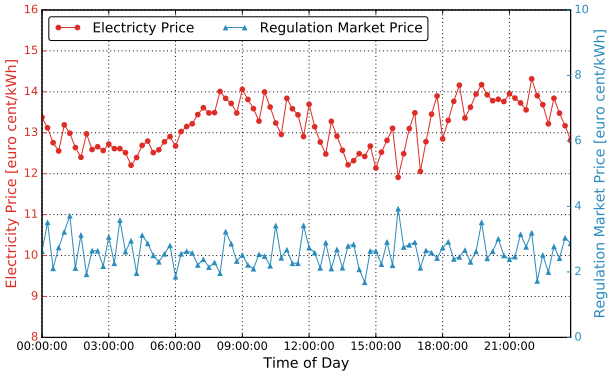


Fig. 1. Electricity and regulation market prices used in the experiments.

are computed as the electricity costs for the charging minus the regulation market credit earned due to idle intervals of the EV. The problem of optimizing the charging schedule of an EV with respect to the charging costs is solved over mixed-integer linear programming with help of CBC (Coin-or branch and cut) [9].

In the experiments, the number M of previous intervals considered in the computation of $unfair_M^i$ according Eq. 2 is set to 5.

B. Optimization of the Profit without Consideration of Fairness

First, the unfairness resulting from the optimization of the price offers solely w.r.t. the expected profit is investigated. We evaluated two algorithms for the maximization of the expected profit: The popular *Covariance Matrix Adaptation Evolution Strategy (CMA-ES)* [10] and an evolutionary algorithm (EA), which we term *Price Optimizing EA (POEA)* in the following.

For CMA-ES, the C implementation provided by Nikolaus Hansen [11] is used. The initial step size σ of CMA-ES is set to 2.0 and for all other parameters the default values are used. The default value for the number λ of offspring per generation is $4 + \lfloor 3 \ln(dim) \rfloor$, where dim is the number of decision variables to optimize.

In POEA, the mutation operator from the Breeder Genetic Algorithm [12] and intermediate recombination[2] [12] are used as variation operators. Mating selection is done over tournament selection with two candidate individuals and a $(\mu + 2)$ replacement strategy is used. The recombination rate in POEA is set to 0.6 and a gene is mutated with a probability of $\frac{1}{dim}$. Furthermore, a population size of 100 is used.

For each interval i, the price offers for the N_i customers are optimized. In both CMA-ES and POEA an individual consists of $6N_i$ real values reflecting the $K + 1 = 6$ price offers for each of the N_i customers. The lower bound for a certain price $p_{i,n}^k$ is set to the corresponding charging costs $c_{i,n}^k$ in order to avoid a negative profit, and the upper bound is set to $5c_{i,n}^k$. It is ensured that prices do not increase with an increasing deadline by adjusting newly generated offspring if necessary. In order to evaluate an individual, the expected profit is approximated with help of Monte-Carlo simulation over 1,000 samples of the customer utilities. In CMA-ES and POEA the same samples are used for the evaluations. The budget of fitness function evaluations in an optimization for an interval i is set to 20,000$\cdot N_i$.

We optimized the expected profit for 30 different days (with different arrival times and energy requirements of the EVs). In order to investigate the relation between the variance in the operating costs and the unfairness, we did the optimizations with different amounts of noise added to the electricity prices shown in Figure 1. More precisely, random numbers drawn from $\mathcal{N}(0, \sigma_P^2)$ are added to the prices and the standard deviation σ_P is varied between zero and three (euro cent per kWh).

The results of the 30 optimization trials with CMA-ES can be seen in Table I. It shows the median of the expected profit (approximated over Monte-Carlo simulation), the medians of $unfair_0^{day}$ and $unfair_5^{day}$, and the median of the expected number of declining customers (also approximated over Monte-Carlo simulation). The results with POEA are shown in Table II.

