A Decentralized Deadline-Driven Electric Vehicle Charging Recommendation

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Abstract—The electric vehicle (EV) industry has been rapidly developing internationally due to a confluence of factors, such as government support, industry shifts, and private consumer demand. Envisioning for the future connected vehicles, the popularity of EVs will have to handle a massive information exchange for charging demand. This inevitably brings much concern on network traffic overhead, information processing, security, etc. Data analytics could enable the move from Internet of EVs to optimized EV charging in smart transportation. In this paper, a mobile edge computing (MEC) supporting architecture along with an intelligent EV charging recommendation strategy is designed. The global controller behaves as a centralized cloud server to facilitate analytics from charging stations (CSs) (service providers) and charging reservation of on-the-move EVs (mobile clients) to predict the charging availability of CSs. Besides, road side units behave as MEC servers to help with the dissemination of the CSs' charging availability to EVs, and collecting their charging reservations, as well as operating decentralized computing on reservations mining and aggregation. Evaluation results show the features of the MEC-based charging recommendation system in terms of communication efficiency (low cost for information dissemination and collection) and improvement of charging performance (reduced charging waiting time and increased fully charged EVs).

Index Terms—Charging recommendation, electric vehicle (EV), mobile edge computing (MEC), Vehicle-to-Infrastructure.

I. INTRODUCTION

THE introduction of electric vehicles (EVs) [1] will have a significant impact on the sustainable economic development of urban cities. However, even if there have been charging service providers available, the utilization of charging infrastructures is still in need of significant enhancement. Such a situation certainly requires the popularity of EVs toward the sustainable, green, and economic market. Enabling the sustainability requires a joint contribution from each domain, e.g., how to schedule charging services for EVs being parked within the grid capacity, how to optimally recommend EV drivers toward the charging station (CS) with the least waiting time, and how to guarantee accurate information involved in decision making.

Unlike many previous works [2] that investigate "charging scheduling" (referred to when/whether to charge) for EVs already been parked at CSs, a few recent works focus on "charging recommendation" (refer to where/which CS to charge) [3] for on-the-move EVs. The latter case has been the most important feature of improving the charging Quality of Experience (QoE), as applied by operators. Thus, it is important to optimally recommend EV drivers regarding where to charge, concerning the service waiting time.

Literature works [4]–[8] have addressed the charging recommendation to improve the charging QoE (e.g., to reduce the service waiting time for charging). Usually, the local condition of CSs (e.g., number of EVs being parked and their remaining charging time) [7] is considered to make a charging recommendation decision. Further advanced solutions utilize the EV's charging reservation [1], [9]–[11] to align with the local condition of CSs. By doing so, it can be predicted at what time and which CS will be congested, so as not be recommended for charging. Here, the charging reservation includes the arrival time (when an EV will arrive at the recommended CS) and the expected charging time at the selected CS (how long its charging time will be).

Practically, EV drivers would also have their parking deadline [11] at CSs (e.g., drivers might be impatient to wait for a long time, or have another daily agent after a certain period of charging). Particularly, in the case of charging during peak time, already deployed charging slots at CSs may not be sufficient to handle such an urgent charging demand (due to limited parking duration). Inevitably, an inappropriate charging recommendation would degrade the charging QoE, as some EVs will have to leave after the deadline even though they have not been charged. Consequently, charging will involve additional effort and energy consumption; such an inconvenience would, however, discourage the willingness to switch from traditional vehicles to EVs.

The centralized cloud (CC) based system [12] is widely applied in the literature for charging recommendation. Such a system generally relies on ubiquitous cellular network and real-time information for optimization. For example, previous work [11] adopted a cloud-based global controller (GC) connecting to all

CSs. Whenever an EV requires charging, it will send a request to the GC through the cellular network seeking the best CS recommendation, and further reports its charging reservation. By facilitating the anticipated EV charging recommendation, the charging availability of the CS can be predicted, so that the cloud will not recommend a CS with low availability.

However, by seamlessly collecting information from EVs and CSs, it is very time consuming for the GC to achieve optimization. The complexity and computation load of the cloud server increases exponentially (depends on those who currently request charging and those who have made charging reservations) with the number of EVs. Moreover, the cellular network is costly and sometime overcongested due to massive accesses, which degrades the quality of communication. The rapid growth of mobile applications has placed severe demands on the cloud infrastructure, which has led to moving computing and data services toward the edge of the cloud, resulting in a novel mobile edge computing (MEC) [13] (also known as fog computing) architecture being developed by the European Telecommunications Standards Institute (ETSI) and creating a new Industry Specification Group in 2014 for this purpose. MEC could reduce data transfer times, remove potential performance bottlenecks, and increase data security and enhance privacy while enabling advanced applications.

As such, in the case of EV charging, a decentralized charging recommendation with the assistance of MEC servers positioned close to EVs is desirable. Apart from the cellular network, a cheaper solution nowadays is the deployment of fixed road side units (RSUs) [14] based on license-free spectrum such as Wi-Fi, but only with limited network coverage. Future intelligent transportation systems (ITS) [15] will necessitate infrastructure-assisted communication for EV charging perspective in addition to road safety perspective. In [10], a decentralized MEC-based information communication technology (ICT) framework has been proposed where it facilitates the RSUs (with MEC servers) to perform information caching, aggregation, and lightweight processing (e.g., access control and information mining); system level communication cost within the charging recommendation system can be reduced. Besides, by cooperating with the cloud server GC, deployed RSUs also help to disseminate and collect information between CSs and EVs ubiquitously.

Understandably, the integration of ICT, transport, and energy is important for the attainability of EV charging [16], [17]. This paper mainly tackles a joint study of former transport planning and ICT, whereas the integration of energy substainability (e.g., smart charging, scheduling of renewable energy) is out of the scope. Beyond the ICT effort investigated in [10], we further take the impact of parking deadline and the decentralized ICT framework into account for the EV charging recommendation decision. More specifically, the EV's parking deadline will influence the estimation of CSs' charging queueing and prediction of their charging availability (in line with EVs' charging reservations collected through the positioned MEC architecture). In particular, the proposed solution on predicting the charging availability is decoupled and associated with a number of time intervals (within a dynamically updated time window). Such a feature benefits the accuracy of the charging recommendation, bounded by a prediction time window and EV mobility.

II. RELATED WORK

A. Cloud/Mobile Edge Computing in Smart Transportation

Smart transportation can fundamentally change urban lives at many levels. Data from service providers and users bridged via a ubiquitous, dynamic, scalable, and sustainable ecosystem would offer a wide range of benefits and opportunities. Most of the existing techniques require a high processing time using conventional methods of data processing [18]. Therefore, the techniques are desirable to efficiently process the data generated from stakeholders, ideally from a distributed manner through ubiquitously disseminated and collected information.

The major difference between cloud computing [12] and MEC [13] is in the location awareness to support application services. This is because the cloud server locates in a centralized place and behaves as a centralized manager to perform computation tasks. Note that MEC servers at different locations can be owned and managed by separate operators and owners. With the collaboration among different operators, they can form a collaborative and decentralized computing system in a wide region.

B. EV Charging Recommendation

As reviewed by the most recent survey [3], fruitful literature works have addressed "charging scheduling" [2], via regulating the EV charging, such as minimizing peak load/cost, flattening aggregated demands, or reducing frequency fluctuations.

