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Combination of Charging Policies for Fair and Efficient EV Charging under Limited Capacity

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***Abstract*—Rule-based charging control based on simple charging policies is a practical approach for distributing a limited amount of energy or power to electric vehicles of multiple users. Depending on the behavior and characteristics of the users, different efficiencies in terms of overall user satisfaction might be achieved with different charging policies. Analogously, users might be treated differently fairly by different policies in the sense that certain policies might result in a much higher dissatisfaction of some users compared to other users. In the present paper, we compare different charging policies with respect to efficiency and fairness and propose a combination of multiple policies in order to achieve a higher efficiency and fairness compared to the single policies. For the parameterization of the combined policy, a multi-objective evolutionary optimization on historical data is proposed. An evaluation in simulation experiments shows that the proposed approach outperforms single charging policies, especially in terms of fairness.**

***Index Terms*—electric vehicle charging, fairness, multi-objective optimization, evolutionary algorithm**

I. Introduction

The increasing penetration of electric vehicles (EVs) imposes challenges to the electrical power grid. One severe issue is that today's grid connections at the building or street level are typically not able to tolerate the load arising from charging several EVs with maximum possible power at the same time. It can be assumed that this does not change in the near future, since an appropriate extension of the power grid is not only expensive but also time consuming. A promising solution is to coordinate the charging of EVs - for example, EVs of multiple parties living in the same building - in a way that avoids overloading the network. However, the limitation of the charging power might mean that some of the EVs are not charged as much as desired or as technically possible. This imposes the question of how to distribute the available power or energy to the EVs in order to achieve a high overall user satisfaction and to treat the users in a fair way. A popular approach for controlling EV charging is the computation of charging plans based on mixed integer linear programming (MILP) [1], [2], [3], [4]. However, this requires knowledge of departure times and energy requirements of the users. The need for information from the users does not only increase requirements for infrastructure, like a terminal to enter the information, but might also annoy the users, who have to provide the information before each charging session. Furthermore, it can be assumed to be challenging for the users to provide accurate information to departure time and/or target state of charge (SOC). For controlling the charging of EVs without knowledge of the charging requirements, rule-based control based on simple charging policies, like equally distributing the energy, is a valid approach [5]. Compared to optimization-based control, rule-based control has the additional advantage of being less compute-intensive and thus causing less additional energy consumption and costs.

In the present paper, we consider a local community that has to share a limited power connection for charging their EVs, with a strong financial interest to keep this limit as low as possible. A coordinated charging plan for all EVs can provide a good level of satisfaction for most users on average but might occasionally not deliver the requested energy. In this work we measure the resulting user dissatisfaction via the time required for charging the EV externally if not enough energy was provided by the community charging. Therefore discomfort is expressed as lost time, which should be easier to interpret than missing energy. Obviously, other measures of user (dis-)satisfaction could be considered, for example based on studies with real users [6]. A critical challenge for the community is to decide how energy should be distributed. It is unlikely that all users will directly agree on the same charging policy, so multiple strategies are likely going to be discussed. The specific preferences of a user could be the result of a purely rational analysis (e.g., users returning home early might prefer a first-come-first-served policy), but could also be derived from more general ethical principles like equality. We therefore propose that instead of agreeing on one charging strategy, the available energy budget is divided into different shares which are distributed via different policies. This leaves more room for compromise and could increase the overall acceptance. The shares of different policies could be decided by a voting process, but in this work we propose to use an evolutionary optimization to compute an optimal weighting of policies. Optimality in this context is defined as a good compromise between average performance (average additional external charging time) and worst-case performance (additional external charging time of the user with the worst situation). The average performance is a typical objective for optimizing technical systems while the maximization of the minimum performance is often considered when assessing the fairness of a system. Obviously, other indicators of fairness

could be used, like minimizing the spread between the worst and the best-of user.

The rest of the paper is organized as follows: In Section II, related work is discussed. Section III outlines the assumed scenario and problem more in detail. Section IV explains the proposed approach and Section V describes the experiments and presents and discusses their results. Finally, Section VI provides a summary and conclusion.

