A Reservation Based Charging Management for On-the-move EV Under Mobility Uncertainty

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***Abstract*—With the continually increased attention on Electric Vehicles (EVs) due to environment impact, public Charging Stations (CSs) for EVs will become common. However, due to the limited electricity of battery, the driver may experience discomfort for long charging waiting time, if travelling towards a CS which is heavily loaded for charging. With this concern, we manage on-the-move EV charging by coordinating which CS to select for charging, and propose a CS-selection scheme considering EVs anticipated charging reservations generally including arrival time and expected charging time, in particular the parking duration is further considered in this paper. Upon this, by addressing mobility uncertainty that EVs may not reach their selected CSs on time due to uncertain traffic condition on the road, a periodical reservation updating for requesting the change of CS-selection decision is proposed to further coordinate charging management. The motivation for this is mainly due to that the mobility uncertainty affects the accuracy of reported reservation information, concerning the arrival time at selected CSs and expected charging time upon arrival. Evaluation results show the effectiveness of our proposal when considering realistic EV and CS characteristics.**

***Index Terms*—Smart Grid, Electric Vehicle Charging, Charging Station Selection, Mobility Uncertainty.**

I. Introduction

Concerning the increasing long-term energy cost and attention on environmental impact, the application of Electric Vehicles (EVs) [1] is promising compared to that of traditional petrol based vehicles in many developed countries. Different from previous works which extensively investigate charging scheduling [2] for EVs already parking at home/Charging Stations (CSs), our research interest addresses another branch which has not received much attention, to manage the charging for on-the-move EVs by selecting appropriate CSs to travel for charging. In general, these public CSs are typically deployed at places where there is high concentration of EVs such as shopping mall parking places. It is highlighted that due to the relatively long charging time of EVs, to optimally manage where to charge has become a critical issue in recent years.

We refer to the charging system adopted by previous works, which utilizes Global Aggregator (GA) or other third party who is interested in EVs charging coordination, to manage on-the-move EV charging in a centralized manner. Here, the GA is the system controller which records the CSs condition information and implements the optimized charging management, upon receiving any charging request from on-the-move EVs. Note that, based on existing fast charging technology, the charging time of an EV typically exceeds tens of minutes [3]. If an EV arrives at a CS of which all charging slots are occupied, this EV must wait until other parking EVs in front of the queue at this CS have completed their charging.

Previous works [4]–[6] have addressed CS-selection to minimize the waiting time of EVs, by estimating a queue of EVs locally parking at a CS. Here, the CS with the highest availability (e.g., minimum charging waiting time) will be selected as a decided plan for an on-the-move EV which requires charging. Naturally, a potential charging hotspot may happen if many EVs travel towards the same CS for charging, due to that the decision is only based on EVs locally parking at CSs. If further considering the predicted EV charging reservation [7] including when the EV will arrive at selected CS for charging and how long its charging time will be upon the arrival, the performance on charging waiting time can be improved.

Due to mobility uncertainty (in relation to accident or traffic jams) on the road, EVs may not guarantee their reported reservations (meaning they may not arrive at selected CSs on time), particularly when the GA is not informed regarding this situation timely. Since to continually obtain the updated EV reservation information improves the accuracy of estimation, the charging waiting time could be reduced if the EV adjusts its movement and travels towards a new CS decided by GA. To our best awareness, none of previous works has addressed the on-the-move EV charging under the mobility uncertainty.

