An EV Charging Management System Concerning Drivers' Trip Duration and Mobility Uncertainty

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***Abstract*—With 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, EV drivers may experience discomfort for long charging waiting time during their journeys. This often happens when a large number of (on-the-move) EVs are planning to charge at the same CS, but it has been heavily overloaded. With this concern, in an EV charging management system, we focus on CS-selection decision making and propose a scheme to manage EVs' charging plans, to minimize drivers' trip duration through intermediate charging at CSs. The proposed scheme jointly considers EVs' anticipated charging reservations (including arrival time, expected charging time) and parking duration at CSs. Furthermore, by tackling mobility uncertainty that EVs may not reach their planned CSs on time (due to traffic jams on the road), a periodical reservation updating mechanism is designed to adjust their charging plans. Results under the Helsinki city scenario with realistic EV and CS characteristics show the advantage of our proposal, in terms of minimized drivers' trip duration, as well as charging performance at the EV and CS sides.**

***Index Terms*—Electric Vehicle, Charging System, CS-Selection Decision Making, Driver's Trip Duration, Mobility Uncertainty.**

I. Introduction

In SmartGrid [1], the application of Electric Vehicles (EVs) [2] is promising compared to traditional petrol based vehicles in many developed countries. Such introduction on EVs concerns the increasing long-term energy cost and attention on environmental impact. However, for many big cities where majority of trip is with long distance, on-the-move EV charging may take place during journey. In this context, the flexibility of charging infrastructure as well as the appropriate decision making to manage charging are vital to the success and long-term viability of EV industry.

Majority of previous works investigate charging scheduling [3] for the use case (concerning when/whether to charge EVs) where EVs have already been parking at homes/Charging Stations (CSs). In contrary, our research interest addresses another use case (concerning where/which CS to charge) that has not received much attention, in order to manage the charging plans for on-the-move EVs. 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 time to charge an EV battery, to optimally manage where to charge has become a critical issue in recent years. This use case cannot be overlooked as it is the most important feature of EV in future smart city [4], especially for fast charging.

We refer to the charging system widely adopted by previous works, which utilize Global Aggregator (GA) or other third party who is interested in EVs charging management. By monitoring CSs' condition, the GA as system controller implements the charging management whenever it receives a charging request from an on-the-move EV. It is worthy mentioning that based on existing fast charging technology, the charging time of an EV typically exceeds tens of minutes [5]. Therefore, a CS would be congested due to serving a large number of charging demands from parking EVs.

A few previous works [6]–[9] have addressed CS-selection decision making to minimize the EVs' charging waiting time, by monitoring the local status of CSs. Basically, the CS with the highest availability (e.g., minimum queuing time [9]) will be selected as the best choice. Inevitably, a potential charging hotspot may happen, if many on-the-move EVs travel towards the same CS for charging. If further bringing an anticipated EV charging reservation [10] (including when the EV will arrive at selected CS for charging, and how long its charging time will be upon the arrival), the congestion at CS could be alleviated. This is because that at what time and which CS will be heavily loaded can be identified, so as to avoid selecting that CS as the charging plan.

To the best of our awareness, no previous works has considered the influence of traffic condition on the charging management. Such traffic condition (referred as traffic jams on the road) results in EVs' mobility uncertainty. In some highly congested area, EVs may stop for certain periods until traffic jams disappear. Therefore, EVs may not guarantee their reported reservations accurately (meaning they may not arrive at selected CSs on time), and particularly the GA is unaware of this condition change timely. Since to continually obtain the updated EVs' reservation information improves the accuracy of CS-selection, the changed CS-selection using updated information is appropriate to improve EV drivers' Quality of Experience (QoE).

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Indeed, EV drivers also have their individual journeys and certain parking duration. However, an inappropriate charging taking place during journey may degrade users' QoE, as they prefer to reach trip destination as soon as possible. On the one hand, drivers may not be willing to wait for a quite long time to charge their EVs. On the other hand, selecting a CS that is far away from the trip destination is not suggested as well. To summarize above, in spite that the parking duration has been addressed in the use case concerning when/whether to charge EVs, a joint consideration on parking duration and trip destination has not been addressed in the use case concerning where/which CS to charge.

In order to minimize the trip duration for on-the-move EVs need charging services, we jointly consider the time to travel towards the selected CS, that taken from certain CS to the trip destination, as well as the time parking at that intermediate CS. It is worthy highlighting this article focuses on the impact of charging management on the EVs trip duration, and not on the power grid (i.e., valley filling [11], [12]). Technically:

- Concerning a city scenario, the CS-selection decision making is based on the reported EVs' reservation information as well as parking duration at selected CSs. This anticipated information is recorded by the GA to estimate the expected charging waiting time at CSs. The EV's trip destination is concerned, so as to find the CS through which an EV deserves charging will experience the shortest trip duration. 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 the EV may depart from a CS before being fully recharged.
- Since the problem of mobility uncertainty has not been addressed in literature, we advertise that EVs are further capable of sending reservation update requests, so that they would be informed by the GA to change their charging plans and experience a shorter time trip duration. This updating process is run periodically, and applicable under the scenario that EV speed is fluctuated due to the traffic jams.

The rest of the article is organized as follows. In Section II we present the related work, followed by Section III in which we introduce the preliminary including network entities definition, assumption, overview of charging system. In Section IV, we introduce our proposed CS-selection decision making scheme. Results are evaluated in Section V, followed by conclusion made in Section VI.

II. Related Work

A most recent survey [13] has identified two EV charging use cases. On the one hand, majority of works in literature [3] address the problem of regulating the EV charging, such as minimizing peak load/cost, flattening aggregated demands or reducing frequency fluctuations. On the other hand, a few works are more concerned with minimizing the charging waiting time of EVs.

In the latter branch, the works in [6], [9] estimate the queuing time at CSs, such that the one with the minimum queueing time is ranked as the best charging option. The work in [7] compares the schemes to select CS based either on the closest distance or minimum waiting time, where results show that the latter performs better given high EVs density under city scenario. In [8], the CS with a higher capability to accept charging requests from on-the-move EVs, will propose this service with a higher frequency, while EVs sense this service with a decreasing function of their current battery levels. The CS-selection scheme in [14] adopts a pricing strategy to minimize congestion and maximize profit, by adapting the price depending on the number of EVs charging at each time point. Note that previous works on CS-selection can usually be integrated with route planning, such as the work in [15] predicts congestion at charging stations and suggests the most efficient route to its user. Besides, reservation based schemes have been proposed to enhance the CS-selection intelligence using anticipated EVs mobility information, such as the works proposed under highway scenario [10] and city scenario [16], [17].

