Analysis of EV Charging Coordination Efficiency in Presence of Cheating Customers

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ABSTRACT Charging coordination is employed to efficiently serve electric vehicle (EV) charging requests without overloading the distribution network. Parameters such as parking duration, battery state-of-charge (SoC), and charging amount are provided by EVs to the charging coordination center to schedule their charging requests efficiently. The existing literature assumes that the customers always provide correct information. Unfortunately, customers may provide false information to gain higher charging priority. Assessing the impact of cheating behavior represents a significant and open problem. Herein paper, the impact of providing false information (e.g., parking duration) on the efficiency of the charging coordination mechanism is investigated. The charging coordination strategy is formulated as a linear optimization problem. Two different objectives are used to assess the impact of the objective function on the amount of performance degradation. Our investigations reveal that the degradation of the efficiency of the charging coordination mechanism depends on the percentage of cheating customers and cheating duration versus the typical parking duration. In addition, the impact of cheating behavior increases with the number of deployed chargers. Thus, the severity of the cheating impact will increase in the future as more fast chargers are allocated in charging networks.

INDEX TERMS Electric vehicle charging, electric vehicles, energy management, optimization, scheduling, smart grids.

NOMENCLATURE

n	Number of time slots.
τ	Duration of a time slot.
$\mathcal{T}$	Set of all time slots.
$\mathcal{V}$	Set of all vehicles.
v	Index of a vehicle.
t	Index of a time slot.
T_v^{arr}	Arrival time of the vehicle v.
T_v^{dep}	Departure time of the vehicle v.
T_v^{park}	Parking duration of the vehicle v.
S_v^{init}	Initial state of charge for the vehicle v.
S_v^{des}	Desired state of charge for the vehicle v.
S_v^{final}	The state of charge for the vehicle v after time slot n.
B_v^{max}	Battery capacity.
ρ_v	Maximum charging rate.
η_v	Charging efficiency.
$D_{v,t}$	Charging decision variable.
$\mathcal{B}$	Set of all busses in the network.
b	Index of a bus.
$P_{b,t}^{\text{G}}$	Active power supply at bus b at time slot t.
$Q_{b,t}^{\text{G}}$	Reactive power supply at bus b at time slot t.
$P_{b,t}^{\text{D}}$	Active power demand at bus b at time slot t.
$Q_{b,t}^{\text{D}}$	Reactive power demand at bus b at time slot t.
$P_{b,t}^{\text{R}}$	Active residential power demand.
$Q_{b,t}^{\text{R}}$	Reactive residential power demand.
$P_{b,t}^{\text{max}}$	Maximum active power limit.
$P_{b,t}^{\text{min}}$	Minimum active power limit.
$Q_{b,t}^{\text{max}}$	Maximum reactive power limit.
$Q_{b,t}^{\text{min}}$	Maximum reactive power limit.
$v_{b,t}$	Voltage value at bus b at time slot t.

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$V_{b,t}$	Voltage magnitude.
$\angle\phi_{b,t}$	Voltage angle.
$V^{\min}$, $V^{\max}$	Voltage limits.
$r_{b,b'}$	Resistance between buses b and b'.
$x_{b,b'}$	Reactance between buses b and b'.
$\mathcal{C}$	Set of all charging stations.
$\mathcal{C}_b$	Set of charging stations connected to bus b.
$\mathcal{V}_c$	Set of vehicles at charging station c.

I. INTRODUCTION

Currently, there is a significant drive towards adopting electric vehicles (EVs) for transportation. EVs represent a promising solution due to their reduced emission of greenhouse gases compared to internal combustion engine vehicles, potential to relieve the dependence on fossil fuels and increase the energy efficiency of vehicles, and reduced cost of electricity compared to oil energy [1]. Despite these benefits, there are still significant technical limitations to the widespread adoption of EVs.

Large-scale adoption of EVs brings new challenges to the power grid. Specifically, the charging characteristics of the customers are highly correlated since most customers tend to charge their vehicles during evening hours when they are home, or during working hours (8:00am-5:00pm) [2]. In addition, if all customers charge their vehicles during the same time interval, the power grid will be overloaded. Furthermore, [3] points out that even a 10% EV market penetration could increase the peak power demand in the grid by 17.9%, while a 20% EV penetration could result in a 35.8% increase in the peak power load.

One way to cope with the increasing charging demands is to upgrade the power grid capacity by installing additional power generation units. However, this translates into an additional cost that is used primarily to cope with the peak loads that last only for short periods during the day. Hence, a more cost-effective solution is highly desirable. A cost-effective solution is attained via the temporal coordination of the EV charging requests. A temporal EV charging coordination scheme helps to flatten and shift the peaks in the daily load profile of a power grid and to prevent the grid's congestion. A temporal EV charging coordination scheme is usually formulated as an optimization problem that aims to schedule when to serve the EV charging requests such that the customers' satisfaction level is maximized subject to the constraints from EVs and the power grid. The customer-related parameters are provided in the charging request, which is sent before arriving at the charging station. A charging request normally provides to the EV charging coordination mechanism customer-related information, such as parking duration, battery state of charge (SoC), and charging amount.

Psychological factors, such as the perceived fairness of the strategy, could affect the users' willingness to engage in grid-to-vehicle (G2V) charging coordination. People tend to be biased, perceiving the fairest strategy as the one that is closer to their self-interests. This self-serving bias can lead to disagreement when trade-offs must be made among the interests of different parties [4]. As such, the customers may provide false information in order to gain higher charging priority. The cheating customers will be in front of the other customers in the charging queue. In addition, other psychological factors relevant to G2V include the users' perceptions on violating their privacy via exchanging the information necessary for charging coordination (their time window of staying at a given location for charging). No data provides an estimate of the percentage of such cheating customers. Our objective in this paper is to investigate the impact of such a cheating behavior on the effectiveness of the charging coordination strategy for different percentages of cheating customers (to conclude a threshold below which such behavior does not cause significant impact while above which a significant impact is observed). Also, we aim to carry out this study at various parking scenarios (at offices, homes, and restaurants/shopping malls) to investigate the impact of the cheating behavior versus the parking duration. Finally, we explore the impact of the cheating behavior versus the charging rate.

A. RELATED WORK

There are two general approaches to schedule EV charging requests. The first approach is a centralized solution. The second approach coordinates the EV charging requests in a distributed manner. The centralized strategy provides better control over the system parameters, while the distributed strategy offers more flexibility for customers and breaks the optimization problem into smaller local problems.

Centralized EV charging coordination mechanisms are proposed in [5]–[12]. The authors in [5] present an optimization strategy that reduces the grid congestion while considering the customer demands. A vast amount of works in the literature employs pricing strategies for charging coordination. For instance, [6] reports a method to determine the optimal charging prices and to route the EVs to the appropriate charging stations, where customers choose their priority level and charging amount through a menu of services. Another strategy is developed in [7] based on a multi-follower Stackelberg game. The work in [8] proposes a charging and discharging coordination mechanism that forecasts the future EV power demand and relies on a two-stage optimization unit. A heuristics-based EV charging coordination mechanism utilizing locally optimal greedy choices in order to minimize both the total charging cost and the peak load is presented in [9]. An EV charging coordination mechanism that aims to flatten the load profile is provided in [10]. The problem is formulated as a finite-horizon dynamic programming and solved via a model predictive control-based algorithm. The charging coordination problem is formulated as a mixed-integer program in [11] for day-ahead scheduling. Then, the precomputed schedules are updated online with the newly received information. A similar approach is used in [12] by employing a dynamic stochastic linear programming method. The proposed method

aims to optimize the charging costs while considering the variations in the system parameters.