Regarding reservation charging aspect, an essential difference between our work and [7] is that the latter assumes highway scenario where the EV will pass through all CSs. Its expected waiting time is calculated for the EV passing through the entire highway, by jointly considering the charging waiting time at a CS that the EV needs charging for the first time and that of any subsequent CS before exiting the highway. In contrary, under our city scenario the EV will head to a single geographically distributed CS for charging, where the expected waiting time is only in relation to that certain CS. Indeed, it is difficult to coordinate the charging plans for all EVs in a large scale range. Using centralized charging management keeps the edge devices (EV side) simper, and favors more sophisticated centralized optimizations from the GA side based on the aggregated global information. In this article, a charging management scheme focusing on CS-selection is presented, with the following contributions:

1: Concerning a city scenario, the CS-selection decision making is based on the reported EVs' reservation information, including their arrival time, expected charging time as well as parking duration at decided CSs. This anticipated information is recorded by the GA to estimate the expected waiting time at a CS. Compared to previous works on CS-selection, the novelty of this estimation jointly considers the parallel charging process via multiple charging slots and the EV parking duration for reservation making, where an EV may depart from a CS before being fully recharged.

2: Since the problem of mobility uncertainty has not been addressed in literature, we propose that EVs are further capable of sending reservation update requests, in order that they would be informed by GA, to change movement and experience a less time waiting for charging at newly selected CSs. This updating process is run periodically, and applicable under the scenario that EVs are with varied moving speed during journeys due to the mobility uncertainty.

II. System Model

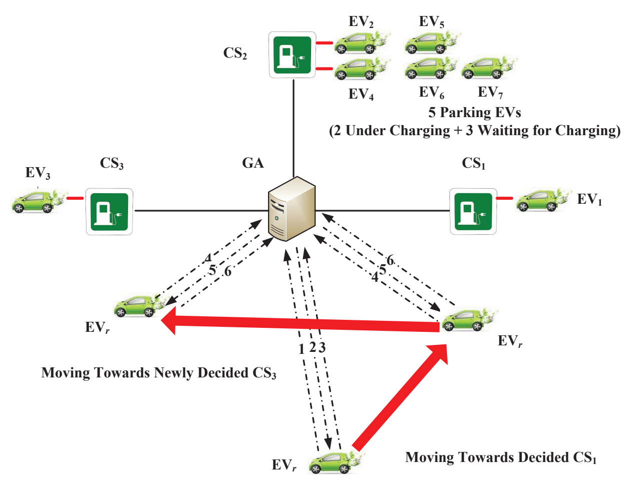


Fig. 1. Overview of On-the-move EV Charging Management

A. Assumption

In this paper, we consider a city scenario where CSs are geographically deployed in a city, the GA globally manages the charging for all EVs in the network. Without loss of generality, EVs are equipped with wireless communication devices such as 3G/4G, which allows them to communicate with the GA through request/reply charging service. Under our scenario, each CS is with multiple charging slots such that a number of EVs can be charged in parallel. As an example in Fig.1, the charging of EV$_5$ will be started if one of the charging slots at CS$_2$ is free. We focus on CS-selection scheme on where to charge, while each CS adopts a Fist Come First Serve (FCFS) scheme to schedule the charging priority of those EVs parking herein, such that the EV with the earliest arrival time will be allocated with the highest charging priority. Particularly, each EV has its individual parking duration at a CS, and in particular, an EV may depart from a CS before being fully charged.

B. Typical Procedure

Based on above, a typical procedure for our proposed EV charging management scheme is listed as follows: 1) For each on-the-move EV needs charging, namely EV$_r$, it informs the GA about this request. 2) The GA then compiles a list of CSs and ranks the most appropriate one, where the decision in relation to the best one is sent back to EV$_r$. 3) EV$_r$ reports its reservation information in relation to this decided CS, including its arrival time, expected charging time and parking duration at this CS. 4) While travelling towards the decided CS, EV$_r$ periodically checks whether that currently selected CS is still a better choice, by sending a reservation update request to the GA. 5) The GA then compares a cost in relation to the currently selected CS as well as that of other CSs. If the currently selected CS is not with the minimum cost, the GA will inform EV$_r$ about a new CS-selection decision. 6) EV$_r$ thus cancels its previous reservation and reports the reservation information in relation to the newly selected CS, then changes its movement towards that place. Steps 4 to 6 are repeated until EV$_r$ reaches any newly decided CS for charging.