Regarding reservation charging aspect, an essential difference between our work and [10] is that the latter assumes highway scenario where the EV will pass through all CSs. Its 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 that time spent at subsequent CSs, before exiting the highway. In sharp contrast, under our city scenario the EV will head to a single geographically distributed CS for charging, where the expected charging waiting time is associated to that certain CS. Different from our previous work [16], [17], we further tackle the limited parking duration at CS (EVs may depart before being fully charged) and the entire trip duration (through an intermediate charging) for CS-selection decision making. Concerning the mobility uncertainty due to traffic jams, a periodical reservation updating is further executed to adjust EVs' charging plans.

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) simple, and favors more sophisticated centralized optimizations from the GA side based on the aggregated global information. Last but not least, the price [18]–[21] differences between CSs concerning business model, and battery exchange service [22] concerning a super fast service provision could be easily integrated into our proposed CS-selection decision making.

III. System Model

A. Definition of Network Entities

Electric Vehicle (EV): Each EV is with a Status Of Charge (SOC) threshold. If the ratio between its current energy and maximum energy is below the SOC threshold, the EV starts to negotiate with the GA to find an appropriate CS for charging. Further to this, the EV also reports its charging reservation to the GA, including "what time it will arrive at decided CS" and "how long its expected charging time will be at that CS".

Charging Station (CS): Each CS is located at a certain location to charge EVs in parallel, based on multiple charging slots. Its condition information (number of EVs already parking at the CS and their charging time) is monitored by the GA.

Global Aggregator (GA): It is a centralized entity to manage charging. Here, the CSs' condition information as well as EVs' charging reservations are needed to make CS-selection decision.

B. Assumption

In this article, we consider a city scenario where CSs are geographically deployed in a city, the GA globally manages the charging plans for all EVs in the network. Without loss of generality, EVs are equipped with wireless communication devices such as 3G/Long Term Evolution (LTE), which allows them to communicate with the GA for request/reply charging services. Each CS is with multiple charging slots such that a number of EVs can be charged in parallel.

If with a low electricity stage, an on-the-move EV (with its certain trip destination) has to firstly head to a selected CS (decided by the GA) for charging. The underlying EV charging scheduling (concerning when/whether to charge EVs) at the CS side, is based on the First Come First Serve (FCFS) order, as widely used for the branch related to EV charging management. This means that the parking EV with an earlier arrival time will be scheduled with a higher charging priority.

If a CS is fully occupied (meaning all its charging slots are currently being used), incoming EVs need to wait until one of its charging slots is free. Particularly, each EV has its individual parking duration at the CS, thus EV may depart from the CS before being fully charged. Upon departure from the CS, the EV will start to travel towards its trip destination again, with an initial maximum moving speed (e.g., speed acceleration).

C. Introduction on Mobility Uncertainty

Partially based on [23], the uncertainty of EV mobility presented in this article is mainly due to several traffic jams happen in a city. Any EV within a certain range of traffic jam will slow down its speed, while it will accelerate the speed once leaving from the range of that traffic jam. In particular, the EV has to temporarily stop, if with a close proximity to the central of traffic jam. In such case, the EV only resumes its movement once the closest traffic jam disappears.

Due to this reason, the variation of moving speed will affect the arrival time at the CS, as well as the electricity consumption for travelling towards that CS. These are included as the charging reservation reported to the GA. If without reservation updating, an on-the-move EV may not reach a CS at the time it previously reserved, whereas the GA still has an obsolete knowledge that 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. Further to this, the mobility uncertainty also affects the travelling time taken from a CS and EV's trip destination.

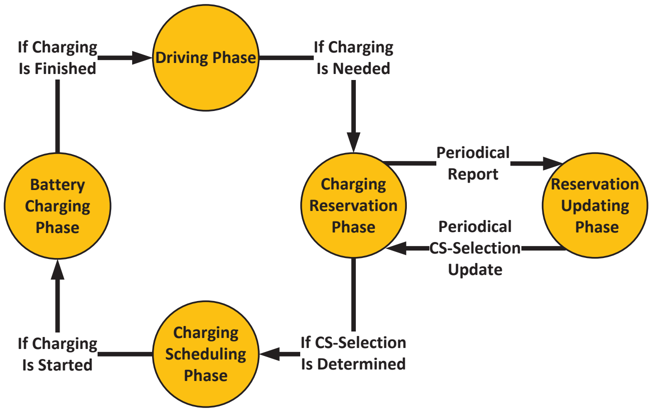


Fig. 1. System Cycle of Proposed EV Charging Management

D. System Cycle of Proposed EV Charging Management

Fig.1 describes the cycle of EV charging management:

Driving Phase: The EV is travelling towards its trip destination. If with a low energy status, that EV then requires a charging service allocated from the GA.

Charging Reservation Phase: Here, once the EV is notified by the GA in terms of CS-selection decision, the EV further reports its charging reservation to the GA.

- **Reservation Updating Phase:** The EV also periodically updates its charging reservation to the GA, due to mobility uncertainty. The updated CS-selection possibly triggers a charging reservation at newly decided CSs.

Charging Scheduling Phase: The EV will wait to be scheduled for charging, upon its arrival at the selected CS.

Battery Charging Phase: The EV is currently being charged within a period of its parking duration. Upon departure (fully/not fully charged), the EV turns to **Driving Phase**.

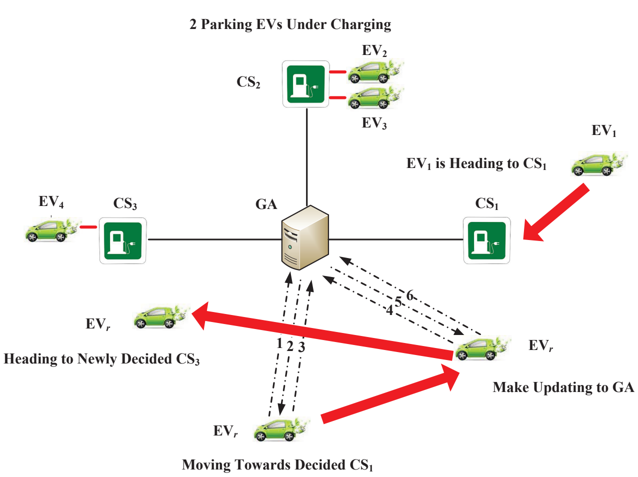


Fig. 2. Overview of Proposed EV Charging Management

Based on Fig.2, a typical procedure for our proposed EV charging management scheme is listed as follows:

1) When one on-the-move EV needs charging service, namely EV_r, it informs the GA about its charging request (including location, trip destination).