II. Related Work

Different approaches for charging control under limited power, which do not consider fairness but only the total amount of unfinished work (in terms of unsatisfied energy demand or number of unfinished charging jobs) can be found in the literature, like dynamic programming [7], rule-based control [5] or MILP [8]. Ottensen [2] proposes a MILP approach that takes fairness into account by formulating the objective function in a way that the relative deviations from the desired amounts of energy are distributed as equal as possible over the EVs. Frendo et al. [9] consider fairness by prioritizing charging all EVs to a certain minimum SOC over charging EVs to the full SOC. They propose a combination of MILP and a heuristic for the charging control. Zeballos et al. [10] compare different policies, like earliest-deadline-first or least-laxity-first for charging control under limited capacity and conclude that the amount of unfinished work is the same for all considered policies but that some of them distribute the unfinished work more unfairly than others. Furthermore, they propose a new policy called least laxity ratio in order to achieve a more fair distribution of available energy. Gerding et al. [11] consider a distribution of energy to multiple EVs to be fair if it is envy-free. An EV i is considered envious of EV j if EV i did not receive the requested (and technically possible) amount of energy and EV j received more energy than EV i during the time EV i is connected to the charging station. The authors propose two online algorithms for charging control, which aim to achieve a good trade-off between efficiency and fairness, and compare them to different simple charging policies. Danner and de Meer [12] define a number of metrics for quality of service for EV charging and assume charging of multiple EVs to be fair if the quality of service is as equal as possible over all EVs. They propose a charging policy called Dynamically Weighted Fair Queuing to achieve a fair charging control. Panayiotou et al. [13] define utilities of users based on the satisfaction of their respective charging requirements. They propose the use of so called α-fairness, which allows to control the trade-off between social welfare and min-max fairness via a parameter α. The authors present an integer linear programming and an ant colony optimization approach for computing α-fair charging schedules. Zhou et al. [14] assume that EVs may delay their departure until their respective energy requirements have been satisfied. They compare different charging policies in terms of efficiency and fairness, where fairness is defined in terms of the maximum delay over all EVs. Tsaousoglou et al. [15] assume an analogous scenario and propose a MILP-based approach for minimizing the maximum delay. In addition, they consider that the charging stations are spread over the distribution network and consider network constraints. Furthermore, there are a number of works [16], [17], [18], [19] dealing with the real-time allocation of power to multiple charging stations in a distribution network based on proportional fairness principles.

III. Problem

We assume a scenario with N EVs/users, who charge at home in a shared parking garage. Furthermore, it is assumed that each of the EVs has its own charging spot and that the users are not willing to charge externally. We consider a certain number D of days and for each day, we consider a time horizon of T time steps of length Δt each. Every day d, each user n initiates a charging session in the corresponding time horizon with arrival and departure time steps $t^A_{n,d}$ and $t^D_{n,d}$, respectively, and arrival battery level $B^A_{n,d}$. In each time step t (with $t^A_{n,d} \leq t \leq t^D_{n,d}$) of a user n's charging session, the user's EV is charged with a certain charging power $P_{n,d,t} \leq P^{max}_n$, where P^{max}_n is the maximum charging power of the user's EV. After the time step, the battery level $B_{n,d,t}$ is

$$B_{n,d,t} = \begin{cases} \min\{C_n, B^A_{n,d} + \Delta t \cdot P_{n,d,t}\} & t = t^A_{n,d} \\ \min\{C_n, B_{n,d,t-1} + \Delta t \cdot P_{n,d,t}\} & \text{else,} \end{cases} \quad (1)$$

where C_n is the battery capacity of the user's EV. The battery level $B_{n,d,t^D_{n,d}}$ after time step $t^D_{n,d}$ is the departure battery level $B^D_{n,d}$ of user n on day d. After charging their EV on a day d, a user drives a certain range and thus consumes a certain amount $E_{n,d}$ of energy before returning for charging on the next day $d+1$. It is assumed that the users want to keep their SOCs over a certain minimum SOC $S^{min} \in [0, 1]$ and that they recharge their EVs externally if that is necessary in order to not fall under the minimum SOC. Thus, it is assumed that the arrival battery level of a user n on day d (except the first day) is

$$B^A_{n,d} = \max\{B^D_{n,d-1} - E_{n,d-1}, S^{min} \cdot C_n\}. \quad (2)$$

Assuming that users can recharge with their respective maximum charging power externally, a user n has to spend on average

$$O_n = \frac{1}{D} \sum_{d=1}^{D} \frac{\max\{0, S^{min} \cdot C_n + E_{n,d} - B^D_{n,d}\}}{P^{max}_n} \quad (3)$$

hours per day for external charging.