C. Mobility Uncertainty

Partially based on [8], the uncertainty of EV mobility presented in this article, is mainly due to several accidents that randomly happen in a city. Any EV within a certain range of the accident will slow down its speed, while it will accelerate the speed once leaving from the range of that accident. In this situation, the variation of moving speed will affect the arrival time at a CS as well as the electricity consumption costed for travelling towards that CS, reported as the reservation information to estimate the expected waiting time at a CS. If without reservation updating, an EV may not reach a CS at a time it previously reserved, whereas the GA still has knowledge that this EV will reach on time. As such, the estimation on how long an incoming EV will wait for charging, is affected by the accuracy of the reservation information due to mobility uncertainty.

III. Reservation Based CS-Selection Scheme

A. Reporting Reservation Information

Based on the notations defined in TABLE I, whenever a CS-selection decision is made and returned to any EV (e.g., EV$_r$) which sent charging request, the following three items together with its ID and the selected CS's ID will be reported to the GA, as the EV's reservation information.

Arrival Time: We denote T_{ev}^{arr} as the time slot that an EV will arrive at the selected CS, following:

$$T_{ev}^{arr} = T_{cur} + T_{ev}^{tra} \tag{1}$$

Here, T_{ev}^{tra} is the travelling time measured from the current location of EV to the selected CS, via the shortest road path. Besides, T_{cur} is the current time in network.

Expected Charging Time: We denote T_{ev}^{cha} as the expected charging time upon that arrival, where:

$$T_{ev}^{cha} = \frac{E_{ev}^{max} - E_{ev}^{cur} + S_{ev} \times T_{ev}^{tra} \times \alpha}{\beta} \tag{2}$$

Here, $(S_{ev} \times T_{ev}^{tra} \times \alpha)$ is the energy consumed for the movement travelling to the selected CS, based on a constant α (depending on a certain type EV) measuring the energy consumption per meter. Therefore, $(E_{ev}^{max} - E_{ev}^{cur} + S_{ev} \times T_{ev}^{tra} \times \alpha)$ is the expected electricity that an EV needs to be recharged, depending on the charging power β provided by CS.

Parking Duration: We denote D_{ev} as the parking duration at a CS, meaning how long an EV will park. Note that an EV may depart from a CS due to a short parking duration, even if the EV battery has not been fully recharged.

TABLE I
LIST OF NOMENCLATURES

LIST	Output including available time per charging slot at CS
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
T_{cur}	Current time in network
S_{ev}	Moving speed of EV
α	Electric energy consumed per meter
D_{ev}	Parking duration of EV at CS
T_{ev}^{park}	Time slot that EV starts to park at CS
β	Charging power at CS
N_C	Number of EVs under charging at CS
N_W	Number of EVs waiting for charging at CS
δ	Number of charging slots at CS
E_{ev}^{max}	Full volume of EV battery
E_{ev}^{cur}	Current volume of EV battery
T_{ev}^{fin}	Charging finish time of EV
N_R	Number of EVs reserved for charging at CS

B. Estimating Available Time for Charging

Before considering those EVs have made reservations and are travelling towards their selected CSs, it is vital to estimate the available time for each charging slot, based on the knowledge of those EVs currently parking at these CSs. Given the parallel charging procedure via multiple charging slots, we define two types of queues respectively. Here, those EVs under charging are characterized in the queue of N_C, while those still waiting for charging are characterized in the queue of N_W.

In special case, the current time in network, as denoted by T_{cur}, is estimated as the available charging time for each charging slot, only if all charging slots are unoccupied. As such, the LIST including these time slots is returned, after the process at line 2 in Algorithm 1.

Alternatively, as the operations presented between lines 5 and 11, the time duration $\frac{E_{ev_{(i)}}^{max} - E_{ev_{(i)}}^{cur}}{\beta}$ to fully recharge the battery of each EV$_i$ in the queue of N_C, will be compared with its parking duration $D_{ev_{(i)}}$.

