Charging Electric Vehicles Fairly and Efficiently

Extended Abstract

Ramsundar Anandanarayanan
IIT Bombay
Mumbai, India
ramsundar@cse.iitb.ac.in

Swaprava Nath
IIT Bombay
Mumbai, India
swaprava@cse.iitb.ac.in

Rohit Vaish
IIT Delhi
New Delhi, India
rvaish@iitd.ac.in

ABSTRACT

Motivated by electric vehicle (EV) charging, we formulate the problem of *fair* and *efficient* allocation of a divisible resource among agents that arrive and depart over time and consume the resource at different rates. The agents (EVs) derive utility from the amount of charge gained, which depends on their own charging rate as well as that of the charging outlet. The goal is to allocate charging time at different outlets among the EVs such that the final allocation is *envy-free, pareto optimal*, and in certain contexts, *group-strategyproof*. The differences in the charging rates of the outlets and the EVs, and a continuous time-window where the arrivals and departures occur make this a non-trivial combinatorial optimization problem. We show possibilities and impossibilities of achieving a combination of properties such as envy-freeness, pareto optimality, leximin, and group-strategyproofness under different operational settings, e.g., when the EVs have (dis)similar charging technology, or when there are one or more dissimilar charging outlets. We complement the positive existence results with polynomial-time algorithms.

KEYWORDS

EV Charging; Divisible Resource Allocation; Fair Division

ACM Reference Format:
Ramsundar Anandanarayanan, Swaprava Nath, and Rohit Vaish. 2024. Charging Electric Vehicles Fairly and Efficiently: Extended Abstract. In *Proc. of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2024), Auckland, New Zealand, May 6 – 10, 2024*, IFAAMAS, 3 pages.

1 INTRODUCTION

Climate change has pushed all nations across the globe to consider low carbon-emitting solutions for their daily routine. In the transportation sector, the *electric vehicles* (EV) have received a significant endorsement by the governments and acceptance from the consumers primarily because of their carbon-friendly behavior and the subsidies provided by the administration in promoting them. This has reflected in the growth of the EV market in various geographies, in particular, in the developing economies [2]. However, the growth of the EV market has also brought in a different challenge which is not very common in the traditional transportation sector. The current battery technology of the EVs typically requires frequent charging (at least once in a day for affordable EVs that run continuously during the day), but each charge takes a significant amount of time (a 20 kW *fast* charger takes approximately 1.5 hours to charge a 30kWh battery). This time constraint, along with relatively smaller number of charging outlets make the allocation of EVs to the charging outlets to be an incredibly complicated combinatorial optimization problem. Ensuring this in a *fair* and *efficient* manner is an important and timely problem to consider. In this paper, we consider the problem of efficient and fair scheduling of EVs in the available charging outlets. We assume that the prices per unit of electricity is fixed (e.g., by some regulatory authority) and not part of the mechanism. However, the arrival and departure time as well as the demand of electricity are assumed to be privately known to the EVs, and needs to be elicited truthfully.

One relevant category of literature for our work is the allocation of divisible resources that involve monetary transfers. Several works in this strand consider the problem of scheduling using payments as a tool to satisfy several objectives [3, 7, 8, 14]. The minimization of cost in EV charging [10, 11, 15] and the computational complexity of battery charging algorithms with monetary payments [5] have also been addressed. The other category comes from the classical field of scheduling [12]. Porter [13] investigates strategic aspects of maximizing weighted completion in online hard real-time scheduling where tasks have weights, release times, deadlines, and durations. In the context of EV charging, Gerding et al. [6] provide several fairness results.

The problems we address in this paper are different from both these strands since we consider mechanisms without monetary transfers, and focus on group-strategyproofness and efficiency properties in addition to fairness. The paper closest to ours is [6], which considers time to be discrete and charging rates of only EV side of the market. The authors do not consider properties like leximin, pareto optimality, or group-strategyproofness. The properties like **`leximin`** and GSP have been investigated before but in a different domain. Particularly, Bogomolnaia and Moulin [4] and Kurokawa et al. [9] show that in matching problems and under dichotomous preferences, a **`leximin`** allocation satisfies PO, EF (classical notion), GSP and proportionality.