Distributed EV charging coordination schemes are presented in [2], [13]–[19]. One of the reasons for using distributed charging scheduling systems is that they run multiple local optimization algorithms in order to avoid processing large amounts of data in a central point. A comprehensive survey on EV distributed charging coordination schemes is provided in [2]. An optimal iterative algorithm is proposed in [13] in order to fill the valleys in the power load profiles. In [14], the authors modeled the charging coordination mechanism as a non-cooperative game, in which the players try to maximize their own payoffs, and the scheduling is performed days in advance. A spatio-temporal direct vehicle-to-vehicle (V2V) charging scheme is presented in [15]. The authors propose a game-theoretic distributed EV charging mechanism in [16]. The optimal solution is obtained by employing the full Nash Folk theorem. A decentralized EV charging coordination scheme is proposed in [17] to valley filling and battery degradation cost reduction. The suggested algorithm models the EV charging problem as a mean-field game. Reference [18] proposes a distributed EV charging coordination algorithm by decoupling the constraints in a centralized charging coordination algorithm via a partial augmented Lagrangian method. An EV charging coordination scheme based on the transactive control scheme is proposed in [19]. The study constructs a transactive market in which the customers provide their power consumption targets and response curves, and the aggregator schedules the customers accordingly.

Some studies in the literature consider the uncertainties in the arrival and departure times of the customers. The authors in [20] provide a price-based charging coordination method considering uncertainties in the system parameters. They model a game minimizing the electricity cost of the utility company and maximizing the revenue of the charging stations. In [21], the charging coordination mechanism is formulated by a Markov decision process with unknown transition probability. A model-free deep reinforcement learning-based method is used for obtaining the optimal strategy. A two-stage optimization algorithm is proposed in [22] to schedule the EV charging requests considering the uncertainties in the market prices and the EV mobility. The work in [23] tries to minimize the mean waiting time for the customers while considering the uncertainties in the arrival of EVs, availability of renewable energy, the electricity price. These studies are not sufficient to provide insights when cheating behavior is considered. There is no available dataset in the literature on the percent of cheating customers and the impact of this amount on the system response. There are also no insights on system response versus parking duration and system response in terms of the number and the charging rate of the chargers.

One common assumption among all existing works in the literature is that all customers provide true information, i.e., no customer cheats while providing the information needed to solve the coordination problem. However, a customer may cheat by reporting a shorter parking duration so that the coordination strategy assigns a higher charging priority to that customer. Such malicious and selfish behavior could adversely affect the efficiency of the coordination algorithm. In this paper, we aim to fill this gap by investigating the impact of false input parameters on the performance of the EV charging coordination strategy.

B. CONTRIBUTIONS

The contributions of this paper are summarized as follows:

- The behavior of the EV charging coordination mechanism is investigated in presence of the cheating customers. This is done by studying the sensitivity of the charging coordination strategy with respect to the amount of deviation in the parking duration of the customers. The analyses are performed comparatively by formulating the EV charging coordination problem as two different linear programs (LPs) with objectives that try to maximize the average and minimum satisfaction rates of the charging requests, where the satisfaction rate is defined in terms of the battery SoC. The effects are examined for different parameters, such as the ratio of the cheating customers, cheating duration, actual parking duration, charging power rate, and the number of charging stations.

- The degradation in the customer satisfaction rate provided by the EV charging mechanism in the presence of cheating behavior is evaluated via extensive simulations. The simulation results suggest that the efficiency of the charging coordination strategy is affected by both the percentage of the cheating customers and the cheating interval. We also concluded that the charging coordination strategy is less sensitive to cheating behavior under the Minimum Satisfaction Rate (MSR) formulation, and it is less prone to the cheating behavior when the actual parking duration is long. We also verified that the charging rate and the number of charging stations in the charging network are the other significant parameters affecting the sensitivity to the cheating behavior.

The rest of the paper is organized as follows. The system model is presented in Section II. The charging coordination problem is formulated together with an optimal strategy, and the sensitivity analysis that focuses on assessing the effect of cheating behavior on the charging coordination efficiency is discussed in Section III. The simulation results are presented in Section IV. Finally, the conclusions are drawn in Section V.

II. SYSTEM MODEL

In this section, we describe the system model for the charging coordination mechanism. First, we introduce the EV charging coordination scheme and the related parameters. Then, we provide the parameters related to the distribution network.

A. EV CHARGING REQUESTS AND COORDINATION

We study the temporal scheduling of EV charging requests for a time window. Each customer arrives at a charging location of his/her choice.

The scheduling of the charging requests is performed by an aggregator. The aggregator behaves as a proxy between the customer and the grid operator. The aggregator collects the charging requests before the arrival of the customers and tries to assign the charging time slots to each individual EV. Time is divided into n slots of equal duration τ. The set of all time slots is given by $\mathcal{T}$.

Customers send a charging request prior to their arrival to the charging station. The arrival and departure times to the charging station are indicated in the charging request, and are denoted by T_v^{arr} and T_v^{dep}, respectively, where $T_v^{\text{arr}}, T_v^{\text{dep}} \in \{1, \ldots, n\}$. The parking duration for the vehicle v is denoted by T_v^{park}. Thus,

$$T_v^{\text{park}} = T_v^{\text{dep}} - T_v^{\text{arr}}. \tag{1}$$

It is important to note that the time parameters represent the time indices, not the absolute time values. That is, the time parameters correspond to a charging time slot in the system model.

The charging request also provides information about the initial and the desired SoC values of the vehicle, which are denoted as S_v^{init} and S_v^{des}, respectively. The SoC value of vehicle v at time slot t is denoted by $S_{v,t}$. For the SoC rates, the value 0 corresponds to a fully empty battery while the value 1 corresponds to a fully charged battery. The final SoC of the vehicle v is denoted as S_v^{final}, which is the SoC at the end of the whole time window, i.e., at the end of the time slot n ($S_{v,n+1}$). The final SoC value is used to calculate the success rate for the satisfaction of the charging requests. A time window can assume any duration, e.g., we set 24 hours for the simulations.

Each vehicle v is characterized by its battery capacity B_v^{max}, maximum charging rate ρ_v, and charging efficiency η_v.

There are two types of chargers in the market. The first group consists of simple on-off controllers and assumes only the discrete values 0 and 1. The second group of chargers presents variable charging rates that are represented by continuous decision variables with values in the interval [0, 1]. The latter group provides more precise control over charging. Therefore, we consider a variable rate charger in our study. The charging decision for the vehicle v in time slot t is denoted by $D_{v,t} \in [0, 1]$.

B. DISTRIBUTION NETWORK MODEL

The set of buses in the distribution network is denoted by $\mathcal{B}$. The active and reactive power supply at bus b and time slot t are represented by $P_{b,t}^{\text{G}}$ and $Q_{b,t}^{\text{G}}$, respectively. The active and reactive power demand (load) introduced by the EVs at bus b in time slot t are denoted by $P_{b,t}^{\text{D}}$ and $Q_{b,t}^{\text{D}}$, respectively. The active and reactive power at each bus of the distribution network should be within the nominal range for proper

operation. Let $P_{b,t}^{\text{max}}$ and $P_{b,t}^{\text{min}}$ denote the maximum and the minimum active power that can be delivered at the bth bus and at time slot t, respectively. Similarly, $Q_{b,t}^{\text{max}}$ and $Q_{b,t}^{\text{min}}$ denote the limits for the delivered reactive power. Note that $P_{b,t}^{\text{D}}$ is equal to the sum of the power rates of the vehicles that are connected to the bus at a specific time instant. The active and reactive components of the residential power load at a bus are denoted by $P_{b,t}^{\text{R}}$ and $Q_{b,t}^{\text{R}}$, respectively.

