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Combination of Charging Policies for Fair and Bias-aware Electric Vehicle Charging

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***Abstract*—Controlled charging can be employed to coordinate the charging of multiple electric vehicles (EVs) under power limitations, such as those imposed by transformer capacity constraints. However, controlled charging may result in reduced satisfaction of the EV users' charging requirements compared to uncontrolled charging. It is desirable to distribute this (dis-)satisfaction fairly among users. Additionally, one might be interested in avoiding systematic bias, which disadvantages groups of users with certain characteristics. The present paper proposes an approach for the automated design of fair and bias-aware charging policies by combining multiple manually designed policies through multi-objective optimization. For the detection of bias in EV charging control, a hierarchical clustering approach is introduced. In simulation experiments, the proposed method reduces bias by an average of 5 % while improving efficiency and fairness by an average of 4 % and 9 %, respectively, compared to manually designed charging policies.**

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

I. Introduction

The increasing adoption of electric vehicles (EVs) imposes the issue that today's grid connections on building and street level are typically not able to handle the load arising from charging a high number of EVs with maximum charging power simultaneously. Dynamic pricing [1] and controlled charging [2] are seen as promising approaches to deal with this problem. The present paper focuses on controlled charging of a group of EVs with a limited power connection. Given the constraints of the available power, it may not be feasible to fully satisfy the charging requirements of all users. Typically, one seeks to achieve high overall satisfaction of the users. However, maximizing the overall satisfaction alone does not necessarily yield a fair distribution of the satisfaction. Fairness is becoming an increasingly important topic in energy management [3], and there are several works proposing approaches for fair EV charging control based on optimization [4]–[6] and on charging policies [7], [8]. These works generally assume that the users' energy requirements and departure times are known in advance. However, users might not be willing or able to provide this information. Therefore, in the present work it is assumed that this information is not available for the charging control.

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In a previous work [9], we proposed an approach for fair and efficient EV charging control based on learning or optimizing a combination of manually designed charging policies on historical data. In simulation experiments, it was shown that the proposed approach is able to outperform the single charging policies, especially in terms of fairness. However, only fairness among individual users was considered. Thus, the approach may still result in an unfair distribution across different groups of users, meaning that there might be users sharing certain characteristics, e.g., driving the same EV model, who are treated notably worse than other users. The decision maker or charging station operator might be interested in reducing such systematic bias. Algorithmic bias has been extensively discussed in the literature, particularly within the domain of machine learning [10]. However, to the best of the authors' knowledge, it has not yet been addressed in the context of EV charging.

The present paper proposes a hierarchical clustering approach to quantify systematic bias in EV charging control. Furthermore, it extends the combined control approach from [9] in order to consider the bias in addition to efficiency and user fairness in the optimization of charging policies. While reducing bias may potentially diminish efficiency and user fairness, the use of Pareto optimization allows the decision maker to weigh these different objectives when selecting an appropriate charging policy. In simulation experiments, the proposed approach is evaluated and the experimental results are analyzed.

The rest of the paper is organized as follows: Section II describes the problem, the proposed extension including the hierarchical clustering approach, and the combined control approach used for the design of charging policies. Section III describes the experiments and presents and discusses their results. Finally, Section IV provides a summary and conclusion.

II. Problem and Approach

A. Basic Problem Definition

A number N of EV users are considered, who share a residential garage for parking and charging at individual charging spots. It is assumed that the total charging power is limited due to transformer constraints and that the limit is notably lower than the sum of the maximum possible charging powers of the EVs. To ensure that the power limit is not violated, a

rule-based charging control is used, which periodically (e.g., every 15 minutes) distributes the available power/energy to connected EVs, which are not fully charged yet, based on a certain charging policy. The rule-based control results in dissatisfaction of users whose charging demands are satisfied less compared to uncontrolled charging. The problem consists in finding or generating a charging policy, which satisfies the users as well as possible.