It can be seen that with an increasing noise on the prices and thus a higher variance of the operating costs, the expected profit increases. Furthermore, POEA yielded higher values for the expected profit than CMA-ES. For all considered values of σ_P, the difference is statistically significant according to the two-sided Wilcoxon signed-rank test with a significance level of 0.01. For a σ_P of 0, the unfairness in the prices resulting from the optimizations with POEA is lower than that yielded by the optimizations with CMA-ES. However, with an increasing σ_P, the unfairness in the results from POEA grows,

[2]The values of α_i in the intermediate recombination are drawn uniform randomly from $[-1.0, 1.0]$.

TABLE I

MEDIANS OF THE EXPECTED PROFIT IN EUROS, OF THE UNFAIRNESS IN EURO CENT PER KWH AND OF THE EXPECTED NUMBER OF DECLINING CUSTOMERS OVER 30 OPTIMIZATION TRIALS FOR DIFFERENT NOISES ON THE ELECTRICITY PRICES. THE OPTIMIZATIONS ARE DONE SINGLE-OBJECTIVE WITH CMA-ES W.R.T. THE EXPECTED PROFIT.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	281.57	299.30	327.44	357.57
$unfair_0^{day}$	1.424	1.369	1.576	1.695
$unfair_5^{day}$	3.541	3.723	3.769	3.784
$\mathbb{E}(decline)$	6.833	6.343	5.698	5.168

TABLE II

MEDIAN RESULTS OF THE SINGLE-OBJECTIVE OPTIMIZATIONS OF THE EXPECTED PROFIT OVER POEA ANALOGOUS TO TABLE I.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	285.51	302.00	329.24	359.03
$unfair_0^{day}$	0.341	1.558	2.266	2.710
$unfair_5^{day}$	0.916	4.715	6.423	7.572
$\mathbb{E}(decline)$	6.174	5.824	5.321	4.870

while with CMA-ES it stays almost constant. Furthermore, the results of CMA-ES lead to a higher expected number of declining customers than the results of POEA.

Figures 2 and 3 show the prices resulting from the optimizations with CMA-ES and POEA, respectively, for the first of the 30 days with $\sigma_P = 3$. The six subplots show for each EV the prices $p1$ to $p6$ for the six possible charging deadlines with the arrival interval of the EV on the x-axis. It can be

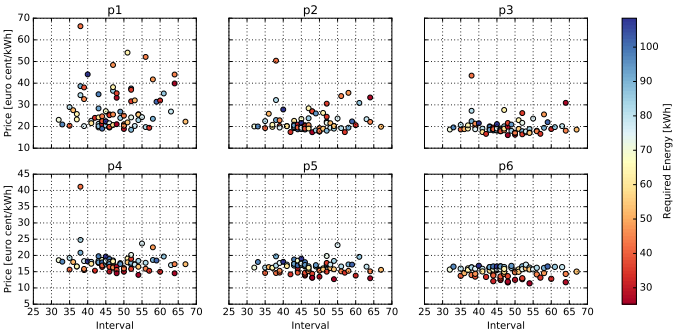


Fig. 2. Price offers in euro cent per kWh for the six possible deadlines resulting from the single-objective optimization of the profit with CMA-ES for the first of the 30 days with $\sigma_P = 3$.

seen that especially for the first two deadlines, the variance in the prices is high. The reason is that with an increasing σ_P, it becomes more profitable for the charging station operator if customers choose late deadlines. Thus, with $\sigma_P = 3$, most of the prices for the first two deadlines are set so high that it is very unlikely that they will be selected by the customers. Hence, the exact values of these prices do not matter for the expected profit, as long as they are high enough. However, the variance in the prices resulting from the optimizations with CMA-ES is lower than that resulting from the optimizations with POEA. Apparently, the operators of POEA induce more variation than the operators of CMA-ES.