2) The GA then compiles a list of CSs and ranks the most appropriate one (in terms of the minimized trip duration through an intermediate charging), and the decision is sent back to EV$_r$.
3) EV$_r$ reports its charging reservation in relation to this selected CS, including its arrival time, expected charging time and parking duration at this CS.
4) When travelling towards the selected CS, EV$_r$ periodically checks whether that currently selected CS is still the best choice, by sending a reservation update request to the GA.
5) The GA then compares a cost in relation to the newly selected CS as well as that of previously selected CS. If charging at the previously selected CS cannot contribute to the minimized trip duration, the GA will inform EV$_r$ about an updated arrangement with the new CS-selection decision.
6) EV$_r$ thus cancels its reservation at the previously selected CS, and reports the updated reservation in relation to the newly selected CS. Finally, EV$_r$ changes its movement towards the location of that newly selected CS.

Steps 4 to 6 are repeated until EV$_r$ reaches the newly selected CS for charging. Note that such new arrangement may change for several times, depending on the frequency of reservation updating request which triggers computing logic shown in Fig.3.

IV. System Design

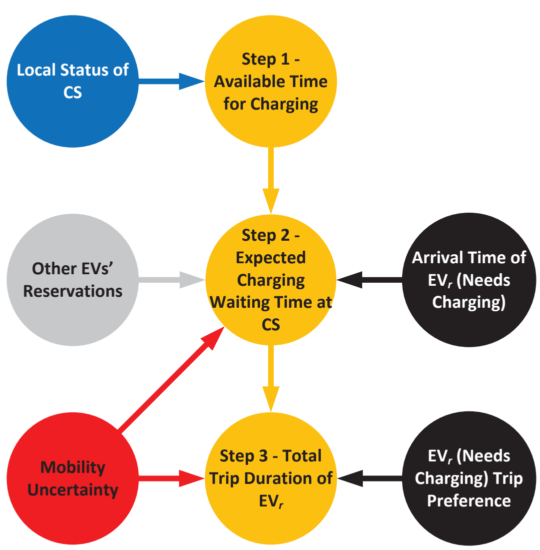


Fig. 3. Flow Chart of Computation Logic

Referred to Fig.3, the total EV trip duration through an intermediate charging, is estimated following three steps.

Step 1: The available time for charging per each charging slot at the CS is estimated based on its local condition.

Step 2: The output of **Step 1** and other incoming EVs' charging reservations are jointly used to estimate the future status of CS. Here, we refer to expected charging waiting time, and take the influence of mobility uncertainty into account.

Step 3: The trip duration for EV$_r$ (The EV needs charging) is estimated, by jointly considering its trip destination, the output from **Step 2** as well as the influence of mobility uncertainty.

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_{jam}	Number of traffic jams
l_{jam}	Location of a traffic jam
$\ell\{ev, l_{jam}\}$	Distance between EV and l_{jam}
$\Re$	Range of traffic jam
S_{ev}^{min}	Minimum Moving speed of EV
S_{ev}^{max}	Maximum Moving speed of EV
N_R	Number of EVs reserved for charging at CS
ECWT$_{cs}$	Expected charging waiting time at CS
N_{cs}	Number of CSs
l_{cs}	Location of a CS
$T_{cs,d}^{min}$	Travelling time from a CS to EV's trip destination
$T_{ev_{(r)}}^{cs,d}$	Trip duration of EV$_r$ through charging at a CS

A. Available Time for Charging Estimation

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 $\left(\frac{E_{ev_{(i)}}^{max} - E_{ev_{(i)}}^{cur}}{\beta}\right)$ 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 be fully recharged before departure, where $\left(T_{cur} - T_{ev_{(i)}}^{park}\right)$ 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 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 $\left(T_{ev_{(i)}}^{park} + D_{ev_{(i)}}\right)$ instead, as the deadline that EV$_i$ will park at this CS. This is because that EV$_i$ can not 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 then estimated as the available charging time for these unoccupied charging slots.

Algorithm 1 Available Time For Charging Estimation

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** $(i = 1;\ i \le N_C;\ i++)$ **do**
6: **if** $\left(\left(T_{cur} - T_{ev_{(i)}}^{park} + \frac{E_{ev_{(i)}}^{max} - E_{ev_{(i)}}^{cur}}{\beta}\right) \le D_{ev_{(i)}}\right)$ **then**
7: LIST.ADD$\left(\frac{E_{ev_{(i)}}^{max} - E_{ev_{(i)}}^{cur}}{\beta} + T_{cur}\right)$
8: **else**
9: LIST.ADD$\left(T_{ev_{(i)}}^{park} + D_{ev_{(i)}}\right)$
10: **end if**
11: **end for**
12: **if** $(N_C < \delta)$ **then**
13: **for** $(j = 1;\ j \le (\delta - N_C);\ j++)$ **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** $(k = 1;\ k \le N_W;\ k++)$ **do**
23: **if** $\left(\left(\text{LIST.GET(0)} - T_{ev_{(k)}}^{park}\right) < D_{ev_{(k)}}\right)$ **then**
24: **if** $\left(\left(\text{LIST.GET(0)} - T_{ev_{(k)}}^{park} + \frac{E_{ev_{(k)}}^{max} - E_{ev_{(k)}}^{cur}}{\beta}\right) \le D_{ev_{(k)}}\right)$ **then**
25: $T_{ev_{(k)}}^{fin} = \left(\text{LIST.GET(0)} + \frac{E_{ev_{(k)}}^{max} - E_{ev_{(k)}}^{cur}}{\beta}\right)$
26: **else**
27: $T_{ev_{(k)}}^{fin} = \left(T_{ev_{(k)}}^{park} + D_{ev_{(k)}}\right)$
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 (in the queue of N_W) has been processed as stated from line 22.

In the latter case, the loop operation starts from sorting the queue of N_W based on FCFS order, following the underlying charging scheduling priority in Section II. 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 $T_{ev_{(k)}}^{fin}$ 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 $\left(\left(\text{LIST.GET(0)} - T_{ev_{(k)}}^{park}\right) < D_{ev_{(k)}}\right)$ at line 23.

- As presented at lines 25 and 27, either $\left(\text{LIST.GET(0)} + \frac{E_{ev_{(k)}}^{max} - E_{ev_{(k)}}^{cur}}{\beta}\right)$ or $\left(T_{ev_{(k)}}^{park} + D_{ev_{(k)}}\right)$ is estimated as $T_{ev_{(k)}}^{fin}$, where $\left(\text{LIST.GET(0)} - T_{ev_{(k)}}^{park}\right)$ is the waiting time for EV$_k$ to start charging.
- Furthermore, the LIST.GET(0) will be replaced with $T_{ev_{(k)}}^{fin}$, while LIST will be sorted with ascending order upon processing each EV$_k$ in the loop.

The above loop operation ends when all EV$_k$ have been processed, and an updated LIST is returned.

