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Published in:
IEEE Transactions on Intelligent Transportation Systems

Link to article, DOI:
10.1109/TITS.2023.3311509

Publication date:
2024

Document Version
Peer reviewed version

Citation (APA):
Tsaousoglou, G., Giraldo, J. S., Pinson, P., & Paterakis, N. G. (in press). Fair and Scalable Electric Vehicle Charging Under Electrical Grid Constraints. *IEEE Transactions on Intelligent Transportation Systems*. https://doi.org/10.1109/TITS.2023.3311509

Fair and Scalable Electric Vehicle Charging Under Electrical Grid Constraints

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***Abstract*— The increasing penetration of electric vehicles brings a consequent increase in charging facilities in the low-voltage electricity network. Serving all charging requests on-demand can endanger the safety of the electrical power distribution network. This creates the issue of fairly allocating the charging energy among electric vehicles while maintaining the system within safe operational margins. However, calculating efficient charging schedules for the charging stations bears a high computational burden due to the non-convexities of charging stations' models. In this paper, we consider a tri-level system with electric vehicles, charging stations, and a power distribution system operator. The objective of each station is formulated as a max-min fairness, mixed-integer linear optimization problem, while the network constraints are modeled using a second-order conic formulation. In order to tackle the computational complexity of the problem, we decompose it and use a novel approximation method tailored to this problem. We compare the performance of the proposed method with that of the popular alternating direction method of multipliers. Our simulation results indicate that the proposed method achieves a near-optimal solution along with promising scalability properties.**

***Index Terms*— Electric vehicles, fairness, power distribution system, distributed optimization.**

Nomenclature

Sets and Indices

Ω_b	Set of nodes, indexed by i, or κ, or j.
Ω_l	Set of lines, indexed by l, or κi, or ij.
Ω_S	Set of charging stations, indexed by s.
Ω_N^s	Set of charging tasks reserved at charging station s, indexed by n.
Ω_T	Set of time periods, indexed by t.
$\mathcal{Y}$	Set of decision variables.
k	Index of algorithm's iterations.

Parameters

a_n	Arrival time period for charging task n.
d_n	Desired completion time period for charging task n.
E_n	Energy requirement for charging task n [kWh].
$\bar{\mathrm{I}}_{ij}$	Maximum current magnitude for line ij [A].
$\mathrm{P}_{i,t}^\mathrm{D}$	Active power demand at node i, period t [kW].
$\overline{\mathrm{p}_s}$, $\underline{\mathrm{p}_s}$	Maximum/Minimum power consumption at charging station s [kW].
$\mathrm{Q}_{i,t}^\mathrm{D}$	Reactive power demand at node i, period t [kvar].
$\mathrm{R_{ij}}$	Resistance of line ij [mΩ].
$\overline{\mathrm{V}}$, $\underline{\mathrm{V}}$	Maximum/Minimum voltage magnitude [kV].
w_n	Priority weight for charging task n.
w_s	Priority weight of station s.
$\mathrm{X_{ij}}$	Reactance of line ij [mΩ].
$\overline{\mathrm{x}_n}$, $\underline{\mathrm{x}_n}$	Maximum/Minimum power allocation for charging task n [kW].
π_t	Wholesale electricity price at t.
δ	Parameter of the approximation model.

Variables

θ_n	Time delay for charging task n.
ζ_s	Auxiliary variable.
$p_{s,t}$	Power consumption profile at charging station s, period t [kW].
$I_{ij,t}^\mathrm{sqr}$	Squared current magnitude at line ij, period t [A^2].
$P_{ij,t}$	Active power flow at line ij, period t [kW].
$P_{0,t}^\mathrm{G}$	Active power injection at the substation, period t [kW].
$Q_{ij,t}$	Reactive power flow at line ij, period t [kvar].
$Q_{0,t}^\mathrm{G}$	Reactive power injection at the substation, period t [kvar].
$u_{n,t}$	Binary variable representing if charging task n is served by timeslot t.
$V_{i,t}^\mathrm{sqr}$	Squared voltage magnitude at node i, period t [kV^2].
$x_{n,t}$	Power consumption for charging task n, period t [kW].
z_s	Auxiliary variable.

Manuscript received 4 March 2022; revised 16 March 2023 and 12 June 2023; accepted 25 August 2023. This work was supported in part by the European Commission through the H2020 Project ebalance+ under Grant 864283. The Associate Editor for this article was S. E. Li.
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Digital Object Identifier 10.1109/TITS.2023.3311509

I. Introduction

A. Motivation and Related Work

VEHICLE electrification is promoted in many countries through attractive subsidy measures or other policy actions. It is estimated that around 130 million private chargers and 13 million public chargers will be installed by 2030. These projections have motivated studies that provide techniques towards controlling Electric Vehicle (EV) charging. A survey on EV charging control can be found in [1]. Depending on the charging station's business model, a charging control algorithm can accommodate different objectives. In [2] and [3], the charging station's objective is to maximize the social welfare among its EVs. In [4] and [5], the objective refers to minimizing the charging station's electricity cost (maximizing its profit respectively) throughout the day. In [6], the objective is to optimize the user's satisfaction in a station with bounded power capacity. These works have used convex optimization methods to formulate and tackle the charging control problem. Fairness among EVs has been the objective of interest in [7], while [8] adopts a charging protocol towards achieving proportional fairness. Finally, a multiobjective approach is presented in [9].

EV charging control inevitably affects the end-user. While small modifications of the charging procedure can go unnoticed, larger deviations and charging delays can interfere with the user's comfort. Towards mitigating this effect, we propose that a charging station adopts a Rawlsian welfare function, i.e. minimizing the highest charging delay among the station's customers, which relates to the concept of max-min fairness. Such an objective has been previously proposed in other, but related, contexts (e.g. [10], [11]).

With increasing levels of charging infrastructure being built in various locations, a system-level approach is necessary towards coordinating the charging decisions of multiple charging stations while also considering the impact on the physical constraints of the electricity grid [12]. Centralized approaches, where all the local information is communicated to a central point, have been proposed for distributed assets with well-defined characteristics e.g. for batteries [13]. However, communicating the needs of charging tasks and local charging station objectives is generally deemed impractical for various reasons. One reason is the difficulty of accurately formulating and representing the local information within a predefined, standardized bidding format [14]. Moreover, having a central entity deciding the charging schedule of each EV in all charging stations raises issues with computational complexity [15], data privacy and security [16], [17], as well as issues with decision-making transparency.