The voltage at bus b is represented by $v_{b,t}$ and it is expressed as $v_{b,t} = V_{b,t} \angle \phi_{b,t}$, where $V_{b,t}$ and $\angle \phi_{b,t}$ denote the magnitude and angle of the complex voltage phasor, respectively. For the nominal operation, the voltage values should lie within the limits represented by the lower and upper voltage values denoted by V^{min} and V^{max}, respectively. The resistance and reactance between buses b and b' of the distribution network are denoted by $r_{b,b'}$ and $x_{b,b'}$, respectively.

The EV charging stations are placed at different locations within the distribution network, and each station is connected to a specific bus in the distribution network. The set of all charging stations is denoted by $\mathcal{C}$ and the set of charging stations connected to the bus b is denoted by $\mathcal{C}_b$. Finally, we denote the set of all vehicles by $\mathcal{V}$ and the set of vehicles at the charging station c by $\mathcal{V}_c$. Each vehicle is located and charged at a single charging station. Therefore, $\{\mathcal{V}_c \mid c \in \mathcal{C}\}$ is a partition of the set $\mathcal{V}$.

III. PROBLEM FORMULATION

Next, we present the problem formulation by defining the objective function and the constraints related to the distribution network and customers.

A. CONSTRAINTS

1) DISTRIBUTION NETWORK-RELATED CONSTRAINTS

The charging coordination strategy should yield to decisions that satisfy the power flow equations. Herein paper, we employ the linear power flow model introduced in [24]. Hence, the active and reactive powers at bus b and time t are given by

$$P_{b,t} = \sum_{b' \in \mathcal{B}, b' \neq b} \alpha_{b,b'}^{(1)}(V_{b,t} - V_{b',t}) + \alpha_{b,b'}^{(2)}(\phi_{b,t} - \phi_{b',t}),$$
$$\forall b \in \mathcal{B}, \forall t \in \mathcal{T}, \tag{2}$$

$$Q_{b,t} = \sum_{b' \in \mathcal{B}, b' \neq b} \alpha_{b,b'}^{(2)}(V_{b,t} - V_{b',t}) - \alpha_{b,b'}^{(1)}(\phi_{b,t} - \phi_{b',t}),$$
$$\forall b \in \mathcal{B}, \forall t \in \mathcal{T}, \tag{3}$$

where

$$\alpha_{b,b'}^{(1)} = \frac{r_{b,b'}}{r_{b,b'}^2 + x_{b,b'}^2}, \quad \alpha_{b,b'}^{(2)} = \frac{x_{b,b'}}{r_{b,b'}^2 + x_{b,b'}^2}, \tag{4}$$

where $r_{b,b'}$ and $x_{b,b'}$ are the resistance and reactance values between buses b and b', respectively.

The total power consumption in the network is the sum of the residential load and the power load introduced by the

EV charging. Hence, we have

$$\sum_{b \in \mathcal{B}} P_{b,t}^{\mathrm{G}} - \sum_{b \in \mathcal{B}} P_{b,t}^{\mathrm{D}} - \sum_{b \in \mathcal{B}} P_{b,t}^{\mathrm{R}} = 0, \quad \forall b \in \mathcal{B}, \ \forall t \in \mathcal{T}, \quad (5)$$

$$\sum_{b \in \mathcal{B}} Q_{b,t}^{\mathrm{G}} - \sum_{b \in \mathcal{B}} Q_{b,t}^{\mathrm{R}} = 0, \quad \forall b \in \mathcal{B}, \ \forall t \in \mathcal{T}. \quad (6)$$

The total power demand (by EVs) at a bus is the sum of the charging powers of the vehicles connected to that bus:

$$P_{b,t}^{\mathrm{D}} = \sum_{c \in \mathcal{C}_b} \sum_{v \in \mathcal{V}_c} p_{v,t}, \quad \forall b \in \mathcal{B}, \ \forall t \in \mathcal{T}, \quad (7)$$

where $p_{v,t}$ is the power load for the vehicle v expressed as

$$p_{v,t} = D_{v,t} \rho_v, \quad \forall v \in \mathcal{V}, \ \forall t \in \mathcal{T}. \quad (8)$$

The active and reactive power values should satisfy the following limits:

$$P_{b,t}^{\min} \leq P_{b,t}^{\mathrm{D}} \leq P_{b,t}^{\max}, \quad \forall b \in \mathcal{B}, \ \forall t \in \mathcal{T} \quad (9)$$

$$Q_{b,t}^{\min} \leq Q_{b,t}^{\mathrm{D}} \leq Q_{b,t}^{\max}, \quad \forall b \in \mathcal{B}, \ \forall t \in \mathcal{T}. \quad (10)$$

The voltage values at each bus satisfy the following constraints:

$$V^{\min} \leq V_{b,t} \leq V^{\max}, \quad \forall b \in \mathcal{B}, \ \forall t \in \mathcal{T}. \quad (11)$$

2) CUSTOMER-RELATED CONSTRAINTS
The customer-provided arrival and departure times at the charging location satisfy:

$$1 \leq T_v^{\mathrm{arr}} < T_v^{\mathrm{dep}} \leq n, \quad \forall v \in \mathcal{V}. \quad (12)$$

The initial and desired SoC values are bounded in the interval [0, 1]. Hence,

$$0 \leq S_v^{\mathrm{init}} < S_v^{\mathrm{des}} \leq 1, \quad \forall v \in \mathcal{V}. \quad (13)$$

We define the time-to-complete-charge (TCC) parameter T_v^{ch} as the time needed to achieve the desirable SoC. The TCC value can be expressed in terms of the initial SoC and the desired SoC as

$$T_v^{\mathrm{ch}} \tau \rho_v \eta_v = B_v^{\max} \left(S_v^{\mathrm{des}} - S_v^{\mathrm{init}} \right), \quad \forall v \in \mathcal{V}. \quad (14)$$

By rearranging the terms, it turns out that

$$T_v^{\mathrm{ch}} = \frac{B_v^{\max} \left(S_v^{\mathrm{des}} - S_v^{\mathrm{init}} \right)}{\tau \rho_v \eta_v}, \quad \forall v \in \mathcal{V}. \quad (15)$$

Vehicle v is not charged more than the requested value since it is not feasible to charge the battery more than T_v^{ch}. Hence, the cumulative decision value for a vehicle satisfies

$$\sum_{t \in \mathcal{T}} D_{v,t} \leq T_v^{\mathrm{ch}}, \quad \forall v \in \mathcal{V}. \quad (16)$$

Vehicle v could not be charged for a total time period larger than the provided parking duration. Therefore, the cumulative decision value for vehicle v is less than or equal to the parking duration, i.e.,

$$\sum_{t \in \mathcal{T}} D_{v,t} \leq T_v^{\mathrm{park}}, \quad \forall v \in \mathcal{V}. \quad (17)$$

(16) and (17) could be combined into a single constraint as

$$\sum_{t \in \mathcal{T}} D_{v,t} \leq \min \left\{ T_v^{\mathrm{park}}, T_v^{\mathrm{ch}} \right\}, \quad \forall v \in \mathcal{V}. \quad (18)$$

An EV can only be charged during the time period between the arrival time T_v^{arr} and departure time T_v^{dep}. Hence, the charging decision must be zero outside this interval.

$$D_{v,t} = 0, \quad \forall t \notin [T_v^{\mathrm{arr}}, T_v^{\mathrm{dep}}], \ \forall v \in \mathcal{V}. \quad (19)$$

In order to constrain the charging decisions to the parking interval, we define $I_{v,t}$ as an indicator matrix for the charging intervals of the EVs

$$I_{v,t} = \begin{cases} 1, & \text{if } T_v^{\mathrm{arr}} \leq t \leq T_v^{\mathrm{dep}}, \\ 0, & \text{otherwise.} \end{cases}, \quad \forall v \in \mathcal{V}. \quad (20)$$

Hence, we have

$$\left(1 - I_{v,t} \right) D_{v,t} = 0, \quad \forall v \in \mathcal{V}, \ \forall t \in \mathcal{T}. \quad (21)$$

Please note that we force $D_{v,t} = 0$ when $I_{v,t} = 0$, i.e., t is not in the parking interval for the EV v.