2 PRELIMINARIES

Consider a set of EVs $N = \{1, 2, \ldots, n\}$ and a set of charging outlets $M = \{1, 2, \ldots, m\}$. The maximum charging rates of the EVs and the outlets are $r_i^{\text{EV}}, i \in N$ and $r_k^{\text{Ch}}, k \in M$ respectively. The rate at which EV i will charge when plugged into an outlet k is given by $r_{ik} = \min\{r_i^{\text{EV}}, r_k^{\text{Ch}}\}$. We consider the EVs as *agents* and an aggregator (manages the charging outlets) in a region as the *planner*. We assume that the planner is non-strategic and its objective is to assign the outlets to the EVs satisfying certain desirable goals. Agent

Proc. of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2024), N. Alechina, V. Dignum, M. Dastani, J.S. Sichman (eds.), May 6 – 10, 2024, Auckland, New Zealand.

Table 1: Summary of results

Properties	Identical cars *Single/Multiple outlet(s)*	Non-identical cars *Single outlet*	*Multiple outlets*
Envy-freeness+Max-Delivered	✓	✗	✗
Envy-freeness+Pareto-Optimality	✓	✓	?
Envy-freeness+Pareto-Optimality+Group-strategyproofness	✓	?	?
Leximin+Group-strategyproofness	✓	✓	✓
Leximin+Envy-freeness+Group-strategyproofness	✓	✗	✗

$i \in N$ comes with type θ_i denoted by the triplet (a_i, d_i, c_i), where a_i and d_i denote the arrival and departure times of the EV within a given time horizon (e.g., a day) and c_i is her demand of electricity. Note that θ_i is agent i's private information and the planner needs to elicit this information. The type profile is denoted by θ and the set of all feasible type profiles is denoted by Θ. When asked about their types, agent $i \in N$ reveals $\hat{\theta}_i = (\hat{a}_i, \hat{d}_i, \hat{c}_i)$, which may be different from θ_i, her true type. Based on the reported types $\hat{\theta}$, we divide the time horizon into a set of non-overlapping and exhaustive time intervals that cover the earliest arrival and the latest departure time in the following way. From $\hat{\theta}$, the time *checkpoints* are identified where an agent either arrives or departs. Let $t_{\text{start}} = \min\{\hat{a}_i : i \in N\}$ and $t_{\text{end}} = \max\{\hat{d}_i : i \in N\}$ be the earliest arrival and the latest departure times respectively. Let the (ascending) sorted order of the time checkpoints except for t_{start} and t_{end} be denoted by $t_1, t_2, \ldots, t_{k(\hat{\theta})}$ such that $\exists i \in N, \ni t_\ell = a_i$ or $d_i, \forall \ell = \{1, 2, \ldots, k(\hat{\theta})\}$. We denote the collection of intervals $\{[t_{\text{start}}, t_1), [t_1, t_2), \ldots, [t_{k(\hat{\theta})}, t_{\text{end}}]\}$ by $I(\hat{\theta})$ where the active agents remain the same in any given interval. We use the index j to denote an interval in $I(\hat{\theta})$ and the set of such indices by $J(\hat{\theta})$. A member of $I(\hat{\theta})$ will be denoted as I_j for $j \in J(\hat{\theta})$. When clear from the context, we will use the shorthand J for $J(\hat{\theta})$. Therefore, the indices of the *active intervals* of agent $i \in N$ are denoted by $J_i := \{j \in J(\hat{\theta}) : I_j \cap (a_i, d_i) \neq \emptyset\}$.

An *allocation* is specified by the three-dimensional matrix $x = [x_{ijk}, i \in N, j \in J, k \in M]$, where x_{ijk} denotes the time allocated to agent i in interval j at charging outlet k. An allocation is said to be feasible if all x_{ijk} are non-negative, agents are allocated at most their demand and only in their active intervals, and the total time allocated to (a) all agents at a given (outlet, interval) is at most the interval's duration (b) each agent across all outlets at a given interval is at most the interval's duration. We denote the allocation to agent i by $x_i := (x_{ijk})_{j \in J, k \in M}$, the complete feasible allocation by $x = (x_i)_{i \in N}$, and the set of all feasible allocations by X.