As a result, distributed algorithms constitute a suitable tool towards optimizing the coordination procedure, e.g. in terms of convergence speed, communication overhead, and global system efficiency. Different ways to coordinate power consumption decisions of charging stations have been proposed in the literature, including methods stemming from queuing theory (e.g. [18], [19]), game theory (e.g. [20] and [21] propose different iterative auction procedures for allocating energy to users and determining their charging schedules), artificial intelligence (e.g. [22], [23] propose Reinforcement (and respectively Supervised) Learning algorithms for employing a transaction, price-based control of EV scheduling), convex optimization (e.g. in [24], EV users submit a convex utility function that represents their charging preferences, and the operator solves a convex optimization program to decide the charging schedules) and distributed optimization (e.g. [25] uses a dual decomposition technique where an operator iteratively updates a set of Lagrange multipliers, to be perceived as energy prices at the EV user side).

However, such studies typically disregard the electrical grid's constraints, while some others consider only a static upper bound on the charging station's power. Examples of studies adopting such a static upper bound include [2], [26], where the authors have proposed online algorithms for allocating charging to EVs in the absence of future information, and [6] where a genetic algorithm was proposed. In contrast, power-network-aware coordination is a more efficient approach, and it is typically achieved by Lagrangian methods [27], [28]; namely, the Alternating Direction Method of Multipliers (ADMM). Nevertheless, these methods are suitable for convex charging station models that facilitate their convergence properties.

TABLE I
CLASSIFICATION OF LITERATURE BASED ON THE RELEVANT FEATURES

	EVs	Fairness	Power-flow constraints	Non-convex models	Distributed Approach
[5], [6], [9]	✔	×	×	✔	×
[2], [3], [4], [26]	✔	×	×	×	✔
[7]	✔	✔	×	✔	✔
[10]	✔	✔	×	✔	×
[11]	×	✔	✔	×	×
[13], [29]	×	×	✔	✔	✔
[19]	✔	×	✔	✔	×
[20], [21], [22], [23], [25]	✔	×	×	✔	✔
[24]	✔	×	✔	×	✔
[27]	×	×	✔	×	✔
[28]	×	✔	×	×	✔
Proposed method	✔	✔	✔	✔	✔

B. Challenges and Contributions

In this paper, departing from the simplifying assumptions mentioned (namely convexity, and static upper bounds on power instead of modeling network constraints), we formulate the objective of an EV charging station as a max-min fairness, mixed-integer linear optimization problem, and consider the coordination problem of multiple stations in a network-constrained power distribution system.

An important observation is that, when the local problems (that need to be repeatedly solved) are non-convex, as in our case, the distributed optimization procedure can become very slow. Improving the solution's computational time is especially important, considering the need to re-solve the dispatch problem during operation (i.e., in a rolling horizon fashion) to account for changes and updated forecasts of the inflexible demand, EV arrivals, etc. Motivated by this issue, this paper proposes an iterative algorithm, configured with an approximation method, explicitly tailored to the problem of fair coordination of EV charging. A comparison table is presented in Table I, where related literature is characterized by the way it deals with relevant features, namely whether it accounts for the load-shifting capabilities of EVs, the fairness objective, the power flow constraints of the electricity network, non-convexities, and distributed implementations such that privacy and scalability issues are addressed.

First, the Alternating Direction Method of Multipliers (ADMM) algorithm is considered as a possible solution to the non-convex problem. It is shown that ADMM suffers from limited scalability with respect to increasing numbers of EVs, since each station is required to solve a mixed-integer linear problem (MILP) at each multiplier iteration. Then, the novel algorithm is presented, which iteratively approximates the original MILP of the charging stations with linear programming. The linear model is iteratively tuned to best approximate the original problem. Thus, the paper's main technical contribution is the design of a novel distributed algorithm for non-convex, constrained optimization problems.

The proposed algorithm is shown to converge to a feasible near-optimal solution, while it exhibits attractive scalability properties. Thus, from a practical point of view, this paper addresses the increasingly emerging issue of fairness in systems with high penetration of EVs, while the proposition's attractive scalability properties offer quite some potential for practical adoption and impact. Overall, and to the best of our knowledge, this is the first paper to propose a distributed algorithm for the described problem and directly compare it with (and outperform) the standard Lagrangian-based approaches.

The remainder of this paper is organized as follows: Section II, formulates the models of the charging stations and the distribution network. In Section III, the fairness optimization objective of each EV charging station is formulated as a max-min, MILP problem, and the dispatch problem, also accounting for alternate-current power flow constraints, is formulated as a mixed-integer non-linear problem and converted into a mixed-integer second-order cone program. An approximation method is presented, that approximates the local problems of the charging stations using a linear program. A novel distributed algorithm is proposed, through which the approximation is iteratively tuned, approaching the optimal solution in a distributed manner. In Section IV, the proposed algorithm is compared to the ADMM approach via simulations and shown to scale better to more extensive settings, while achieving a near-optimal solution. Finally, Section V concludes the paper.

II. System Model

We consider a set Ω_{S} of EV-charging stations, responsible for serving charging requests of arriving EVs within a certain time horizon Ω_{T}. The stations are connected to an electrical power distribution network, constituted by a set of nodes $b \in \Omega_b$ and a set of branches $l \in \Omega_l$. For each station $s \in \Omega_{\mathrm{S}}$, we assume a reservation system that accepts charging tasks for the planning horizon. More precisely, for a station s located at node b, the set of charging tasks reserved for the station is denoted as Ω_{N}^s, where $\Omega_{\mathrm{N}}^s = \{1, 2, \ldots, N_s\}$, with N_s being the number of charging tasks at station s, e.g., the number of EV spots in a parking lot.

A. Charging Station's Model

An EV needs to be charged from the station up to a specific battery level and within certain time preferences or constraints. We say that an EV brings a charging task to the station, and we use the terms EV and charging task interchangeably. Consider a charging task n, of some station s, i.e., $n \in \Omega_{\mathrm{N}}^s$. The task is characterized by the tuple $\mathrm{A}_n = (\mathrm{a}_n, \mathrm{d}_n, \mathrm{E}_n, \overline{\mathrm{x}_n})$ which is comprised by the task's arrival time a_n, the task's desired departure time d_n, the task's required charging energy E_n, and the task's maximum charging rate $\overline{\mathrm{x}_n}$. The power consumption $x_{n,t}$ allocated to task n in timeslot t, is a decision variable determined by the station.