Due to a limited capacity of the grid connection point, the total charging power is limited by a certain value P^{lim}. Increasing this limit might require costly hardware upgrades and potentially higher peak demand fees. Thus, there might be time steps in which not all connected EVs can be charged with their maximum possible power. We assume that the distribution of the available energy to the connected EVs is done according to a certain charging policy *chp*. That the EVs cannot always charge with maximum power might result in dissatisfaction of the users. Let *uctl* denote uncontrolled charging and O^{chp}_n denote the time user n requires for external

charging if the EV charging is done with policy *chp*. Then the dissatisfaction A_n of user n with charging policy *chp* can be expressed as the additional external charging time compared to uncontrolled charging:

$$A_n = O_n^{chp} - O_n^{uctl}. \tag{4}$$

The efficiency of a charging policy can be measured in terms of the mean additional charging time per day $\overline{A}$ over all users:

$$\overline{A} = \frac{\sum_{n=1}^{N} A_n}{N}, \tag{5}$$

where a lower value of $\overline{A}$ indicates a higher efficiency. However, even with a high efficiency, some of the users might be treated very disadvantageously. Thus, in order to achieve fair charging, one is interested in also reducing the maximum additional charging time per day $\hat{A}$ over all users:

$$\hat{A} = \max\{A_n | n = 1, \ldots, N\}. \tag{6}$$

IV. Approach

Since the behavior and the EV properties vary among the users, different users might benefit differently from different charging policies. While one user might benefit most from equally distributing the available energy, another user might benefit more from a first-come-first-served policy. Analogously, it depends on the characteristics of the single users, which charging policy yields the best performance over the whole group of users. Thus, there is no single policy, which works best in all situations. We propose to combine multiple basic charging policies and to parameterize the combined policy based on historical data in order to achieve an efficient and fair charging control. More precisely, we propose to combine K charging policies $chp_1, \ldots, chp_K$ as follows: In each time step, a fraction w_{chp_1} of the available energy $\Delta t \cdot P^{lim}$ is distributed to the connected EVs with policy chp_1, then a further fraction w_{chp_2} of the available energy is distributed with policy chp_2, and so on, where $w_{chp_k} \in [0, 1]$ for $k = 1, \ldots, K$, and $\sum_{k=1}^{K} w_{chp_k} = 1$. In order to determine a good setting of the weights $w_{chp_1}, \ldots, w_{chp_K}$, we propose to optimize the weights with respect to mean and maximum additional charging times $\overline{A}$ and $\hat{A}$ computed on historical data. The latter means that the additional charging times for a given weight setting are computed by simulating the charging with this weight setting, considering historical behavior of the users (e.g., the behavior in the previous 100 days). The charging behavior and EV characteristics of the users could be directly logged by the charging equipment. The daily energy consumptions of the users could be either logged by the EVs or reported by the users. Since the two objectives of minimizing $\overline{A}$ and minimizing $\hat{A}$ are slightly conflicting, we propose to optimize weights using a multi-objective optimization with the two objectives

$$f1 = \min_{w_{chp_k}, k=1,\ldots K} \overline{A}, \tag{7}$$

$$f2 = \min_{w_{chp_k}, k=1,\ldots K} \hat{A}, \tag{8}$$

and to select a solution from the resulting Pareto set.

V. Experiments

In simulation experiments, we evaluated the proposed approach. We executed ten trials. In each trial, 1100 days of the scenario described in Section III are simulated with different charging policies. It is assumed that all days are weekdays and there are no special days, like national holidays. Different random number generator seeds are used for the simulations in the different trials. The considered charging policies are outlined in subsection V-A. In each trial, the first 100 days of the simulation are used for training. That means, they are used as historical data on which the weights of the combined policy are optimized. The remaining 1000 days are used as test data on which the different charging policies are evaluated. For the multi-objective optimizations, we used the popular Non-dominated Sorting Genetic Algorithm II (NSGA-II) [20] implemented in the Python library pymoo [21]. We used a population size of 20, executed 100 generations per optimization, and left the remaining hyperparameters of NSGA-II to the default values from pymoo. The setup of the simulations is described more in detail in Section V-B.

