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Hierarchical Event-Triggered Online Charging Management of Time-Varying Network of Electric Vehicles Based on Cooperative Game Theory

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ABSTRACT:
This article reports on a method for detecting disconnection between electric vehicle parking lots during charge management and uncertainties and how to deal with these issues. In this study, each parking lots has an aggregator that can exchange information with other parking lot aggregators through a communication graph. A cyber-attack or communication failure may cause a problem in the connection between the aggregators and their information exchange. To detect the loss of contact between the aggregators or uncertainties, a method based on the mean field game is developed through a distributed consensus algorithm. Since the number of vehicles in every parking lot, power consumption and generation are uncertain, the smoothness of the network load curve is disrupted. so, in this work an online optimization based on receding horizon concept is proposed to monitor network load every hour. However, due to the complexity of online calculations and disconnection detection, the optimization is implemented in an event-based manner. Although several distributed event-triggered methods have been introduced recently, these methods generally require state estimators to calculate the event-triggered error, the latest states and the threshold which increases the computation cost. However, the proposed event-triggered control method only requires mean field game information to compute the event-triggered conditions and requires less computations. To have convergent game, a time-varying network topology is suggested when the communication of parking lots is lost and the disconnection event is triggered. To validate the effectiveness of our method, we conduct computer simulations that demonstrate their achievements.

KEYWORDS: Aggregative Games, Consensus Algorithm, Electric Vehicles, Event Trigger, Switching Topology.

1. INTRODUCTION

The rapid development of societies and the increase in energy demand cause environmental/air pollution. Due to massive consumption of fossil energy, energy shortage, and environmental pollution, the use of Electrical Vehicles (EVs) has been welcomed. Low carbon emissions, energy saving, and environmental compatibility are the advantages of these vehicles [1, 2]. There are many parking lots including EVs that can be connected to the grid for charging or discharging. With the increasing burden of EVs on the grid, their charging rate should be controlled because the lack of control of EVs in the grid will cause voltage drops or blackouts [3]. In this respect, a lot of research has been conducted on the planning and optimal charging of EVs, among these studies centralized, decentralized, and

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hierarchical methods are the main streams [4]. Although centralized charging control is simple compared to decentralized control, it is not suitable for large-scale charging networks [5]. If an error occurs in the central controller, the entire system will be disrupted. On the other hand, distributed and decentralized systems are more scalable and flexible to system changes and can include concepts such as topology change [6, 7]. A decentralized EV charging control scheme is reported in [8], which allows to flatten the demand profile during overnight charging meeting grid constraints. Another advantage of decentralized control is preserving the privacy of information.

In [9], a fully decentralized cooperative algorithm is designed for the optimal charging of EVs that preserves agent privacy and user satisfaction. In a decentralized method, the charging management of EVs could be modeled as a game, where different algorithms have been presented based on the access level of each agent to others' information [10, 11]. In [12], an aggregative game model is presented for the day-ahead EV charging scheduling to manage EVs interaction and its impact on electricity prices.

The authors of [13] have suggested a mean field game algorithm to determine the charging of Plug-in Hybrid Electric Vehicle (PHEV) customers to optimize the combination of gasoline and battery modes according to distance and travel time. Also, a linear quadratic mean field game theory to manage parking lots and implement decentralized control for charging EVs population is proposed in [14].

In large scale systems, the communication of EVs through a single aggregator becomes difficult due to their dispersion in different parking lots and geographical locations. Therefore, they are usually grouped into several categories and connected with aggregators. This method is referred to as the hierarchical method. In this way, control and computational load are divided among several aggregators to exchange information through a communication network. In this way, there is no need for an extensive network. In [15], an improved policy for optimizing PEV charging by coordination of aggregators is proposed. This policy minimizes the energy costs of the aggregators.

Research presented in [16] investigates multiple parking lots that exchange energy with each other and grid operator through a new energy management framework and maximize the profit of parking lot owners. In [17] a coordination method of several EV aggregators is presented to smooth the load curve by considering peak shaving and valley filling. A two-layer algorithm is implemented to establish coordination in the control of EVs charging between aggregators and the distribution system operator. However, in [15-17] aggregators do not collaborate with each other. In some research, the aggregators exchange information with each other [18-21]. A two-layer distributed optimization platform with the alternating direction method of the multiplier is suggested to optimize the charging/discharging population of EVs considering coordinated aggregators [18]. The authors of [19] have proposed a cooperative hierarchical multi-agent system for scheduled EV charging to minimize the demand charges.

Another study represents an operational strategy for charging stations in that EVs can be charged via solar energy or the grid [20]. Aggregators' collaborative scheduling is considered to maximize their profits. In [21], a two-layer hierarchical control structure is suggested to control the charging of EVs in networked parking lots. At the lower layer, EVs compete with each other to achieve their optimal charge profile, while at the higher level, the aggregators exchange information through a directed communication graph to evaluate the overall mean field value and send it to their vehicles. Concerning the previous studies, the charge control of vehicles is done by several aggregators. In most of the proposed methods, the aggregators are not connected to each other online, and exchanging information is done in offline simulation conditions. Also, the number of cars is constant. Uncertainties such as an unspecified number of vehicles in the grid or inexact generation of renewable resources [22, 23] as a local power supply or in non-EV electrical loads at charging stations in residential buildings have not been appropriately considered due to offline optimization. These uncertainties could cause problems in grid reliability and thus provoke one to solve the optimization problem online, which becomes very time-consuming when the number of agents is large. For this purpose, the event trigger method is suggested to decrease the time and volume of calculations and save communication bandwidth [24, 25]. Recently, the event-based control method has been used in control systems to decrease the communication and computational volume, which can achieve satisfactory performance. In [26], the event-based control strategy is suggested to implement the consensus protocol to reduce communication in the interconnected systems. The authors of [27] have proposed an event-triggered control strategy to avoid data transmission in distributed cooperative control continuously. In [28], event trigger mechanism is implemented to reduce the communication resource and bandwidth. In [29] the agents interact locally and exchange their state information with each other to reach a group decision value. The general approach is to employ event-triggering laws with threshold mechanisms that depend on the states of the agents. Although several distributed event-triggered control methods have been introduced recently, these methods generally require state estimators to calculate the event-triggered error, which increases the computation cost [30]. However, the proposed event-triggered control method only requires mean field game information to compute the event-triggered conditions, which has a low computational volume. In the mentioned papers, the defined event relies on the error, the latest states, and the threshold and mean field game concept in multi-agent systems is not employed.