The prices resulting from the optimizations with POEA for

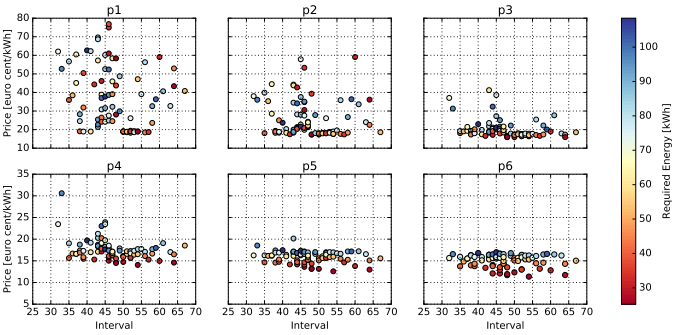


Fig. 3. Price offers, analogous to Figure 2, resulting from the optimization with POEA.

the first of the 30 days with $\sigma_P = 0$ are shown in Figure 4. Although the variance is not as high as with $\sigma_P = 3$,

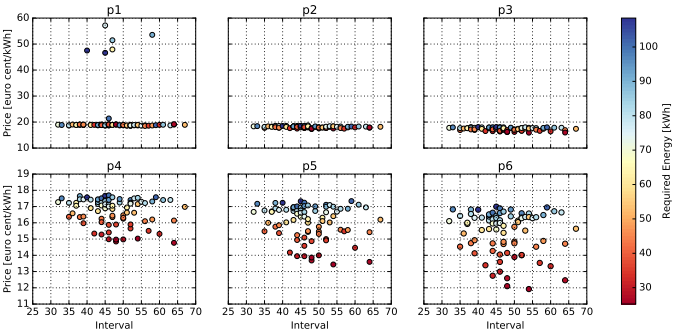


Fig. 4. Price offers resulting from the single-objective optimization of the profit with POEA for the first of the 30 days with $\sigma_P = 0$.

these prices are likely to be perceived as unfair. There are prices of about 60 cent per kWh for the first deadline, while most of the customers get an offer around 20 cent per kWh. The unfairness resulting from the prices shown in Figure 4 is $unfair_0^{day} = 0.31$ and $unfair_5^{day} = 1.48$, respectively.

A typical process of an optimization with CMA-ES and POEA, respectively, is shown in Figure 5. With CMA-ES,

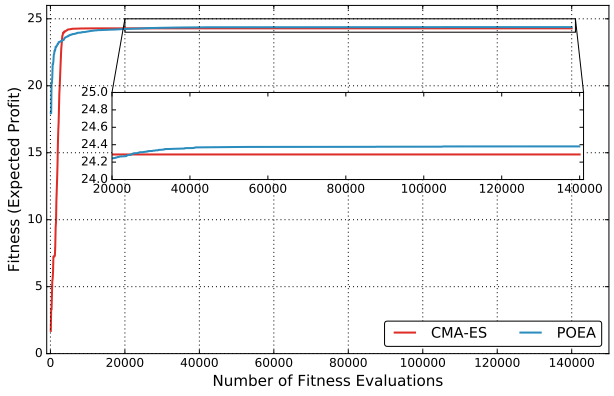


Fig. 5. Process of a single-objective optimization of the expected profit with CMA-ES and with POEA. The optimization is for interval 46 of the first day with $\sigma_P = 0$ and with 7 EVs arriving in the interval.

the fitness improves very quickly at the beginning and after

around 3,000 fitness evaluations it is higher than with POEA. However, CMA-ES converges fast and is outperformed by POEA after around 20,000 fitness evaluations. Apparently, POEA is better able to escape local optima than CMA-ES. An increase of the initial step size and/or of the number of offspring did not improve the results of CMA-ES.

Since POEA yields a higher expected profit than CMA-ES, it is used for the single-objective optimizations in the experiments described in the following two sections.