Finally, the SoC $S_{v,t}$ progresses over time as follows

$$S_{v,t+1} = S_{v,t} + D_{v,t} \frac{\tau \rho_v \eta_v}{B_v^{\max}}, \quad \forall v \in \mathcal{V}, \ \forall t \in \mathcal{T}. \quad (22)$$

B. CHARGING COORDINATION
In this subsection, we introduce the charging coordination problem and discuss its solution methodology by exploiting duality methods from linear optimization. We define two different objectives for the EV charging coordination scheme in order to assess the impact of the selection of the objective on the optimization problem. The objectives are defined as Average Satisfaction Rate (ASR) and MSR, which try to maximize the average and minimum charging satisfaction rates of the customers, respectively. The ASR formulation aggressively tries to maximize the average satisfaction rate without considering individual customer satisfaction rates. On the other hand, the MSR formulation tries to provide a fair distribution of electric charge among the customers by trying to maximize the minimum customer satisfaction at the expense of a lower average satisfaction rate. We study the impact of the customer cheating on the performance of the EV charging mechanism under both formulations in order to compare the susceptibility of both formulations.

1) AVERAGE SATISFACTION RATE (ASR)-BASED FORMULATION
In this formulation, the average satisfaction rate of the charging requests is used as a metric to quantify the efficiency of the charging coordination strategy. This is defined as the ratio of the amount of the final SoC S_v^{final} to the requested SoC S_v^{des} for each customer. Hence, the objective function is defined in terms of the satisfied charging requests as follows:

$$U_{\mathrm{avg}} = \frac{1}{N_v} \sum_{v \in \mathcal{V}} \frac{S_v^{\mathrm{final}}}{S_v^{\mathrm{des}}}. \quad (23)$$

The objective function value is in the range [0, 1], where $U_{\mathrm{avg}} = 0$ corresponds to completely unsatisfied customers (no charging request has been served) and $U_{\mathrm{avg}} = 1$ corresponds to fully satisfied charging requests.

We can rewrite the objective function as

$$U_{\mathrm{avg}} = \frac{1}{N_v} \sum_{v \in \mathcal{V}} \frac{S_v^{\mathrm{final}}}{S_v^{\mathrm{des}}}$$
$$= \frac{1}{N_v} \left(\sum_{v \in \mathcal{V}} \frac{1}{S_v^{\mathrm{des}}} \left(\sum_{t=1}^{n} \frac{\tau \rho_v \eta_v}{B_v^{\mathrm{max}}} D_{v,t} + S_v^{\mathrm{init}} \right) \right). \quad (24)$$

Hence, we can express the objective function as

$$U_{\mathrm{avg}} = \sum_{v \in \mathcal{V}} \sum_{t=1}^{n} \gamma_v D_{v,t} + \Psi, \quad (25)$$

where $\gamma_v = \tau \rho_v \eta_v / N_v S_v^{\mathrm{des}} B_v^{\mathrm{max}}$ and $\Psi = 1/N_v \sum_{v \in \mathcal{V}} S_v^{\mathrm{init}} / S_v^{\mathrm{des}}$ are constants.

The charging coordination problem is formulated as:

$$\max_{D_{v,t}} \sum_{v \in \mathcal{V}} \sum_{t=1}^{n} \gamma_v D_{v,t} + \Psi$$
$$\text{s.t. } (2), (3), (5), (7) - (11), (15), (18), (21) \text{ and } (22)$$
$$D_{v,t} \in [0, 1], \quad \forall v \in \mathcal{V}, \ \forall t \in \mathcal{T}. \quad (26)$$

2) MINIMUM SATISFACTION RATE (MSR)-BASED FORMULATION

In order to ensure fairness for each customer, we use an objective function that maximizes the minimum charging amount among the customers. Similarly, the satisfaction rate for a customer v is defined as the ratio of the amount of the final SoC S_v^{final} to the requested SoC S_v^{des}. The objective function is expressed as

$$U_{\mathrm{min}} = \min_v \frac{S_v^{\mathrm{final}}}{S_v^{\mathrm{des}}}. \quad (27)$$

Hence, the charging coordination problem is formulated as:

$$\max_{D_{v,t}} \min_v \frac{S_v^{\mathrm{final}}}{S_v^{\mathrm{des}}}$$
$$\text{s.t. } (2), (3), (5), (7) - (11), (15), (18), (21) \text{ and } (22)$$
$$D_{v,t} \in [0, 1], \quad \forall v \in \mathcal{V}, \ \forall t \in \mathcal{T}. \quad (28)$$

The max-min problem (28) can be transformed to a maximization problem by introducing an auxiliary variable. Let the variable W stand for a lower bound on the satisfaction rate of each customer, i.e.,

$$W \leq \frac{S_v^{\mathrm{final}}}{S_v^{\mathrm{des}}}, \quad \forall v \in \mathcal{V}. \quad (29)$$

Hence, the maximum value of the variable W with respect to the decision variables provides the solution to (28).

Therefore, the optimization problem can be rewritten in the following form

$$\max_{D_{v,t}} W$$
$$\text{s.t. } W \leq \frac{S_v^{\mathrm{final}}}{S_v^{\mathrm{des}}}, \quad \forall v \in \mathcal{V},$$
$$(2), (3), (5), (7) - (11), (15), (18), (21) \text{ and } (22)$$
$$D_{v,t} \in [0, 1], \quad \forall v \in \mathcal{V}, \ \forall t \in \mathcal{T}, \quad (30)$$

For both formulations of the optimization problem, the objective functions are linear. Since all the constraints are also linear, (26) and (30) are LPs and can be solved efficiently using the interior point methods [25].

C. TOLERANCE OF THE COORDINATION STRATEGY TO CHEATING BEHAVIOR

The battery parameters, such as the SoC and battery capacity, and the other vehicle-related parameters, such as the charging rate and efficiency, can be easily monitored by the charging station coordinator. Hence, the customers are less likely to provide false information about those parameters. On the other hand, the time-related parameters provided by the customers are more prone to cheating behavior. Consequently, we investigate the impact of providing false information about the time-related parameters. The problem is formally defined as follows. We aim to find how the objective function is affected if a customer lies about the departure time. That is, what would be the difference in the objective function if the time of departure changes, and hence, the parking duration undergoes a variation:

$$T_v^{\mathrm{dep}'} = T_v^{\mathrm{dep}} - \Delta T_v^{\mathrm{dep}}. \quad (31)$$

The falsified parking duration is given by

$$T_v^{\mathrm{park}'} = \left(T_v^{\mathrm{dep}} - \Delta T_v^{\mathrm{dep}} \right) - T_v^{\mathrm{arr}} = T_v^{\mathrm{park}} - \Delta T_v^{\mathrm{dep}}. \quad (32)$$

Define the vector of departure times as T^{dep}. The entries of the vector ΔT^{dep} are nonzero for the cheating customers and zero for the others. Let $U_i^*(T^{\mathrm{park}})$ denote the optimal value for (26) and (30) with respect to the parking duration parameter T^{park}. The optimal value under a cheating scenario is given as $U_i^*(T^{\mathrm{park}} - \Delta T^{\mathrm{dep}})$. Hence, the degradation in the satisfaction rate metric is expressed as:

$$\Delta U_i^*(T^{\mathrm{park}}) = U_i^*(T^{\mathrm{park}}) - U_i^*(T^{\mathrm{park}} - \Delta T^{\mathrm{dep}}). \quad (33)$$

We will study the effect of the false information about the parking duration numerically in the following section.