In recent years, the "charging recommendation" problem has started to gain interest from industries thanks to the popularity of EVs. The generic solutions [4], [7] make decisions based on the queueing information at CSs, and the one with the minimum queueing time is recommended. This feature has been evaluated in [5] against the charging recommendation just taking the closest distance to the CS; the former is deemed as an effective guidance in an urban city with limited charging infrastructures. The charging recommendation solution in [8] adopts a pricing strategy to minimize congestion and maximize profit, by adapting the price depending on the number of EVs charging.

Beyond that, the integration of the ICT and energy network is of importance for the sustainability of EV charging, where a set of works have addressed the constraint of energy network and study its impact. From the ICT aspect, additional communication signaling is built to support the advanced charging recommendation and brings the anticipated EVs mobility information (charging reservations). The work in [9] concerns a highway scenario where the EV will pass through all CSs. The expected charging waiting time is calculated for the EV passing through the entire highway, by jointly considering the charging waiting time at a CS where the EV needs charging for the first time and the time spent at subsequent CSs, before exiting the highway. Other works [1], [10], [11] focus on urban city scenarios, where the EV travels toward a single geographically distributed CS for

charging. The expected waiting time for charging is associated with that CS, rather than a subsequent charging in the case of the highway.

III. PROVISIONING OF MEC-BASED CHARGING RECOMMENDATION SYSTEM

In this section, we mainly introduce entities and system signaling of the proposed MEC-based system, together with an analysis on its advantage.

A. Charging System Cycle

Driving: This happens when the EV is traveling on the road (following a route in the city).

Charging Recommendation: If an EV's remaining electricity is below the state of charge (SOC) threshold value, the charging recommendation is required to guide it on where to charge.

Charging Scheduling: This happens when EVs have reached a CS. The CS implements a certain policy to schedule which EV is to be charged. Here, the first come first serve (FCFS) is widely applied in the problem of charging recommendation, where the EV with the earliest arrival time is scheduled as the highest priority.

Battery Charging: This phase reflects a continuous procedure to charge EVs, until they are fully charged. After that, those fully charged EVs will resume to the *Driving Phase*.

Typically, the system is a status transfer within four phases, while the *Charging Scheduling* has been extensively covered by the literature. The focus of this paper is on *Charging Recommendation* with interdisciplinary efforts from ICT.

B. Network Entities

1) *Stakeholders:* The EV below the SOC threshold (a value under which the EV should seek charging) needs to find a CS for charging. As long as the EV has been recommended to charge at a CS, the EV further reports its charging reservation associated with that CS.
   The CS is equipped with a number of plug-in charging slots to charge multiple EVs in parallel. Particularly, its local queuing information is monitored by the cloud server GC to compute the charging availability. This refers to the earliest time when a charging slot of the CS is unoccupied.
2) *Cloud server:* It is a logical server that is built and delivered through a cloud computing platform over CSs and EVs. Here, the GC manages the CSs' charging availability, based on the monitored CSs' local queueing information, and EVs' charging reservations (collected by MEC servers).
3) *MEC server:* The MEC servers collected at RSUs provide a set of middle-ware services associated with applications, wherein it implements two key operations as follows.
   a) Disseminate CSs' charging availability (computed by the GC) to EVs.
   b) Enable information mining and aggregation (complementarily with authentication) for opportunistically collected EVs' charging reservations.
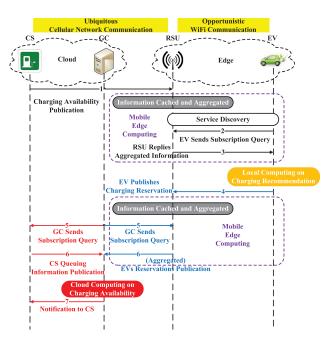

Fig. 1. Signaling process for the MEC-based system.

TABLE I
COMMUNICATION TECHNOLOGIES IN MEC- AND CLOUD-BASED SYSTEMS

	GC↔MEC Server	GC↔CS	MEC Server↔EV	GC↔EV
MEC-based System	Internet, Cellular network	Internet, Cellular network	WiFi communication	N/A
Cloud-based System	N/A	N/A	N/A	Cellular network

C. Communication Technologies

As shown in Fig. 1, the communication technology applied between GC and CSs can be simply based on reliable Internet or cellular network, mainly because they are fixed network entities. However, there is a necessity to scalably and ubiquitously disseminate CSs' charging availability (computed by the GC) to EVs, and collect EVs' charging reservations. Although 3G/LTE can be applied thanks to ubiquitous coverage, EVs' charging requests are just on-demand, whereas CSs charging availability is fluctuated within certain periods (e.g., minutes level). Besides, EVs' charging reservations are generated only when they have been given the charging recommendation. This motivates the application of short-range and on-demand communication with EVs. Motivated by the above-mentioned discussion, the opportunistic communication paradigm, e.g., delay/disruption tolerant networking [19], between EVs and MEC servers is desirable, which alleviates the burden of solely relying on the cellular network. Table I summarizes communication technologies in MEC- and cloud-based systems.

Furthermore, rather than using the point-to-point-based communication, the topic-based communication (e.g., publish/subscribe pattern [20]) mainly offers communications decoupled in space that subscribers do not need to know the

TABLE II
TOPICS DEFINED IN THE MEC-BASED SYSTEM

Topic	Publisher	Subscriber	Payload
CA_Update	CS	RSUs	<CS ID, CS's charging availability, dissemination time slot>
Aggregated_CA_Update	RSUs	EVs	<Aggregated CS IDs and CSs' charging availability, dissemination time slot>
Charging_Reservations_Update	EVs been recommended charging	RSUs	<EV ID, parking duration, arrival time, expected charging time>
Aggregated_Charging_Reservations_Update	RSUs	GC	<Aggregated EVs' reservations cached by RSUs>
Local_Queuing_Update	CSs	GC	<CS's local queuing information, including number of EVs being parked at CS and their charging time>
CA_Prediction	GC	CSs	<Predicted charging availability of each CS>

location and address of publishers and vice versa. It is potentially in time as the system is able to store events for clients who are temporally disconnected.

The solutions to achieve trusted message exchange for the case of EV charging is to encrypt the sensitive information and hide the real identity. One development aspect of the encryption involves the light-weight and highly secured encryption algorithm, while another one is to design an efficient and scalable key management scheme. As for the privacy, a pseudonym is proposed to hide the identities. This includes the pseudonym changing algorithms and pseudonym reuse schemes, both are required to be implemented in efficient and scalable manners. The future challenges based on the MEC system are considered based on the nature of a large number of connected EVs, high mobility, wide coverage area, and heterogeneous communication systems.

D. Proposed MEC-Based System

It is assumed that the locations of all CSs are already known by EVs, e.g., through the vehicle on-board unit. Here, EVs access CSs' charging availability from MEC servers, make a local charging recommendation, and further report charging reservations (through MEC servers to the GC). The GC analyzes the EVs' charging reservations together with CSs' local queuing information to predict the CSs' charging availability. Fig. 1 illustrates a typical procedure.