A. Charging Policies

We consider the following policies for the charging control:
Equal Distribution (ED): In each time step, the available power/energy is distributed as equally as possible to the connected EVs.
First-come-first-served (FCFS): EVs with earlier arrival time are preferred over EVs with later arrival time as follows: From the available power, as much as possible is allocated to the EV that arrived first. From the remaining power, as much as possible is allocated to the EV that arrived second, and so on.
Less Energy First (LEF): EVs with a lower battery level are preferred over EVs with a higher battery level analogous to the FCFS policy.
Lower SOC First (LSF): EVs with a lower SOC are preferred over EVs with a higher SOC analogous to the FCFS policy.
Less Charged First (LCF): EVs with a lower amount of energy charged since their last arrival are preferred over EVs with a higher amount of charged energy analogous to the FCFS policy.
Combined Charging (CC): The combination of the previously described five basic policies in the given order as explained in Section IV

B. Simulation Setup

We consider $N = 100$ users and simulate for each day $T = 96$ time steps of a length Δt of 0.25 h. The time horizon represents the time period from 12 pm to 12 pm on the following day. We assume a power limit P^{lim} of 20 kW for the EV charging. This power limit was chosen based on prior simulations indicating that at this level most of but not all charging jobs could be completed. We leave a thorough analysis of the charging quality trade-off to future work. According to an analysis of real-world residential charging data by Sørensen et al. [22], on weekdays, the number of EV arrivals peaks in the time between 3 pm and 8 pm and the

number of departures peaks in the time between 6 am and 8 am. Based on this, we set the arrival and departure times as follows: For each user n a mean arrival time μ_n^A is sampled from a truncated Gaussian distribution with a lower bound of 5 (i.e., 1 pm), a mean of 25 (i.e., 6 pm), an upper bound of 45 (i.e., 11 pm), and a standard deviation of 8 (i.e., 2 hours). The daily arrival time steps of a user n are sampled from a truncated Gaussian distribution with lower bound 1 (i.e., 12 pm), a mean of μ_n^A, an upper bound of 96 (i.e., 11:45 pm the following day), and a standard deviation of 2 (i.e., 30 minutes) and are rounded to the closest integers. Analogously, for each user n a mean departure time μ_n^D is sampled from a truncated Gaussian distribution with a lower bound of 65 (i.e. 4 am, following day), a mean of 77 (7 am, following day), an upper bound of 89 (i.e., 10 am, following day) and a standard deviation of 4 (i.e., 1 hour) and the daily departure time steps are sampled from a truncated Gaussian distribution with the corresponding arrival time steps as lower bounds, a mean of μ_n^D, an upper bound of 96 and a standard deviation of 2 (i.e., 30 minutes). The daily energy consumptions $E_{n,d}$ of the users are set based on daily driving ranges $R_{n,d}$

$$E_{n,d} = c \cdot R_{n,d}, \tag{9}$$

where c is the energy consumption per km, which we assume constant and identical for all EVs. Based on an analysis of real-world data, Weiss et al. [23] report an energy consumption between 0.10 and 0.33 kWh/km for electric passenger cars. Hence, we assume a consumption of $c = 0.2$ kWh/km in the simulations. In order to compute daily driving ranges, we set a mean driving range μ_n^R per user n, which is sampled from a truncated Gaussian distribution with a lower bound of 15 (km), a mean of 30 (km), an upper bound of 100 (km) and a standard deviation of 10 (km). The daily driving ranges of user n are sampled uniformly distributed from the interval $[0.9 \cdot \mu_n^R, 1.1 \cdot \mu_n^R]$.

We randomly assign an EV model to each user, where we consider the five EV models with the highest market share in Germany in 2020 according to [24]. The battery capacities C and maximum charging powers P^{max} of these models are obtained from EV database [25]. We assume that the users have only access to AC charging stations. The probabilities of the EV models to be assigned to a user are set proportional to the sales numbers reported by [24]. Table I lists the considered EV models together with their technical data and probabilities.

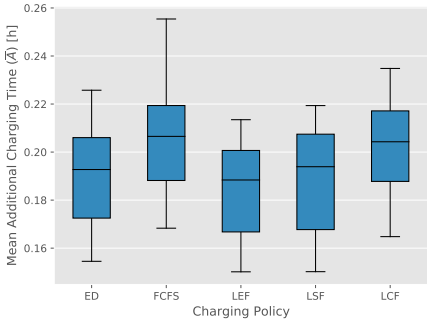
TABLE I: Overview to considered EV models.