IV. SIMULATION RESULTS

Extensive simulations have been performed to evaluate the performance of the proposed EV charging coordination scheme in both the absence and presence of cheating customers. First, we introduce the system setup common for all simulations. In the subsequent subsection, we examine
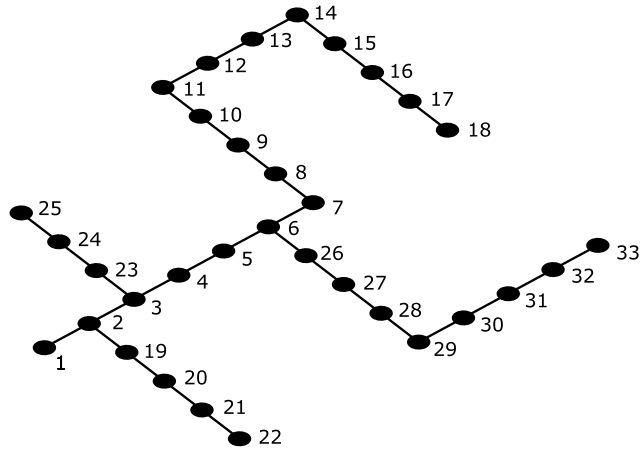
FIGURE 1. Schematic of the 33-bus system used in the simulations.

FIGURE 2. Average number of the EV arrivals per hour during 24 hours according to the EV charging sessions dataset.

TABLE 1. Parameters used in the simulations.

Parameter	Value
Number of buses	33
Base voltage	12.66kV
Number of charging stations	5
Charging station locations	$10, 16, 25, 26, 27$
Charging rate options	$36, 72, 144$kW
Charging efficiency	0.9
Battery capacity	85 kWh
Initial SoC interval	$[0.1, 0.3]$
Desired SoC interval	$[0.9, 1.0]$
Decision intervals	15min
Total time interval	24h

the system performance for the baseline setup, in which we investigate the performance of the EV charging coordination algorithm in the absence of the cheating customers. Next, we examine the effect of the falsified information under different system variables, such as the ratio of the number of cheating customers to all customers, percent of deviation in the parking duration, number of EV charging stations, and the charging rate.

A. SYSTEM SETUP

The performance of the charging coordination strategy is evaluated using a 33-bus system model. The bus system is rated at 12.66 kV, where the base load is 3720 kW and 2300 kVAr [26]. The schematic of the bus system is shown in Fig. 1.

Five charging stations are located at buses 10, 16, 25, 26, and 27. The charging rate ρ_v is 72 kW, which is the charging rate of the state-of-the-art fast chargers [27]. The charging efficiency η_v is taken to be 0.9. The battery capacity of the EVs is chosen to be 85 kWh, which is the battery capacity of Tesla Model S [28]. The initial SoC and the desired SoC of the EVs are uniformly distributed in the intervals [0.1, 0.3], and [0.9, 1.0], respectively.

We have modeled the EV arrivals by using the EV charging sessions data published for the city of Dundee [29]. The dataset consists of the entries for EV charging sessions at charge points throughout the city. We have obtained the EV arrivals by calculating the average number of transactions for a time period of 24 hours. Fig. 2 shows the arrival rates per hour for a 24 hour time period. The mean arrival rate is further scaled to adapt to our setup as well as analyze the effect of the mean arrival rate. The parking duration values are chosen randomly.

The decisions are made for 15 minute intervals over a total time interval of 24 hours. The simulations are performed using Python language, and the LPs are defined and solved using CVXPY convex optimization library [30]. A summary of the simulation parameters is provided in Table 1.
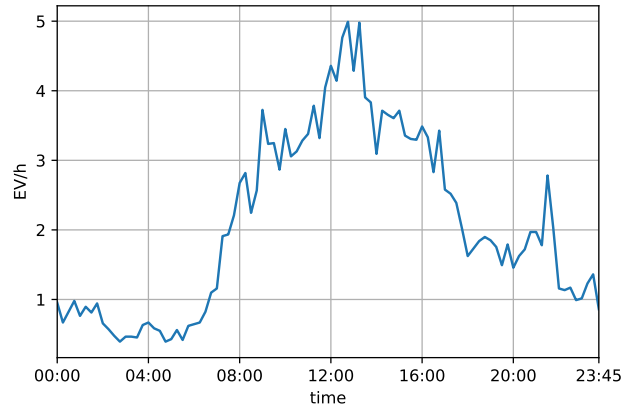
B. NO CHEATING

First, we need to verify that the charging coordination strategy works efficiently when there is no cheating behavior. The first important parameter affecting the charging coordination performance is the mean EV arrival rate to the charging stations. Accordingly, the proposed strategies are tested under three different conditions, which cover low to high EV arrival rates. The average number of EV arrivals are chosen as 40, 60, and 80 EVs per hour. Since we use the real EV arrival values from the dataset, we have scaled the values in Fig. 2 to change the mean arrival rate in order to examine the impact of different EV penetration levels. For this analysis, we set the charging rate of the chargers as 72kW. The plots of the average satisfaction rate vs. average parking duration for the three cases are shown in Fig. 3. We also provide the performance curves for the first-come-first-served (FCFS) scheme as a benchmark for the proposed charging schemes.

As seen from Fig. 3, the average number of arrivals affects the system performance significantly. The charging coordination strategy with the ASR formulation reaches an average satisfaction rate of 90% for an average parking duration of 3 hours for the average arrival rates of 40 EV per hour, whereas it reaches the same average satisfaction rate for 8 hours parking duration under the MSR formulation. This is expected since the objective function of the MSR formulation is to
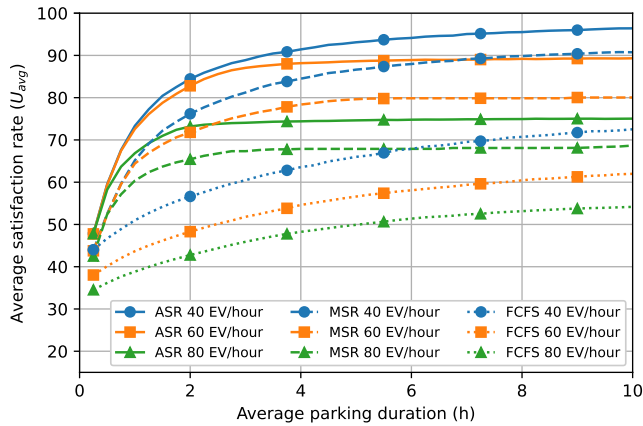
FIGURE 3. Average satisfaction rate vs. average parking duration for the average satisfaction rate (ASR) and minimum satisfaction rate (MSR) formulations as well as the first-come-first-served (FCFS) scheme as a benchmark. The curves for each method are plotted for mean arrival rates 40, 60, and 80, respectively.

FIGURE 4. Minimum satisfaction rate vs. average parking duration for the average satisfaction rate (ASR) and minimum satisfaction rate (MSR) formulations as well as the first-come-first-served (FCFS) scheme as a benchmark. The curves for each method are plotted for mean arrival rates 40, 60, and 80, respectively.

charge EVs in a fair scheme as opposed to increasing the charging satisfaction rate in an average sense. For the arrival rates higher than 60 EV/h, the satisfaction rate converges to a relatively lower value since the distribution network technical limits become more dominant. The main factor limiting the performance is the power limits of the buses to which the charging stations are connected. It goes without saying that the proposed EV charging schemes under both formulations provide more than 20% performance gain compared to the FCFS charging scheme.