Step 1: The GC periodically (with time interval Δ) disseminates its computed CSs' charging availability to all legitimate MEC servers (positioned at RSUs), via "*CA_Update*" topic defined in Table II. RSUs further aggregate the information from all CSs and get cached. Note that the information disseminated at the previous Δ, which to be further cached at MEC servers, will be replaced with the one that associates with the current Δ. This guarantees the information accuracy involved for charging recommendation. The RSU receiving the dissemination from all CSs will aggregate and cache their information.

Steps 2 and 3: Upon encountering an RSU, the EV would subscribe to the cached information from the RSU through the P/S system. In particular, the EV only subscribes to the information that is recently published using the "*Aggregated_CA_Update*" topic. This reduces the redundant access signaling, particularly when an EV frequently encounters several RSUs in a short time (still within the current dissemination interval Δ). For example, if an EV has already obtained information from RSU_1 within
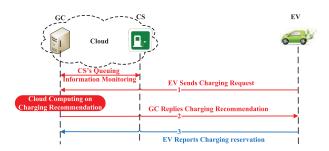

Fig. 2.   Signaling process for the CC-based system.

interval Δ, its subscription will be denied by RSU_2 within the same interval.

Step 4: The EV makes a charging recommendation in the case of low energy status and publishes its charging reservation to any encountered MEC server along the road. Here, the "*Charging_Reservations_Update*" topic is applied, with the EV as publisher and RSUs (MEC servers) as subscribers. Each RSU mines the valid EV's charging reservation and aggregates them. The valid charging reservation refers to that of which EV's arrival is supposed to be later than ($\Delta + \mathcal{P}$), where $\mathcal{P}$ is the time slot of the previous dissemination. This is because an EV's reservation will be deleted by its selected CS when it is parked therein. Then, any arrival occurring before the next dissemination will be removed from RSUs; this potentially reduces the size of data to be uploaded to the GC.

Steps 5 and 6: At the GC side, it sets two separate topics to collect information from CSs and RSUs.

1) The local condition of CSs includes the number of EVs being parked and their required battery charging time. This is accessible by sending a subscription via the "*Local_Queuing_Update*" topic.
2) The GC also accesses the aggregated EVs' charging reservations from all RSUs, using the "*Aggregated_Charging_Reservations_Update*" topic.

Step 7: The GC then predicts the charging availability of CSs and pushes them for dissemination at the following time slot, using the "*CA_Prediction*" topic.

E. Other Alternative Systems

1) CC-Based System: It is implemented in a centralized manner in the cloud system, as shown in Fig. 2.
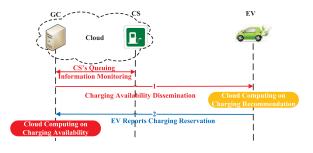
Fig. 3.   Signaling process for the DC-based system.

Step 1: The EV, which needs charging, sends its charging recommendation request to the GC through the cellular network.

Step 2: Upon receiving the request from an EV, the GC makes a charging recommendation based on the intelligence proposed in Section IV, and further replies back to the pending EV.

Step 3: The EV that accepts the decision, then starts a journey toward the recommended CS. Meanwhile, it reports its charging reservation to the GC, so that the GC can estimate the occultation of the reserved CS in the near future.

2) Decentralized Cloud (DC) Based System: This is the distributed version of the CC-based system (based on cellular network), as shown in Fig. 3.

Step 1: Each CS periodically (with interval Δ) broadcasts its charging availability to all EVs, also through the cellular network communication. This mechanism also equals the case that each EV subscribes to CS's charging availability from the GC, through topic-based P/S communication, where there is no RSU involved to help decentralize the global computation.

Step 2: The EV individually makes charging recommendation and reports its charging reservation to the GC through the same communication channel. Upon directly receiving the EV's charging reservations and continuously monitoring the CSs' local queuing information, the GC predicts the charging availability of CSs and notifies them for dissemination the next time around.

F. Discussion

Denoting N_{ev}, N_{mec}, and N_{cs} as the number of EVs, MEC servers, and CSs, respectively, the communication costs of the MEC- and cloud-based systems are analyzed as follows.

MEC-Based System: As shown in Fig. 1, the delay is mainly from the time for the EV to encounter an RSU, as the communication between RSUs and GC is through cellular network or Internet. Therefore, the dissemination cost is scaled by $O(\Theta \times N_{ev})$; recall that Θ is the possibility that an EV encounters at least one of N_{mec} RSUs [10]

$$\Theta \leq 1 - \prod_{i=1}^{N_{mec}} \left\{ 1 - \left[\frac{(i-1)X + F + R}{S \cdot \Delta} \right] \right\} \quad (1)$$

where X is the distance between adjacent RSUs, and S is the EV speed, R is the V2I communication range, while F is a constant that shows the distance from the EV to the first RSU. Note that R depends on the transmission power and other practical

configurations at the EV side, as it is the initiator to establish communication with the RSU for information subscription.

Next, concerning aggregated EVs' reservations uploading to the GC before $(\Delta + \mathcal{P})$, the reservation cost is scaled by $O(\frac{N_{mec}}{\Delta})$, as the communication is established from N_{mec} RSUs within interval Δ. As such, excluding the deployment of RSUs, in nature, a larger N_{ev} drives the sustainable communication efficiency for the long-term popularity of EVs.

CC-Based System: The GC experiences a cost of $O(N_{ev})$ for handling the charging requests/reservations from N_{ev} EVs.

DC-Based System: The GC experiences a cost of $O(\frac{N_{ev}}{\Delta})$ for periodically disseminating the CS's charging availability, and $O(N_{ev})$ for handling EVs' charging reservations.

The CC-based system suffers from privacy concerns, in which the driving behavior (e.g., location) has to be included when communicating with the GC (see Step 1 in Fig. 2). Besides, the DC-based system does not involve MEC servers; it, however, relies on the broadcast communication feature under the environment of a ubiquitous cellular network. This is much expensive than the MEC-based system, as the latter just requires a short-range wireless communication network between MECs servers and a large number of EVs. In reality, the number of RSUs is less than that of EVs, given by $(N_{mec} \ll N_{ev})$. However, the number of charging services is higher than the actual number of EVs N_{ev}. This is because each EV needs to charge more than once. This claims the communication efficiency of MEC-based system over CC-based system.

IV. DESIGN OF CHARGING RECOMMENDATION

Previous works [9], [11] have proposed the formulation on how to minimize the charging waiting time for all EVs in the network. Generally, an even distribution of EVs among CSs contributes to the minimized charging waiting for EVs. In the following part, the proposed charging recommendation solution is presented through the decentralized manner that is applicable to the MEC-based ICT framework. Note that the proposed solution focuses on how to distribute EVs among all CSs in a decentralized manner (through the ICT framework), while any user-driven solution by taking into consideration the trip destination and pricing will be of interest in further studies.

In Fig. 4, the CS's charging availability is predicted without/with EVs' charging reservations (shown in Table IV), as detailed in Algorithm 3 (requires the estimation of CS's local queuing from Algorithm 2) and Algorithm 4, respectively. Then, Algorithm 1 will produce the CS's charging availability associated with each time slot, where these time slots are decoupled from an estimation time window $\mathcal{W}$. With this knowledge disseminated from CSs, the EV locally makes a charging recommendation, via the output of Algorithm 5.