B. Detail of Mobility Uncertainty

Algorithm 2 Mobility Uncertainty

1: Randomly generate N_{jam} traffic jams
2: **for** each EV in network **do**
3: **for** $\forall l_{jam} \in N_{jam}$ **do**
4: calculate $(\ell\{ev, l_{jam}\}, \ell\{ev, l_{jam}\} < \Re)$
5: **end for**
6: $l_{jam}^{min} \leftarrow \arg\min(\ell\{ev, l_{jam}\}, \ell\{ev, l_{jam}\} < \Re)$
7: **if** $\left(l_{jam}^{min} \ne null\right)$ **then**
8: **if** $\left(\ell\left\{ev, l_{jam}^{min}\right\} < \Re\right)$ **then**
9: **if** $\left(\ell\left\{ev, l_{jam}^{min}\right\} < \frac{\Re}{10}\right)$ **then**
10: $S_{ev} \to 0$
11: **else**
12: $S_{ev} \to S_{ev} - \left(\left(S_{ev} - S_{ev}^{min}\right) \times \lambda\right), \lambda \in [0,1]$
13: **end if**
14: **else**
15: $S_{ev} \to S_{ev} + \left(\left(S_{ev}^{max} - S_{ev}\right) \times \lambda\right), \lambda \in [0,1]$
16: **end if**
17: **end if**
18: **end for**

In Algorithm 2, we detail the implementation of mobility uncertainty due to traffic jams. Here, a number of N_{jam} traffic jams periodically happen in city. The locations l_{jam} of those traffic jams are randomly chosen from the city topology.

For each on-the-move EV, its moving speed is varied depends on the most closest traffic jam. Finding the location of closest traffic jam l_{jam}^{min} is determined by operations between lines 3 and 6. Here, $\Re$ is the range of traffic jam. The speed is fluctuated only if the l_{jam}^{min} is found. This means that there is the closest traffic jam from which the distance to EV is smaller than $\Re$.

- If the distance between EV and its closest traffic jam $\ell\left\{ev, l_{jam}^{min}\right\}$ is smaller than $\Re$, the EV speed S_{ev} is reduced with a random value λ at line 12.
- Particularly, S_{ev} turns to 0 if $\left(\ell\left\{ev, l_{jam}^{min}\right\} < \frac{\Re}{10}\right)$, presented between lines 9 and 10. This implies that EV is close to the centra of l_{jam}^{min}, and thus temporarily stops.
- At line 15, if $\ell\left\{ev, l_{jam}^{min}\right\}$ is larger than $\Re$, the EV speed is accelerated with a random value λ. This implies that the EV is out of the range of the closest traffic jam l_{jam}^{min}.

C. Reporting Reservation Information

Whenever a CS-selection decision is made and returned to the EV$_r$ (the EV needs charging service) 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 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.

The assumption that the reservation information is trustworthy, is vulnerable without ensuring the integrity of messages from EVs to the GA on end-to-end aspects. E.g., forged or wrong reservation information are continuously delivered by the GA to compute quite imprecise estimation for charging waiting time. The general secured vehicular communication framework in [24] can be applied to enable secured delivery of EVs' reservation requests towards the GA.

D. Expected Charging Waiting Time Estimation

At the GA side, the decision making on estimating the expected charging waiting time at a CS, further considers those reported EVs' reservation information. Upon this anticipated information, the expected charging waiting time ECWT$_{cs}$ at a CS can be estimated. In this context, the GA will keep track of the charging time of EVs locally parking at a CS, as well as other EVs (with an earlier arrival time than EV$_r$) heading to this CS.

The detail regarding this is presented in Algorithm 3, where N_R stands for the number of EVs have reserved for charging at a CS. The Algorithm 3 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 $T_{ev_{(i)}}^{arr}$ which is earlier than $T_{ev_{(r)}}^{arr}$, the former will involve the dynamic update of the LIST as returned by Algorithm 3. This means only those EVs (in the queue of N_R) with an earlier arrival time than EV$_r$, are considered for calculating the expected charging 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 of LIST for the following loop operation:

Algorithm 3 Expected Charging Waiting Time Estimation

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** $\left(T_{ev_{(i)}}^{arr} < T_{ev_{(r)}}^{arr}\right)$ **then**
5:     **if** $\left(\text{LIST.GET(0)} > T_{ev_{(i)}}^{arr}\right)$ **then**
6:       **if** $\left(\left(\text{LIST.GET(0)} - T_{ev_{(i)}}^{arr}\right) < D_{ev_{(i)}}\right)$ **then**
7:         **if** $\left(\left(\text{LIST.GET(0)} - T_{ev_{(i)}}^{arr} + T_{ev_{(i)}}^{cha}\right) \leq D_{ev_{(i)}}\right)$ **then**
8:           $T_{ev_{(i)}}^{fin} = \left(\text{LIST.GET(0)} + T_{ev_{(i)}}^{cha}\right)$
9:         **else**
10:           $T_{ev_{(i)}}^{fin} = \left(T_{ev_{(i)}}^{arr} + D_{ev_{(i)}}\right)$
11:         **end if**
12:       **end if**
13:     **else**
14:       **if** $\left(T_{ev_{(i)}}^{cha} \leq D_{ev_{(i)}}\right)$ **then**
15:         $T_{ev_{(i)}}^{fin} = \left(T_{ev_{(i)}}^{arr} + T_{ev_{(i)}}^{cha}\right)$
16:       **else**
17:         $T_{ev_{(i)}}^{fin} = \left(T_{ev_{(i)}}^{arr} + D_{ev_{(i)}}\right)$
18:       **end if**
19:     **end if**
20:     replace the LIST.GET(0) with $T_{ev_{(i)}}^{fin}$
21:     sort LIST with ascending order
22:   **end if**
23: **end for**
24: **if** $\left(\text{LIST.GET(0)} > T_{ev_{(r)}}^{arr}\right)$ **then**
25:   **return** $\text{ECWT}_{cs} = \left(\text{LIST.GET(0)} - T_{ev_{(r)}}^{arr}\right)$
26: **else**
27:   **return** $\text{ECWT}_{cs} = 0$
28: **end if**

- In one case, if $T_{ev_{(i)}}^{arr}$ is earlier than the earliest available time considering all charging slots, as given by $\left(\text{LIST.GET(0)} > T_{ev_{(i)}}^{arr}\right)$ at line 5, the charging finish time $T_{ev_{(i)}}^{fin}$ is calculated by aggregating this available time for charging and the corresponding expected charging time $T_{ev_{(i)}}^{cha}$.
  In particular, the condition $\left(\left(\text{LIST.GET(0)} - T_{ev_{(i)}}^{arr} + T_{ev_{(i)}}^{cha}\right) \leq D_{ev_{(i)}}\right)$ at line 7 implies that EV$_i$ could be fully recharged before departure and vice versa, where $\left(\text{LIST.GET(0)} - T_{ev_{(i)}}^{arr}\right)$ reflects the time to wait for charging. Following lines 8 and 10, $T_{ev_{(i)}}^{fin}$ 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 $\left(\left(\text{LIST.GET(0)} - T_{ev_{(i)}}^{arr}\right) < D_{ev_{(i)}}\right)$ at line 6.
- In another case as presented at line 13, EV$_i$ will not wait for additional time to start charging. Here, $T_{ev_{(i)}}^{fin}$ is calculated by considering $T_{ev_{(i)}}^{arr}$, $T_{ev_{(i)}}^{cha}$ and $D_{ev_{(i)}}$ following the calculations at lines 15 and 17.