The minimum satisfaction rates are also shown in Fig. 4 for the same system parameters as Fig. 3. For a mean EV arrival rate of 40 EV/h, both ASR and MSR formulations provide a minimum customer satisfaction rate of 30%, whereas the FCFS scheme is only able to provide 10%. The MSR formulation is able to keep the 30% minimum satisfaction rate even for the higher EV arrival rates. On the other hand, the ASR scheme could not perform well for higher EV arrival rates since it may discard some EVs in order to keep the average satisfaction rate high. There is an interesting result that the minimum satisfaction rate for ASR under high EV penetration drops from 30% to 10% even though the parking duration increases from 1 hour to 4 hours. The reason for such a counter-intuitive result is that ASR scheme aggressively tries to maximize the average satisfaction rate by charging some EVs less since it does not consider any fairness metric among the customers. The minimum satisfaction rate could not increase more than 30% since it is limited by the parking duration of the EVs that are staying at the charging stations less than the TCC value they provide.

C. CHEATING

In this subsection, we analyze the performance degradation in the presence of cheating customers. The deviations in the parking duration could heavily impact the system performance. In order to assess the performance impact of the different ratios of cheating customers, we have performed
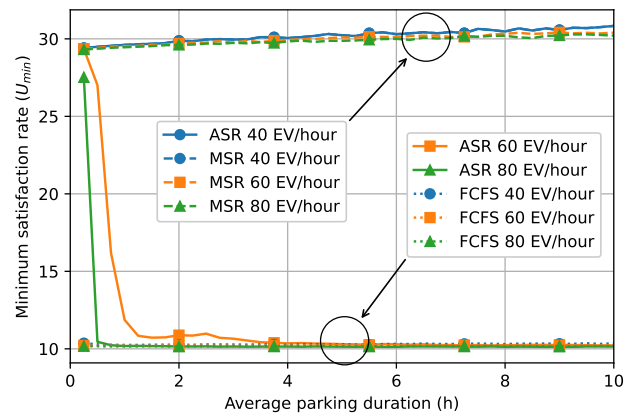
experiments for a varying percentage of cheating customers. The sensitivity of the average satisfaction rate metric U_{avg} with respect to the cheating amount is tested by fixing the average number of EV arrivals and the parking duration in order to remove the other effects introduced by the other system parameters. The average number of EV arrivals are chosen as 60 EV/h. The average EV parking duration is chosen for three different scenarios. The first scenario is for the charging stations located near restaurants at which the customers stay for a short time interval. The second scenario is for moderate parking duration, such as near shopping malls. The charging stations at the residential or office areas constitute the third scenario, where the customers stay for longer time periods. Hence, we choose the actual parking duration values for the three scenarios as 2, 4, and 8 hours, respectively. The ASR formulation presents approximately 82%, 88%, and 89% average satisfaction rate, respectively, under the chosen parameters if there is no cheating. Similarly, the MSR formulation presents 72%, 78%, and 80% average satisfaction rate, respectively, in the baseline setup. Fig. 5 shows the deviation in the satisfaction rate with respect to the average difference between the actual and provided parking duration by each customer for the three scenarios.

The sensitivity of the coordination strategy with respect to the parking duration of the customers depends on the aforementioned EV and distribution network-related parameters. In order to examine the effect of the deviation of the parking duration from the actual value, we selected and fixed the system parameters. In the next step, the parking duration values for the customers deviated from the actual value in order to evaluate the performance degradation in the satisfaction rate of the charging coordination strategy. If we compare the three plots in Fig. 5, we conclude that the degradation in the average satisfaction rate heavily depends on the actual parking duration. The higher the parking duration, the more robust the system to the cheating behavior. For instance, if we fix the ratio of the cheating customers to 50% and the cheating
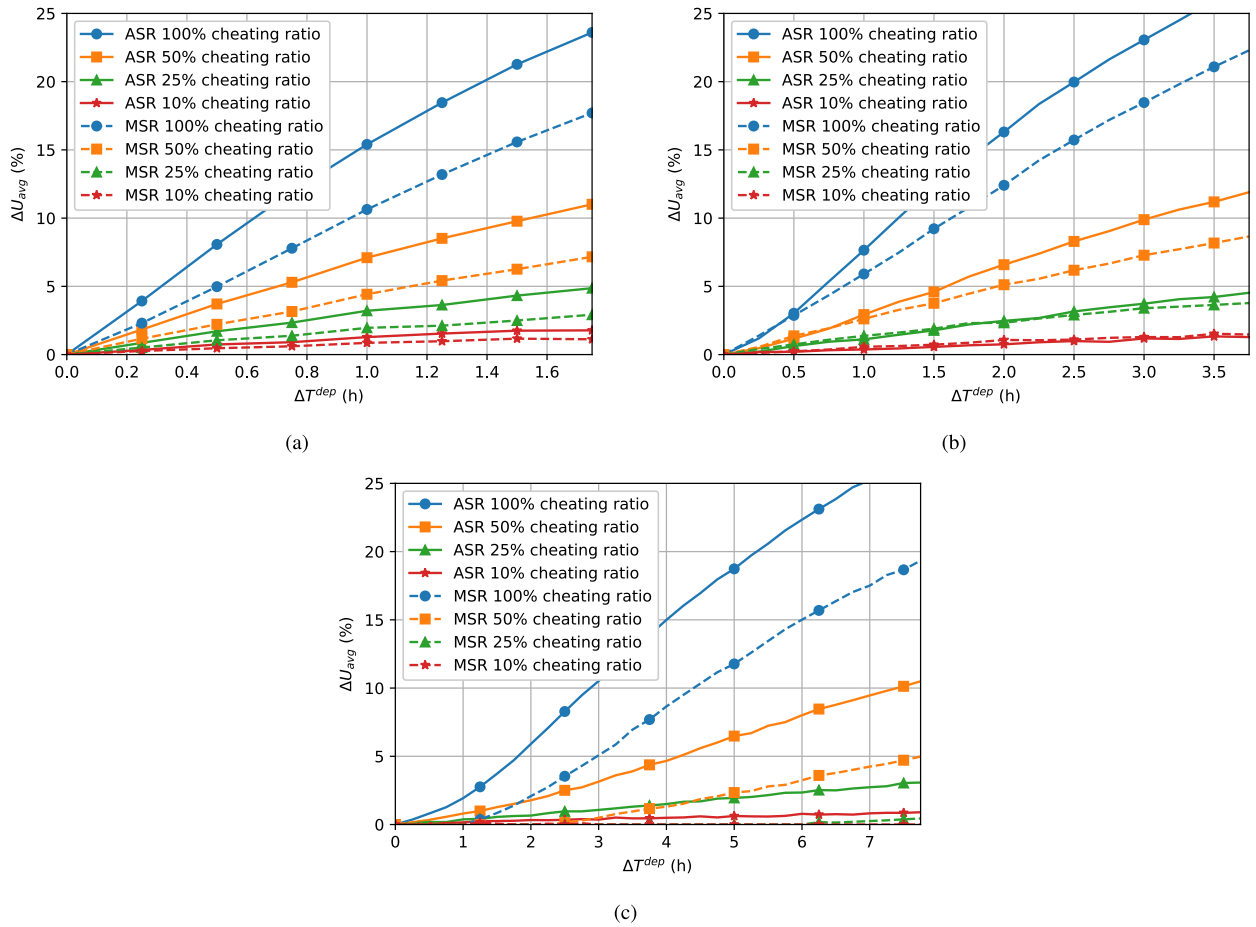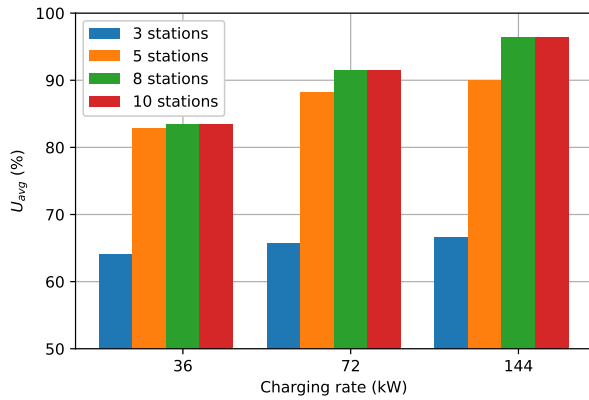
FIGURE 5. Deviation in the average satisfaction rate vs. cheating duration for three scenarios with different actual parking duration. The curves in (a), (b), and (c) are plotted for the actual parking duration of 2, 4, and 8 hours, respectively. Curves for each scenario are plotted for a cheating customer ratio of 100%, 50%, 25%, and 10%, respectively.