- In one case, the condition $\left(\left(T_{cur} - T_{ev_{(i)}}^{park} + \frac{E_{ev_{(i)}}^{max} - E_{ev_{(i)}}^{cur}}{\beta}\right) \leq D_{ev_{(i)}}\right)$ implies this EV$_i$ can fully recharge its battery before departure, where $(T_{cur} - T_{ev_{(i)}}^{park})$ is the time duration since the arrival of EV$_i$. As such, the charging finish time (about when the charging of EV$_i$ will finish) $T_{ev_{(i)}}^{fin}$ of this EV$_i$ is given by $\left(\frac{E_{ev_{(i)}}^{max} - E_{ev_{(i)}}^{cur}}{\beta} + T_{cur}\right)$ only.
- In another case, $T_{ev_{(i)}}^{fin}$ is given by $(T_{ev_{(i)}}^{park} + D_{ev_{(i)}})$ instead, as the deadline that EV$_i$ will park at this CS as EV can be fully recharged.

Upon above processing for those EVs under charging, the presentation between lines 12 and 16 implies that all charging slots have not been fully occupied, as there are still $(\delta - N_C)$ slots free for charging. Here, T_{cur} is thus estimated as the available charging time for these unoccupied charging slots.

Algorithm 1 EstimateAvailableTimeForCharging

1: **if** no EV is under charging **then**
2: add T_{cur} in LIST with δ times
3: **return** LIST
4: **end if**
5: **for** $(i = 1;\ i \leq N_C;\ i++)$ **do**
6: **if** $\left(\left(T_{cur} - T_{ev_{(i)}}^{park} + \frac{E_{ev_{(i)}}^{max} - E_{ev_{(i)}}^{cur}}{\beta}\right) \leq D_{ev_{(i)}}\right)$ **then**
7: LIST.ADD$\left(\frac{E_{ev_{(i)}}^{max} - E_{ev_{(i)}}^{cur}}{\beta} + T_{cur}\right)$
8: **else**
9: LIST.ADD$(T_{ev_{(i)}}^{park} + D_{ev_{(i)}})$
10: **end if**
11: **end for**
12: **if** $(N_C < \delta)$ **then**
13: **for** $(j = 1;\ j \leq (\delta - N_C);\ j++)$ **do**
14: LIST.ADD(T_{cur})
15: **end for**
16: **end if**
17: **if** no EV is waiting for charging **then**
18: **return** LIST
19: **else**
20: sort the queue of N_W according to FCFS
21: sort LIST with ascending order
22: **for** $(k = 1;\ k \leq N_W;\ k++)$ **do**
23: **if** ((LIST.GET(0) $- T_{ev_{(k)}}^{park}) < D_{ev_{(k)}}$) **then**
24: **if** $\left(\left(\text{LIST.GET(0)} - T_{ev_{(k)}}^{park} + \frac{E_{ev_{(k)}}^{max} - E_{ev_{(k)}}^{cur}}{\beta}\right) \leq D_{ev_{(k)}}\right)$ **then**
25: $T_{ev_{(k)}}^{fin} = \text{LIST.GET(0)} + \frac{E_{ev_{(k)}}^{max} - E_{ev_{(k)}}^{cur}}{\beta}$
26: **else**
27: $T_{ev_{(k)}}^{fin} = T_{ev_{(k)}}^{park} + D_{ev_{(k)}}$
28: **end if**
29: replace LIST.GET(0) with $T_{ev_{(k)}}^{fin}$ in LIST
30: sort LIST with ascending order
31: **end if**
32: **end for**
33: **return** LIST
34: **end if**

Then, Algorithm 1 will return that LIST including the available time for each charging slot, either if there is no EV waiting for charging as the condition stated at line 17, or a loop operation for each EV$_k$ waiting for charging has been processed as stated at line 22.