C. Optimization of the Profit Ensuring Maximum Fairness

In the following, the effect of maximizing the fairness on the resulting expected profit is investigated. For this purpose the expected profit is optimized in the following way: In order to ensure that $unfair_0^{day}$ is zero, for each interval i with $N_i > 0$, six prices per kWh, which are used for all N_i customers, are optimized w.r.t. the expected profit. This ensures similar prices per kWh for all EVs arriving in the same interval. In order to ensure $unfair_M^{day} = 0$, the same approach is used for intervals i with $N_i > 0$ and with no customers in the M previous intervals. And for intervals i with at least one customer in the M previous intervals, $unfair_M^i$ is minimized. The optimizations are done with POEA with 20,000·N_i fitness evaluations and with an algorithm configuration as described in the previous section.

Again, the price offers are optimized for 30 different days (the same as used for the optimizations described in Section III-B) with different amounts of noise on the electricity prices. Table III shows the median results of the optimizations of the profit with ensuring $unfair_0^{day} = 0$. Additionally, the

TABLE III
MEDIAN RESULTS, ANALOGOUS TO TABLE I, RESULTING FROM THE OPTIMIZATIONS OVER POEA ENSURING $unfair_0^{day} = 0$.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	282.30	294.64	317.79	344.52
$unfair_0^{day}$	0.0	0.0	0.0	0.0
$unfair_5^{day}$	0.260	2.180	3.417	4.503
$\mathbb{E}(decline)$	7.322	7.453	7.392	7.308
$\Delta(profit)$	-1.12 %	-2.44 %	-3.48 %	-4.04 %

percentage difference between the median of the expected profit in Table II and that in Table III is provided. One can see that not only $unfair_0^{day}$ is optimal, but that also $unfair_5^{day}$ is considerably lower compared to the results in Table II. The expected profit also decreases and the percentage reduction is the higher the more noise is added to the electricity prices. However, the decrease is in a range that might be acceptable for the charging station operator.

Table IV shows the results of the optimizations ensuring a minimal $unfair_5^{day}$. There is a significant decrease in the expected profit, which is probably not acceptable for the operator.

Additionally, it can be seen that ensuring a minimal $unfair_0^{day}$ and especially a minimal $unfair_5^{day}$ leads to a higher expected number of declining customers compared to the optimizations without consideration of fairness. Besides

TABLE IV
MEDIAN RESULTS, ANALOGOUS TO TABLE I, RESULTING FROM THE OPTIMIZATIONS OVER POEA ENSURING $unfair_5^{day} = 0$.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	267.77	269.27	284.77	298.31
$unfair_0^{day}$	0.0	0.0	0.0	0.0
$unfair_5^{day}$	0.0	0.0	0.0	0.0
$\mathbb{E}(decline)$	6.404	5.704	9.278	10.970
$\Delta(profit)$	-6.21 %	-10.84 %	-13.51 %	-16.91 %

the reduction of the expected profit, this is a second drawback of ensuring an optimal fairness.

The prices resulting from the optimizations ensuring a minimal $unfair_5^{day}$ for the first day with $\sigma_P = 0$ are shown in Figure 6. Not surprisingly, all customers get the same

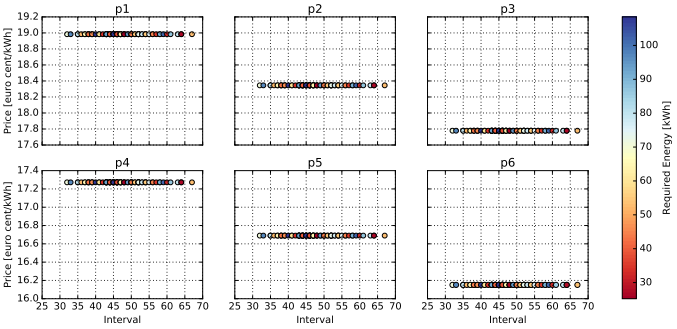


Fig. 6. Price offers for the six possible deadlines resulting from the optimization with ensuring an optimal $unfair_5^{day}$ for the first of the 30 days with $\sigma_P = 0$.