By replacing the earliest available time for charging with each $T_{ev_{(i)}}^{fin}$, 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 the 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 the 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 charging waiting time at CS, as EWCT_{cs} presented between lines 25 and 27. Note that the condition $\left(\text{LIST.GET(0)} > T^{arr}_{ev_{(r)}}\right)$ implies that the charging for EV_r has to wait for additional $\left(\text{LIST.GET(0)} - T^{arr}_{ev_{(r)}}\right)$ time duration.

E. CS-Selection Decision Making

Algorithm 4 CS-Selection Decision Making

1: **for** $\forall l_{cs} \in N_{cs}$ **do**
2: calculate $T^{tra}_{ev_{(r)}}$
3: calculate $T^{min}_{cs,d}$
4: calculate ECWT_{cs} via Algorithm 3
5: **if** $\left(\left(T^{cha}_{ev_{(r)}} + \text{ECWT}_{cs}\right) \leq D_{ev_{(r)}}\right)$ **then**
6: $T^{cs,d}_{ev_{(r)}} = T^{tra}_{ev_{(r)}} + T^{cha}_{ev_{(r)}} + \text{ECWT}_{cs} + T^{min}_{cs,d}$
7: **else**
8: $T^{cs,d}_{ev_{(r)}} = T^{tra}_{ev_{(r)}} + D_{ev_{(r)}} + T^{min}_{cs,d}$
9: **end if**
10: **end for**
11: $l^{min}_{cs} \leftarrow \arg\min\left(T^{cs,d}_{ev_{(r)}}\right)$
12: **return** l^{min}_{cs}

By running Algorithm 3, the expected charging waiting time at CS (with location l_{cs}) can be estimated. Upon this, the total trip duration for EV_r can be calculated based on following inputs:

1) The travelling time from the current location of EV_r to the selected CS, given by $T^{tra}_{ev_{(r)}}$.
2) The duration (including the time to wait for charging and expected charging time) staying at the selected CS, is given by the calculation at line 6 or 8 in Algorithm 4.
3) The estimated minimum travelling time from the selected CS to the trip destination of EV_r, given by $T^{min}_{cs,d}$. As stated in assumption of Section II, upon a (fully/not fully) recharged service at the selected CS, EV_r will start to travel towards its destination, with the maximum moving speed S^{max}_{ev}. Therefore, $T^{min}_{cs,d}$ can be obtained by the shortest distance between that CS and trip destination, divided by S^{max}_{ev}.

Based on above, we define $T^{cs,d}_{ev_{(r)}}$ as the trip duration for EV_r through an intermediate charging. In Algorithm 4, $T^{cs,d}_{ev_{(r)}}$ is obtained as follows:

- In one case, the total trip duration for EV_r through a *fully* recharged service at an intermediate CS, is given by:

$$T^{cs,d}_{ev_{(r)}} = T^{tra}_{ev_{(r)}} + T^{cha}_{ev_{(r)}} + \text{ECWT}_{cs} + T^{min}_{cs,d} \tag{3}$$

  Note that the condition $\left(\left(T^{cha}_{ev_{(r)}} + \text{ECWT}_{cs}\right) \leq D_{ev_{(r)}}\right)$ at line 5 holds true for a full recharging. This implies EV_r will be fully recharged before its departure deadline $D_{ev_{(r)}}$.

- In another case, a *not-fully* recharged service due to limited $D_{ev_{(r)}}$ turns to following calculation at line 8:

$$T^{cs,d}_{ev_{(r)}} = T^{tra}_{ev_{(r)}} + D_{ev_{(r)}} + T^{min}_{cs,d} \tag{4}$$

  This implies that EV_r can only be charged for a period of $D_{ev_{(r)}}$.

By running $T^{cs,d}_{ev_{(r)}}$ for each CS, the one meets the minimum trip duration for EV_r is selected, and then the GA returns the location of selected CS, as l^{min}_{cs} back to EV_r.

F. Reservation Updating

Once EV_r has confirmed the CS-selection decision (based on the minimum trip duration) from the GA by reporting its charging reservation, EV_r will further periodically send the reservation update request during its journey. The GA then runs Algorithm 4 based on the updated information obtained from CSs and other EVs making reservations. Under such updated condition, the $\overline{\text{CS}}$ (newly decided CS) which meets the minimum trip duration for EV_r is found.

Algorithm 5 Reservation Updating

1: find $l_{\overline{cs}}$ via Algorithm 4
2: **if** $(l_{\overline{cs}} \neq l_{cs})$ **then**
3: **if** $\left(T^{\overline{cs},d}_{ev_{(r)}} < T^{cs,d}_{ev_{(r)}}\right)$ **then**
4: **if** $\left(\left(T^{cha}_{ev_{(r)}} + \text{ECWT}_{\overline{cs}}\right) \leq D_{ev_{(r)}}\right)$ **then**
5: cancel reservation at CS
6: make reservation at $\overline{\text{CS}}$
7: change charging plan towards $\overline{\text{CS}}$
8: **else if** $\left(\left(T^{cha}_{ev_{(r)}} + \text{ECWT}_{\overline{cs}}\right) > D_{ev_{(r)}}\right)$ **then**
9: cancel reservation at CS
10: make reservation at $\overline{\text{CS}}$
11: change charging plan towards $\overline{\text{CS}}$
12: **end if**
13: **end if**
14: **end if**

If the $\overline{\text{CS}}$ is different from the one decided previously, a comparison is then made in terms of total trip duration $T^{\overline{cs},d}_{ev_{(r)}}$. The core idea is to monitor the entire network condition through periodically updated EVs' reservations, and adjust the CS-selection decision making to minimize the trip duration for EV_r. Here, the decision change logic is only executed if $T^{\overline{cs},d}_{ev_{(r)}}$ is shorter than that of previously selected CS, given by $\left(T^{\overline{cs},d}_{ev_{(r)}} < T^{cs,d}_{ev_{(r)}}\right)$.

Driven by this decision change, EV_r will then confirm this new decision. It next informs the GA to cancel its reservation at the previously selected CS, and records a new reservation at $\overline{\text{CS}}$ (the newly decided CS). Above operations run periodically, while no additional communication will be established if there is no decision change. In order not to include too much communication overhead due to a subtle reduced trip duration, only the following two conditions will trigger decision change.