More precisely, it is assumed that historical data of charging behaviors and demands of the users over D days in the past is available, what allows to evaluate different charging policies on this historical data in simulation. Furthermore, it is assumed that the users have the possibility to charge externally at public charging stations or their workplaces, but prefer charging at home. Therefore, the dissatisfaction of users is expressed in terms of the additional time they have to spend per day for external charging compared to uncontrolled charging. For a user u, this additional external charging time per day $T_{u,add}$ in the historical time period of D days resulting from the use of a charging policy CP is computed as:

$$T_{u,add}(CP) = \frac{T_{u,CP} - T_{u,UC}}{D}, \tag{1}$$

where $T_u(CP)$ and $T_u(UC)$ denote the time the user has to spend for external charging according to a simulation on the historical data with charging policy CP and with uncontrolled charging, respectively.

We want to find a charging policy, which minimizes the total dissatisfaction of the users measured as the mean additional external charging time per day over all users:

$$\min_{CP} \overline{T}_{add}(CP) = \frac{\sum_{u=1}^{N} T_{u,add}(CP)}{N}. \tag{2}$$

Additionally, we are interested in achieving a fair distribution of dissatisfaction among users, guided by the popular min-max fairness principle. Therefore, minimizing the maximum additional external charging time across all users is considered as a second objective:

$$\min_{CP} \hat{T}_{add}(CP) = \max\{T_{u,add}(CP) | u = 1, \ldots, N\}. \tag{3}$$

B. Problem Extension

The problem definition as described in the previous subsection is analogous to that from [9]. It considers fairness among individual users but does not consider the characteristics of the users in the fairness definition. Certain user characteristics, such as a high charging demand, a low maximum charging power of the EV, or a low charging duration can significantly impact user satisfaction. Consequently, there may be a systematic bias leading to a notably higher dissatisfaction of users with certain characteristics compared to other users. Aside from trying to increase the fairness among the individual users, we also address and attempt to reduce this group bias. Thus, in the present work it is proposed to add the minimization of the bias as a third objective. For the computation of the group bias, an adapted version of the hierarchical clustering approach, introduced by Misztal-Radecka and Indurkhya [11] for the detection of bias in recommendation systems, is proposed.

The characteristics of a user u are represented in form of F numerical features $f_{u,1}, \ldots, f_{u,F}$. These features might, for example, include the maximum charging power of the user's EV or the average daily driving range of the user. Let the users be divided into G distinct groups, $g_1, \ldots, g_G$, where the users in one group are similar in terms of their features. The average daily external charging time over all users in a group g can then be computed as

$$\overline{T}_g(CP) = \frac{\sum_{u \in g} T_{u,add}(CP)}{|g|}. \tag{4}$$

In order to reduce the group bias, we want to avoid that a group of at least c_{min} similar users with a high average daily external charging time can be found and thus we define a third objective as:

$$\min_{CP} \hat{T}_g(CP) = \max_{g=g_1,\ldots,g_G} \overline{T}_g(CP), \tag{5}$$

where $g_1, \ldots, g_G$ are determined with a hierarchical clustering approach. The approach iteratively splits users into groups using k-Means clustering on their features in order to find a group with a high average daily external charging time as outlined in Algorithm 1.

Algorithm 1 Hierarchical clustering.

```
max_bias = -1
clusters_out = []
for i = 1, ..., I do
    clusters = [cluster consisting of all users]
    seed = rand()
    for j = 1, ..., J do
        g = clusters[j%|clusters|]
        if |g| < 2 · c_min then
            continue
        g_1, g_2 = k_means(g, seed+j)
        if |g_1| < c_min or |g_2| < c_min then
            continue
        if max{T̄_{g_1}(CP), T̄_{g_2}(CP)} ≥ T̄_g(CP) then
            remove g from clusters and add g_1 and g_2
    if max_{g∈clusters} T̄_g(CP) >max_bias then
        max_bias = max_{g∈clusters} T̄_g(CP)
        clusters_out = clusters
return clusters_out
```

Each of the I outer iterations of the algorithm starts with initializing a list of clusters consisting of only one cluster, which comprises all users. In each of the J inner iterations, a cluster g is picked from the list and if its size is at least twice the minimum cluster size c_{min}, k-Means is used to split it into two clusters g_1 and g_2 based on the features of the users contained in the cluster g. If the resulting clusters satisfy the minimum cluster size and if at least one of them has an average daily external charging time, which is at least as high as that of the original cluster g, then g is replaced by g_1 and g_2 in the list of clusters. The algorithm returns the clusters

corresponding to the highest maximum average daily external charging time found in one of the outer iterations. The reason for executing multiple outer iterations is that the results of the k-Means clustering depend on the random number generator seed and therefore, the clustering is repeated using different seeds.