price offers. Only the prices in the first interval with at least one connected EV are actually optimized w.r.t. the profit and the same prices are used for the subsequent intervals. Thus, the total expected profit highly depends on the optimization for the first interval, which does not regard EVs in other intervals. In order to determine the theoretically achievable profit with optimal fairness, we repeated the optimizations with ensuring a minimal $unfair_5^{day}$ with the modification that the prices for all 80 customers per day are done at once. In practice, this requires a perfect foresight in terms of the arrival times and the energy requirements of the EVs arriving during the day. The results are shown in Table V. It can

TABLE V
MEDIAN RESULTS, ANALOGOUS TO TABLE I, RESULTING FROM THE OPTIMIZATIONS OVER POEA ENSURING $unfair_5^{day} = 0$ WITH PERFECT FORESIGHT.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	279.25	287.66	305.55	326.66
$unfair_0^{day}$	0.0	0.0	0.0	0.0
$unfair_5^{day}$	0.0	0.0	0.0	0.0
$\mathbb{E}(decline)$	7.733	8.295	8.712	9.106
$\Delta(profit)$	-2.19 %	-4.75 %	-7.20 %	-9.02 %

be seen that also with perfect foresight – which is usually not available – the expected profit notably reduces compared to the optimizations without consideration of the fairness,

while the expected number of declining customers is again comparatively high.

D. Multi-objective Optimization of Fairness and Profit

The previous two sections have shown that optimizing the price offers solely for expected profit results in prices that are very likely to be perceived as unfair, while ensuring maximum fairness of the prices reduces the expected profit and potentially leads to an increase in the number of declining customers. By the use of multi-objective optimization it might be possible to achieve better tradeoffs between profit and fairness. This is investigated in the present section. For the multi-objective optimizations, NSGA-II (Non-dominated Sorting Genetic Algorithm II) [13] is used. In order to ensure that the resulting Pareto set approximations contain individuals resulting in a high expected profit, NSGA-II is combined with POEA: For each interval i, a single-objective optimization of the expected profit as described in Section III-B is performed with POEA with a budget of 10,000$\cdot N_i$ fitness function evaluations. The result is used to initialize one individual of the start population of NSGA-II which is run for further 30,000$\cdot N_i$ fitness function evaluations in order to maximize the expected profit and to minimize the unfairness in a multi-objective optimization. From the resulting approximation of the Pareto set, the solution that yields the highest expected profit is selected.

In the experiments, version 1.1.6 of the C implementation of NSGA-II provided by Kanpur Genetic Algorithms Laboratory [14] is employed. The population size of NSGA-II is set to 60, the mutation rate to $\frac{1}{dim}$ and the crossover rate to 0.9. The parameters η_c and η_m of the real-valued crossover and mutation operators of NSGA-II are set to 5 and 20, respectively. POEA is parametrized as described in Section III-B.

Table VI shows the results with $unfair_0$ as second objective in NSGA-II and Table VII shows the results with $unfair_5$ as second objective. It can be seen that although the solutions

TABLE VI
MEDIANS OF THE EXPECTED PROFIT, OF THE UNFAIRNESS AND OF THE EXPECTED NUMBER OF DECLINING CUSTOMERS OVER 30 OPTIMIZATION TRIALS FOR DIFFERENT NOISES ON THE ELECTRICITY PRICES. THE OPTIMIZATIONS ARE DONE USING A COMBINATION OF POEA AND NSGA-II WITH THE EXPECTED PROFIT AND $unfair_0$ AS OBJECTIVES. THE INDIVIDUALS YIELDING THE HIGHEST EXPECTED PROFIT ARE SELECTED FROM THE RESULTING PARETO SETS.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	285.52	302.07	329.27	359.02
$unfair_0^{day}$	0.095	0.131	0.165	0.173
$unfair_5^{day}$	0.384	2.551	3.630	4.114
$\mathbb{E}(decline)$	6.259	5.919	5.416	4.931

with the highest expected profit are selected from the Pareto sets, the unfairness significantly decreases compared to the results in Table II, while the expected profit is nearly the same. In fact, the expected profit is even slightly higher because the number of fitness function evaluations is also higher than for the single-objective optimizations. However, a look at