In the latter case, the loop operation starts from sorting the queue of N_W based on FCFS order, following the charging scheduling priority. Meanwhile, the LIST in relation to those EVs under charging is sorted with ascending order, where the earliest available time for charging considering all charging slots at a CS, as denoted by LIST.GET(0) is at the head of LIST. In detail, to calculate the charging finish time $T^{fin}_{ev_{(k)}}$ of each EV$_k$ waiting for charging, needs to consider the earliest available time of charging slots. Note that only the EV$_k$ can be charged during its parking duration will involve calculation, as the condition given by $((\text{LIST.GET(0)} - T^{park}_{ev_{(k)}}) < D_{ev_{(k)}})$ at line 23. As presented at lines 25 and 27, either $\left(\text{LIST.GET(0)} + \frac{E^{max}_{ev_{(k)}} - E^{cur}_{ev_{(k)}}}{\beta}\right)$ or $(T^{park}_{ev_{(k)}} + D_{ev_{(k)}})$ is estimated as the remaining charging time of EV$_k$ considering its departure, where $(\text{LIST.GET(0)} - T^{park}_{ev_{(k)}})$ is the waiting time of EV$_k$ to start charging. Furthermore, the LIST.GET(0) will be replaced with $T^{fin}_{ev_{(k)}}$, while LIST will be sorted with ascending order upon processing each EV$_k$ for each loop. The above loop operation ends when all EV$_k$ have been processed.

C. CS-Selection Decision Making

At the GA side, the decision making on estimating the expected waiting time at a CS, further considers those reported EVs' reservation information. The detail regarding this is presented in Algorithm 2, where N_R stands for the number of EVs have reserved for charging at a CS. The Algorithm 2 sorts the queue of N_R following FCFS order, which is same as the charging scheduling priority. In this case, EV$_i$ stands for the i^{th} EV in the queue of N_R.

As highlighted at line 4, for each $T^{arr}_{ev_{(i)}}$ which is earlier than $T^{arr}_{ev_{(r)}}$, the former will involve the dynamic update of the LIST as returned by Algorithm 2. This means only those EVs with an earlier arrival time than EV$_r$, are considered for calculating the expected waiting time. Here, the purpose of such updating is to estimate when a charging slot will be available upon the arrival of EV$_r$. Note that the LIST is initially sorted according to the ascending order, such that the earliest available time for charging is at the head for the following loop operation:

- In one case, if $T^{arr}_{ev_{(i)}}$ is earlier than the earliest available time considering all charging slots, as given by $(\text{LIST.GET(0)} > T^{arr}_{ev_{(i)}})$ at line 5, the charging finish time $T^{fin}_{ev_{(i)}}$ is calculated by aggregating this available time for charging and the corresponding expected charging time $T^{cha}_{ev_{(i)}}$, considering its parking duration $D_{ev_{(i)}}$. Particularly, the condition $((\text{LIST.GET(0)} - T^{arr}_{ev_{(i)}} + T^{cha}_{ev_{(i)}}) \leq D_{ev_{(i)}})$ implies that EV$_i$ could fully recharge its battery before departure and vice versa, where $(\text{LIST.GET(0)} - T^{arr}_{ev_{(i)}})$ reflects the time to await until the charging is started. Following the calculation of $T^{fin}_{ev_{(i)}}$ between lines 8 and 10, $T^{fin}_{ev_{(i)}}$ is thus calculated considering above condition. Note that only the EV$_i$ can be charged before departure, would involve the calculation, as the condition given by $((\text{LIST.GET(0)} - T^{arr}_{ev_{(i)}}) < D_{ev_{(i)}})$ at line 6.