- In the ideal case, the decision change is made given $\left(\left(T^{cha}_{ev_{(r)}} + \text{ECWT}_{\overline{cs}}\right) \leq D_{ev_{(r)}}\right)$. This guarantees EV_r can still be fully recharged at $\overline{\text{CS}}$.
- Otherwise, if EV_r cannot be fully recharged at both previous CS and $\overline{\text{CS}}$ given by condition at line 8, the $\overline{\text{CS}}$

from which EV$_r$ will experience a shorter trip duration is still selected.

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 3. In the worst case, an inaccurate estimation may result in a longer expected charging waiting time for EV$_r$, and its complete charging service may not be finished due to limited parking duration.

G. Discussion

Actually, the decision change for EV$_r$ is based on three aspects:

- The time spent to travel towards that CS.
- The time spent at CS (expected time to wait for charging + expected charging time).
- The travelling time spent from that certain CS to the destination of EV$_r$.

Our design has an arbitrage to omit decision changed in line with a subtly reduced trip duration. This is achieved by holding the condition that, the sum of time to wait for charging and expected charging time, cannot exceed the EV parking duration. If a CS-selection decision will change, we obtain:

- The expected charging time is increased due to energy consumption from movement.
- Also, the travelling time towards the current CS is reduced, due to a proximity to CS.

As such, a substantially reduced time to wait for charging, plays an important role in improving the total trip duration (Such waiting time has significant impact on re-selecting a new CS that is geographically different from previous CS). Even if they adjust charging plans after the decision change of EV$_r$, there is no disadvantage for other EVs, given by the certain parking duration (meaning they move towards a newly selected CS, but experience a longer charging waiting time and trip duration).

Based on above, we further introduce the following notations to facilitate problem formulation of charging waiting time:

- $\gamma_{l_{cs}}$: Number of EVs currently parking at a CS.
- $\omega_{l_{cs}}$: Average charging waiting time for each EV currently parking at a CS.
- $\mathcal{W}$: Total charging waiting time for all EVs in network.

Straightforwardly, we obtain:

$$\text{To minimize } \mathcal{W} = \sum_{l_{cs} \in N_{cs}} \gamma_{l_{cs}} \times \omega_{l_{cs}} \qquad (5)$$

Here, note that $\gamma_{l_{cs}}$ is a function of N_{cs}. This is because that a larger number of N_{cs} enables a small $\gamma_{l_{cs}}$ EVs distributed at each CS. Furthermore, $\omega_{l_{cs}}$ is related to $\gamma_{l_{cs}}, \delta, \beta$. This is reflected by the fact, a larger number of $\gamma_{l_{cs}}$ EVs intend to charge at a CS, inevitably increases their average charging waiting time at this CS. Of course, both a fast charging power β and more charging slots δ will reduce such time.

In order to achieve the minimum waiting time for EVs allocated at N_{cs} CSs, thus $\gamma_{l_{cs}} \times \omega_{l_{cs}}$ should be equal among all CSs, as ideal situation. Since all CSs share the same β and δ, we obtain $\gamma_{l_{cs}} = \mathcal{F}(\frac{1}{N_{cs}})$, and $\omega_{l_{cs}} = \mathcal{F}(\frac{\gamma_{l_{cs}}}{\delta \times \beta})$ to achieve the minimum charging waiting time. The following evaluation results will address all factors involved in this discussion.

Due to mobility uncertainty, the charging management towards an equal number of EVs associated to each CS is difficult to achieve. Therefore, a frequently updated charging reservation from EVs, contributes to balancing the charging load at each CS, so as to reduce waiting time.

V. Performance Evaluation

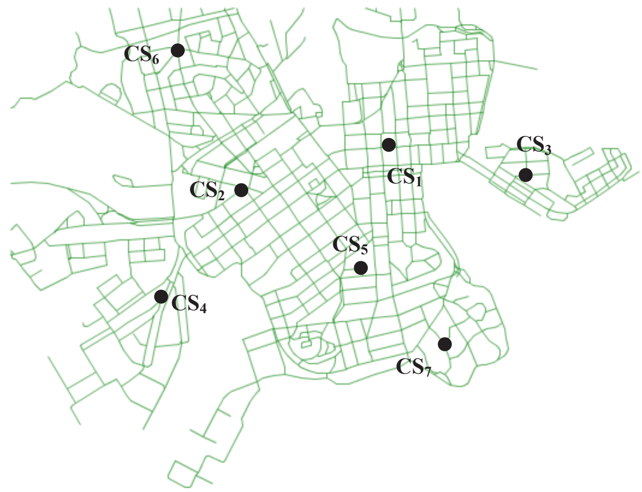


Fig. 4. Simulation Scenario of Helsinki City

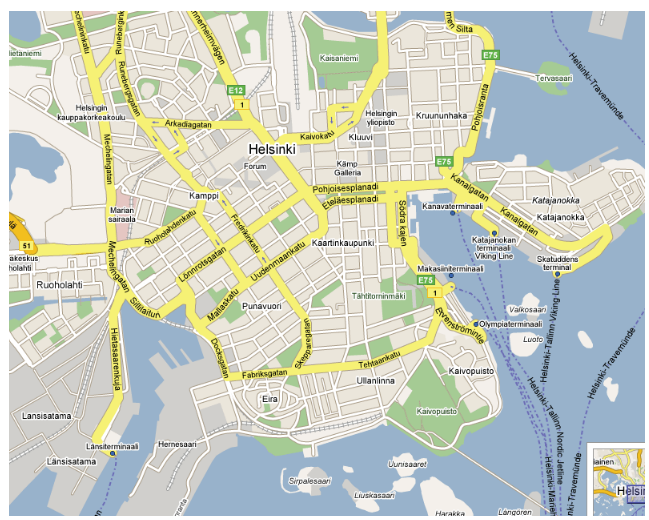


Fig. 5. Google Map of Helsinki City

We have built up an entire EV charging system in Opportunistic Network Environment (ONE) [25]. In Fig.4, the default scenario with 4500×3400 m^2 area is shown as the down town area of Helsinki city abstracted from Google map (Fig.5) in Finland. Here, 240 EVs with $[30 \sim 50]$ km/h variable moving speed are initialized in the network. The destination of each EV trip is randomly selected from a location in the map. Particularly, once the current destination is reached, a new destination is randomly chosen again. Such procedure is repeated until the EV reaches the SOC threshold and then requests charging service. The configuration of EVs follows the charging specification {Maximum Electricity Capacity (MEC), Max Travelling Distance (MTD), Status Of Charge (SOC) threshold}. We configure three types of EVs, which are:

- Coda Automotive [26] {33.8 kWh, 193 km, 30%}, average energy consumption 0.1751 kWh/km.
- Wheego Whip [27] {30 kWh, 161 km, 40%}, average energy consumption 0.1863 kWh/km.
- Hyundai BlueOn [28] {16.4 kWh, 140 km, 50%}, average energy consumption 0.1171 kWh/km.