Furthermore, in most of the similar works, link disconnection between aggregators has been neglected to consider as an event, while the connection between the aggregators may be interrupted due to an attack or a communication error [31]. Due to the correct charging/discharging of electric vehicles in the parking lots, these disconnections should be recognized. In some papers, observer-based or external estimator methods have been used to detect disconnectivity of an agent or an edge, and agent states are estimated [32-34]. The authors of [32] have presented a model of external estimators to monitor the connection status of two arbitrarily chosen agents, and investigate disconnection between agents through decision rules. In [33], the observer-based event-triggering consensus control problem is investigated for a discrete-time multi-agent system with lossy sensors and cyber-attacks. In [34], observability of the system is employed to establish conditions for the discernibility of the edge disconnection. Since the numerical mean-field values are specific and constant, the mentioned research works are different from the present study.

The present paper proposes a framework to cover multiple aggregators' hierarchical infrastructures in the presence of uncertainties and communication failure through an event trigger-based receding horizon control when the population of EVs is large. In this work, it is assumed that there are a large and unspecified number of vehicles in the grid. These vehicles can be charged/discharged [35] in the parking lot of residential buildings and controlled by local aggregators. Due to the difference in geographical location of the parking lots and the increase in the communication links by the direct or indirect central aggregator, the vehicles are divided into several groups with local aggregators. Each local aggregator is in connection with some neighbors, and vehicles' charging and discharging are controlled by implementing the mean-field game method so that the load curve becomes smoother considering the constraints. Communication among aggregators is a directed graph, and it may be disconnected in some hours and reconnected in others, and they have a time-varying network. It is assumed that all parking lots send their information signal to each other simultaneously. Based on the mean-field value of each parking lot and the overall mean-field value, the disconnected link is detected, and the relevant event is defined. In these circumstances, convergence conditions are provided for the existing parking lots network by replacing the proposed topology. In other words, for disconnection errors, one issue is error detection, and the other is compensating for the situation. Monitoring the difference between the overall mean-field value and the mean-field value of each parking lot for detecting disconnection is suggested. As a solution, a new topology is proposed. Links connected to a disconnected parking lot now connect to a parking lot that is no longer receiving information. It is assumed that the communication links between all parking lots are established by default, but the network is based on a defined directed graph.

According to the circumstances, we will have two types of events in the system. The event is defined either for disconnection detection or sense of uncertainty existence in the parking lots. This study aims to solve the defined optimization problem repeated with the new information at discrete instants when the communication topology changes because of disconnection or the event-triggering condition meets.

In other words, this work presents a hierarchical event-triggered method that can identify disconnections directly and only through aggregators' information (mean-field values) and define it as an event in the communication network of the parking lots. Furthermore, our method can make the grid load curve smoother through the receding horizon idea of predictive control despite uncertainties in the number of EVs, energy production, or consumption load of the grid.

The main contributions of this paper can be summarized as follows.

- Disconnection detection of parking lots based on the mean-field game theory and predictive idea to optimize vehicle charging/discharging considering uncertainty in some vehicles, solar energy generation, and load demand
- Suggestion of a new topology in a time-varying network of parking lots considering the convergence.
- Implementing an event-based solution to reduce the computation volume.

The paper is organized as follows. The problem statement and system formulation are presented in Section 2. Section 3 addresses the online optimization scheme of parking lots. The simulation results are presented and discussed in Section 4, and finally, the conclusions are given in Section 5.

2. MATHEMATICAL MODEL OF EV AGGREGATION

2.1. Problem Description

Consider the charging coordination problem for a population of EVs that have been distributed in P different parking lots of residential buildings. Each EV (EV_n, $n \in N$) can be charged/discharged during some time slots $t \in T = \{1, \cdots, 24\}$. Every parking lot $p \in P$ has a local aggregator that can exchange information with some other parking lot aggregators through a communication network defined by time-varying directed graph $G(P, E)$, where P is the set of parking lots and E is the set of directed edges representing the communication links connecting these parking lots (Fig. 1) [36]. Self-loop is represented by $(p, p) \in E$, for $\forall\, p \in P$ and neighbor of parking lot p which sends information is shown by $(p, p') \in E$, for $\forall\, p' \in P$. The adjacency matrix associated with the communication graph is defined as $A = [a_{p,p'}] \in R^{p \times p'}$, where $a_{p,p'}$ denotes the connection between the parking p and parking p'. The element $a_{p,p'}$ is in (0, 1] if (p, p') in E, and zero, otherwise. Each vehicle controls its charged and discharged energy $q_{p,n}^{t} = [q_{p,n}^{C,t}\ \ q_{p,n}^{D,t}]^T$ and minimizes its objective function by satisfying constraints $0 \le q_{p,n}^{C,t} \le q_{p,n}^{C,\max}$ and $0 \le q_{p,n}^{D,t} \le q_{p,n}^{D,\max}$. $q_{p,n}^{C,t} > 0$ and $q_{p,n}^{D,t} < 0$

indicate charge and discharge of the battery from/to the grid, respectively when EVs are connected to the grid. $q_{p,n}^{C,\max}$ and $q_{p,n}^{D,\max}$ represent the maximum charging and discharging power of the battery, respectively.

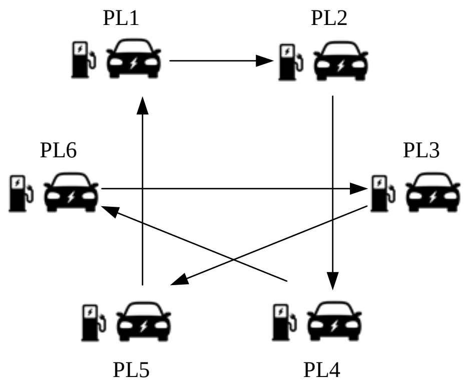

Fig. 1. Schematic of the proposed network of parking lots.