Algorithm 2 EstimateExpectedWaitingTime

1: sort the queue of N_R according to FCFS
2: sort LIST returned by Algorithm 1, with ascending order
3: **for** $(i = 1;\ i \leq N_R;\ i++)$ **do**
4: **if** $(T^{arr}_{ev_{(i)}} < T^{arr}_{ev_{(r)}})$ **then**
5: **if** $(\text{LIST.GET(0)} > T^{arr}_{ev_{(i)}})$ **then**
6: **if** $((\text{LIST.GET(0)} - T^{arr}_{ev_{(i)}}) < D_{ev_{(i)}})$ **then**
7: **if** $((\text{LIST.GET(0)} - T^{arr}_{ev_{(i)}} + T^{cha}_{ev_{(i)}}) \leq D_{ev_{(i)}})$ **then**
8: $T^{fin}_{ev_{(i)}} = \text{LIST.GET(0)} + T^{cha}_{ev_{(i)}}$
9: **else**
10: $T^{fin}_{ev_{(i)}} = T^{arr}_{ev_{(i)}} + D_{ev_{(i)}}$
11: **end if**
12: **end if**
13: **else**
14: **if** $(T^{cha}_{ev_{(i)}} \leq D_{ev_{(i)}})$ **then**
15: $T^{fin}_{ev_{(i)}} = T^{arr}_{ev_{(i)}} + T^{cha}_{ev_{(i)}}$
16: **else**
17: $T^{fin}_{ev_{(i)}} = T^{arr}_{ev_{(i)}} + D_{ev_{(i)}}$
18: **end if**
19: **end if**
20: replace the LIST.GET(0) with $T^{fin}_{ev_{(i)}}$
21: sort LIST with ascending order
22: **end if**
23: **end for**
24: **if** $(\text{LIST.GET(0)} > T^{arr}_{ev_{(r)}})$ **then**
25: **return** Expected Waiting Time = LIST.GET(0) $- T^{arr}_{ev_{(r)}}$
26: **else**
27: **return** Expected Waiting Time = 0
28: **end if**

- In another case as presented at line 13, EV$_i$ will not wait for additional time to start charging. Here, $T^{fin}_{ev_{(i)}}$ is calculated by considering $T^{arr}_{ev_{(i)}}$, $T^{cha}_{ev_{(i)}}$ and $D_{ev_{(i)}}$ following the calculation at lines 15 and 17.

By replacing the earliest available time for charging with each $T^{fin}_{ev_{(i)}}$, the available time for charging per charging slot is dynamically updated, until all EV$_i$ in the queue of N_R have been processed. Note that the LIST will be sorted with ascending order after the process of each EV$_i$, such that the earliest available time for charging is always at the head of LIST for further calculation in next loop.

Upon this loop operation, the arrival time of EV$_r$ will be compared with the earliest available time for charging, denoted as the head value in LIST. Then, their differential is estimated as the expected waiting time, as presented between lines 25 and 27. Note that the condition $(\text{LIST.GET(0)} > T^{arr}_{ev_{(r)}})$ implies that the charging for EV$_r$ has to wait for additional $(\text{LIST.GET(0)} - T^{arr}_{ev_{(r)}})$ time duration, as the targeted expected waiting time. By running Algorithm 2 in relation to each CS, the GA will select the CS with the minimum value of such expected waiting time, to provide charging service to EV$_r$.

D. Reservation Updating

Once EV$_r$ has confirmed the selection decision (based on the minimum charging waiting time calculated above) from the GA by reporting its reservation, it will start to periodically send the reservation update request (including updated arrival time, expected charging time and parking duration) during its journey. Here, the costs (in relation to how long EV$_r$'s charging will be) at other unselected CSs are also calculated, where the one with the minimum cost will be returned. The selection cost measuring a sum of the waiting time to start charging for EV$_r$ (via Algorithm 2 with other EVs' updated reservation) and its expected charging duration at a CS, is given by:

$$\text{COST} = \text{Expected Waiting Time} + T^{cha}_{ev_{(r)}} \tag{3}$$

If the minimum cost in relation to other unselected CSs is lower than that of currently selected CS, EV$_r$ will be informed by the GA that the charging plan is changed at a newly selected CS with the minimum cost. No additional communication will be established if there is no decision change. Upon only receiving the notification about decision change, EV$_r$ will then confirm this new decision, by informing the GA to cancel the reservation at previously selected CS and record this new reservation. Above operations run for each update interval, until EV$_r$ has arrived at the CS returned by GA.