Let $\boldsymbol{p}_s = \left\{p_{s,t}\right\}_{t\in\Omega_{\mathrm{T}}}$ denote the power consumption profile of station s through the scheduling horizon Ω_{T}, where:

$$p_{s,t} = \sum_{n\in\Omega_{\mathrm{N}}^s} x_{n,t}, \quad \forall\ t \in \Omega_{\mathrm{T}} \tag{1}$$

The aggregate power consumption (or injection) of a charging station at t is constrained by an upper (lower) bound, which represents the capacity of the station's transformer,

$$\underline{\mathrm{p}_s} \le p_{s,t} \le \overline{\mathrm{p}_s}, \quad \forall\ t \in \Omega_{\mathrm{T}} \tag{2}$$

while the power allocation of each task is bounded by its characteristics:

$$\underline{\mathrm{x}_n} \le x_{n,t} \le \overline{\mathrm{x}_n}, \quad \forall\ n \in \Omega_{\mathrm{N}}^s,\ t \in \Omega_{\mathrm{T}} \tag{3}$$

No power can be allocated to task n, before the task's arrival time:

$$x_{n,t} = 0, \quad \forall\ n \in \Omega_{\mathrm{N}}^s,\ t \in \Omega_{\mathrm{T}} : t < \mathrm{a}_n \tag{4}$$

while all tasks should be completed during the time horizon:

$$\mathrm{E}_n - \sum_{t\in\Omega_{\mathrm{T}}} x_{n,t} \le 0, \quad \forall\ n \in \Omega_{\mathrm{N}}^s \tag{5}$$

A task departs from the station once its energy requirement E_n has been allocated to it. Let the binary variable $u_{n,t}$ denote whether charging task n departs by time slot t. It is

$$\sum_{\tau\in\Omega_{\mathrm{T}}:\mathrm{a}_n\le\tau\le t} x_{n,\tau} \ge u_{n,t}\,\mathrm{E}_n, \qquad \forall\ n \in \Omega_{\mathrm{N}}^s,\ t \in \Omega_{\mathrm{T}} \tag{6}$$

$$u_{n,t} \in \{0,\ 1\}, \qquad \forall\ n \in \Omega_{\mathrm{N}}^s,\ t \in \Omega_{\mathrm{T}} \tag{7}$$

Note that variable $u_{n,t}$ is forced to zero, unless the accumulated energy allocation of n until timeslot t, fulfils the task's energy requirement. Moreover, a task cannot depart before its desired departure time d_n:

$$\sum_{t\in\Omega_{\mathrm{T}}:t<\mathrm{d}_n} u_{n,t} = 0, \quad \forall\ n \in \Omega_{\mathrm{N}}^s \tag{8}$$

Finally, each task departs exactly once:

$$\sum_{t\in\Omega_{\mathrm{T}}} u_{n,t} = 1, \quad \forall\ n \in \Omega_{\mathrm{N}}^s \tag{9}$$

Depending on the power allocation, task n may suffer a delay of θ_n timeslots beyond its desired departure time d_n, i.e.:

$$\theta_n = \sum_{t\in\Omega_{\mathrm{T}}} t\,u_{n,t} - \mathrm{d}_n, \quad \forall\ n \in \Omega_{\mathrm{N}}^s \tag{10}$$

B. Distribution Network Model

The combination of vectors $\{\boldsymbol{p}_s\}_{s\in\Omega_{\mathrm{S}}}$ needs to satisfy the set C of distribution network constraints, i.e., $\{\boldsymbol{p}_s\}_{s\in\Omega_{\mathrm{S}}} \in C$. The feasible set C is defined by constraints (11)–(17) adapted from [30]. Active power balance in the network is ensured by

$$\sum_{\kappa i\in\Omega_l} P_{\kappa i,t} - \sum_{ij\in\Omega_l}\left(P_{ij,t} + \mathrm{R}_{ij} I_{ij,t}^{\mathrm{sqr}}\right) + P_{i,t}^{\mathrm{G}} = \mathrm{P}_{i,t}^{\mathrm{D}} + \sum_{s\in\Omega_{\mathrm{S}}:s=i} p_{s,t} \forall\ i \in \Omega_b,\ t \in \Omega_{\mathrm{T}} \tag{11}$$

The reactive power balance is represented as

$$\sum_{\kappa i\in\Omega_l} Q_{\kappa i,t} - \sum_{ij\in\Omega_l}\left(Q_{ij,t} + \mathrm{X}_{ij} I_{ij,t}^{\mathrm{sqr}}\right) + Q_{i,t}^{\mathrm{G}} = \mathrm{Q}_{i,t}^{\mathrm{D}}, \forall i \in \Omega_b, t \in \Omega_{\mathrm{T}} \tag{12}$$

where $\mathrm{P}_{i,t}^{\mathrm{D}}$ and $\mathrm{Q}_{i,t}^{\mathrm{D}}$ denote the active and reactive power demands at node i and timeslot t, $P_{\kappa i,t}$, $Q_{\kappa i,t}$ are the active and reactive power flows to node i form parent nodes κ, $I^{\text{sqr}}_{ij,t}$ is the squared magnitude of the current flowing in line ij at t, and $(P_{ij,t} + \text{R}_{ij} I^{\text{sqr}}_{ij,t})$, $\left(Q_{ij,t} + \text{X}_{ij} I^{\text{sqr}}_{ij,t}\right)$ are the active/reactive power flows from i to its descendant nodes j. For the purposes of this work, we assume that the charging stations introduce only active power to the system. It should also be pointed out that $P^{\text{G}}_{i,t} = Q^{\text{G}}_{i,t} = 0$ for all buses but the substation,

$$P^{\text{G}}_{i,t}, Q^{\text{G}}_{i,t} = 0, \quad \forall i \in \Omega_b/\{0\} \tag{13}$$

while $V^{\text{sqr}}_{i,t} = 1.0$ pu for the substation. The voltage magnitude drop between nodes i and j is represented by:

$$V^{\text{sqr}}_{i,t} - 2\left(\text{R}_{ij} P_{ij,t} + \text{X}_{ij} Q_{ij,t}\right) - \left(\text{R}^2_{ij} + \text{X}^2_{ij}\right) I^{\text{sqr}}_{ij,t} = V^{\text{sqr}}_{j,t}, \quad \forall ij \in \Omega_l, t \in \Omega_{\text{T}} \tag{14}$$

while branch power flows are calculated using

$$V^{\text{sqr}}_{j,t} I^{\text{sqr}}_{ij,t} = P^2_{ij,t} + Q^2_{ij,t}, \quad \forall ij \in \Omega_l, t \in \Omega_{\text{T}} \tag{15}$$