As the estimation of charging availability per CS depends on whether there have been EVs remotely reserved for charging, such complexity is $O(N_{ev}^2)$ since both the EVs locally parked and those remotely reserved are considered in Algorithm 4. In Algorithm 3, the complexity is $O(N_{ev})$ as there is no EV reserved for charging. All notations are defined in Table III.
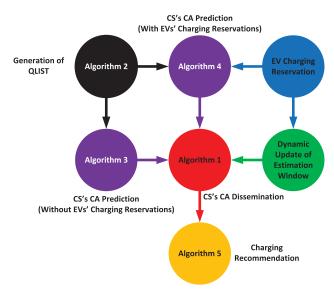
Fig. 4.   Process flow of charging recommendation.

TABLE III
LIST OF NOTATIONS

Δ	Charging availability dissemination interval
S_{ev}	Moving speed of EV
α	Electric energy consumed per meter
T_{cur}	Current time in the network
δ	Number of charging slots at CS
N_W	Number of EVs waiting for charging at CS
N_C	Number of EVs under charging at CS
E_{ev}^{max}	Full volume of EV battery
E_{ev}^{cur}	Current volume of EV battery
β	Charging power at CS
T_{ev}^{fin}	Charging finish time of EV
T_{ev}^{arr}	EV's arrival time at CS
T_{ev}^{tra}	EV's travelling time to reach CS
T_{ev}^{cha}	Expected charging time upon arrival of EV
N_R	Number of EVs reserved for charging at CS
$\mathcal{W}$	Prediction time window
$\mathcal{H}$	Number of entries within $\mathcal{W}$
$\mathcal{K}$	A time slot of $\mathcal{H}$
$CA_{\mathcal{K}}$	The given charging availability at $\mathcal{K}$
D_{ev}	Time duration that EV will park at CS
RLIST	Set including a number EVs made charging reservation at CS
QLIST	Set including available time per charging slot at CS

TABLE IV
CHARGING RESERVATION FORMAT

EV ID	Selected CS	Parking Deadline	Arrival Time	Expected Charging Time
EV_1	CS_1	1200s	17260s	892s

A. EV's Charging Reservation

The EV's charging reservation is generated from the EV that had made the charging recommendation and relayed through the MEC servers to the GC. As an example in Table IV, such information normally includes the ID of the recommended CS, the EV's parking deadline, arrival time at that CS, and the EV's expected charging time there, specifically as shown.

Algorithm 1: CA-Dissemination.

1: **for** $(i = 1; \ i \leq \mathcal{H}; \ i++)$ **do**
2:      $\mathcal{K}_i = \left(T_{cur} + (i-1) \times \frac{\mathcal{W}}{\mathcal{H}} \right)$
3:      **if** $(N_R \neq 0)$ **then**
4:          sort the queue of N_R according to FCFS
5:          **for** $(j = 1; \ j \leq N_R; \ j++)$ **do**
6:              **if** $\left(T_{ev_{(j)}}^{arr} < \mathcal{K}_i \right)$ **then**
7:                  add EV_j into RLIST
8:              **end if**
9:          **end for**
10:         **if** $(|RLIST| \neq 0)$ **then**
11:             $CA_{\mathcal{K}_i} = CA\text{-Prediction}\,(RLIST, \mathcal{K}_i)$ via Algorithm 4
12:         **else**
13:             $CA_{\mathcal{K}_i} = CA\text{-Prediction}\,(\mathcal{K}_i)$ via Algorithm 3
14:         **end if**
15:     **else**
16:         $CA_{\mathcal{K}_i} = CA\text{-Prediction}\,(\mathcal{K}_i)$ via Algorithm 3
17:     **end if**
18:     add $< \mathcal{K}_i, \ CA_{\mathcal{K}_i} >$ in entry i
19: **end for**

Arrival Time: The arrival time T_{ev}^{arr} reflects the time when an EV reaches the recommended CS, where the value counts for the traveling time T_{ev}^{tra} from the current location of EV to the recommended CS

$$T_{ev}^{arr} = T_{cur} + T_{ev}^{tra}. \qquad (2)$$

Expected Charging Time: The expected charging time T_{ev}^{cha} at the selected CS is given by

$$T_{ev}^{cha} = \frac{E_{ev}^{max} - E_{ev}^{cur} + S_{ev} \times T_{ev}^{tra} \times \alpha}{\beta}. \qquad (3)$$

Here, $(S_{ev} \times T_{ev}^{tra} \times \alpha)$ is the energy consumed for the movement traveling to the selected CS, based on a constant α (depending on a certain type EV) measuring the energy consumption per meter.

Parking Deadline: D_{ev} is defined as a limitation on how long an EV will stay to wait for charging at the recommended CS.

B. Charging Availability Dissemination

Upon receiving EVs' charging reservations, each GC computes the charging availability for all connected CSs, associated with a number of time slots $\mathcal{K}$ that is beyond the interval Δ. Here, given that there are predefined $\mathcal{H}$ time slots associated within $\mathcal{W}$, the gap between adjacent $\mathcal{K}$ time slots is calculated by $\frac{\mathcal{W}}{\mathcal{H}}$.

Algorithm 1 is implemented by the GC and disseminates information formatted in Table V. The time slot at the ith entry is calculated by $\mathcal{K}_i = \left(T_{cur} + (i-1) \times \frac{\mathcal{W}}{\mathcal{H}} \right)$, where T_{cur} is the current time in the network. Understandably, $\mathcal{K}_i$ indicates a time slot beyond the current network time T_{cur}. An entire process of CS's information dissemination is presented as follows.

TABLE V
FORMAT OF CS'S CHARGING AVAILABILITY DISSEMINATION

–CS ID–		
CS$_3$		
–Dissemination Time Slot–		
10800s		
–Charging Availability Predicted Within $\mathcal{W}$–		
Entry	Decoupled Time Slot	Charging Availability
1	10860s	10892s
2	10920s	10920s
3	10980s	10980s

1) The EV$_j$ (in the queue of N_R), which has reported charging reservation to the recommended CS (while its arrival time $T^{\text{arr}}_{\text{ev}_{(j)}}$ is earlier than $\mathcal{K}_i$), will be recorded into a list, namely RLIST. Here, we consider that there will be other EVs (in the queue of N_R) that reserve and reach at the same CS before the time slot $\mathcal{K}_i$ as the condition $\left(T^{\text{arr}}_{\text{ev}_{(j)}} < \mathcal{K}_i\right)$ at line 6. In this context, the charging availability estimated at $\mathcal{K}_i$, as denoted by $\text{CA}_{\mathcal{K}_i}$, is calculated via Algorithm 4.

Note that, at line 11, the prediction of the CS's charging availability via Algorithm 4 requires an input of charging reservations of those EV$_j$ with an earlier arrival time than $\mathcal{K}_i$. This is given by the condition at line 10 in Algorithm 1. Otherwise, Algorithm 3 is applied by only examining the local conditions of CSs (e.g., number of EVs being parked and remaining charging time).

2) Alternatively, Algorithm 3 is also applied if there are no EVs' charging reservations, as presented between lines 15 and 16.

Then, a pair of $\langle \mathcal{K}_i, \text{CA}_{\mathcal{K}_i} \rangle$ stating the "$\langle$time slot, charging availability at time slot$\rangle$" will be prepared for dissemination. The information is then disseminated as shown in Step 1 in Fig. 1.