The motivation behind this considers the mobility uncertainty, that the varied EV moving speed S_{ev} during journey will inevitably affect the accuracy of EVs' reservation information used in Algorithm 2. In the worst case, an inaccurate estimation may result in a longer expected waiting time for EV$_r$, and its charging may not be finished due to a certain parking duration. Note that $T^{cha}_{ev_{(r)}}$ will be gradually increased when sending reservation updating request at each time, because much electricity will be consumed for movement. As such, a changed CS-selection decision mainly concerns on a further reduced expected waiting time at other CSs. With this in mind, to select the CS with the minimum cost through periodical reservation updating can adjust the charging plan of EV$_r$ and the decision will be converged, since the smallest cost implies the highest possibility that the charging of EV$_r$ could be finished before its parking duration $D_{ev_{(r)}}$.

IV. Performance Evaluation

We have built up an entire EV charging system in Opportunistic Network Environment (ONE) [9]. In Fig.2, the default scenario with 4500×3400 m^2 area is shown as the down town area of Helsinki city in Finland. Here, 240 EVs with $[5 \sim 15]$ m/s variable moving speed are initialized in the network. The configuration of EVs follows the charging specification {Maximum Electricity Capacity (MEC), Max Travelling Distance (MTD), Status Of Charge (SOC)}. We configure three types of EVs, which are Coda Automotive [10] {33.8 kWh, 193 km, 30%}, Wheego Whip [11] {30 kWh, 161 km, 40%} and Hyundai BlueOn [12] {16.4 kWh, 140 km, 50%}. Here, the electricity consumption for the Traveled Distance (TD) is calculated based on $\frac{\text{MEC}\times\text{TD}}{\text{MTD}}$. Each type is with 80 EVs. Besides, 7 CSs are provided with sufficient electric energy and 3 charging slots through entire simulation, using the fast charging rate of 62 kW. If the ratio between its current energy and maximum energy is below the value of SOC, the EV would travel towards a decided CS for charging. Here, the shortest path towards CS is formed considering road topology. Particularly, 30 randomly generated accidents happen for every 900s in the city, and the warning distance is 300m. Therefore, each EV will adjust its moving speed, if the distance between its location and an accident place is smaller than 300m.

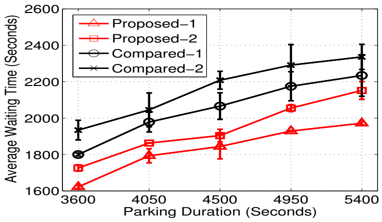
Fig. 2. Simulation Scenario of Helsinki City

The average waiting time reflects the average period between the time an EV arrives at the selected CS and the time it fully finishes recharging its battery, considering the full charging can not be finished within parking duration. Here, the following schemes are evaluated for comparison: **1) Proposed-1:** The complete version of our proposal, where the default reservation update interval is 100s. **2) Proposed-2:** Our proposal without reservation updating. **3) Compared-1:** The CS-selection is based on the minimum queuing time at a CS, referring to the calculation in [13]. **4) Compared-2:** The CS-selection is based on the closest distance between the EV sending charging request and a CS.

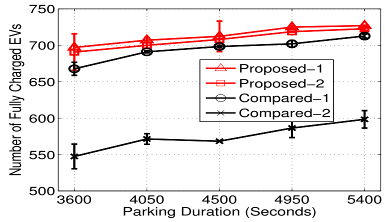
In Fig.3(a), we observe that a longer parking duration increases the average waiting time. This is because more EVs will stay at CSs until being fully recharged, as such a total waiting time considering all parking EVs will be increased. Particularly, our proposal without reservation updating still achieves a better performance, than the CS-selection schemes based on local queueing time and distance. Further to this, since EVs with uncertain mobility benefit from the reservation updating, our proposed CS-selection is dynamically adjusted. Since the EV charging plan is coordinated by reporting reservation as well as reservation updating, our proposal achieves a higher number of charged EVs in Fig.3(b), where the version without reservation updating is the secondary, due to not adjusting CS-selection decision. Here, the CS-selection scheme based on the closest distance is the worst, because it does not consider how many EVs are parking at a CS. Thus a closer CS does not mean it is occupied by a less number of EVs. Of course, a longer parking duration leads to a higher number of charged EVs, as more EVs can be fully recharged. Our observation in Fig.3(c) shows that our expected waiting time estimation in relation to EVs' parking duration is advanced, by achieving a less number of discharged EVs. The CS-selection based on the closest distance discharges the highest number of EVs, due to not considering number of parking EVs and their parking duration. Particularly, the performance between the two versions of proposal is close following a longer parking duration, which means that less