amount to 1 hour, the charging coordination mechanism with ASR faces 8%, 3%, 0.5% performance drop under the three scenarios, respectively. We also conclude that the MSR formulation is less prone to the cheating behavior compared to the ASR formulation. The reason is that the MSR formulation considers the least charged vehicle, as opposed to the ASR formulation, which considers the average satisfaction rate. Hence, there is a trade-off that although the ASR provides a higher satisfaction rate in the baseline setup, the MSR offers less susceptibility to the cheating behavior.

For instance, as shown in Fig. 5(c), the relatively smaller amounts of cheating are acceptable. If the parking duration deviates from the actual value by 1 hour for 50% of the customers, the performance drop is less than 1%. However, if the deviation gets higher around 4 hours, the performance degradation becomes approximately 5%. If the ratio of the cheating customers to all the customers in the system gets lower, the performance degradation gets lower. Nevertheless, it is worth noting that even if the ratio of the cheating customers is low at the beginning, that ratio could increase with time, and the reduction in the satisfaction rate could

potentially be catastrophic if no precaution is taken to overcome the cheating behavior. Fig. 5(a) states that there is a 15% performance drop if the parking duration deviates by 1 hour in a cheating scenario. The value of degradation in the satisfaction rate is around the performance gain introduced by the smart EV charging coordination algorithms compared to an uncoordinated scheme. For instance, the results in Fig. 5(a) suggest that the optimal EV charging coordination mechanism offers an improvement in the performance around 20% over an FCFS strategy. This suggests a remarkable result that when the customers provide false information about their parking duration, in some sense, we lose the performance gain provided by the smart charging coordination method.

One of the most important factors affecting the system performance is the allocation of the charging stations. As mentioned earlier, one could improve the system performance by allocating more charging stations. In order to see how the system behaves when we change the number of charging stations, we have assigned different numbers of charging stations to the charging network. It is worth noting that we need to consider the network topology when we are
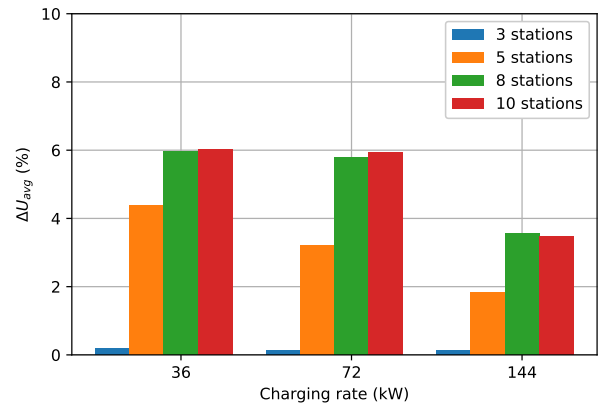
(a) Average satisfaction rate for the ASR formulation.
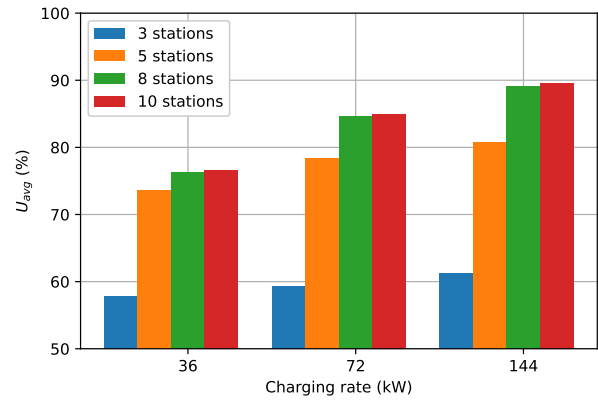
(b) Average satisfaction rate for the MSR formulation.
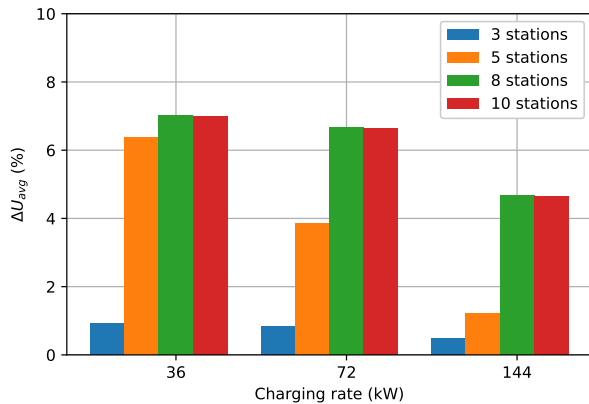
(c) Deviation of the average satisfaction rate for the ASR formulation.

(d) Deviation of the average satisfaction rate for the MSR formulation.

FIGURE 6. The results for the charger analysis. The figures (a) and (b) shows the satisfaction rates and the figures (c) and (d) shows the deviation in the satisfaction rates in presence of cheating users.

allocating the chargers. We have determined the bus locations of each charging station considering the residential power load at the connected node and allocated the EV charging stations at the buses with the residential power loads. We have considered four different setups in which the number of charging stations is chosen as 3, 5, 8, and 10, respectively. We also varied the charging power rate of the EV chargers in order to examine the effect of the charging rate. The charging rates are chosen as 36, 72, and 144 kW per charger, respectively.

In parallel with the conclusions from the previous analyses, Fig. 6 states that the MSR formulation is less sensitive to the cheating behavior compared to the ASR formulation, although it performs worse in the baseline setup, i.e., when there is no cheating customer. It is intuitive that if we increase the number of charging stations in the network, the average satisfaction rate increases. On the other hand, according to the results in Fig. 6(a) and Fig. 6(b), the system performance does not improve if we add more charging stations after 8 charging stations. It is because the total power load in the distribution network is limited by the generated power. Hence, the generated power should be considered in

addition to the bus power limits when introducing additional EV charging stations in the network. Fig. 6(c) and Fig. 6(d) suggest that increasing the number of charging stations in the network also increases the susceptibility of the EV charging coordination scheme to the cheating behavior, which may be counter-intuitive. The reason can be explained by considering the constraints in the problem formulation. We have introduced two main types of constraints for the charging coordination problem: (i) timing and customer-related constraints and (ii) distribution network-related constraints. If the number of charging stations is low, the charging network gets congested easily, and therefore, the distribution network-related constraints become more dominant. On the other hand, if the number of charging stations is high, the charging network is less prone to congestion, and the distribution network-related constraints get less dominant, and customer-related parameters, such as the parking duration, become more significant. Thus, even if increasing the number of chargers improves the system performance, it also increases the susceptibility of the system performance to the cheating behavior. Hence, the cheating behavior is expected to pose a more significant problem as the EV charging

network grows in the future. Increasing the number of chargers increases the deployment and operational costs as well. Fig. 6(c) and Fig. 6(d) point out also another significant result that increasing the charging rate decreases the sensitivity of the system performance with respect to the cheating amount. When the charging power increases, the TCC values for the vehicles decrease. This is because the parking duration gets relatively significant with respect to the TCC values. Hence, the parking duration gains more relative importance if the TCC values are smaller.