Also, $soc_{p,n}^{t}$ denoted the State of Charge (SoC) of the battery of EV n in parking lot p at $t \in T$ with dynamics defined as follows [37].

$$soc_{p,n}^{t} = soc_{p,n}^{t-1} + \frac{\gamma_{p,n}}{\delta_{p,n}} q_{p,n}^{C,t} - \frac{{\gamma_{p,n}}^{-1}}{\delta_{p,n}} q_{p,n}^{D,t}, \quad 0 \le soc_{p,n}^{t} \le 1, \tag{1}$$

where, $\gamma_{p,n}$ is the charging efficiency and $\delta_{p,n}$ is the battery size.

2.2. System cost function

The following optimization problem is solved for every EV $n \in N$ in each parking lot $p \in P$ in parallel for the next 24 hours to obtain an optimal response.

$$\begin{aligned} &\text{minimize } J_{p,n}(q_n, \bar{p}) \\ &\text{subject to } 0 \le soc_{p,n}^{t} \le 1 \\ &0 \le q_{p,n}^{C,t} \le q_{p,n}^{C,\max} \\ &0 \le q_{p,n}^{D,t} \le q_{p,n}^{D,\max} \\ &soc_{p,n}^{t} = soc_{p,n}^{t-1} + \frac{\gamma_{p,n}}{\delta_{p,n}} q_{p,n}^{C,t} - \frac{{\gamma_{p,n}}^{-1}}{\delta_{p,n}} q_{p,n}^{D,t} \end{aligned} \tag{2}$$

The cost function is defined as

$$J_{p,n}(q_n, \bar{p}) = \pi_{p,n}^{t}(p_{p,n}^{t}, \bar{p}^{t}) p_{p,n}^{t} + C_{p,n}(q_{p,n}^{t}) \tag{3}$$

$\pi_{p,n}^{t}(p_{p,n}^{t}, \bar{p}^{t})$ represents the function of energy price and is defined as follows.

$$\pi_{p,n}^{t}(p_{p,n}^{t}, \bar{p}^{t}) = a_{e,n}^{t} p_{p,n}^{t} + b_{e,n}^{t} \bar{p}^{t} + c_{e}^{t} \tag{4}$$

where, $a_{e,n}^{t}$ and $b_{e,n}^{t}$ are positive constants and c_{e}^{t} is the time-of-use pricing term, which could be different during the day. $\bar{p}$ represents the average consumption of all parking lots.

$$\bar{p} = \frac{1}{P} \sum_{p \epsilon P} \sum_{n \epsilon N} \frac{1}{N} p_{p,n} \tag{5}$$

$C_{p,n}(q_{p,n}^{t})$ is the battery degradation cost and is defined as

$$J_{p,n}(q_n, \bar{p}) = \pi_{p,n}^{t}(p_{p,n}^{t}, \bar{p}^{t}) p_{p,n}^{t} + C_{p,n}(q_{p,n}^{t}), \tag{6}$$

where, e and f are positive constant parameters [38]. Each residential building has non-EV electrical loads and also may be supplied by solar energy [39] as well. The amount of non-EV electrical loads is defined by $d_{p,n}^{t}$, which can be estimated for the next day. Therefore, the total load of the EV owner $n \in N$ in the parking lot $p \in P$ including the consumption of EV is as follows.

$$J_{p,n}(q_n, \bar{p}) = \pi_{p,n}^t(p_{p,n}^t, \bar{p}^t)p_{p,n}^t + C_{p,n}(q_{p,n}^t) \tag{7}$$

The goal of each EV owner is to minimize its cost function to obtain the optimal values of $q_{p,n}^{C,t}$ and $q_{p,n}^{D,t}$ over $X_{p,n} = \{(q_{p,n})|(1) \text{ and } (7)\}$.

Lemma 1: When $\pi_{p.n}^t(p_{p.n}^t, \bar{p}^t)$ increases over the feasible set $X_{p,n}$ in solution to the optimization problem, we will have $q_{p,n}^{C,t}\, q_{p,n}^{D,t} = 0$, $\forall t \in T$.

Proof. Proof is provided in [13].

3. ONLINE CONTROL SCHEME FOR TIME VARYING NETWORK OF EV PARKING LOTS

3.1. Hierarchical Mean Field Control

As mentioned, each parking lot has its aggregator which is connected to its neighbors. With common term $\bar{p}$ in the cost function of all EVs, information is exchanged only between EVs and their local aggregator. Each aggregator estimates the local mean-field value with the participation of neighboring aggregators for the next stage through a directed communication graph. Then aggregator broadcasts it to its EVs. This estimation helps the EVs to compute the best response of their cost function for the next iteration. This calculation continues in each parking lot's interaction with its local aggregator until all parking lots converge to a multi-population ε-Nash equilibrium [21].

Definition 1 (mean-field Nash equilibrium): A set of strategies $x^* \in X$ is a mean-field ε-Nash equilibrium with multi population and $\varepsilon > 0$, if for all $n \in N$ and $p \in P$ we have

$$J_{p,n}(x_{p,n}^*, \tfrac{1}{P}\sum_{p\epsilon P}\sum_{n\epsilon N}\tfrac{1}{N}x_{p,n}) \le \varepsilon + \min_{y\in X_{p,n}} J_{p,n}(y, \tfrac{1}{PN}y + \tfrac{1}{P}\sum_{n'\epsilon N-\{n\}}\tfrac{1}{N}x_{p,n}^* + \tfrac{1}{P}\sum_{p'\epsilon P-\{p\}}\sum_{n'\epsilon N-\{n\}}\tfrac{1}{N}x_{p,n}^*) \tag{8}$$

x^* is a multi-population Nash equilibrium if (8) holds with $\varepsilon = 0$.

Algorithm 1: ε-Nash equilibrium determination algorithm in several parking lots.