TABLE VII
MEDIAN RESULTS, ANALOGOUS TO TABLE VI, WITH $unfair_5$ AS SECOND OBJECTIVE OF NSGA-II.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	285.57	302.12	329.26	359.12
$unfair_0^{day}$	0.097	0.147	0.193	0.278
$unfair_5^{day}$	0.260	0.457	0.859	1.048
$\mathbb{E}(decline)$	6.317	6.004	5.410	4.862

the resulting prices shows that the fairness can be further improved without decreasing the expected profit. This can be seen in Figure 7, which shows the prices for the first of the 30 days with $\sigma_P = 3$ resulting from the optimizations with $unfair_5$ as second objective. There is less variance in the

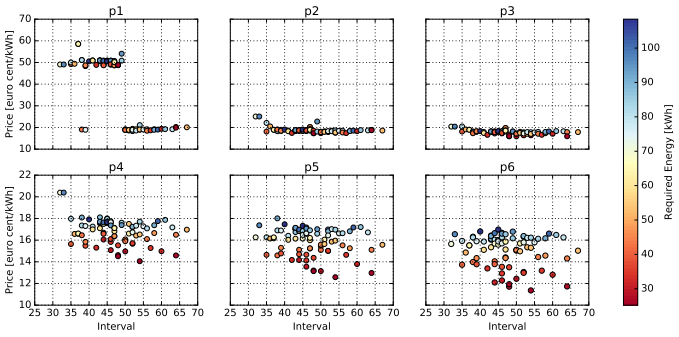


Fig. 7. Price offers for the six possible deadlines resulting from the multi-objective optimization w.r.t. the expected profit and $unfair_5$ with selection of the solutions with the highest expected profit for the first of the 30 days with $\sigma_P = 3$.

prices compared to those shown in Figure 3, but several of the prices – especially for the first deadline – are unnecessarily high. The main reason for this is that in the first interval i with at least one connected EV, $unfair_5^i = 0$ holds independently of the amounts of the prices as long as the prices for the connected EVs are identical or only one EV is connected. As with the single-objective optimizations described in Section III-B, this may result in high prices in this interval i. In subsequent intervals, the prices are either set similarly high in order to decrease the unfairness, or they are set lower if this is beneficial for the expected profit. This suggests that the results can be improved by considering the amounts of the prices in the optimizations. We repeated the multi-objective optimizations with the maximum price

$$\max_{\substack{1 \le n \le N_i \\ 0 \le k \le K}} p_{i,n}^k \tag{6}$$

as a third objective in NSGA-II. However, NSGA-II is modified in the following way: The maximum price is not used to determine if an individual dominates another. Only the expected profit and the unfairness are used for this purpose. Thus, the maximum price is only relevant for the crowding distance operator of NSGA-II. This ensures that the expected profit and the unfairness are still the main objectives in the optimization.

The results of the optimizations with the maximum price as third objective in NSGA-II can be seen in Tables VIII and IX. It can be seen that the usage of the maximum price as third objective helps to notably reduce $unfair_5^{day}$, especially for high values of σ_P. With $unfair_5$ as second objective, also $unfair_0^{day}$ decreases compared to the optimizations without the maximum price objective. The expected number of declining customers slightly increases compared to the optimizations without consideration of fairness (Table II). The resulting prices for the first day with $\sigma_P = 3$ can be seen in Figure 8. The shown prices result in an unfairness of $unfair_0^{day} = 0.130$ and $unfair_5^{day} = 0.294$, respectively.