The utility function of agent $i \in N$ is given by $u_i : X \to \mathbb{R}_{\geqslant 0}$. Formally, $u_i(x) = u_i(x_i) = \min\{c_i, \sum_{j \in J_i} \sum_{k \in M} x_{ijk} r_{ik}\}$, $\forall i \in N$. More generally, we define the utility of an agent $i \in N$ for any agent h's allocation x_h as $u_i(x_h) = \min\{c_i, \sum_{j \in J_i} \sum_{k \in M} x_{hjk} r_{ik}\}$. Note that this is computed at i's charging rate and active interval.

Given the reported type profile $\hat{\theta}$, the planner decides the allocation which is given by the function $f : \Theta \to X$. We next formalize the desirable properties of this function.

Definition 1 (Pareto Optimality (PO)). An allocation $x \in X$ is *Pareto optimal* if there does not exist $y \in X$ such that, $u_i(y) \geqslant u_i(x), \forall i \in N$ and $u_{i'}(y) > u_{i'}(x)$, for some $i' \in N$. An allocation function f is PO if for every $\theta \in \Theta$ the allocation $f(\theta)$ is Pareto optimal.

Definition 2 (Max-Delivered (MD)). An allocation x' is Max-Delivered (MD) if $x' \in \operatorname{argmax}_{x \in X} \sum_{i \in N} \sum_{j \in J_i} \sum_{k \in M} x_{ijk} r_{ik}$. In other words, maximum resource is delivered to agents. An allocation function f is MD if for every $\theta \in \Theta$, $f(\theta)$ satisfies MD.

Definition 3 (Manipulability). An allocation function f is (a) *manipulable* if there exists $\theta \in \Theta$ and $i \in N$, s.t. $u_i(f(\theta'_i, \theta_{-i})) > u_i(f(\theta_i, \theta_{-i}))$ for some θ'_i, and (b) *group manipulable* if there exists $\theta \in \Theta$ and $S \in 2^N \setminus \emptyset$, s.t. for every $i \in S$, $u_i(f(\theta'_S, \theta_{-S})) > u_i(f(\theta_S, \theta_{-S}))$, for some θ'_S.

We call an allocation function *strategyproof* (SP) if it is not manipulable, and *group strategyproof* (GSP) if it is not group manipulable. Note that, since manipulability implies group manipulability, group strategyproofness implies strategyproofness.

On the fairness front, we want our allocation to be EF among the agents. We say an agent i envies another agent i_1's bundle (x_{i_1}) if its valuation for x_{i_1} is greater than x_i when both bundles are evaluated at i's charging rate and active interval.

Definition 4 (Envy-freeness (EF)). An allocation x is *envy-free* (EF) if $u_i(x_i) \geqslant u_i(x_{i'})$ for every $i, i' \in N$, where x_i and $x_{i'}$ are the allocations of agents i and i' respectively. An allocation function f is EF if $f(\theta)$ is EF for every $\theta \in \Theta$.

Definition 5 (Leximin). An allocation is **leximin** if it maximizes the minimum utility that any agent receives; and subject to this, maximizes the second least utility, and so on. Formally, let $u^{(1)}(x), u^{(2)}(x), \ldots, u^{(n)}(x)$ denote the non-decreasing order of agent utilities for an allocation $x \in X$. Then, x is **leximin** if it maximizes the above utilities in the lexicographic order. An allocation function f is **leximin** if $f(\theta)$ is **leximin** for every $\theta \in \Theta$.

3 RESULTS AND CONCLUSIONS

Our results are summarized in Table 1 and also the open questions for future investigation. For complete details on the proofs and algorithms refer to full version [1].

ACKNOWLEDGMENTS

SN acknowledges the support of grants MTR/2021/000367 and CRG/2022/009169 from SERB, a TCAAI grant (DO/2021-TCAI002-009), and a TCS grant (MOU/CS/10001981-1/22-23). RV acknowledges support from DST INSPIRE grant no. DST/INSPIRE/04/2020/000107 and SERB grant no. CRG/2022/002621.