Initialization $k \leftarrow 1, \forall p \in P$
Iteration k
Optimization: for each $p \in P$
$x_{p,n}^*(z_p(k)) = \arg\min_{y\in X_{p,n}} J_{p,n}(y, z_p(k)),\ n = 1,2,\dots,N,$
$g(z_p(k)) = \frac{1}{N}\sum_{n=1}^{N} x_{p,n}^*(z_p(k)),$
Communication and update:
$z_p(k+1) = (1-\mu_k)\sum_{p'\in P} v_{p,p'}(k)\, z_{p'}(k) + \mu_k g(z_p(k)),$
$k \leftarrow k+1.$

Each local aggregator updates the local mean-field term by running the Krasnoselskii-Mann iteration [40, 41] and sends it to its EVs until they reach a consensus on the overall mean-filed term. This optimization algorithm is summarized in Algorithm 1 which is based on the mean-field method. Based on Algorithm 1, at the bottom level as solving the optimization problem, EVs in every parking lot calculate their optimal solution and each aggregator p calculates the local mean value $g(z_p(k))$. At the top level as communication and update, $z_p(k)$ is updated by aggregator p via exchanging information with neighboring aggregators. $v_{p,p'}(k)$ are elements of communication weights of adjacency matrix $V(k)$ of the communication graph G. The element $v_{p,p'}$ is in (0, 1] if (p, p') in V, and zero, otherwise. $z_p(k)$ and $z_{p'}(k)$ are the local mean-field estimations at iteration k by the local aggregator of parking lots p and p', respectively, and are broadcasted to their EVs. $\mu_k \in (0,1)$ is the learning rate such that $\sum_{k=0}^{\infty}\mu_k = \infty$ and $\sum_{k=0}^{\infty}{\mu_k}^2 < \infty$. The strategies of aggregators converge to the fixed point of $g(z_p(k))$.

It is proved that the aggregators reach a consensus on the overall mean-field term, $\bar{z}$, over the whole population after k iterations [20] where $\bar{z}$ is defined as follows.

$$\bar{z}^k = \frac{1}{P}\sum_{p=1}^{P} z_p(k) \tag{9}$$

For an infinite population of EVs, Algorithm 1 converges to the unique Nash equilibrium point of the game.

3.2. Event-based Predictive Optimization

Hierarchical optimization between local aggregators of parking lots based on the mean-field game is proposed to control the charging of EVs in networked parking lots. It is assumed that the number of vehicles in each parking lot and the daily power production profiles of solar panels vary every hour. Due to the uncertainties, the implementation of the receding horizon approach provides the required feedback to optimize the charge/discharge information every hour. These uncertainties could cause problems in grid reliability and therefore motivate one to solve the optimization problem online. This, however, could increase the complexity of the calculations when the number of EVs increases. Here, the use of an event trigger scheme could reduce the number of optimization runs significantly, i.e., the optimization is executed when an event condition such as uncertainties is detected. Besides, communication between aggregators may be disrupted through attacks or communication failure. Therefore, the parking lot aggregators will have a time-varying network and some of them may be disconnected for some hours and reconnected again. A disconnected communication problem will also be defined as an event. According to the parking lot conditions, two types of events are defined. The first event relates to uncertainty and the second depends on the disconnection between aggregators. The allowable range for the changes in the mean-field value of each parking lot including vehicles and local aggregator is defined. All changes outside the permissible range for the mean-field value of each parking lot are considered an event. The proposed event condition has the following form

$$z_p(t) - z_p(t-1) \le \alpha\, z_p(t-1), p \in P, 0 \le \alpha \le 1. \tag{10}$$

According to this rule, the threshold depends on the error of the estimated signals in the last two hours. The closer α is to one, the quality of the response is similar to offline conditions, and fewer events are detected in the system. When α is chosen near zero, more events are detected, and the volume of calculations increases, but the result is better. The optimization problem in (2) is performed when the event is identified based on real-time monitoring of the local mean-field values of each parking lot. This reduces the amount of computing and execution time and eliminates the need to perform optimization every hour. At the same time, the difference between the overall mean field value in (9) and the mean-field value of each parking lot is also monitored. If this difference is more than the permissible range, it will be assumed that a communication link has been broken. The proposed event condition has the following form

$$\bar{z}(t) - z_p(t) \le \beta\, \bar{z}(t), \;\; p \in P, \;\; 0 < \beta < 1. \tag{11}$$

According to this rule, the threshold depends on the error of the overall mean-field value and mean-field value of each parking. The parameter β can be selected between zero and one. As long as this condition is met, there is no disconnection between aggregators. This condition will not be fulfilled when there is no signal from one of the parking lots.

When a parking lot is disconnected, the related aggregator does not send the mean-field value to the neighboring parking lots. Therefore, the difference between the overall mean-field and the unreceived signal will be an indication of information loss. In this case, a new topology is replaced, and the optimization problem in (2) is run again for the new condition. Whenever the broken link is restored, the network topology is reset to the previous condition. Note that when an event occurs in one parking lot, the information of all connected parking lots is updated because of aggregator connections. In this implementation, the convergence of the mean value based on (9) has been confirmed.

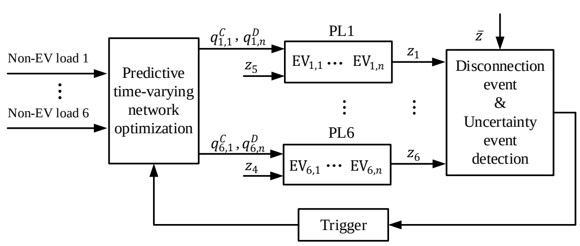

Fig. 2. Schematic of event-based predictive optimization.

Exactly the same as mentioned, Fig. 2 illustrates the proposed event-triggered scheme and how components relate to each other. When the event conditions are met, the optimization program will be executed. Therefore, the future requested charging of EVs in the parking lots is determined. Also, the mean-field values will be updated by local aggregators. Each aggregator optimizes its mean value and sends it again to the EVs under its control. Its mean value is optimized according to the optimal response of vehicles in the parking lot as well as the mean values of the neighboring parking lots, which is determined based on the communication graph. For example, as shown in Fig. 2, the first parking lot also receives information about the local mean value of the fifth parking lot. The sixth parking lot also uses the local mean-field value of the fourth parking lot in its calculations. Otherwise, if an event is not detected, the corresponding values of the previous hour will be used without running the optimization problem at the next sampling time.