To summarize the proposed extension: It is proposed to consider a third objective $\hat{T}_g(CP)$ according to Eq. (5), which expresses the group bias. If this objective has a certain value x for a certain charging policy CP, then it is possible to identify a group of at least c_{min} similar users with (hierarchical) k-Means clustering, whose average daily additional charging time with policy CP is x time units.

C. Approach

In order to find a charging policy that performs well on the available historical data, with respect to the three considered objectives, the combined control approach from [9] is used. It combines K manually designed charging policies $CP_1, \ldots, CP_K$, like, for example, first-come-first-served, or equal distribution, as follows: First a fraction w_1 of the available energy is distributed to the connected EVs with policy CP_1, then another fraction w_2 of the available energy is distributed using policy CP_2, and so on, with $\sum_{k=1}^{K} w_k = 1$, and $w_k \in [0, 1]$ for $k = 1, \ldots, K$. The fractions (in the following referred to as weights) are optimized with respect to the considered objectives in simulation on the historical data. Since three partly conflicting objectives are considered, a multi-objective optimization is used, which approximates a Pareto front of different weight settings.

III. Simulation Experiments

A. Experimental Setup

In experiments, 20 simulation trials are executed in order to evaluate the proposed approach. In each trial, 1100 days of charging of $N = 100$ users under a power limit of 20 kW are simulated with different charging policies. Different random number generator seeds are used for the simulations in the different trials. The following charging policies are considered in the experiments:

Equal Distribution (ED): In each time step, the available energy is distributed as equally as possible to the connected EVs.

First-come-first-served (FCFS): EVs with earlier arrival times are prioritized over EVs with later arrival times as follows: As much as possible of the available energy is allocated to the EV that arrived first. From the remaining energy, as much as possible is allocated to the EV that arrived second, and so on.

Less Energy First (LEF): EVs arriving with less energy in the battery are prioritized over EVs with higher energy values analogous to the FCFS policy.

Lower SOC First (LSF): EVs with lower SOCs are prioritized over EVs with higher SOCs analogous to the FCFS policy.

Less Charged First (LCF): EVs with lower amounts of energy charged per time step since their arrival are prioritized over EVs with higher amounts of charged energy per time step since their arrival analogous to the FCFS policy.

Combined Control (CC): The combination of the previously described five basic policies in the order they were mentioned (i.e., CP_1 = ED, CP_2 = FCFS, ...) as explained in Section II-C. Since a complete front of charging policies is computed, one policy CC_sel is selected from the front (described in Section III-B) and is evaluated more in detail.

In each trial of the experiments, 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 control are optimized. The remaining 1000 days are used as test data on which the different charging policies are evaluated. For the multi-objective optimizations, the popular Non-dominated Sorting Genetic Algorithm II (NSGA-II) [12] implemented in the C++ library pagmo [13] is used with a population size of 100, a crossover probability of 0.95, a mutation probability of 0.20, and distribution indexes of $\eta_c = 10$ and $\eta_m = 20$ for the real-valued crossover and mutation, respectively. In each trial, 100 generations of the optimization are executed.

As previously described, in practice one would setup simulations based on historical data. Since we do not have real-world historical data available, we assume artificially generated user behaviors and characteristics in the simulations, which are setup as described in [9]: First, average arrival and departure times, average daily driving ranges and EV models of the individual users are randomly sampled using different random number generator seeds in the different trials. The daily arrival and departure times and driving ranges of the users are sampled from distributions around their mean values. The simulations are done with a temporal resolution of 15 min, meaning that the charging control distributes the available energy to connected EVs every 15 minutes, and it is assumed that users charge externally if this is necessary to arrive at home with an SOC of at least 10 %. The five EV models with the highest market share in Germany in 2020 are considered in the simulations and are assigned to the users with probabilities proportional to their sales numbers. The considered EV models, their maximum (AC) charging powers P^{max}, battery capacities Cap, and probabilities for assignment P^{model} are listed in Table I. More details to the simulation setup can be found in [9].

TABLE I
EV MODELS CONSIDERED IN THE SIMULATIONS.