Upper and lower bounds on nodal voltage magnitudes and current magnitudes are enforced by

$$\underline{\text{V}}^2 \le V^{\text{sqr}}_{i,t} \le \overline{\text{V}}^2 \quad \forall i \in \Omega_b, t \in \Omega_{\text{T}} \tag{16}$$

$$0 \le I^{\text{sqr}}_{ij,t} \le \overline{\text{I}}^2_{ij} \quad \forall ij \in \Omega_l, t \in \Omega_{\text{T}} \tag{17}$$

III. Problem Formulation and Solutions

The aim of each station s is to minimize the maximum weighted delay $\max_{n \in \Omega^s_{\text{N}}} \{\text{w}_n \theta_n\}$ among its tasks. A different maximum delay among EVs corresponds to different quality-of-service levels that the station can guarantee to its customers. Thus, we assume that the station features a cost function of the form $\text{w}_s \max_{n \in \Omega^s_{\text{N}}} \{\text{w}_n \theta_n\}$, where w_s is the station's cost parameter that depends on its business model. For example, a station with a low w_s is willing to receive lower priority for power allocation, which results in lower station costs but also worse delay guarantees for its EVs. On the other hand, a station can guarantee a low delay to all its EVs by having a high w_s. This comes at a higher cost for the station, and consequently also for its customers.

An operator entity, namely the Distribution System Operator (DSO), is responsible for operating the system within safe operational conditions by modeling the power flows of the underlying physical grid. Moreover, constraint satisfaction should be achieved in an efficient manner. Thereby, the DSO is after calculating the economically optimal dispatch, i.e. the dispatch that minimizes the horizon cost $\sum_{t \in \Omega_{\text{T}}} \pi_t P^{\text{G}}_{0,t}$ of the energy $P_{0,t}$ that needs to be drawn from the main electrical system, at a timeslot-varying price π_t.

Hence, the DSO needs to solve a distribution level Optimal Power Flow (OPF) problem to fulfill this objective. Thus, the system-wide problem can be formulated as

$$\begin{aligned} \min_{\mathcal{Y}} \quad & \left\{ \sum_{s \in \Omega_{\text{S}}} \text{w}_s \max_{n \in \Omega^s_{\text{N}}} \{\text{w}_n \theta_n\} + \sum_{t \in \Omega_{\text{T}}} \pi_t P^{\text{G}}_{0,t} \right\} \\ \text{s.t.} \quad & \\ & (1) - (10), \quad \forall s \in \Omega_{\text{S}} \\ & (11) - (17) \end{aligned} \tag{18}$$

In problem (18), set $\mathcal{Y}$ contains the decision variables $p_s, x_n, u_n, \theta_n, P_{\kappa i}, P_{ij}, I^{\text{sqr}}_{ij}, Q_{\kappa i}, Q_{ij}, V^{\text{sqr}}_i$. By introducing slack variables ζ_s and replacing (15) with

$$V^{\text{sqr}}_{j,t} I^{\text{sqr}}_{ij,t} \ge P^2_{ij,t} + Q^2_{ij,t}, \quad \forall ij \in \Omega_l, t \in \Omega_{\text{T}} \tag{19}$$

problem (18) can be reformulated as

$$\begin{aligned} \min_{\mathcal{Y}, \zeta_s} \quad & \left\{ \sum_{s \in \Omega_{\text{S}}} \text{w}_s \zeta_s + \sum_{t \in \Omega_{\text{T}}} \pi_t P^{\text{G}}_{0,t} \right\} \\ \text{s.t.} \quad & \zeta_s \ge \text{w}_n \theta_n, \quad \forall s \in \Omega_{\text{S}}, n \in \Omega^s_{\text{N}} \\ & (1) - (10), \quad \forall s \in \Omega_{\text{S}} \\ & (11) - (14), (16), (17), \text{ and } (19) \end{aligned} \tag{20}$$

Notice that (18) is a mixed-integer non-linear program (MINLP), while the equivalent problem (20) is a mixed-integer second-order cone program (MISOCP) based on a well-known convex relaxation [31]. However, its solution requires the information of all charging tasks, i.e., the tuples $\{\text{A}_n\}_{n \in \Omega^s_{\text{N}}}$, of all EVs of each station $s \in \Omega_{\text{S}}$, in a centralized fashion. Towards solving problem (20) in a distributed fashion, we consider the ADMM as a benchmark approach, which is commonly used in the literature, and then we present a novel algorithm which scales better to larger instances of our problem, in comparison to the ADMM. Improving the scalability properties is particularly important since problem (20) needs to be repeatedly solved at each operational timeslot, to account for updated forecasts of demand, EV arrivals, etc.

In subsection III-A, we present the ADMM benchmark for this problem, while in subsection III-B we present the proposed novel algorithm. We note that the methods to be presented are directly extendable to a stochastic formulation with realization scenarios for future prices and demand. We omit the presentation of a stochastic formulation to avoid adding nonessential extra notation.

A. The ADMM Benchmark

We consider a decomposition of problem (20), where each station s solves a local problem, deciding only on ζ_s and local variables $\mathcal{Y}_s = \{p_{s,t}, x_{n,t}, u_{n,t}, \theta_n\}$, where $\mathcal{Y}_s \subset \mathcal{Y}$ and the DSO decides only on variables $\mathcal{Y}_{\text{DSO}} = \{P_{\kappa i}, P_{ij}, I^{\text{sqr}}_{ij}, Q_{\kappa i}, Q_{ij}, V^{\text{sqr}}_i, P^{\text{G}}_{0,t}, Q^{\text{G}}_{0,t}\}$, where $\mathcal{Y}_{\text{DSO}} \cup \mathcal{Y}_s = \mathcal{Y}$. Note that $P^{\text{G}}_{0,t}, Q^{\text{G}}_{0,t}$ is the active and reactive power injection at the substation. Depending on whether the active power balance constraints are satisfied, a set of Lagrange multipliers are updated, denoted as $\lambda_{i,t}$. Thus, the problem is decomposed into local subproblems, i.e., one for each station $s \in \Omega_{\text{S}}$. By taking the augmented Lagrangian of problem (20)

$$\mathcal{L}_a\left(\mathcal{Y}, \zeta_s, \lambda_{i,t}\right) = \sum_{s \in \Omega_{\text{S}}} \text{w}_s \zeta_s + \sum_{t \in \Omega_{\text{T}}} \pi_t P^{\text{G}}_{0,t} + \sum_{i \in \Omega_b} \sum_{t \in \Omega_{\text{T}}} \left(\lambda_{i,t} f_t + \frac{\rho}{2} \| f_t \|^2\right) \tag{21}$$

where

$$f_t = \sum_{\kappa i \in \Omega_l} P_{\kappa i,t} - \sum_{ij \in \Omega_l} \left(P_{ij,t} + \text{R}_{ij} I^{\text{sqr}}_{ij,t}\right) + P^{\text{G}}_{i,t} - \text{P}^{\text{D}}_{i,t} - \sum_{s \in \Omega_{\text{S}}: s = i} p_{s,t} \tag{22}$$

the ADMM benchmark is defined based on the following iterative variable update rules:

Charging Station

$$\{y^{(k+1)}\}_{y\in\mathcal{Y}_s} = \{\boldsymbol{p}_s^{(k+1)}, \zeta_s^{(k+1)}, x_n^{(k+1)}, u_n^{(k+1)}, \theta_n^{(k+1)}\} = \mathrm{argmin}_{\mathcal{Y}_s,\zeta_s}\mathcal{L}_a\left(\mathcal{Y}^{(k)}, \zeta_s, \lambda_{i,t}^{(k)}\right)$$
$$\text{s.t. } \zeta_s \geq \mathrm{w}_n\theta_n, \quad \forall n \in \Omega_{\mathrm{N}}^s \quad (1)-(10) \tag{23}$$

DSO

$$\{y^{(k+1)}\}_{y\in\mathcal{Y}_{\mathrm{DSO}}} = \mathrm{argmin}_{\mathcal{Y}_{\mathrm{DSO}}}\mathcal{L}_a\left(\mathcal{Y}^{(k+1)}, \zeta_s^{(k+1)}, \lambda_{i,t}^{(k)}\right) \quad \text{s.t. } (12)-(14),\ (16),\ (17),\ \text{and } (19) \tag{24}$$

Coordinating Entity[1]

$$\lambda_{i,t}^{(k+1)} = \lambda_{i,t}^{(k)} + \rho f_t^{(k+1)} \tag{25}$$

where Eq. (25) determines the multiplier update between iterations, as a function of the power imbalance at node i and timeslot t.

It should be highlighted that the ADMM, or any other distributed optimization approach, does not provide convergence guarantees for non-convex problems. However, ADMM has been shown to converge, in practice, for dispatch problems in low-voltage networks (e.g. [29]).

Updating the decisions of a charging station requires solving problem (23). Note that (23) is a MILP which needs to be solved iteratively by each station for every multiplier update. This can seriously harm the computational time of the iterative approach. In the next subsection, we propose a linear approximation of the station's local problem, which is iteratively tuned to approach the original station's model.

B. Proposed Decentralized MILP Model

The simple Lagrangian of problem (20) reads as

$$\mathcal{L}\left(\mathcal{Y}, \zeta_s, \lambda_{i,t}\right) = \sum_{s\in\Omega_{\mathrm{S}}} \mathrm{w}_s\,\zeta_s + \sum_{t\in\Omega_{\mathrm{T}}} \pi_t P_{0,t}^{\mathrm{G}} + \sum_{i\in\Omega_b}\sum_{t\in\Omega_{\mathrm{T}}} \lambda_{i,t} f_t \tag{26}$$

By decomposing problem (20), we define the local subproblem of each charging station as:

$$\min_{\mathcal{Y}_s,\zeta_s} \left\{\mathrm{w}_s\,\zeta_s + \sum_{t\in\Omega_{\mathrm{T}}} \lambda_{s,t} \sum_{n\in\Omega_{\mathrm{N}}^s} x_{n,t}\right\}$$
$$\text{s.t. } \zeta_s \geq \mathrm{w}_n\theta_n, \quad \forall n \in \Omega_{\mathrm{N}}^s \quad (1)-(10) \tag{27}$$

where $\lambda_{s,t}$ refers to the multiplier of node i where s is located. Notice that problem (27) is defined as minimizing the simple Lagrangian (26), where the terms of f_t, that are not depended on local variables, $\mathcal{Y}_s$ are discarded. In the iterative method to be presented, we propose that each station, instead of problem (27), solves the following approximate problem:

$$\min\left\{\mathrm{w}_s\,z_s + \sum_{t\in\Omega_{\mathrm{T}}} \lambda_{s,t} \sum_{n\in\Omega_{\mathrm{N}}^s} x_{n,t}\right\}$$
$$\text{s.t. } z_s \geq \mathrm{w}_n \sum_{t\in\Omega_{\mathrm{T}}:t\geq \mathrm{d}_n} \delta^{t-\mathrm{d}_n} x_{n,t}, \quad \forall n \in \Omega_{\mathrm{N}}^s \quad (1)-(4),\ (5) \tag{28}$$

where z_s is an auxiliary variable that replaces ζ_s, while the DSO solves

$$\min_{\mathcal{Y}_{\mathrm{DSO}}}\{\mathcal{L}\}, \quad \text{s.t. } (12)-(14),\ (16),\ (17),\ \text{and } (19) \tag{29}$$

The term $\sum_{t\in\Omega_{\mathrm{T}}:t\geq \mathrm{d}_n} \delta^{t-\mathrm{d}_n} x_{n,t}$ penalizes the station for allocating power to task n in time slots that come after the task's desired departure time d_n, so that problem (28) constitutes an approximation of the original local problem (27). However, in order for this approximation to perform well, information from other stations and from the system, need to be incorporated into the station's problem by adjusting the value of the penalization parameter δ. In order to tune the approximation to approach the optimal solution to (20), an appropriate value for parameter δ needs to be established by the DSO. For this purpose, an iterative algorithm is proposed, as described in Algorithm 1.

The DSO begins with $\delta^{(0)}$ and updates $\delta^{(k)}$ at each iteration k of the outer-loop of Algorithm 1. A set of Lagrange multipliers $\lambda_{s,t}$ are iteratively updated in an inner loop. Each station solves its approximation local problem (28) using the current value of $\delta^{(k)}$ and the latest updated multipliers $\lambda_{s,t}$. The final state of the inner loop is characterized by a set of equilibrium multipliers $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$, which are a function of $\delta^{(k)}$ and correspond to the value of $\delta^{(k)}$ for the current iteration k of the outer loop.