The suggested optimization is explained in Algorithm 2. According to this algorithm, each parking lot p plans its optimal strategy, and the local aggregator estimates its mean-field value based on the communication graph at each iteration, and sends it back to EVs in parking lot p.

Algorithm 2: The proposed event triggered hierarchical mean filed algorithm.

Initialization $z(0)$, $k \leftarrow 0$, trig_num, $t = 1$, T_conv,
Optimization:
For $t = 1$,
For each $p \in P$
Iteration:
For $K \in T$_conv
For $n \in N_p$
$q_{p,n}^{*}(z_p(k)) = \arg\min J_{p,n}(q_{p,n}, z_p(k))$,
$n = 1,2,\cdots, N_p$,
$p_{p,n}^{*}(z_p(k)) = d_{p,n} + q_{p,n}^{C*}(z_p(k)) - q_{p,n}^{D*}(z_p(k))$,
End
$g(z_p(k)) = \frac{1}{N_p}\sum_{n=1}^{N_p} p_{p,n}^{*}(z_p(k))$,
$z_p(k+1) = (1-\mu_k)(\sum_{p' \in P} v_{p,p'}(k)\, z_{p'}(k)) + \mu_k g(z_p(k))$,
$k \leftarrow k+1$,
End
Monitoring:
while $\big(z_1(t) - z_1(t-1) \leq \alpha z_1(\mathrm{t}-1)\big) \& \big(z_2(t) - z_2(t-1) \leq \alpha z_2(\mathrm{t}-1)\big) \&$
$(z_3(t) - z_3(t-1) \leq \alpha z_3(\mathrm{t}-1)) \& (z_4(t) - z_4(t-1) \leq \alpha z_4(\mathrm{t}-1)) \&$
$\big(z_5(t) - z_5(t-1) \leq \alpha z_5(\mathrm{t}-1)\big) \& (z_6(t) - z_6(t-1) \leq \alpha z_6(\mathrm{t}-1))$
$\& (z(t) - z_1(t)) \leq \beta z(t)$
do
$p_{p,n}^{*}(z_p(k)) = d_{p,n} + q_{p,n}^{C*}(z_p(k)) - q_{p,n}^{D*}(z_p(k))$,
$lp(t) = \sum_{n=1}^{N_p} p_{p,n}^{*}(z_p(k))$, $t = 1,2,\cdots,24$,
$g(z_p(k)) = \frac{1}{N_p}\, lp(t)$
$z_p(k+1) = (1-\mu_k)(\sum_{p' \in P} v_{p,p'}(k)\, z_{p'}(k)) + \mu_k g(z_p(k))$,
Otherwise
Set $m = t$
Uncertainty event Trigger optimization:
For $t \in \mathcal{T}$
For each $p \in P$
$P = 1,2,\cdots,6$.
Iteration:
For $K \in T$_conv
For $n \in N_p$
$q_{p,n}^{*}(z_p(k)) = \arg\min J_{p,n}(q_{p,n}, z_p(k))$,
$p_{p,n}^{*}(z_p(k)) = d_{p,n} + q_{p,n}^{C*}(z_p(k)) - q_{p,n}^{D*}(z_p(k))$,
$t = m, \cdots, 24$, $n = 1,2,\cdots, N_p$,
End
$g(z_p(k)) = \frac{1}{N_p}\sum_{n=1}^{N_p} p_{p,n}^{*}(z_p(k))$,
$z_p(k+1) = (1-\mu_k)(\sum_{p' \in P} v_{p,p'}(k)\, z_{p'}(k)) + \mu_k g(z_p(k))$,
$k \leftarrow k+1$.
End
Set trig_num = trigg_num + 1.
Set $t = m$ **and back to monitoring**
Disconnection event Trigger optimization:
For $t \in \mathcal{T}$
For each $p \in P$
$P = 1,2,\cdots,5$.
Iteration:
For $k \in T$_conv
For $n \in N_p$
$q_{p,n}^{*}(z_p(k)) = \arg\min J_{p,n}(u_{p,n}, z_p(k))$,
$p_{p,n}^{*}(z_p(k)) = d_{p,n} + q_{p,n}^{C*}(z_p(k)) - q_{p,n}^{D*}(z_p(k))$,

$t = m, \cdots, 24, n = 1,2, \cdots, N_p,$
End
$g(z_p(k)) = \frac{1}{N_p} \sum_{n=1}^{N_p} p_{p,n}^*(z_p(k)),$
$z_p(k+1) = (1 - \mu_k)(\sum_{p' \in P} v_{p,p'}(k)\, z_{p'}(k)) + \mu_k g(z_p(k)),$
$k \leftarrow k + 1.$
End
Set trig_num = trig_num + 1.
Set $t = m$ **and back to monitoring**

Mean-field values of parking lots and overall mean-field value are monitored every hour for detecting uncertainties and communication disconnection that may occur in the system and computations are performed by the idea of feedback in MPC for the next hours. When the values exceed the pre-defined settings, the optimization program runs again. Otherwise, charging is performed according to the data obtained in the previous hours.