Model	P^{max} (AC)	Cap	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

In the experiments, the computation of the bias objective, as outlined in Section II-B, is done as follows: The characteriza-

tion and clustering of users is done based on five features: their average arrival times, their average departure times, their average daily driving ranges, and their EVs' maximum charging powers and battery capacities. The minimum cluster size c_{min} is set to 10, and the numbers I and J, of outer and inner iterations, respectively, of the hierarchical clustering are set to 100 both. In practice, the operator could of course select other user characteristics as features or a different value for the minimum cluster size according to their preferences.

B. Experimental Results

Figure 1 exemplary shows the results on the 100 days training data for the first of the 20 trials. It shows the mean

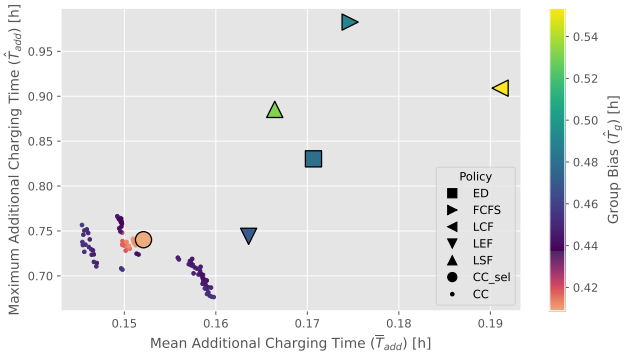

Fig. 1. Results on training data in the first of the 20 trials. Shown are the three objective values resulting from the five basic charging policies, the Pareto front approximation computed with the combined control approach (CC) and a solution selected from the front (CC_sel).

and maximum daily additional external charging times over all users as well as the (color-coded) group biases resulting from the different basic charging policies and from the combined control CC with the weight settings in the computed Pareto front approximation (plotted with a small marker size for the sake of clarity). As one can see, the combined control approach is able to find charging policies, which dominate all the basic policies. In practice, one has to select a solution from the Pareto front approximation. An option is to identify and select a knee point of the front [14]. However, in the following a simpler approach for selecting a solution or a charging policy is assumed: Each user "votes" for the solution from the front, which yields the lowest daily additional external charging time for that user and the solution with the highest number of user votes is selected. In Figure 1, the selected solution is indicated as CC_sel. It corresponds to the solution, with the lowest group bias. In 13 of the 20 trials, an extreme point of the front is selected by the procedure described above, but not always the one with the lowest group bias. Seven times the solution with the lowest maximum additional charging time is selected, four times the solution with the lowest mean additional charging time, and two times the solution with the lowest group bias. In Figure 1, one can see that the solution with the lowest group bias still yields a group bias that is notably higher than the mean additional charging time over all users, meaning that there are still notably disadvantaged groups of users. Figure 2

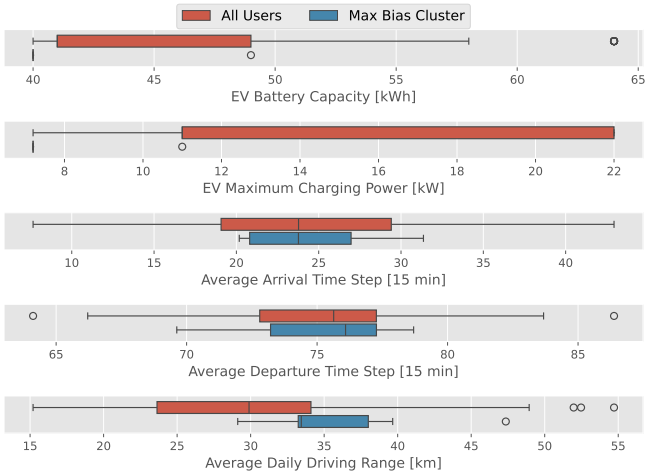

Fig. 2. Distributions of features (EV capacity and maximum charging power, average arrival and departure times, and average daily driving range) over all users and over the maximum bias cluster identified for the selected policy CC_sel on the training data in the first trial.

shows the distributions of the five used features over all users and over the users of the maximum bias cluster computed with the hierarchical clustering approach on the training data for the CC_sel policy shown in Figure 1. Note that the average arrival and departure times are expressed as number of (15 minute) interval since noon. For example, an arrival time of 9 corresponds to 2 pm and a departure time of 81 corresponds to 8 am on the following day. From Figure 2, one can see that the users in the identified cluster have low EV battery capacities and maximum charging powers and high average daily driving ranges. It is not surprising that the charging requirements of such users are not satisfied well.