Lemma 1: For a given value $\delta^{(k)}$, the inner loop of Algorithm 1 is guaranteed to converge to an equilibrium.

Proof: Consider local problems (28) that are solved in line 5 of the algorithm. These problems taken together, constitute a decomposed convex program, the centralized form of which is defined as

$$\min_{\mathcal{Y},z_s}\left\{\sum_{s\in\Omega_{\mathrm{S}}} \mathrm{w}_s\,z_s + \sum_{t\in\Omega_{\mathrm{T}}} \pi_t P_{0,t}^{\mathrm{G}}\right\}$$
$$\text{s.t. } z_s \geq w_n \sum_{t>\mathrm{d}_n} \delta^{t-\mathrm{d}_n} x_{n,t}, \quad \forall s \in \Omega_{\mathrm{S}}, \forall n \in \Omega_{\mathrm{N}}^s$$
$$(1)-(4),\ (5) \quad (11)-(14),\ (16),\ (17),\ \text{and } (19) \tag{30}$$

The equilibrium multipliers $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$ of the algorithm's inner loop, are the optimal dual variables that correspond to constraints (11) of problem (30) and since (30) is a convex problem, it can be solved to optimality by a dual decomposition algorithm (e.g. ADMM). Thus, the optimal set of dual variables, i.e., the equilibrium multipliers, can always be obtained. □

Once the inner loop has converged to the equilibrium multipliers, each station is required to solve the original, MILP local problem (27) using $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$. The resulting profile $\boldsymbol{p}_s$

[1] Depending on regulatory aspects, the role of the Coordinating Entity can be assumed by the DSO itself or by a third party, e.g. a market operator.

Algorithm 1 The proposed algorithm

```
1:  Initialize k = 0, δ^(0) = 1
2:  while {p_s}_{s∈Ω_S} ∉ C:
3:    initialize λ_{s,t} = 0, ∀ s, t
4:    repeat:
5:      each station solves (28), DSO solves (29)
6:      if f_t > β
7:        [λ update rule]
8:      else
9:        λ̃_{s,t}(δ^(k)) = λ_{s,t}
10:       break
11:   each station re-calculates p_s by solving problem (27)
      using λ̃_{s,t}(δ^(k))
12:   if {p_s}_{s∈Ω_S} ∉ C
13:     k = k + 1
14:     δ^(k) = δ^{k−1} + ε
```

of each station is communicated to the DSO, and the latter checks if the network constraints are satisfied. In the case that network constraints are violated, the DSO increases the value of δ by setting $\delta^{(k+1)} = \delta^{(k)} + \varepsilon$. The inner loop is executed again, using the updated value $\delta^{(k+1)}$.

The above procedure iterates until the DSO identifies a value of $\delta^{(k)}$ and a corresponding set of equilibrium multipliers $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$, for which the combination of problems (27) results in a set of station power profiles that respect the network constraints, i.e., $\left\{\boldsymbol{p}_s\left(\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)\right)\right\}_{s\in\Omega_{\mathrm{S}}} \in C$.

With respect to the behavior of the equilibrium multipliers $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$, calculated by the algorithm's inner loop, we write the following lemma

Lemma 2: The equilibrium multipliers $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$ resulting from the inner loop of Algorithm 1 are increasing with every outer-loop iteration.

Proof: Notice that $\delta^{(k)}$ is increasing with every iteration of k. Thus, it suffices to show that the derivative of $\widetilde{\lambda}_{s,t}$ with respect to δ is higher or equal than zero, i.e. $\frac{\partial \widetilde{\lambda}_{s,t}(\delta)}{\partial \delta} \geq 0$. Problem (30) is convex. Therefore, it admits to strong duality and the optimal dual variables $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$ satisfy the KKT conditions. By considering the stationarity conditions of (30), we have

$$\widetilde{\lambda}_{s,t}(\delta) = \nu_n \mathrm{w}_n \delta^{t-\mathrm{d}_n} + \phi(\cdot), \quad \forall n \in \Omega_{\mathrm{N}}^s : \mathrm{d}_n < t \tag{31}$$

where $\widetilde{\lambda}_{s,t}$ is the optimal dual variable that corresponds to equality constraint (11), ν_n is the optimal dual variable that corresponds to inequality constraint $z_s \geq w_n \sum_{t>\mathrm{d}_n} \delta^{t-\mathrm{d}_n} x_{n,t}$ of problem (30), and the expression $\phi(\cdot)$ contains the terms that are not dependent on δ. Since we are interested in the rate of change of $\widetilde{\lambda}_{s,t}$ as a function of δ, i.e. in the derivative $\frac{\partial \widetilde{\lambda}_{s,t}(\delta)}{\partial \delta}$, those terms will be zero when we take the derivative. By taking the derivative $\frac{\partial \widetilde{\lambda}_{s,t}(\delta)}{\partial \delta}$, we have that

$$\frac{\partial \widetilde{\lambda}_{s,t}(\delta)}{\partial \delta} = \nu_n \mathrm{w}_n (t - \mathrm{d}_n)\delta^{t-\mathrm{d}_n-1}, \quad \forall n \in \Omega_{\mathrm{N}}^s : \mathrm{d}_n < t \tag{32}$$

Since ν_n is non-negative (by the KKT conditions), we have that $\frac{\partial \widetilde{\lambda}_{s,t}(\delta)}{\partial \delta} \geq 0$, which completes the proof. □

The intuition behind Lemma 2, is that a higher value of δ makes the stations less elastic by placing higher coefficients on the timeslots that come after the deadline d_n of each task. Thus, a higher δ makes the stations less eager to shift their consumption, which means that higher multipliers are needed in order to make the problem feasible. This intuition guides us to formulate the following conjecture

Conjecture 1: For lower values of ε, the probability of non-convergence for Algorithm 1 diminishes.