3.3. The Proposed Topology

As said before, communication between aggregators may be interrupted through attacks or communication failure. Therefore, the parking lot aggregators will have a time-varying network, and the links among them may be disconnected for some hours and reconnected again. It is proposed that disconnections can be detected by examining the difference between the overall mean-field value and the mean-field value of the disconnected parking lot. As a solution to remaining convergence conditions in the parking lots network, links to a disconnected parking lot from other parking lots will now connect to a parking lot that no longer receives disconnected parking information. Also, it is assumed that the information is sent by the aggregators concurrently. A case study is described for clarifying and simulated as follows. Consider parking lot 1 calculates z_1 based on its information and information of parking lot 5 according to (9) and sends it to parking lot 2. Now consider that the communication signal between these two parking lots (1 and 5) is cut off which could be detected by the value of $\bar{z} - z_1$. Therefore, based on the proposed topology, z_5 is sent to parking lot 2 as the received signal of parking lot 1. In this example, parking lot 1 had only one received signal from other neighboring parking lots (parking lot 5). This issue can be expanded to all incoming values to disconnected parking lot and will be sent to the parking lot that no longer receives the information. In disconnection status, five parking lots exchange information with each other and reach a consensus. When a connection is interrupted, information about the interrupted parking lot is updated locally, but it is not able to communicate it. When the connection is reestablished, the parking lots network will return to the previous topology with six parking lots. It is assumed that the communication links exist between all parking lots, but information exchange is based on a communication graph. The equations of the mean-field of each parking lot are given in Algorithm 1. According to this algorithm, the final value of the Nash equilibrium point should converge to the overall mean field value of $\bar{z}$.

In this study, the link disconnection of parking lots 1, 2, and 6 is investigated randomly. The topology of the parking lots' communication at the time of disconnection of parking lots 1, 2, and 6 is shown in Fig. 3.

When all parking lots exchange information with each other, the following equations could be considered for example for z_1 and z_2.

$$z_1(k+1) = (1 - \mu) z_5(k) + \mu \frac{1}{N_1} \sum_{n=1}^{N1} p_n^*\big(z_1(k)\big) \tag{12}$$

$$z_2(k+1) = (1 - \mu) z_1(k) + \mu \frac{1}{N_2} \sum_{n=1}^{N2} p_n^*\big(z_2(k)\big) \tag{13}$$

Now assume that z_1 is not received by parking lot 2 due to a disconnection between these two parking lots. Thus, instead of z_1 in (13), z_5 could be used in disconnected hours. This is shown in the following equations.

$$z_1(k+1) = \omega z_1(k) + \nu z_1(k-1) \tag{14}$$

$$z_2(k+1) = (1 - \mu) z_5(k) + \mu \frac{1}{N_2} \sum_{n=1}^{N2} p_n^*\big(z_2(k)\big) \tag{15}$$

In fact, parking lot 1 uses a linear combination of its previous data during the disconnection hours (14) and parking lot 2 uses data from parking lot 5 (15). After reconnection, the previous equations, i.e. (12) and (13), are used again in the optimization. Fig. 3.a is explained in Algorithm 3 to clarify the proposed topology.

Algorithm 3: Topology change algorithm when disconnecting between two parking lots.

Initialization $k \leftarrow 1, \forall p \in P$
Iteration k

Disconnected: P1 from P2 $\in P$
Connected: P5 to P2 $\in P$
P1: $z_1(k+1) = \omega z_1(k) + \nu z_1(k-1)$
P2: $z_2(k+1) = (1-\mu)z_5(k) + \mu \frac{1}{N_2} \sum_{n=1}^{N2} p_n^*(z_2(k))$
Reconnected: P1 connected to P2 again
P1: $z_1(k+1) = (1-\mu)z_5(k) + \mu \frac{1}{N_1} \sum_{n=1}^{N1} p_n^*(z_1(k))$
P2: $z_2(k+1) = (1-\mu)z_1(k) + \mu \frac{1}{N_2} \sum_{n=1}^{N2} p_n^*(z_2(k))$
$k \leftarrow k+1.$

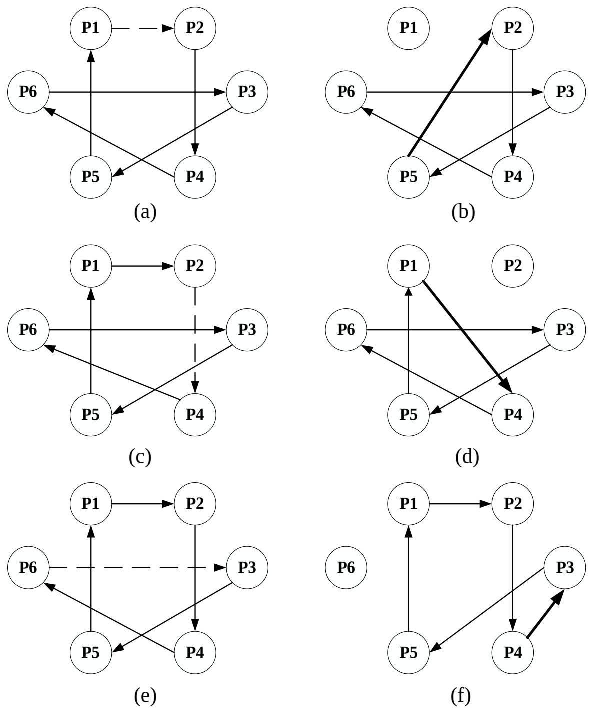

Fig. 3. a) Link disconnection between P1 and P2, b) Instead of P1, P5 is connected to P2, c) Link disconnection between P2 and P4, d) Instead of P2, P1 is connected to P4, e) Link disconnection between P3 and P6, and f) Instead of P6, P4 is connected to P3.

3.4. Convergence

Based on Theorems 1 and 2 in [21], the local mean-field terms in this work reach a consensus. The weighted adjacency matrix of the communication graph of parking lots is doubly stochastic, and the union of the time-varying connection graphs is strongly connected over a finite horizon.

Assumption 1: The weighted adjacency matrix V is doubly stochastic, i.e.

1) $v_{p,p'} \geq 0$,
2) $\sum_{p' \in P} v_{p,p'} = 1$, for all $p \in P$,
3) $\sum_{p' \in P} v_{p',p} = 1$, for all $p \in P$,
4) $\exists\, \eta \in (0,1)$: $v_{p,p'} \geq \eta$ for all $(p, p') \in E$.

At the time of disconnection of one parking lot, other parking lots will converge according to the proposed topology, and the disconnected parking lot data is updated using a linear combination of its previous data. In this paper, ω and ν in (14) are considered 1 and 0, respectively. When the connection is resumed, all parking lots will converge together because convergence does not depend on their initial conditions. Of course, the value of the convergence points will be slightly different in these two cases due to the temporary loss of the disconnected parking lot data.