V. CONCLUSION

This paper investigated the sensitivity of the EV charging coordination efficiency in the presence of cheating customers who provide false information about their parking duration. First, we modeled the EV charging coordination problem as an LP that aims to maximize the customer satisfaction rate while respecting the distribution network technical limits and the customer-related constraints. In the next step, we tested the efficiency of the coordination strategy when a portion or all of the customers cheat by providing falsified information about their parking duration. The simulation results demonstrate that efficiency is adversely affected by the presence of cheating customers. The degradation in the customer satisfaction rate induced by the cheating behavior is dependent on the actual parking duration. Higher parking duration, such as near residential and office areas, makes the charging coordination strategy less susceptible to cheating behavior. However, the charging stations at locations where customers have shorter parking duration are more prone to the cheating behavior. Increasing the number of chargers and decreasing the charging power rate increases the susceptibility of the system to the cheating behavior since we have limited power resources.

The adversarial effects of the cheating behavior of customers open the door for the development of techniques for cheating customer detection and robust EV charging coordination. As a future research direction, robust EV charging coordination algorithms need to be developed by taking into account the fact that customers may provide erroneous information. Also, mitigation strategies are necessary to compensate for the adverse effects caused by the provided false information by the cheating customers.

REFERENCES

[1] W. Tang, S. Bi, and Y. J. Zhang, "Online charging scheduling algorithms of electric vehicles in smart grid: An overview," *IEEE Commun. Mag.*, vol. 54, no. 2, pp. 76–83, Dec. 2016.

[2] N. I. Nimalsiri, C. P. Mediwaththe, E. L. Ratnam, M. Shaw, D. B. Smith, and S. K. Halgamuge, "A survey of algorithms for distributed charging control of electric vehicles in smart grid," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 11, pp. 4497–4515, Nov. 2020.

[3] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802–810, May 2011.

[4] L. Babcock and G. Loewenstein, "Explaining bargaining impasse: The role of self-serving biases," *J. Econ. Perspect.*, vol. 11, no. 1, pp. 109–126, Feb. 1997.

[5] O. Sundstrom and C. Binding, "Flexible charging optimization for electric vehicles considering distribution grid constraints," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 26–37, Mar. 2012.

[6] A. Moradipari and M. Alizadeh, "Pricing and routing mechanisms for differentiated services in an electric vehicle public charging station network," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1489–1499, Mar. 2020.

[7] A. Laha, B. Yin, Y. Cheng, L. X. Cai, and Y. Wang, "Game theory based charging solution for networked electric vehicles: A location-aware approach," *IEEE Trans. Veh. Technol.*, vol. 68, no. 7, pp. 6352–6364, Jul. 2019.

[8] M. F. Shaaban, M. Ismail, E. F. El-Saadany, and W. Zhuang, "Real-time PEV charging/discharging coordination in smart distribution systems," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1797–1807, Jun. 2014.

[9] W. Wu, Y. Lin, R. Liu, Y. Li, Y. Zhang, and C. Ma, "Online EV charge scheduling based on time-of-use pricing and peak load minimization: Properties and efficient algorithms," *IEEE Trans. Intell. Transp. Syst.*, early access, Sep. 2, 2020, doi: 10.1109/TITS.2020.3014088.

[10] W. Tang and Y. J. A. Zhang, "A model predictive control approach for low-complexity electric vehicle charging scheduling: Optimality and scalability," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1050–1063, Mar. 2016.

[11] O. Frendo, N. Gaertner, and H. Stuckenschmidt, "Real-time smart charging based on precomputed schedules," *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6921–6932, Nov. 2019.

[12] S. Liu and A. H. Etemadi, "A dynamic stochastic optimization for recharging plug-in electric vehicles," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4154–4161, Sep. 2018.

[13] L. Gan, U. Topcu, and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 940–951, May 2013.

[14] Z. Liu, Q. Wu, S. Huang, L. Wang, M. Shahidehpour, and Y. Xue, "Optimal day-ahead charging scheduling of electric vehicles through an aggregative game model," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 5173–5184, Sep. 2018.

[15] E. Bulut, M. C. Kisacikoglu, and K. Akkaya, "Spatio-temporal non-intrusive direct V2 V charge sharing coordination," *IEEE Trans. Veh. Technol.*, vol. 68, no. 10, pp. 9385–9398, Oct. 2019.

[16] M. Latifi, A. Rastegarnia, A. Khalili, and S. Sanei, "Agent-based decentralized optimal charging strategy for plug-in electric vehicles," *IEEE Trans. Ind. Electron.*, vol. 66, no. 5, pp. 3668–3680, May 2019.

[17] M. A. Tajeddini and H. Kebriaei, "A mean-field game method for decentralized charging coordination of a large population of plug-in electric vehicles," *IEEE Syst. J.*, vol. 13, no. 1, pp. 854–863, Mar. 2018.

[18] P. Wang, S. Zou, and Z. Ma, "A partial augmented Lagrangian method for decentralized electric vehicle charging in capacity-constrained distribution networks," *IEEE Access*, vol. 7, pp. 118229–118238, 2019.

[19] M. Shahidehpour, Y. Xue, Z. Liu, Q. Wu, S. Huang, and K. Ma, "Two-stage optimal scheduling of electric vehicle charging based on transactive control," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 2948–2958, May 2018.

[20] Y. Zhou, R. Kumar, and S. Tang, "Incentive-based distributed scheduling of electric vehicle charging under uncertainty," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 3–11, Sep. 2019.

[21] Z. Wan, H. Li, H. He, and D. Prokhorov, "Model-free real-time EV charging scheduling based on deep reinforcement learning," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 5246–5257, Sep. 2019.

[22] I. Momber, A. Siddiqui, T. G. S. Román, and L. Söder, "Risk averse scheduling by a PEV aggregator under uncertainty," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 882–891, Mar. 2015.

[23] T. Zhang, W. Chen, Z. Han, and Z. Cao, "Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price," *IEEE Trans. Veh. Technol.*, vol. 63, no. 6, pp. 2600–2612, Jul. 2014.

[24] H. Yuan, F. Li, Y. Wei, and J. Zhu, "Novel linearized power flow and linearized OPF models for active distribution networks with application in distribution LMP," *IEEE Trans. Smart Grid*, vol. 9, no. 1, pp. 438–448, Jan. 2018.

[25] S. Boyd, S. P. Boyd, and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[26] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Trans. Power Del.*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989.

[27] (2021). *Tesla Supercharging. Tesla Motors*. [Online]. Available: https://www.tesla.com/support/supercharging

[28] (2021). *Tesla Model's. Tesla Motors*. [Online]. Available: https://www.tesla.com/models

[29] (2021). *Electric Vehicle Charging Sessions Dundee. Dundee City Council*. [Online]. Available: https://data.dundeecity.gov.uk/dataset/ev-charging-data

[30] S. Diamond and S. Boyd, "CVXPY: A Python-embedded modeling language for convex optimization," *J. Mach. Learn. Res.*, vol. 17, no. 83, pp. 1–5, 2016.

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