By Lemma 2, we have that higher values of δ result in higher equilibrium multipliers $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$. Consequently, with higher multipliers, the second term of problem (27) is more weighted, which results in more consumption shifts and higher delays for the charging stations. This leads us to expect that, if this consumption shifting happens gradually, the aggregated active power profile of the system (as resulting from line 11 of the algorithm) will become flatter (i.e., exhibit a lower peak-to-average ratio) in each iteration of the outer loop, thereby enhancing the chances of finding a feasible allocation. Note, however, that if the step ε is not small enough, the equilibrium multipliers $\widetilde{\lambda}_{s,t}\left(\delta^{(k)}\right)$ can increase abruptly between two consecutive iterations, and the overly high multipliers would cause the charging stations to simultaneously shift their consumption to less popular timeslots (through line 11), which will result in a reverse peak effect. Thus, in conclusion, Lemma 2 implies that for smaller values of ε, Algorithm 1 runs a higher chance of convergence, while for higher values of ε, the algorithm will diverge. This intuition cannot be proved analytically, since $\sum_{s\in\Omega_{\mathrm{S}}} \mathrm{w}_s\, \zeta_s$ dependency on δ is non-linear (i.e., they are linked through Algorithm 1, which contains a set of local MILP problems). However, in the next Section, we will test this hypothesis using simulations.

With respect to the scalability of Algorithm 1 and the ADMM benchmark, we make the following remark

Remark 1: In contrast to the ADMM approach, Algorithm 1 avoids the need to solve the non-convex problem (23) at each update of the multipliers. Instead, in its inner loop, it solves the much faster, approximate linear program (28) for each multiplier update and it only solves MILP (27) after the multipliers have converged, in order to check the choice of δ. This allows Algorithm 1 to scale better to larger problems.

Moreover, while the optimal multipliers can be volatile from one day to another, the value of parameter δ is not expected to exhibit the same volatility, since it is not linked to the particular instance of the problem's parameters, but rather, it is related to the more general issue of tailoring the formulation of problem (28) to approximate problem (27). Thus, after applying the algorithm to several instances of the system, the DSO could observe the confidence interval of parameter δ and start initializing it at some value higher than 1. In turn, a higher initial value for δ, would act as a warm start, which further reduces the computational time of Algorithm 1. These expectations are tested in the next Section.

IV. Evaluation

In this section, we evaluate the proposed algorithm using simulations. For this purpose, we considered a radial 11 kV distribution system with 34 buses, shown in Fig. 1, with a peak total nominal power of 6.2 MW and 4.1 Mvar [32]. Charging stations are placed in nodes 5, 9, 13, and 22. For a horizon of 12 timeslots, we assumed a number of 100 charging tasks, unless stated otherwise, distributed randomly among stations.

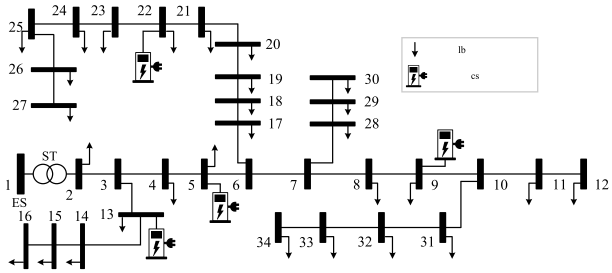

Fig. 1. 34-bus test system with four EV charging stations.

TABLE II

VALUES/DISTRIBUTIONS OF SETTING'S PARAMETERS

Parameter	Comments	Value	Average Value	Standard deviation
E_n	-	-	8	2
$\underline{\mathrm{x}_n}$	$\forall n$	0	-	-
$\overline{\mathrm{x}_n}$	$\forall n$	$\mathrm{E}_n/3$	-	-
w_n	-	-	0.01	0.003
w_s	$\forall s$	1	-	-
e	-	0	-	-

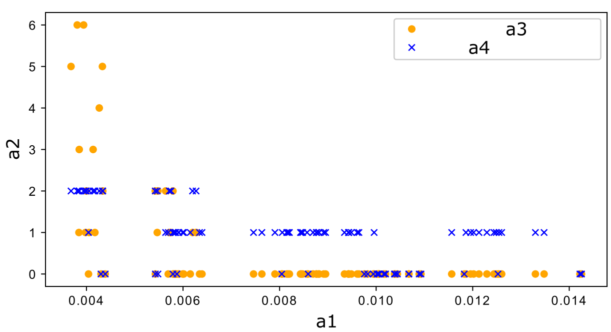

Fig. 2. Delay suffered by EVs as a function of their priority weights w_n for the fairness and social welfare optimization case.

The EV arrival times were sampled from a random normal distribution ($\mu = 3, \sigma = 1$) and rounded to the nearest integer below (with timeslot 1 as the minimum), thus simulating a rush hour. The task's deadline is sampled from a random uniform distribution within the interval $[\mathrm{a}_n + \mathrm{E}_n/\overline{\mathrm{p}_s}, 12]$. The values or random distributions for the rest of the system's parameters are presented in Table II.

First, we showcase the difference between the proposed fair solution and the case where the average delay among EVs is optimized (i.e. the typical Social Welfare maximization approach). In Fig. 2, the delay of each EV is plotted against its priority weight w_n for the two cases. As can be observed, the socially optimal dispatch sacrifices some low-priority EVs (they suffer a delay of 5-6 timeslots) to the benefit of the rest. In contrast, the proposed fair approach maintains the delay of all EVs below 3 timeslots, at the cost of a higher average delay.

Through experimentation, it was observed that in line 2 of Algorithm 1, the decisive constraint was constraint (17). That is, the maximum value $\max_{ij,t} I^{\mathrm{sqr}}_{ij,t}$ of the currents flowing in the power distribution system's lines was above the upper bound $\overline{\mathrm{I}}^2_{ij}$. However, for small values of step ε, the value of $\max_{ij,t} I^{\mathrm{sqr}}_{ij,t}$ exhibited a decreasing trend along with the increase in parameter δ. Intuitively, by increasing δ, the

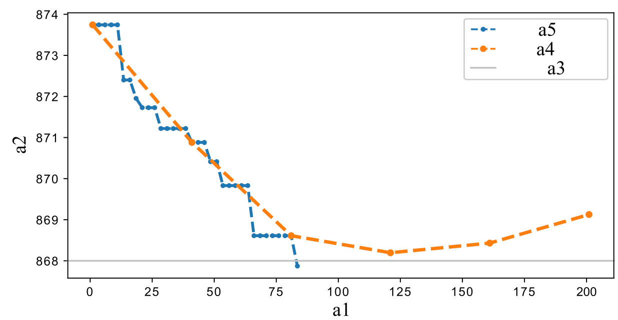

Fig. 3. Evolution of the value of maximum current $\max_{ij,t} I^{\mathrm{sqr}}_{ij,t}$, across lines of the power distribution network, as a function of parameter δ.

charging stations are made less elastic, i.e., more resistant to shifting the consumption of their EVs to later timeslots. Thus, with higher δ the inner loop of Algorithm 1 converges to higher equilibrium multipliers $\tilde{\lambda}_{s,t}(\delta)$ as shown in Lemma 2. In turn, each time the stations solve problems (27) with increasing multipliers for the congested timeslots, they increasingly shift electricity consumption to less congested timeslots. This causes a flattening of the loads across the time horizon, which causes a decrease in the values of the power distribution system's lines' currents. On the other hand, if parameter δ is updated using a large step, the algorithm can miss the feasible points and start diverging. This behavior is depicted in Fig. 3, where the maximum value of the lines' currents ($\max_{ij,t} I^{\mathrm{sqr}}_{ij,t}$) is plotted against the value of δ for two different cases (2.5 and 40) of the update step ε. As can be observed from the figure, in the case of a small step, the algorithm's progress is monotonous until it finally converges to a point where all currents lie below the upper bound, while in the case of a large step the algorithm diverges. These observations provide an empirical verification of Conjecture 1.