ETHICS STATEMENT

This paper adheres to the principles of research ethics, research integrity, and social responsibility. The research conducted in this paper is purely theoretical, and no human or animal subjects were involved in the research. Therefore, there were no ethical concerns related to the treatment of participants or the use of personal data. Also, designing fair and efficient protocols in a resource allocation setting, e.g., allocating spectrum, electricity, etc., without money is a standard practice both in computer science and economics. Therefore the results presented in this paper do not consider anything that adversely impacts the society.

REFERENCES

[1] Ramsundar Anandanarayanan, Swaprava Nath, and Rohit Vaish. 2024. Charging Electric Vehicles Fairly and Efficiently. (2024). https://www.cse.iitb.ac.in/~swaprava/papers/fair-EV-web.pdf

[2] World Bank. 2022. *Electric Vehicles: An Economic and Environmental Win for Developing Countries.* https://www.worldbank.org/en/news/feature/2022/11/17/electric-vehicles-an-economic-and-environmental-win-for-developing-countries

[3] Abdoulmenim Bilh, Kshirasagar Naik, and Ramadan El-Shatshat. 2016. A novel online charging algorithm for electric vehicles under stochastic net-load. *IEEE Transactions on Smart Grid* 9, 3 (2016), 1787–1799.

[4] Anna Bogomolnaia and Hervé Moulin. 2004. Random matching under dichotomous preferences. *Econometrica* 72, 1 (2004), 257–279.

[5] Mathijs De Weerdt, Michael Albert, and Vincent Conitzer. 2017. Complexity of scheduling charging in the smart grid. *arXiv preprint arXiv:1709.07480* (2017).

[6] Enrico H. Gerding, Alvaro Perez-Diaz, Haris Aziz, Serge Gaspers, Antonia Marcu, Nicholas Mattei, and Toby Walsh. 2019. Fair Online Allocation of Perishable Goods and its Application to Electric Vehicle Charging. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*. International Joint Conferences on Artificial Intelligence Organization, 5569–5575. https://doi.org/10.24963/ijcai.2019/773

[7] Enrico H Gerding, Valentin Robu, Sebastian Stein, David C Parkes, Alex Rogers, and Nicholas R Jennings. 2011. Online Mechanism Design for Electric Vehicle Charging. In *Autonomous Agents and Multi Agent Systems (AAMAS)*.

[8] Enrico H Gerding, Sebastian Stein, Sofia Ceppi, and Valentin Robu. 2016. Online mechanism design for vehicle-to-grid car parks. In *25th International Joint Conference on Artificial Intelligence 2016*. AAAI Press, 286–293.

[9] David Kurokawa, Ariel D Procaccia, and Nisarg Shah. 2018. Leximin allocations in the real world. *ACM Transactions on Economics and Computation (TEAC)* 6, 3-4 (2018), 1–24.

[10] Zhaoxi Liu, Qiuwei Wu, Shaojun Huang, Lingfeng Wang, Mohammad Shahidehpour, and Yusheng Xue. 2017. Optimal day-ahead charging scheduling of electric vehicles through an aggregative game model. *IEEE Transactions on Smart Grid* 9, 5 (2017), 5173–5184.

[11] Rahul Mehta, Dipti Srinivasan, Ashwin M Khambadkone, Jing Yang, and Anupam Trivedi. 2016. Smart charging strategies for optimal integration of plug-in electric vehicles within existing distribution system infrastructure. *IEEE Transactions on Smart Grid* 9, 1 (2016), 299–312.

[12] Michael L Pinedo. 2012. *Scheduling*. Vol. 29. Springer.

[13] Ryan Porter. 2004. Mechanism design for online real-time scheduling. In *Proceedings of the 5th ACM conference on Electronic commerce*. 61–70.

[14] Sebastian Stein, Enrico Gerding, Valentin Robu, and Nick Jennings. 2012. A model-based online mechanism with pre-commitment and its application to electric vehicle charging. In *Autonomous Agents and Multi Agent Systems (AAMAS)*.

[15] Bo Sun, Zhe Huang, Xiaoqi Tan, and Danny HK Tsang. 2016. Optimal scheduling for electric vehicle charging with discrete charging levels in distribution grid. *IEEE Transactions on Smart Grid* 9, 2 (2016), 624–634.