Model	P^{max} **(AC)**	C	P^{model}
Renault Zoe	22 kW	41 kWh	0.33
Volkswagen e-Golf	7.2 kW	40 kWh	0.19
Tesla Model 3	11 kW	49 kWh	0.17
Volkswagen ID.2	11 kW	58 kWh	0.16
Hyundai Kona	11 kW	64 kWh	0.15

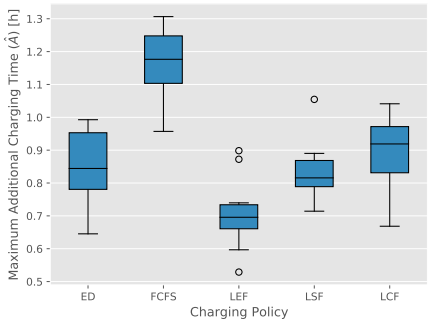
It is assumed that at the beginning of the simulation (more precisely at the beginning of the 100 days training period and at the beginning of the 1000 days test period), all EVs have a battery level corresponding to an SOC of 0.5.

C. Experimental Results

Figure 1 shows the additional charging times per day with the five basic policies in the 100 day training period. More precisely, the distributions over the 10 trials are shown. Figure 1a shows the distribution of the mean additional charging time $\overline{A}$ and Figure 1b shows the distribution of the maximum additional charging time $\hat{A}$. One can see that policies yielding lower mean values also yield lower maximum values. Thus, efficiency and fairness are not completely conflicting. The LEF policy performed best on the training data, yielding the lowest mean additional charging time in 9 of the 10 trials and the lowest maximum additional charging time in 8 of the 10 trials. The FCFS policy performed notably worst, especially in terms of $\hat{A}$. Furthermore, one can see that there is more variance among the different policies for $\hat{A}$ than for $\overline{A}$.



(a)



(b)

Fig. 1: Distribution of mean (a) and maximum (b) additional external charging times per day with different basic charging policies on 100 days training data over 10 trials.

Figure 2 exemplary shows for one of the 10 trials the Pareto front approximation resulting from the optimization in red together with the performances of the basic charging policies. In all trials, settings of weights were found that let the combined charging policy outperform all the basic policies in both objectives. However, these are only results on the 100 days training data, on which the weights were optimized. As a consequence, it only shows that by setting the weights to optimum values, the combined policy can outperform the basic

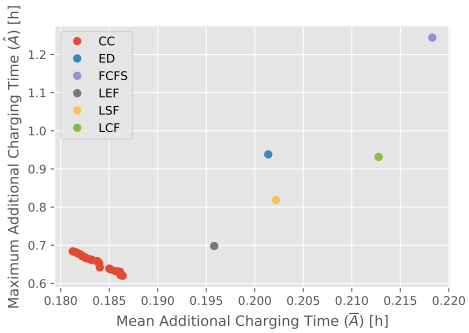


Fig. 2: Pareto front approximation and results of the basic charging policies on training data in one of the 10 trials.

policies, but it does not show a practical benefit since during the 100 days it is not known what the optimum weight setting is. Hence, we evaluated the generalization of the approach on the 1000 days test data. More precisely, we evaluated in each trial the two weight settings corresponding to the extreme points of the Pareto front approximation on the test data. That means, the two weights of the Pareto set, which yielded the best first objective and best second objective, respectively, on the training data. In the following, we denote the combined policy with these weights as CC_f1 and CC_f2, respectively. In practice, one could select a compromise solutions, for example knee points or solutions of interest [26]. Specifically one could ask the community for their preferred balance and use an approach similar to Schmitt et al. [27] to select the best trade-off.

A more simple approach than tuning weights of a combined policy could be to select the basic policy which performed best on the training data for charging control in the future. We also evaluated this approach on the test data and denote the basic policies, which yielded the best first and best second objective, as BF_f1 and BF_f2, respectively. Note that these might be different policies in different trials.

Figure 3 shows the results with the different charging policies on the test data. Figure 3a shows the distribution of the mean additional charging time and Figure 3b the distribution of the maximum additional charging time over the 10 trials. One can see that the combined policy generalizes to the test data. The CC_f1 policy performs best in the first objective and the CC_f2 policy performs best in the second objective. In all 10 trials, CC_f1 yields a lower mean additional charging time than BF_f1 and CC_f2 yields a lower maximum additional charging time than BF_f2. Averaged over the 10 trials, the mean additional charging time is 0.018 h (1.08 min) lower with CC_f1 than with BF_f1 and the maximum additional charging time is 0.092 h (5.52 min) lower with CC_f2 than with BF_f2. In 7 of the 10 trials, CC_f1 yields also a lower maximum additional charging time than BF_f2 (on average 0.005 h (0.3 min) lower) and in 9 of the 10 trials, CC_f2 yields a lower mean additional charging time than BF_f1 (on average 0.008 h (0.48 min)) lower. Hence, one can conclude that the combined