Here, the electricity consumption for the Traveled Distance (TD) is calculated based on $\frac{\text{MEC}\times\text{TD}}{\text{MTD}}$, as widely used in literature such as [15]. Each type is with 80 EVs, and all EVs' batteries are with full volume at beginning, depending on their types. Besides, 7 CSs are provided with sufficient electric energy and 5 charging slots through entire simulation, using the fast charging rate of 62 kW. This is different from previous works on demand response where the charging power is dynamically adjusted. Furthermore, using the constant charging power in our work can refer to many previous works on common CS-selection schemes e.g, [10], [16]. 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 the Helsinki road topology. In reality, we believe the GA is with a super power and super computation capability to make charging plans for all EVs in large scale network.

Under this configuration, the charging management is essential as some EVs need to wait additional time for charging, until a charing slot is available. The following schemes are evaluated for comparison:

- **MTD&RU**: The proposed CS-selection scheme with minimum trip duration, with periodical reservation updating. The default updating interval is 100s.
- **MTD**: The proposed CS-selection scheme with minimum trip duration, without reservation updating.
- **MCWT**: The CS-selection is based on the minimum expected charging waiting time as proposed in [16]. This scheme does not consider the limited EV parking duration.
- **MQT**: The CS-selection is based on the minimum queuing time as proposed in [9].

The simulation represents a 12 hours' duration with a 0.1s resolution. So, the EVs positions, speeds and energies are updated every 0.1s, on the road or in a CS. Particularly, $N_{jam} = 30$ randomly generated traffic jams happen for every 300s, while its range is 300m. Therefore, each EV will adjust its moving speed, if the distance between its location and a traffic jam is smaller than 300m. All traffic jams will last for 100s since generation. The following performance metrics are evaluated:

- **Average Charging Waiting Time**: The average period between the time an EV arrives at the selected CS and the time it finishes (full) recharging its battery. This is the performance metric at the EV side.
- **Number of Fully Charged EVs**: The total number of fully charged EVs in the network. This is the performance metric at the CS side. It is appreciated that EVs can be fully charged within their limited parking duration. In the worst case, traveling to a CS but could not have chance for charging within the parking duration, certainly degrades user QoE. If that happens, the EV needs charging service would have to continuously find a CS for charging.
- **Average Trip Duration**: The average time that an EV experiences for its trip, through recharging service at an intermediate CS. This is the performance metric at the EV side.
- **Number of Decision Changes**: Number of decision changes for CS-selection, this only happens in MTD&RU. This is the performance metric at system level.

A. Influence of Parking Duration

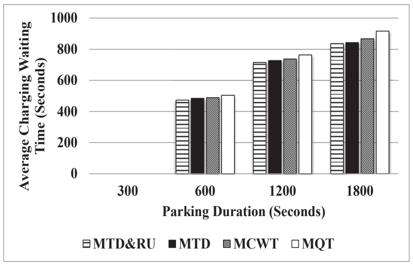
In Fig.6(a), we observe that a longer parking duration increases the average charging waiting time. This is because more EVs can be fully charged at CSs, as such the time for other parking EVs waiting for charging is increased. Particularly, MTD without reservation updating still achieves a better performance, than MCWT and MQT, due to taking the parking duration into account. Concerning uncertain EVs mobility due to traffic jams, MTD&RU benefits from the reservation updating to adjust EVs' charging plans. Due to the same reason, in Fig.6(b), MTD&RU charges a higher number of EVs compared to MTD. In Fig.6(c), both MTD&RU and MTD achieve much reduced trip duration than other schemes. In spite that the advantage of MCWT over MQT has already been examined in [16], both MTD&RU and MTD outperforms MCWT.

Particularly, if with an extremely short parking duration e.g., 300s, the waiting time is always zero and the EVs are never fully charged, with only the trip duration is captured.

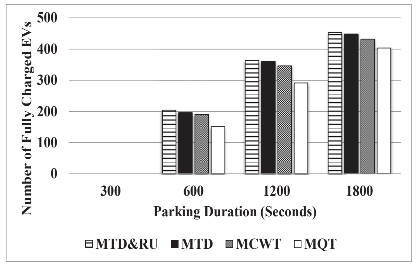
B. Influence of Charging Slots

If increasing the number of charging slots at CSs, all performances are improved in Fig.7(a), Fig.7(b) and Fig.7(c) respectively. In particular, MQT benefits more from increased charging slots than other schemes. This implies that only considering the local condition of CSs is not suggested for achieving an optimal performance, particularly when CSs are in congestion. Here, the proposed MTD&RU and MTD still show their shorter charging waiting time over MCWT, even with 3 charging slots that highly possible to overload CSs. Besides, the total trip duration is remarkably reduced by MTD&RU and MTD.

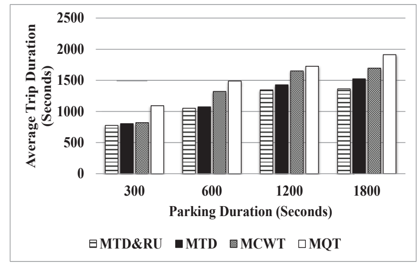
Fig.8 further shows the number of charged EVs at each CS. It is observed that MTD&RU and MTD achieve a relatively balanced distribution among CSs, compared to MCWT and MQT. This reflects advantage of our proposed estimation on charging waiting time, concerning limited parking duration.



(a) Average Charging Waiting Time

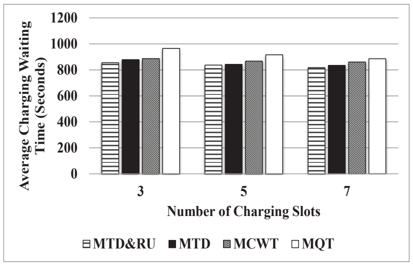


(b) Number of Fully Charged EVs

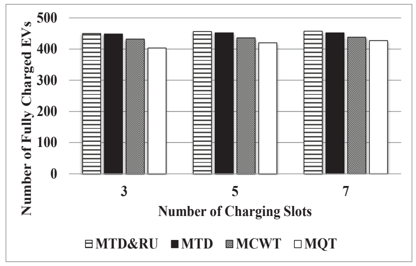


(c) Average Trip Duration

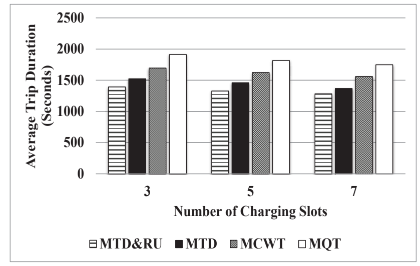
Fig. 6. Influence of Parking Duration, 3 Charging slots