TABLE II
INFLUENCE OF RESERVATION UPDATING INTERVAL

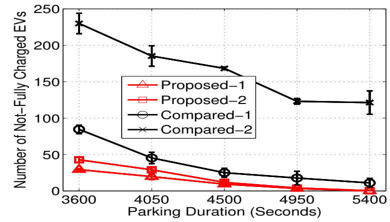
	Average Waiting Time	Number of Fully Charged EVs	Number of Not-Fully Charged EVs	$\frac{\text{Number of CS-Selection Change}}{\text{Number of Reservation Reporting}}$
Proposed-1 (100s)	1617s (±23)	700 (±5)	21 (±1)	0.7148 (±0.0097)
Proposed-1 (200s)	1701s (±27)	697 (±2)	35 (±3)	0.4587 (±0.0123)
Proposed-1 (300s)	1722s (±16)	693 (±4)	43 (±5)	0.2753 (±0.0221)



(a) Average Waiting Time

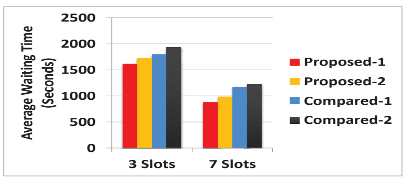


(b) Number of Fully Charged EVs

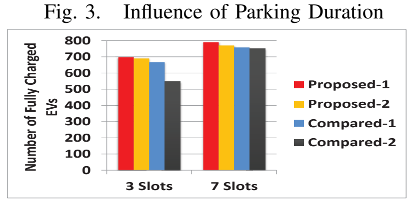


(c) Number of Not-Fully Charged EVs

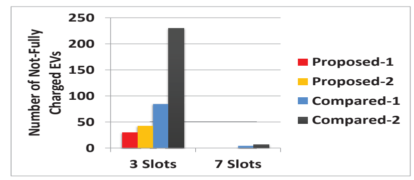
Fig. 3. Influence of Parking Duration



(a) Average Waiting Time



(b) Number of Fully Charged EVs



(c) Number of Not-Fully Charged EVs

Fig. 4. Influence of Charging Slots

EVs will be discharged if they will stay long enough at CS.

Results in TABLE II show that a frequent reservation updating interval improves the charging performance. This is because of a frequent CS-selection change, where the proposal in case of 100s interval is with the highest ratio of $\frac{\text{Number of CS-Selection Change}}{\text{Number of Reservation Reporting}}$. In other words, the CS-selection decision in case of 100s update interval will be changed most likely, based on a frequent updated EV's reservation information. In contrast, more EVs can not finish their charging before departure, based on the inaccurate decision making given 300s update interval. If increasing the number of charging slots at CSs, all performances are improved in Fig.4(a), Fig.4(b) and Fig.4(c). In particular, using distance for CS-selection benefits more from this situation than other schemes.

V. CONCLUSION

Considering that EVs may depart from that CS before being fully charged, we proposed a CS-selection scheme targeting to minimize the waiting time for charging, via the reported EVs' reservation information. The waiting time to start EV charging is estimated for making CS-selection decision. It is highlighted that under the scenario where the uncertain mobility affects the accuracy of EVs' reservation information, a reservation updating operation is further proposed to adjust the EV charging plan, such that the waiting time for charging is further optimized. Evaluation results under the Helsinki city scenario showed the effectiveness of our proposal, in terms of CS-selection decision making and reservation updating.

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