C. Dynamic Update of $\mathcal{W}$

Note that $\mathcal{W}$ is updated based on a dynamic adaption mechanism. This is triggered by the event that an EV is making charging reservations at the recommended CS within a time slot $\mathcal{K}$, then the traveling time $T^{\text{tra}}_{\text{ev}}$ of the EV is compared with the value of estimation window $\mathcal{W}$ that is currently applied in the charging system. The larger value is updated as the new estimation window of $\mathcal{W}$.

The advantage is to gradually learn the charging demand distribution of EVs. This is to say, if most of EVs are with shorter $T^{\text{tra}}_{\text{ev}}$ toward CSs recommended to them, a much urgent charging will be prepared. As such, the way to predict the CSs' charging availability will be with a tight $\mathcal{W}$ (or say smaller $\mathcal{W}$), such that the accuracy is adjusted with $\frac{\mathcal{W}}{\mathcal{H}}$.

D. Prediction of Charging Availability Without EVs' Charging Reservations

Here, as no EVs' charging reservations are available, the charging availability is computed solely based on the CSs' local queueing information. A set QLIST is defined to represent the available time of all charging slots locally at a CS.

Algorithm 2: Generation of QLIST.

1: **for** $(i = 1; i \leq N_C; i++)$ **do**
2:    **if** $\left(\left(T_{\text{cur}} - T^{\text{arr}}_{\text{ev}_{(i)}} + \frac{E^{\max}_{\text{ev}_{(i)}} - E^{\text{cur}}_{\text{ev}_{(i)}}}{\beta}\right) \leq D_{\text{ev}_{(i)}}\right)$ **then**
3:       add $\left(\frac{E^{\max}_{\text{ev}_{(i)}} - E^{\text{cur}}_{\text{ev}_{(i)}}}{\beta} + T_{\text{cur}}\right)$ into QLIST
4:    **else**
5:       add $\left(T^{\text{arr}}_{\text{ev}_{(i)}} + D_{\text{ev}_{(i)}}\right)$ into QLIST
6:    **end if**
7: **end for**
8: **if** $(N_C < \delta)$ **then**
9:    **for** $(j = 1; j \leq (\delta - N_C); j++)$ **do**
10:       add (T_{cur}) into QLIST
11:    **end for**
12: **end if**
13: sort the queue of N_W according to FCFS
14: **for** $(k = 1; k \leq N_W; k++)$ **do**
15:    sort QLIST in an ascending order
16:    **if** $\left(\left(\text{QLIST}_1 - T^{\text{arr}}_{\text{ev}_{(k)}}\right) < D_{\text{ev}_{(k)}}\right)$ **then**
17:       **if** $\left(\left(\text{QLIST}_1 - T^{\text{arr}}_{\text{ev}_{(k)}} + \frac{E^{\max}_{\text{ev}_{(k)}} - E^{\text{cur}}_{\text{ev}_{(k)}}}{\beta}\right) \leq D_{\text{ev}_{(k)}}\right)$
      then
18:          $T^{\text{fin}}_{\text{ev}_{(k)}} = \left(\text{QLIST}_1 + \frac{E^{\max}_{\text{ev}_{(k)}} - E^{\text{cur}}_{\text{ev}_{(k)}}}{\beta}\right)$
19:       **else**
20:          $T^{\text{fin}}_{\text{ev}_{(k)}} = \left(T^{\text{arr}}_{\text{ev}_{(k)}} + D_{\text{ev}_{(k)}}\right)$
21:       **end if**
22:       replace QLIST$_1$ with $T^{\text{fin}}_{\text{ev}_{(k)}}$ in LIST
23:       sort QLIST in an ascending order
24:    **end if**
25: **end for**
26: **return** QLIST

---

1) Generation of QLIST: As each CS has δ charging slots to charge parked EVs in parallel, we consider two types of queues localized at the CS. Here, EVs being charged are included in the queue of N_C, while those waiting for charging (due to all δ charging slots of a CS have been occupied by other EVs for charging) are characterized in the queue of N_W.

From line 1 at Algorithm 2, for each EV$_i$ being charged, the time length $(\frac{E^{\max}_{\text{ev}_{(i)}} - E^{\text{cur}}_{\text{ev}_{(i)}}}{\beta})$ to fully recharge its battery (in the queue of N_C), will be compared with its parking duration $D_{\text{ev}_{(i)}}$. The comparison outcome is applied to estimate the time that EV$_i$ will take to finish its charging.

1) In one case, the condition $((T_{\text{cur}} - T^{\text{arr}}_{\text{ev}_{(i)}} + \frac{E^{\max}_{\text{ev}_{(i)}} - E^{\text{cur}}_{\text{ev}_{(i)}}}{\beta}) \leq D_{\text{ev}_{(i)}})$ implies that EV$_i$ can be fully recharged before departure. Here, $(T_{\text{cur}} - T^{\text{arr}}_{\text{ev}_{(i)}})$ is the time duration to wait for charging since the arrival of EV$_i$. As such, at line 3, the charging finish time (about when the charging of EV$_i$ will finish) $T^{\text{fin}}_{\text{ev}_{(i)}}$ of EV$_i$ is given by a summation of $(\frac{E^{\max}_{\text{ev}_{(i)}} - E^{\text{cur}}_{\text{ev}_{(i)}}}{\beta} + T_{\text{cur}})$ only.

2) In another case, $T^{\text{fin}}_{\text{ev}_{(i)}}$ is given by $(T^{\text{arr}}_{\text{ev}_{(i)}} + D_{\text{ev}_{(i)}})$ at line 5, as the time slot that EV$_i$ leaves from CS.

Algorithm 3: CA-Prediction ($\mathcal{K}$).

1: sort QLIST from Algorithm 2 in an ascending order
2: **if** $\text{QLIST}_1 > \mathcal{K}$ **then**
3:     **return** QLIST_1
4: **else**
5:     **return** $\mathcal{K}$
6: **end if**

Furthermore, the presentation between lines 8 and 12 reflects a case that not all δ charging slots have been occupied by other EVs for charging. Therefore, it is easy to determine that there are still $(\delta - N_C)$ slots that can be reserved by incoming EVs for charging. As such, the available charging time for these unoccupied charging slots is all unified as T_{cur}.

Then, Algorithm 2 first sorts the queue of N_W based on the FCFS order, by following the charging scheduling in Section III. Besides, QLIST that includes those EVs under charging will be sorted in an ascending order. Here, the earliest available time for charging at a CS is deemed as the first element in QLIST, and we denote that time as QLIST_1 (the first element of sorted QLIST).

In detail, to calculate the charging finish time $T_{\text{ev}_{(k)}}^{\text{fin}}$ of each EV_k (in the queue of N_W), the earliest available time of charging slots is required to be known. In principle, it is crucial to consider EV_k that at least will be charged during its parking duration $D_{\text{ev}_{(k)}}$ to involve calculation. This constraint is defined by $((\text{QLIST}_1 - T_{\text{ev}_{(k)}}^{\text{arr}}) < D_{\text{ev}_{(k)}})$ at line 16.