TABLE VIII
MEDIAN RESULTS, ANALOGOUS TO TABLE VI, WITH $unfair_0$ AS SECOND OBJECTIVE AND THE MAXIMUM PRICE AS THIRD OBJECTIVE IN NSGA-II.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	285.53	302.06	329.27	359.09
$unfair_0^{day}$	0.106	0.145	0.167	0.159
$unfair_5^{day}$	0.325	1.976	2.678	3.223
$\mathbb{E}(decline)$	6.256	5.936	5.395	4.941

TABLE IX
MEDIAN RESULTS, ANALOGOUS TO TABLE VI, WITH $unfair_5$ AS SECOND OBJECTIVE AND THE MAXIMUM PRICE AS THIRD OBJECTIVE IN NSGA-II.

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	285.58	302.13	329.27	359.12
$unfair_0^{day}$	0.101	0.117	0.163	0.159
$unfair_5^{day}$	0.257	0.374	0.527	0.532
$\mathbb{E}(decline)$	6.332	6.031	5.429	4.978

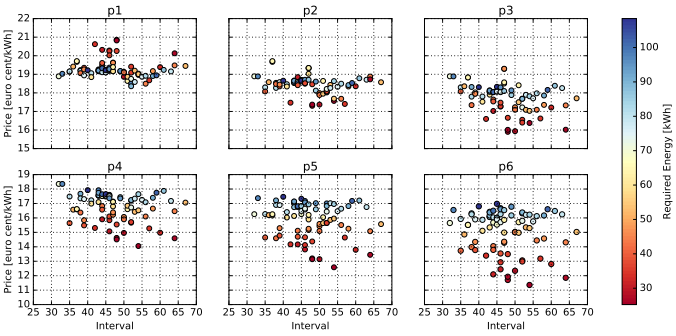


Fig. 8. Price offers, analogous to Figure 7, with the maximum price as a third objective in NSGA-II.

Several of the Pareto fronts (in terms of the expected profit and the unfairness) resulting from the multi-objective optimizations have a shape like the fronts shown in Figure 9. One can see that in these fronts solutions exist that have an expected profit near to that of the solution with the highest expected profit, but with a significantly lower unfairness. Such a solution might be preferred over the solution with the highest expected profit. We compared three approaches for the automated selection of such compromise solutions: Compromise programming [15], the ϵ-constraint method [16] and the bend-angle approach [17]. Compromise programming

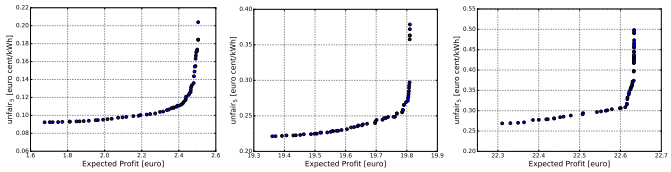


Fig. 9. Examples of Pareto front approximations resulting from the multi-objective optimization of the expected profit and $unfair_5$ with consideration of the maximum price.

selects the point that has the smallest distance to the ideal point in objective space, where the ideal point is composed of the best values found for each objective. The ϵ-constraint method selects the point that yields the minimum unfairness with the constraint that the expected profit is not less than 99 % of the maximum expected profit in the Pareto front approximation. The bend-angle approach selects the point with the highest bend-angle between itself and the corner points of the approximated Pareto front (see [17] for the definition of bend-angle). All three approaches are applied on the first two objectives (expected profit and unfairness) and the third objective (maximum price) is not considered in the selection of a solution. Table X shows the results with $unfair_5$ as second objective and with the selection of solutions with the three previously described approaches.

TABLE X
MEDIAN RESULTS, ANALOGOUS TO TABLE IX, WITH SELECTION OF SOLUTIONS OVER THE COMPROMISE PROGRAMMING METHOD (A), THE ϵ-CONSTRAINT METHOD (B), AND THE BEND-ANGLE METHOD (C).