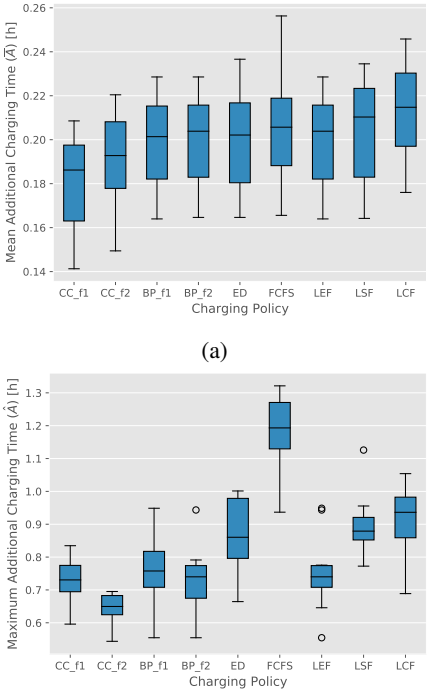


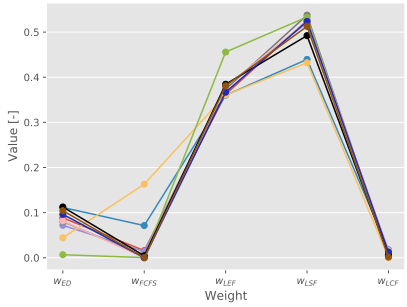
Fig. 3: Distribution of mean (a) and maximum (b) additional external charging times with different charging policies on 1000 days test data over 10 trials.

policy is especially promising for improving the fairness - it can yield a notable improvement in the maximum additional charging time compared to the single basic policies, while still yielding a good mean additional charging time. The combined policy CC_f2 reduces the maximum additional charging time per day by on average 11.7% compared to the best single policy BF_f2. Whether the absolute improvements justify the extra effort might be debatable, thus investigating possible ways to reduce the effort to determine a good parameterization could be a valuable direction of future work.

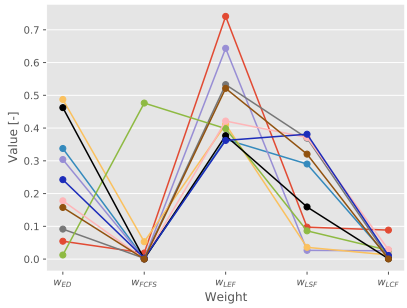
Figure 4 shows the optimized weights in the 10 trials. Figure 4a shows the weights yielding the best first objective (i.e., the weights corresponding to CC_f1) and Figure 4b shows the weights yielding the best second objective (i.e., the weights corresponding to CC_f2). Interestingly, the CC_f1 weights typically weight the LSF policy higher than the LEF policy, while it is the other way around for the CC_f2 weights. The FCFS and LCF policies are mostly weighted low, which is not surprising since on the training data these two policies yielded the highest additional charging times. The ED policy tends to be weighted higher by the CC_f2 weights than by the CC_f1 weights. The CC_f2 weights exhibit a higher variance over the 10 trials than the CC_f1 weights.

VI. Conclusion

An evaluation of different policies for distributing a limited amount of energy to multiple EVs in simulation experiments



(a)



(b)

Fig. 4: Weights yielding the best mean (a) and maximum (b) additional external charging times on 100 days training data in the 10 trials.

has shown that the policies differ in terms of efficiency and especially in terms of fairness. In order to achieve a higher efficiency and fairness, we proposed the combination of multiple policies. A multi-objective optimization is proposed for parameterizing the combined policy and thus tailoring it to the characteristics of the users and their EVs. In experiments, the proposed approach notably outperformed the single charging policies. A drawback of the proposed approach is that its parameterization requires to record detailed data to the users' charging and driving behavior. However, in a deeper analysis of the experimental results (not shown in the present paper), we identified notable correlations between certain statistics of user behavior and EV characteristics and optimum settings of the parameters. In future work, this relation could be investigated more in detail and it might be evaluated whether it is possible to derive a good parameter setting from aggregated user statistics, which are easier to obtain than detailed user data.

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