1) Then from lines 17 and 21, either $(\text{QLIST}_1 + \frac{E_{\text{ev}_{(k)}}^{\max} - E_{\text{ev}_{(k)}}^{\text{cur}}}{\beta})$ or $(T_{\text{ev}_{(k)}}^{\text{arr}} + D_{\text{ev}_{(k)}})$ calculates $T_{\text{ev}_{(k)}}^{\text{fin}}$, in particular, $(\text{QLIST}_1 - T_{\text{ev}_{(k)}}^{\text{arr}})$ is referred for EV_k to wait for charging.

2) Upon $T_{\text{ev}_{(k)}}^{\text{fin}}$ been given, QLIST_1 will be replaced with $T_{\text{ev}_{(k)}}^{\text{fin}}$. Then, QLIST will be re-sorted in an ascending order upon processing each EV_k in the loop.

The aforementioned loop operation is finished when all EV_k (in the queue of N_W) have been processed and updated QLIST is generated.

2) Charging Availability Computing: Based on Algorithm 2 with QLIST being generated, the CS's local queueing information is computed to predict the charging availability associated with $\mathcal{K}$ in Algorithm 3. Here, as QLIST_1 is later than $\mathcal{K}$, the charging availability is represented as QLIST_1, and otherwise as $\mathcal{K}$. This depends on whether the CS will be available for charging at the time slot $\mathcal{K}$.

E. Prediction of Charging Availability With EVs' Charging Reservations

Recall that Algorithm 1 has already included a number of EVs into RLIST, which is an input for Algorithm 4. This guarantees that the charging availability of the CS is predicted by tracking the EVs that will reach the reserved CS within $\frac{\mathcal{W}}{\mathcal{H}}$ and the charging time of EVs that are parked there. Here, the latter information is provided by QLIST generated via Algorithm 2 and sorted in an ascending order.

Algorithm 4: CA-Prediction (RLIST, $\mathcal{K}$).

1: sort the queue of N_R according to FCFS
2: sort QLIST returned by Algorithm 2, in an ascending order
3: **for** $(i = 1; i \le N_R; i++)$ **do**
4:     **if** RLIST contains EV_i **then**
5:         **if** $\left(\text{QLIST}_1 > T_{\text{ev}_{(i)}}^{\text{arr}} \right)$ **then**
6:             **if** $\left(\left(\text{QLIST}_1 - T_{\text{ev}_{(i)}}^{\text{arr}} \right) < D_{\text{ev}_{(i)}} \right)$ **then**
7:                 **if** $\left(\left(\text{QLIST}_1 - T_{\text{ev}_{(i)}}^{\text{arr}} + T_{\text{ev}_{(i)}}^{\text{cha}} \right) \le D_{\text{ev}_{(i)}} \right)$ **then**
8:                     $T_{\text{ev}_{(i)}}^{\text{fin}} = \left(\text{QLIST}_1 + T_{\text{ev}_{(i)}}^{\text{cha}} \right)$
9:                 **else**
10:                    $T_{\text{ev}_{(i)}}^{\text{fin}} = \left(T_{\text{ev}_{(i)}}^{\text{arr}} + D_{\text{ev}_{(i)}} \right)$
11:                 **end if**
12:             **end if**
13:         **else**
14:             **if** $\left(T_{\text{ev}_{(i)}}^{\text{cha}} \le D_{\text{ev}_{(i)}} \right)$ **then**
15:                 $T_{\text{ev}_{(i)}}^{\text{fin}} = \left(T_{\text{ev}_{(i)}}^{\text{arr}} + T_{\text{ev}_{(i)}}^{\text{cha}} \right)$
16:             **else**
17:                 $T_{\text{ev}_{(i)}}^{\text{fin}} = \left(T_{\text{ev}_{(i)}}^{\text{arr}} + D_{\text{ev}_{(i)}} \right)$
18:             **end if**
19:         **end if**
20:         replace QLIST_1 with $T_{\text{ev}_{(i)}}^{\text{fin}}$
21:         sort QLIST in an ascending order
22:     **end if**
23: **end for**
24: **if** $(\text{QLIST}_1 > \mathcal{K})$ **then**
25:     **return** QLIST_1
26: **else**
27:     **return** $\mathcal{K}$
28: **end if**

At line 5 in Algorithm 4, for each EV_i (in the queue of N_R) with its $T_{\text{ev}_{(i)}}^{\text{arr}}$ prior to the earliest available time for charging QLIST_1, EV_i will be taken into account for the update of QLIST. This means that only those EVs (in the queue of N_R) arriving later than QLIST_1 will not have an influence on QLIST. Note that QLIST has been previously sorted in an ascending order. This guarantees that the earliest time that one of the charging slots will be free, it is ready for taking the subsequent EV's charging.

1) In one case, the condition $(\text{QLIST}_1 > T_{\text{ev}_{(i)}}^{\text{arr}})$ at line 5 implies that $T_{\text{ev}_{(i)}}^{\text{arr}}$ is prior to the earliest available time LIST_1. This causes the charging finish time $T_{\text{ev}_{(i)}}^{\text{fin}}$ to be calculated by summating QLIST_1 and the expected charging time $T_{\text{ev}_{(i)}}^{\text{cha}}$.

In particular, at line 7, the condition $((\text{QLIST}_1 - T_{\text{ev}_{(i)}}^{\text{arr}} + T_{\text{ev}_{(i)}}^{\text{cha}}) \le D_{\text{ev}_{(i)}})$ implies that within the parking duration $D_{\text{ev}_{(i)}}$, EV_i could be fully recharged. Recall that $(\text{QLIST}_1 - T_{\text{ev}_{(i)}}^{\text{arr}})$ is the time to wait until the charging is started. In this context, given by the cases at lines 7 and 9, $T_{\text{ev}_{(i)}}^{\text{fin}}$ is given by $(\text{QLIST}_1 + T_{\text{ev}_{(i)}}^{\text{cha}})$ or $(T_{\text{ev}_{(i)}}^{\text{arr}} + D_{\text{ev}_{(i)}})$.

Algorithm 5: Charging Recommendation Strategy.

1: **for** $(i = 1; \ i \leq (\mathcal{H} - 1); \ i++)$ **do**
2:   **if** $\left(\mathcal{K}_i \leq T_{\text{ev}_{(r)}}^{\text{arr}}\right) \&\& \left(\mathcal{K}_{i+1} > T_{\text{ev}_{(r)}}^{\text{arr}}\right)$ **then**
3:     $\mathcal{A} = \left(\text{CA}_{\mathcal{K}_{(i)}} + \dfrac{T_{\text{ev}_{(r)}}^{\text{arr}} \times \left(\text{CA}_{\mathcal{K}_{(i+1)}} - \text{CA}_{\mathcal{K}_{(i)}}\right)}{\mathcal{K}_{(i+1)}}\right)$
4:   **end if**
5: **end for**
6: **if** $\left(\mathcal{K}_1 > T_{\text{ev}_{(r)}}^{\text{arr}}\right)$ **then**
7:   $\mathcal{A} = \text{CA}_{\mathcal{K}_{(1)}}$
8: **else if** $\left(\mathcal{K}_{\mathcal{H}} \leq T_{\text{ev}_{(r)}}^{\text{arr}}\right)$ **then**
9:   $\mathcal{A} = \text{CA}_{\mathcal{K}_{(\mathcal{H})}}$
10: **end if**
11: **if** $\left(\mathcal{A} > T_{\text{ev}_{(r)}}^{\text{arr}}\right)$ **then**
12:   **if** $\left(\mathcal{A} - T_{\text{ev}_{(r)}}^{\text{arr}} + T_{\text{ev}_{(r)}}^{\text{cha}} \leq D_{\text{ev}_{(r)}}\right)$ **then**
13:     **return** $\mathcal{A} - T_{\text{ev}_{(r)}}^{\text{arr}} + T_{\text{ev}_{(r)}}^{\text{cha}}$
14:   **else**
15:     **return** $D_{\text{ev}_{(r)}}$
16:   **end if**
17: **else**
18:   **if** $\left(T_{\text{ev}_{(r)}}^{\text{cha}} \leq D_{\text{ev}_{(r)}}\right)$ **then**
19:     **return** $T_{\text{ev}_{(r)}}^{\text{cha}}$
20:   **else**
21:     **return** $D_{\text{ev}_{(r)}}$
22:   **end if**
23: **end if**