So far, we discussed only the results on the training data, which is assumed to be historical data. For a full evaluation, it has to be evaluated whether the combined control policies, which are optimized on the training data, generalize to the 1000 days of unseen test data. Figure 3 shows the distributions of the three objectives on the test data for the basic charging policies and the (based on the training data) selected combined policy over the 20 trials. As one can see, the combined policy CC_sel generalizes well to the test data and yields the best objective values. It is followed by the LEF policy, which performs best among the basic charging policies. This observation is supported by the critical difference diagram shown in Figure 4. It shows the mean ranks (the lower, the better) of the different charging policies, including the selected combined policy CC_sel, over the 20 trials on the test data with respect to the three objectives. Furthermore, the diagram shows which ranks are statistically significantly different from others by indicating statistically indistinguishable ranks with brackets under the corresponding average ranks. A Friedman test with a significance level of 0.05 is used to test whether there are any statistical differences in the data. A Wilcoxon signed-rank test with significance level 0.05 and with Holm correction is used for pairwise tests. As one can see, the CC_sel policy

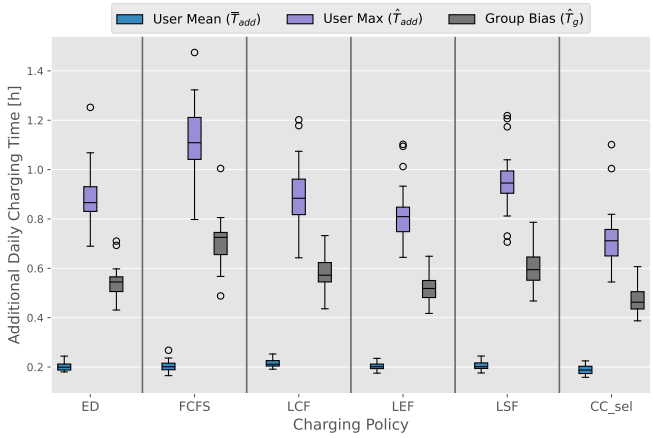

Fig. 3. Distributions of the three objectives on the test data over the 20 trials with different charging policies.

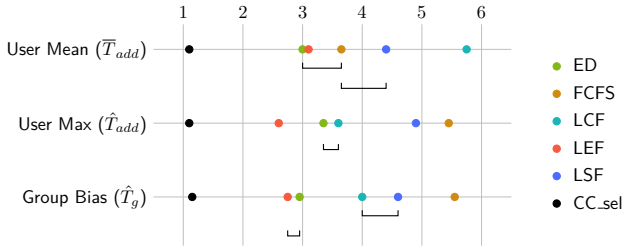

Fig. 4. Critical difference diagram comparing the performance of different charging policies on the test data.

performs significantly best over all three objectives with mean ranks close to the best possible value of one. From the basic charging policies, the LEF and ED policies yielded the best mean ranks. Interestingly, the LCF policy performed worst with respect to efficiency but moderately with respect to user fairness and group bias. It is not surprising that the FCFS policy yielded the highest group biases since it is obviously biased towards users with early arrival times.

A more in-depth analysis of the objective values achieved on the test data in the 20 trials shows that on average the combined control policy CC_sel yields a 4.4 % lower mean additional external charging time, a 8.5 % lower maximum additional external charging time, and a 5.1 % lower group bias than any of the basic charging policies. By using another strategy for selecting a solution from the Pareto front approximation than described above, the decision maker can shift the focus more in the direction of one of the objectives (at the cost of the other two objectives).

IV. Conclusion and Summary

The present paper proposed and evaluated an approach to design an electric vehicle charging policy based on historical data, considering not only efficiency and fairness over individual users but also potential bias towards certain user characteristics and behavior. The use of a hierarchical clustering method is proposed to quantify this bias, and the charging policy is designed by optimizing a combination of manually crafted charging policies through multi-objective optimization. Simulation experiments have demonstrated that the proposed combined control strategy enhances efficiency and fairness while reducing systematic bias compared to standalone, manually designed charging policies.

As future work, we plan to investigate ways to evolve charging strategies from scratch, which might be more powerful than the combination of existing policies.

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