(a) Average Charging Waiting Time

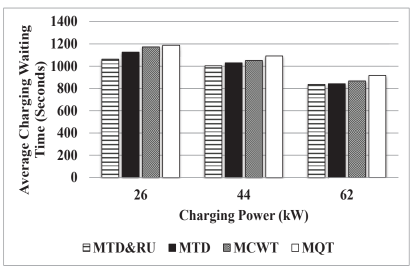


(b) Number of Fully Charged EVs

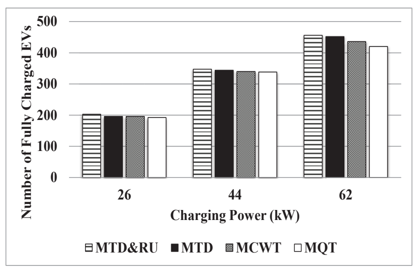


(c) Average Trip Duration

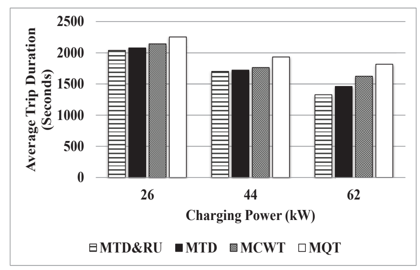
Fig. 7. Influence of Charging Slots



(a) Average Charging Waiting Time



(b) Number of Fully Charged EVs



(c) Average Trip Duration

Fig. 9. Influence of Charging Power

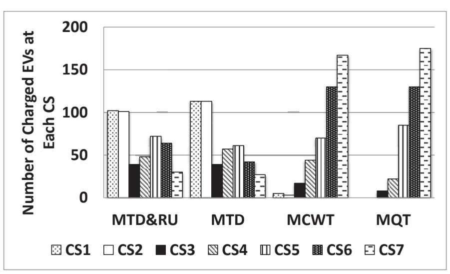


Fig. 8. Distribution of Number of Charged EVs at Each CS, 5 Charging Slots

C. Influence of Charging Power

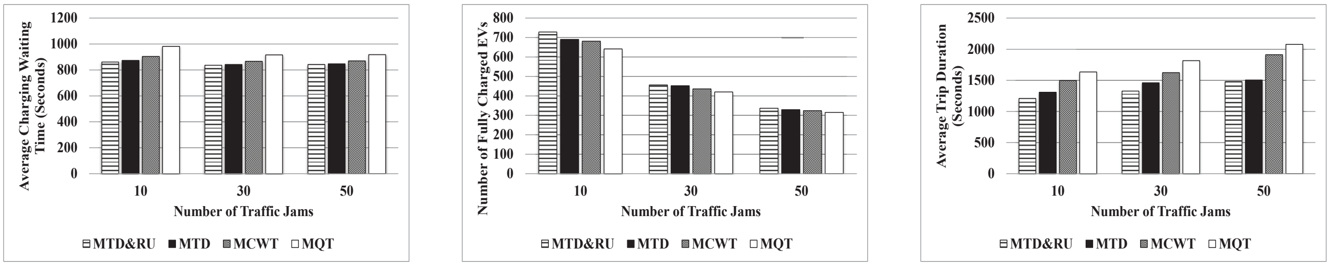
Results in Fig.9(a), Fig.9(b) and Fig.9(c) show that reduced charging power however makes more EVs get stuck at CSs. Thus, the charging waiting time and trip duration are increased, while number of charged EVs is reduced.

D. Influence of Mobility Uncertainty

Here, we examine the influence of mobility uncertainty in term of number of traffic jams. In Fig.10(a), the average charging waiting time is reduced, if N_{jam} is increased from 10 to 30, and with a fluctuation from 30 to 50 traffic jams. Meanwhile, the number of charged EVs is dramatically reduced in Fig.10(b). This is because more EVs have to reduce speed or even stop when moving on the road, thus they cannot be charged timely. Due to the same reason, the average trip duration is increased in Fig.10(c). Here, the proposed MTD&RU and MTD also outperform other schemes in this case.

E. Influence of Reservation Updating Interval

Results in TABLE II show that a frequent reservation updating interval improves the charging performance. This is because an updated CS-selection is made frequently, such that the EV charging planning would be adjusted depending on the dynamically generated traffic jams. From 50s to 10s updating interval, we observe a subtle improvement regarding number



(a) Average Charging Waiting Time (b) Number of Fully Charged EVs (c) Average Trip Duration

Fig. 10. Influence of Traffic Jams

TABLE II
INFLUENCE OF RESERVATION UPDATING INTERVAL

Updating Frequency	Average Charging Waiting Time	Number of Charged EVs	Average Trip Duration	Number of Decision Changes
10s	830s	460	1321s	230
50s	834s	456	1327s	65
100s	836s	456	1326s	18
200s	841s	449	1388s	13
300s	844s	442	1404s	7

of charged EVs as well as average trip duration. While, there is a huge communication overhead given 10s updating interval. Here, the communication overhead is reflected by number of CS-selection changes, as a decision change is normally in line with operations for reservation canceling and remaking. By jointly considering these, we choose 100s reservation updating interval as a trade-off between charging performance and communication overhead under our scenario.

F. Future Works

There are several concerns leading to our future works:

- It is user-friendly to further concern a dedicated amount of user-reserved energy charging service. This is different from the perceived fully charged service in this article. Bringing such additional user specific requirement is one of the efforts towards better user QoE.
- It is worth to bring advanced charging technologies, such as battery switch to provide fast services (which just takes few minutes). In more detail, the EV could deplete its battery upon arriving at a CS, then switches with a fully charged battery. The depleted battery from the EV is charged by CS itself.
- Since the decision making for on-the-move EV charging management relies on the GA, the charging system suffers more from security and scalability aspects. Attackers can manipulate the reservation reported from EVs, and also the CS-selection decisions from the GA to EVs. Furthermore, if the GA fails to work, the charging management system will not work. Future work could focus on provisioning of an efficient, scalable communication framework.

VI. CONCLUSION

In this article, we proposed a CS-selection scheme in a charging management system to minimize the EVs' trip duration. The selection computation takes EVs' parking duration and their charging reservations into account, so as to capture an accurate condition of CSs and anticipated EVs mobility. It is highlighted that under the scenario where the mobility uncertainty influences the accuracy of EVs' reservation information, a periodical reservation updating is executed to adjust the charging plans. Evaluation results under the Helsinki city scenario showed the advantage of our proposal, in terms of a shorter EVs' trip duration through intermediate charging, a shorter charging waiting time as well as a higher number of charged EVs.

ACKNOWLEDGMENT

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