Note that as the condition given by $((\text{QLIST}_1 - T_{\text{ev}_{(i)}}^{\text{arr}}) < D_{\text{ev}_{(i)}})$ at line 6, we only consider that EV_i could be charged before $D_{\text{ev}_{(i)}}$ to involve the calculation.

2) In another case, $T_{\text{ev}_{(i)}}^{\text{fin}}$ is calculated by considering $T_{\text{ev}_{(i)}}^{\text{arr}}$, $T_{\text{ev}_{(i)}}^{\text{cha}}$, and $D_{\text{ev}_{(i)}}$ following the calculations at lines 15 and 17. This only happens when $(\text{QLIST}_1 \leq T_{\text{ev}_{(i)}}^{\text{arr}})$, meaning that the CS has already been available for charging when EV_i arrives.

By replacing QLIST_1 with each $T_{\text{ev}_{(i)}}^{\text{fin}}$ in each loop round, QLIST will be dynamically updated. Furthermore, QLIST will be sorted in an ascending order after processing each EV_i, such that the first element QLIST_1 is updated. The loop operation ends when all EV_i (in the queue of N_R) have been processed.

F. Charging Recommendation

Here, EV_r is denoted as the EV that needs to make a charging recommendation, other than those EVs that are either being parked or on the move. Two bounding time slots can be obtained via the condition at line 2 of Algorithm 5, such that the arrival time of EV_r, denoted as $T_{\text{ev}_{(r)}}^{\text{arr}}$, is between these two time slots $\mathcal{K}_i$ and $\mathcal{K}_{i+1}$. In this case, the outcome of the charging availability is then passed to a temporary variable $\mathcal{A}$, with $\mathcal{A} = (\text{CA}_{\mathcal{K}_i} + \frac{T_{\text{ev}_{(r)}}^{\text{arr}} \times (\text{CA}_{\mathcal{K}_{i+1}} - \text{CA}_{\mathcal{K}_i})}{\mathcal{K}_{i+1}})$ at line 3, considering a ratio between $T_{\text{ev}_{(r)}}^{\text{arr}}$ and $\mathcal{K}_{i+1}$. From this calculation, it is aimed to capture the charging availability upon its arrival time $\text{EV}_{(r)}$ that is between $\mathcal{K}_i$ and $\mathcal{K}_{i+1}$.
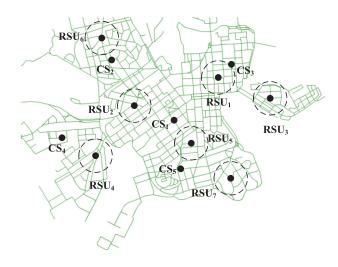

Fig. 5. Helsinki city scenario.

There are also two cases if $T_{\text{ev}_{(r)}}^{\text{arr}}$ is out of the bound of the estimation window $\mathcal{W}$.

1) Due to that $T_{\text{ev}_{(r)}}^{\text{arr}}$ is earlier than the earliest estimation time slot in entries $\mathcal{H}$, denoted as $\mathcal{K}_1$, the charging availability upon the arrival of EV_r is given by $\text{CA}_{\mathcal{K}_{(1)}}$ at line 7.

2) Besides, due to that $T_{\text{ev}_{(r)}}^{\text{arr}}$ is later than the latest time slot in entries $\mathcal{H}$, the charging availability in this case is given by $\text{CA}_{\mathcal{K}_{(\mathcal{H})}}$ at line 9.

Next, EV_r will predict an expected time for which it would stay at the recommended CS before the parking deadline by considering its parking duration $D_{\text{ev}_{(r)}}$.

1) Basically, if EV_r arrives later than $\mathcal{A}$, this means it still needs to wait for additional time until a charging slot is available. In this case, the condition $(\mathcal{A} - T_{\text{ev}_{(r)}}^{\text{arr}} + T_{\text{ev}_{(r)}}^{\text{cha}} \leq D_{\text{ev}_{(r)}})$ indicates EV_r can be fully recharged within the parking deadline $D_{\text{ev}_{(r)}}$; thus, its expected staying time is calculated by $(\mathcal{A} - T_{ev_{(r)}}^{\text{arr}} + T_{\text{ev}_{(r)}}^{\text{cha}})$ at line 13. Otherwise, only $D_{\text{ev}_{(r)}}$ is referred as the staying time at line 14.

2) Such a policy between lines 18 and 22 can be also applied to the case if EV_r arrives no later than $\mathcal{A}$. In this case, as EV_r does not need to wait for additional time to start charging, the comparison is just between $T_{\text{ev}_{(r)}}^{\text{arr}}$ and $D_{\text{ev}_{(r)}}$.

V. PERFORMANCE EVALUATION

A. Scenario Configuration

The entire system for EV charging is built in Opportunistic Network Environment [21]. In Fig. 5, the default scenario with 4500×3400 m^2 area is shown as the downtown area of Helsinki city in Finland. $N_{\text{ev}} = 300$ EVs with $S_{\text{ev}} = [30 \sim 50]$ km/h variable moving speed are initialized considering road safety in a city. The configuration of EVs follows the charging specification of *Hyundai BlueOn*, with a maximum electricity capacity of 16.4 kWh, max traveling distance 140 km, and SOC $[15 \sim 45]\%$. Besides, $N_{\text{cs}} = 5$ CSs are provided with sufficient electric energy and $\delta = 5$ charging slots through entire simulation, using the fast charging rate of $\beta = 62$ kW. $R = 300$ m radio coverage is applied for $N_{\text{mec}} = 7$ RSUs and $N_{\text{ev}} = 300$ EVs.
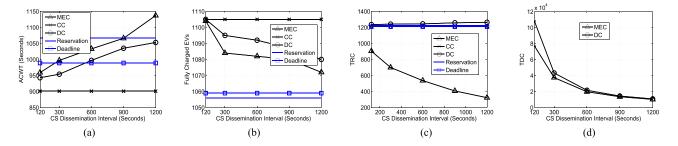
Fig. 6.   Influence of CS dissemination interval Δ. (a) ACWT. (b) Fully charged EVs. (c) TRC. (d) TDC.

The default dissemination interval of CS's charging availability is $\Delta = 120$ s, and the simulation time is 43 200 s = 12 h.

The following schemes are evaluated for comparison.