4. SIMULATION RESULTS

In this simulation, six parking lots are considered with an unknown variable number of vehicles per hour, such that an average of 100 vehicles is considered in each parking lot. The number of vehicles in each parking lot is allowed to decrease/increase by 20% around the average value. Vehicles belong to three groups: Fisker, Nissan, and Toyota. They have different battery capacities {22, 24, 27} and maximum charge/discharge rates per hour {4-6} [42, 43]. The initial charge of the vehicles is also selected as a variable. Vehicles are either charged or discharged. The parameters of EVs are given in Table 1.

Table 1. Parameters of EVS and network price [11].

Parameter	Value	Description
e	1.2	Battery degradation cost parameter
f	0	Battery degradation cost parameter
δ	{22,24,27}kW	Battery capacity size
γ	0.95	Charging efficiency
SoC	[0 1]	Lower and upper level on SOC
a_e	1000	Price coefficient
b_e	13.5	Price coefficient
c_e	0	Price coefficient

The profile of solar panels and non-EV electrical loads have been taken from [44] and [45]. In order to run the algorithm, we assign $\mu_k = 0.3/k$ where k is associated with the iteration number. Also, according to simulation results, we select $\alpha = 0.1$ and $\beta = 0.25$.

To check the disconnection status between the parking lots and detect the disconnection, following scenario is simulated. It is assumed that parking lots 1, 2, and 6 do not send information at some distinct times. Parking lot 1 is cut off at 7 a.m., 8 a.m., and 2 p.m. and does not send data to parking lot 2. Parking lot 2 is cut off at 11 a.m., 12 a.m., and 8 p.m. and does not send data to parking lot 4, and parking lot 6 is cut off at 6 a.m., 5 p.m., and 6 p.m. and does not send data to parking lot 3. The connection and disconnection times of parking lots 1, 2, and 6 are shown in Fig. 4.

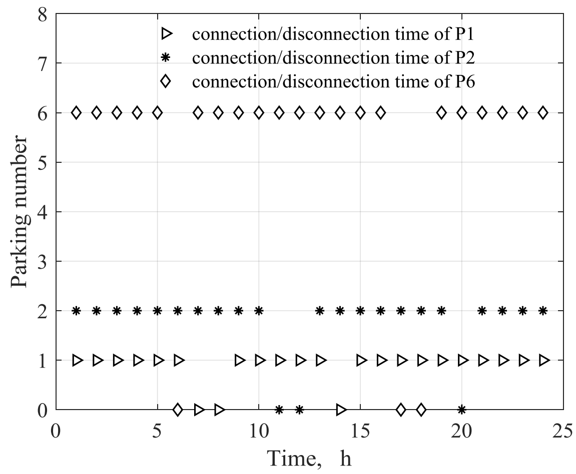

Fig. 4. Connection and disconnection times of parking lots 1, 2, and 6.

This scenario has been simulated in two cases. When disconnection is not detected and when it is detected. In the remaining hours, the connection between parking lots 1 and 2 is established, and the optimization process is carried out with the previous network structure. During the disconnection, the network topology is modified as described before to reach the convergence. Considering the difference in the mean values at the time of disconnection, the optimization program is run again. Therefore, the number of events increases according to the number of interruptions. In this case, it increases from 6 to 9 events. The advantage of having two different signals from the parking lots not only enables the detection of uncertainties but also the communication status between the parking lots and the information exchanged between them could be updated. The simulation results are shown in Figs. 5 to 7.

By detecting the disconnection, the charging and discharging values of the vehicles will be closer to the actual values due to optimization. During connected hours, the parking lots topology is fixed but during the disconnected hours we will have modified topology.

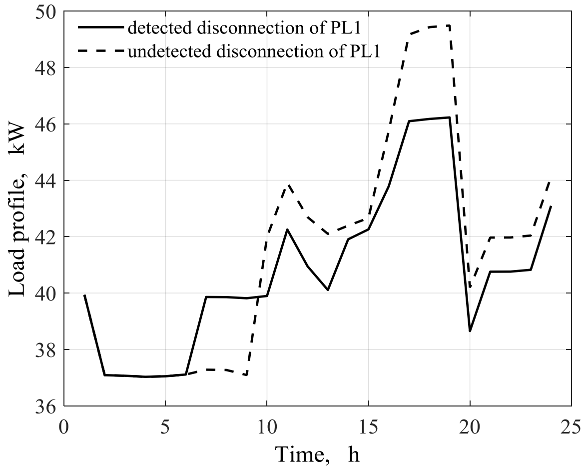

Fig. 5. Simulation results for parking lot 1 in detected and undetected disconnection.

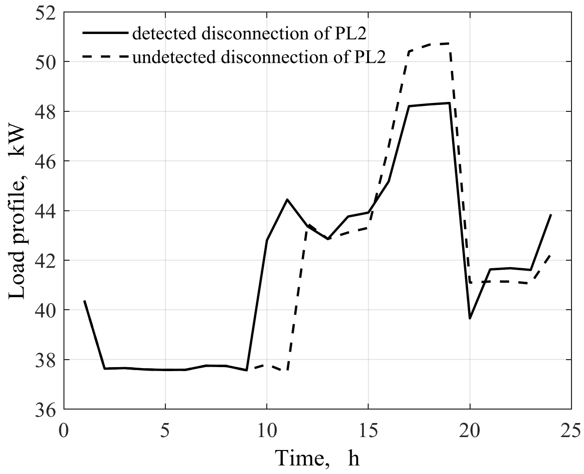

Fig. 6. Simulation results for parking lot 2 in detected and undetected disconnection.

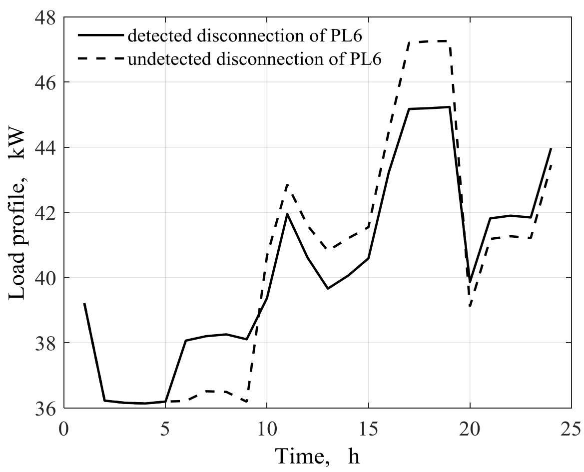

Fig. 7. Simulation results for parking lot 6 in detected and undetected disconnection.