More generally, Conjecture 1 indicates that the chance of non-convergence for Algorithm 1 diminishes as the step parameter ε becomes smaller. In this test, we tried different values of step ε, and tested each value for a number of 100 experiments. By counting the times that the algorithm failed to converge, we estimate the probability of non-convergence as a function of ε. The results are shown in Fig. 4 for different values of ε, where it is observed that for small values of ε, the algorithm converged in all of the experiments, while for higher values of ε, the chances of Algorithm 1 not converging increase, thus experimentally verifying Conjecture 1.

The algorithm's behavior exhibited through Figs 3 and 4 provides a useful, practical tool in the hands of the DSO: If the DSO observes that the value of $\max_{ij,t} I^{\mathrm{sqr}}_{ij,t}$ starts increasing after a certain iteration of the Algorithm's outer loop, it can safely infer that the value of ε is too high and the Algorithm will not converge. Therefore, the DSO can interrupt the Algorithm's execution and start over, using a lower step which, by Fig. 4, increases the chances of convergence. Moreover, in the case where non-convergence persists (e.g. the original problem is infeasible), the DSO can retrieve the best dispatch found through the algorithm's iterations and, starting from that, some other protocol would be activated (e.g. load curtailment).

In order to evaluate the quality of the solution provided by Algorithm 1, we define a performance metric $\mathcal{F}$, noted as the

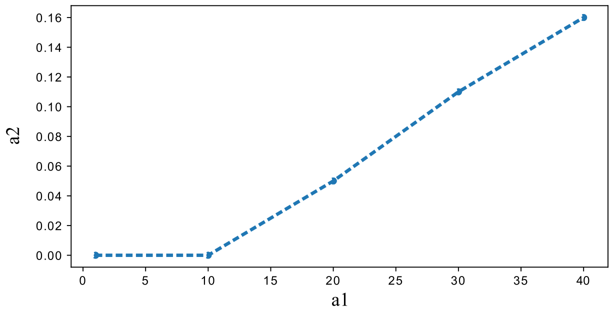

Fig. 4. Probability of non-convergence as a function of the step ε.

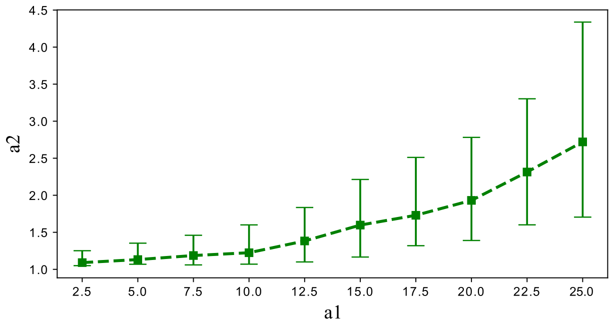

Fig. 5. Fairness factor (optimality loss) for different values of step ε.

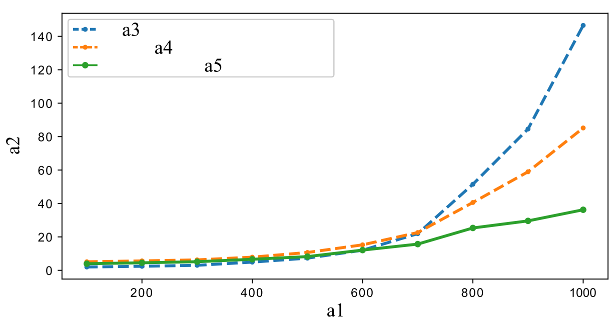

Fig. 6. Scalability of the proposed algorithm compared to ADMM.

algorithm's fairness factor. Factor $\mathcal{F}$ is defined as the ratio between the objective value of problem (20) achieved by the proposed algorithm, to the optimal objective value achieved by solving problem (20) centrally. Naturally, it is $\mathcal{F} \geq 1$. A lower fairness factor means better performance, while a fairness factor of 1 means that the algorithm achieves exactly the fairest solution. The metric $\mathcal{F}$ was evaluated for various experiments. The average and lower-upper values among the experiments are depicted for different choices of step ε, in Fig. 5. For small values of ε, the algorithm achieves a near-optimal solution on average.

Finally, we compare the proposed algorithm with the ADMM benchmark regarding scalability. For Algorithm 1, we also tested an extra version in which we warm-start parameter δ, based on the lowest past observation of its final value, to enhance the algorithm's computational time further. The results for the three approaches are depicted in Fig. 6. The experiments were run in an i5, 2.7GHz computer with 8GB RAM and two cores, using CPLEX. For small numbers of users, the proposed algorithm does not achieve a lower computational time than the ADMM benchmark (and it even does a little worse). Nevertheless, as expected by Remark 1, the proposed algorithm scales much better to larger problems (mainly when the warm-start of δ is also featured).

V. Conclusion

In this paper, we considered a system with multiple charging stations drawing charging power from a low-voltage electricity grid, where each charging station wants to achieve a fair charging schedule for its electric vehicles. The problem of each charging station was modeled as a max-min, mixed-integer linear program. At the same time, the constraint satisfaction problem of the grid operator was modeled as a second-order cone program. A novel distributed algorithm was proposed for achieving coordination, i.e., satisfying the system constraints in a globally efficient manner. The proposed algorithm achieved better scalability than the ADMM benchmark by approximating each station's MILP with a linear program, thus avoiding the need to solve many non-convex local subproblems at each iteration. The approximation was made effective by iteratively tuning a penalization parameter. Our simulation results indicate that the algorithm is able to achieve near-optimal solutions while effectively scaling to settings with high levels of EV penetration.

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