1) *MEC:* The proposed charging recommendation scheme in Section IV, based on the MEC framework in Section III.
2) *CC and DC:* They are with the same charging recommendation scheme with MEC, but with centralized and distributed cloud computing framework.
3) *Reservation [10]:* Previous works take the EVs' charging reservation to predict the CSs' charging availability, however, not addressing the EVs' parking deadline. Here, the cloud computing framework is positioned.
4) *Deadline [11]:* Previous works taking the parking deadline into the account of charging recommendation, based on the cloud computing framework. This scheme differs from the CC for the computation intelligence to predict CSs' charging availability.

The simulation evaluates metrics at the EV and CS sides as well as communication costs at the system level.

1) *Average Charging Waiting Time (ACWT):* The average period between the time an EV arrives at the recommended CS and the time it finishes (full) recharging its battery. This is the performance metric at the EV side.
2) *Fully Charged EVs:* The total number of fully charged EVs; this is the performance metric at the CS side.
3) *Total Reservation Cost (TRC):* The total number signaling reported for EV's charging reservations to the GC. In MEC, this counts for the signaling from RSUs to the GC, whereas other schemes count from EVs to the GC.
4) *Total Dissemination Cost (TDC):* In MEC, this counts for the signaling from RSUs to the EVs, whereas in DC, this counts from GC to EVs.

B. Performance Results

1) Influence of CS Dissemination Interval Δ: Results in Fig. 6(a) and (b) show that a frequent dissemination interval helps to maintain the optimality of the charging recommendation. This means that as the information is replaced at RSUs frequently, EVs that have passed by would fetch the cached information that is more fresh. In comparison to DC, the CC achieves the better performance by making decision using a seamless cellular network communication, compared to the opportunistic communication between RSUs and EVs as applied in the MEC system. Furthermore, concerning the feature
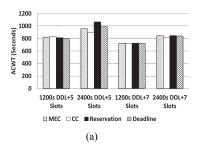
of charging recommendation, the CC outperforms reservation and deadline, thanks to decoupling the decision making within a small-time interval $\mathcal{W}$. It is also observed that the deadline outperforms reservation, as the former takes the EVs' parking deadline into account.
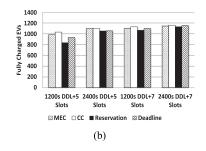
In Fig. 6(c), the MEC-based system is with decreased TRC, which follows the analysis in Section III. However, other compared charging recommendations with the cloud-based system are with a much higher TRC. The benefit of reduced TRC is from the aggregation and mining functions at RSUs, which filter invalid EVs' charging reservations (which to be not uploaded to the GC) for computation. Besides, the dissemination cost is shown in Fig. 6(d), where the cost in MEC is lower than in DC-based systems (with $\Delta = 120$ s). This shows the efficiency of using on-demand and short-range wireless communication in the MEC-based system together with access control, compared to the long-range cellular link and broadcasting communication in the DC-based system. In the following sections, DC is excluded, while only the nature of charging recommendation solutions is discussed.

2) Influence of Parking Deadline D_{ev}: In Fig. 7(b), a longer parking deadline D_{ev} increases the fully charged EVs. This is generally referred to the situation that EVs being parked at CSs will have much chance to be fully charged, compared to the case with 1200 s parking deadline, while such increase brings increased ACWT in Fig. 7(a) as well. In Fig. 7(c), it is observed that a shorter parking deadline leads to a much higher TRC. This is because of those EVs that are not fully charged and would subsequently need charging after a shorter period. As such, the charging reservation is increased corresponding to such frequent charging demands.

Apart from the above-mentioned general observation, further details are comparable in the cases of 5 and 7 charging slots. The latter case alleviates the charging congestion at CSs; as such, it delivers a lower AWCT and higher fully charged EVs as well as reduced TRC (more significant in the case of 1200 s parking deadline).

3) Influence of EV Density N_{ev}: In Fig. 8(a), the AWCT is increased from the case of 100 EVs, as more EVs will be fully charged (with 300 and 500 EVs). However, Fig. 8(b) shows that the fully charged EVs are first increased from 100 to 300 EVs cases, and then decreases from 300 to 500 EVs cases. This reflects the 500 EVs case results in severe charging congestion, so some EVs are not fully charged. Such an outcome is also associated with the TRC, wherein Fig. 8(c) shows the TRC in
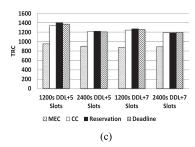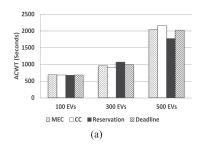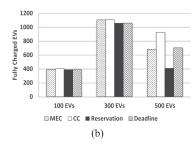
Fig. 7. Influence of EVs' parking deadline D_{ev}. (a) ACWT. (b) Fully charged EVs. (c) TRC.
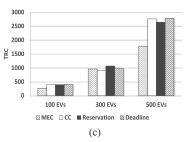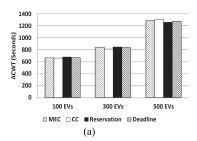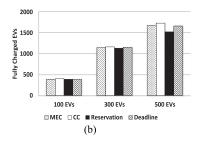

Fig. 8. Influence of EVs' density N_{ev}, with $\delta = 5$ charging slots. (a) ACWT. (b) Fully charged EVs. (c) TRC.
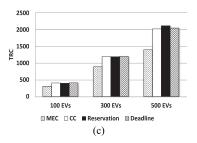

Fig. 9. Influence of EVs' density N_{ev}, with $\delta = 7$ charging slots. (a) ACWT. (b) Fully charged EVs. (c) TRC.

the case of 500 EVs, is much higher than the fully charged EVs in the same case of Fig. 8(b). The mismatch is because of the EVs that were not fully charged but later need charging (with additional charging reservations sent).

If setting 7 charging slots at each CS, where the fully charged EVs is increased in Fig. 9(b), along with increased ACWT in Fig. 9(a). Compared with that in Fig. 8(b) where there is a decrease of fully charged EVs from 300 to 500 EVs cases, the situation here implies the effect of parking deadline with limited charging infrastructures. Of course, the MEC-based system still achieves the lowest TRC in Fig. 9(c), similar to the previous observation.

VI. CONCLUSION

This paper investigated EV charging recommendation via MEC architecture, with RSUs positioned physically and MEC functions virtually to help with information dissemination and collection. The information access control, aggregation, and mining are enabled at MEC servers, while the charging recommendation takes the EV's charging reservation and its parking deadline into account. Results show that the proposed solution achieves a comparable performance in terms of charging waiting time as a benefit to the user, and a number of fully

charged EVs as a benefit to the service provider. Future works would be on integration of the power network.

With the ever increasing penetrations in EVs, the resultant charging energy imposed on the electricity network could lead to grid issues, such as voltage limits violation, transformer overloading, and feeder overloading at various voltage levels. Coordination of the charging energy with a renewable energy source provides a more straightforward approach to cope with the potential network issues as mentioned previously. Future works would be on the integration of power network to achieve an interdisciplinary work on ICT, route planning, and energy integration.

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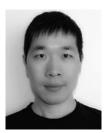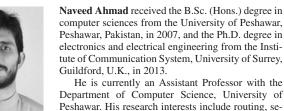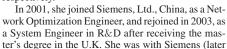
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