	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	284.59	299.83	325.87	354.98
$unfair_0^{day}$	0.043	0.053	0.067	0.074
$unfair_5^{day}$	0.123	0.160	0.200	0.254
$\mathbb{E}(decline)$	6.461	6.339	6.193	5.669
		(a)		
	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	283.22	299.39	326.37	355.94
$unfair_0^{day}$	0.024	0.047	0.063	0.068
$unfair_5^{day}$	0.085	0.165	0.223	0.257
$\mathbb{E}(decline)$	6.887	6.769	6.150	5.606
		(b)		
	$\sigma_P = 0$	$\sigma_P = 1$	$\sigma_P = 2$	$\sigma_P = 3$
$\mathbb{E}(profit)$	284.43	301.97	327.05	356.30
$unfair_0^{day}$	0.040	0.054	0.068	0.086
$unfair_5^{day}$	0.122	0.178	0.233	0.271
$\mathbb{E}(decline)$	6.148	6.450	5.951	5.489
		(c)		

With the bend-angle approach the resulting expected profit is slightly higher than with the other two approaches, but the unfairness is also higher. One cannot say that one of the approaches dominates another. Compared to the results yielded by selecting the solution with the maximum expected profit (Table IX), all three approaches are able to notably reduce the unfairness with only small decreases in the expected profit. However, there is also a small increase in the expected number of declining customers.

Figure 10 shows the prices for the first of the 30 days resulting from the optimization with decision making over

the ϵ-constraint approach. It can be seen that especially in

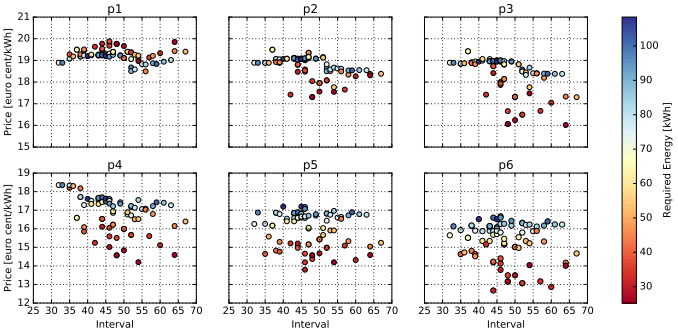


Fig. 10. Price offers, analogous to Figure 8, with selection of solutions over the ϵ-constraint approach.

early intervals, the variance in the prices is lower than in the prices shown in Figure 8, resulting in a lower unfairness. The corresponding unfairness is $unfair_0^{day} = 0.058$ and $unfair_5^{day} = 0.192$, respectively.

IV. Conclusion

In the present work, the consideration of fairness in the optimization of dynamic prices for charging electric vehicles is investigated. Two formal definitions of price unfairness are provided, in order to be able to increase the fairness over numerical optimization. Experiments have shown that optimizing the prices solely regarding the profit results in a high unfairness, especially when the variance in the operating costs is high, while maximizing the fairness notably reduces the expected profit. Additionally, the experimental results suggest that increasing the fairness while keeping the expected profit as high as possible results in an increase of the expected number of declining customers – at least with the type of customer utility function used in the experiments.

It has been shown that by simply considering the fairness as a second objective besides the profit and selecting the solution with the highest expected profit, the fairness can be significantly increased without impact on the profit and with only a slight increase in the expected number of declining customers. Furthermore, it turned out that the results can be further improved by the use of the maximum price as a third objective.

By using appropriate decision making methods like the bend-angle approach for the selection of solutions, the fairness can be further increased with only minor reductions in the expected profit. It can be expected that such an increase in the perceived fairness has a positive effect on the charging station operator's long-term profit.

The definition of unfairness used in this work is based on interpersonal comparisons. Another factor influencing the degree of perceived fairness is self-comparison: A customer expects that the price he/she has to pay for a certain product does not change much over time. Thus, a possible direction of future work is to investigate how it can be ensured that the price offers resulting from the optimization are similar for similar situations or operating conditions, respectively. A possible way to deal with this issue might be to store optimization results in a database and to incorporate this historical data into the optimization.

A further direction of future work might be to include the objectives used in [4] (minimizing the number of declining customers and the rejection rate) in the price optimization with consideration of fairness, resulting in five objectives. This probably requires the use of a many-objective optimization algorithm, such as NSGA-III [18].

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