Fig. 8 shows the convergence of five parking lots when parking lot 1 is disconnected at 8 a.m. This situation is recognized, and the optimization program is executed with the modified topology. There is a time-varying network between the parking lots. Parking lot 1 does not receive information, and information about parking lot 5 is sent to parking lot 2 (Fig. 3b). Meanwhile parking lot 1 uses its previous hour data to solve the optimization.

Fig. 9 also shows the convergence of six parking lots after the reconnection of parking lot 1 at noon. In this case, the network topology will return to its previous state, and all six parking lots will converge. Fig. 10 shows the standard deviation values (σ) for each of the six parking lots in detected and undetected disconnection optimization.

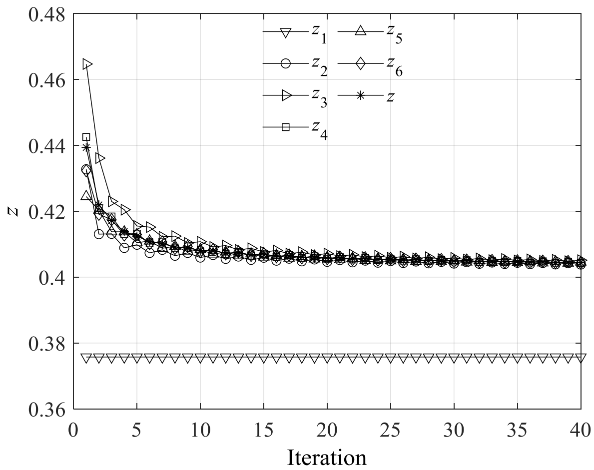

Fig. 8. Simulation results for parking lot 1 in detected disconnection at 8 a.m. and convergence of other parking lots.

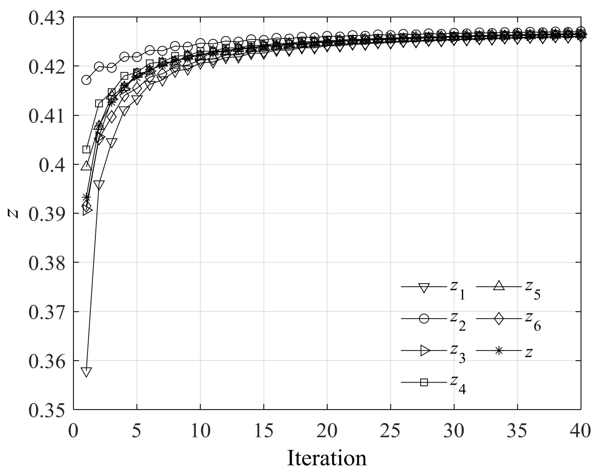

Fig. 9. Simulation results for parking lot 1 in connected condition at 12 and convergence of all parking lots.

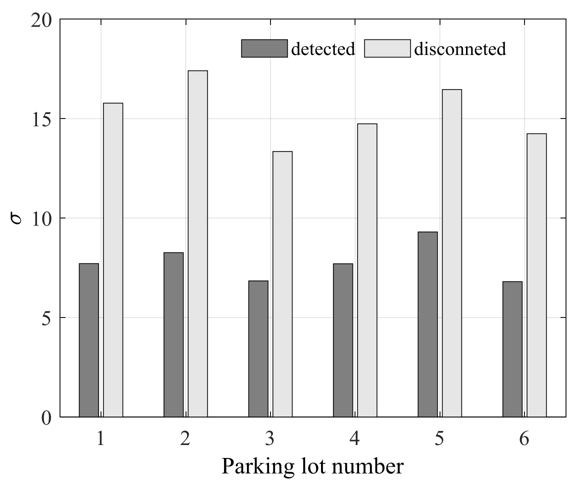

Fig. 10. Variance values of different parking lots in detected disconnection and undetected disconnection.

The simulations were performed using MATLAB version R2014a in a computer with the following specifications: Processor: Intel Core™ i5-2500 CPU @ 3.30 GHz 3.30 GHz, Installed memory (RAM): 4.00GB (3.49

GB usable), System type: 32-bit operating system.

5. CONCLUSIONS

Due to the unknown number of electric vehicles in parking lots and the uncertainty of solar energy generation, electric vehicle charging and discharging optimization is implemented online through mean-field game theory and the receding horizon scheme of MPC. Executing an optimization program every hour causes an increase in the volume of calculations, so the event trigger idea is suggested. In the meantime, the disconnection of the parking aggregators is also raised along with the existing uncertainties. Several distributed event-triggered control methods introduced recently, generally require state estimators to calculate the event-triggered error, the latest states, and the threshold which increases the computation cost. However, the proposed event-triggered control method only requires parking lots mean-field values to compute the event-triggered conditions, which has a low computational cost.

Since it is not possible to make a definitive diagnosis by only checking the mean-field value of each parking lot, it is suggested to use also the difference between the mean-field values of parking lots and the overall mean-field value to determine the disconnection of the communication links. In this case, the optimization program is executed again. Actually, this paper is facing two types of events in the system: one related to uncertainties and another related to disconnections. So, the optimization is done again according to uncertainty detection or communication disconnection in the parking lots. At the time of the link disconnection, a new topology is proposed for the disconnected parking lot and the neighboring parking lots in connection with it. Considering that the communication between aggregators is strongly connected and only at certain hours this communication link is interrupted, the issue of convergence in this system is established.

Data Availability. Data underlying the results presented in this paper are available from the corresponding author upon reasonable request.

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Conflicts of interest. The authors declare no conflict of interest.

Ethics. The authors declare that the present research work has fulfilled all relevant ethical guidelines required by COPE.

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