Reservation-Based EV Charging Recommendation Concerning Charging Urgency Policy

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Abstract

Electric Vehicles (EVs) are environmental friendly comparing with traditional internal combustion vehicles (ICVs), and have great application potential to achieve green transportation. However, due to the battery technology under development, the charging time of EVs is still longer than refuelling time of ICVs. Importantly, CS-Selection scheme (which/where to charge) and charging scheduling (when/whether to charge) are key solutions, for coping with long charging time and uneven distribution of Charging Stations (CSs) in urban city. In this paper, we propose an Urgency First Charging (UFC) scheduling policy, which orders EVs via their charging urgency (calculated by their charging demand and remaining parking duration). With the underlying UFC policy, we further propose a reservation-based CS-Selection scheme that selects the optimal CS with the minimum trip duration (summation of travelling time through CS, and the charging time spent at CS), where the EVs would further report their reservations to help anticipate the service congestion status of CSs in future. We have conducted simulations through Helsinki's city traffic scenarios. The simulation results show that our proposed CS-Selection scheme has advantages in improving users quality of experience, which shortens the overall trip duration of EVs and fully charges more EVs before departure deadline.

Index Terms

Electric Vehicle, EV Charging Recommendation, Charging Scheduling, CS-Selection, Charging Urgency.

I. Introduction

In the past few decades, human consumption of fossil fuels is constantly increasing. This causes undesirable impact of environment, such as greenhouse effect. Thus Electric Vehicles (EVs) have attracted more attention as they are more environmentally friendly comparing with traditional Internal Combustion Vehicles (ICVs). Here, EVs use electrical energy as the power supplement, this alleviates carbon dioxide

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and harmful gases generated by ICVs. Meanwhile, EVs allow lower travelling costs considering potential shortage of fossil fuels [1].

However, there are still constraints for the substantial replacement of ICVs by EVs, as EVs need to recharge to extend travel distance. Due to the current charging technology limitation, the charging time of EVs is often longer than the refueling time of ICVs. As such, EV drivers may experience long time to wait for charging, and this degrades the charging service quality. Meanwhile, inappropriate distribution of CSs has an adverse impact on EV charging, deemed as a challenge in ensuring the stable charging service. As the distribution of Charging Stations (CSs) depends on urbanization policy, in some area, EVs may experience extra time to find CSs for charging.

Most previous works on EVs charging problem have focused on the parking mode, where EVs have been parked in a fixed place (CS or communities with charging equipment, etc.) [2], [3], [4], [5]. Here, the charging scheduling optimization is the key to solve the problem concerning when/whether to charge. In previous work [3], the First In First Serve (FIFS) policy is applied to order EVs charging. However, the FIFS policy is lack of flexibility when processes EVs with different charging energy demands. For example, the work in [6] proposes a charging scheduling policy where the charging order of EVs depends on their charging demand rather than their arrival time.

In addition, the on-the-move mode is also crucial. Here, EVs driving on the road need to solve the problem of where/which CS to get charging service. Due to the dynamic charging demand in time and spatial dimension, some CSs are overloaded and unable to meet the charging demand of EVs, thus charging congestion [7] will happen. This will reduce the Quality of Experience (QoE) of EV drivers, because EVs have to wait till a charging slot becomes available. Therefore, an efficient CS-Selection scheme is required to coordinate demand from on-the-move EVs and alleviate charging congestion at CSs. Since CS-Selection scheme aims to guide EVs towards CSs with higher availability [8], [9], [10] (meaning the faster time to available for charging or more free charging slots), it is important to accurately capture the status of all EVs and CSs in the network. Here, the Global Aggregator (GA) is utilized to capture status and make CS-Selection decision via aggregated CSs charging status and EVs requests. The work in [10] selects the CS with the minimum waiting time (the time EV spends until a charging slot becomes available), and proves that it has advantages over selecting the closest CS. However, since the charging status at CSs are uncertain (due to lack of information of moving EVs travelling towards CSs), the CS-Selection decision is non-optimal. The work in [2] develops a reservation mode. Here, EVs send their reservations to improve the accuracy of CSs charging status. Considering the practical case, EVs usually have their trip destinations, and would not park at a fixed CS for a long time. The works in [11], [12] introduce the parking duration as the upper time limitation that an EV parks at CS, but limited parking duration can lead that many EVs have to depart before they get fully recharged.

In this paper, we propose an Urgency First Charging (UFC) charging scheduling policy and a reservation-based CS-Selection scheme underlying the UFC charging scheduling policy. These approaches aims to reduce the charging congestion problems that exists in large-scale EVs applications. Technically:

1) Firstly, we propose a UFC scheduling policy, which calculates charging urgency by EVs' charging demand and parking duration. Here, the charging urgency is enabled as a metric for prioritized scheduling. The EV with higher charging urgency is allowed to be preempted charged. The UFC policy is different from previous works without considering the parking duration (like in works [3], [4], [6]) and those without providing preempted charging (like in works [3], [11]), instead, it guarantees as many EVs as possible to get fully charged before their departure.
2) Further to UFC scheduling policy, we propose a reservation-based CS-Selection scheme via a total trip duration estimation (based on the summation of time spent at CS and travelling time towards and departs from the CS). Here, the estimation of the time spent at CS applies the UFC scheduling policy. Many previous CS-Selection schemes are based on historic data (like in works [2], [10]), it is novel in our proposed CS-Selection which is based on real-time charging status at CSs. Meanwhile, in our proposed scheme, EVs are asked to send their charging reservations. Such reservations would benefit the overall allocation of EVs in the network and would significantly improve the user's QoE.

II. Related Work

There are two main use cases in solving the charging problem of EVs. The first use case addresses charging scheduling when EVs are under parking mode, since a single CS might be unable to handle charging demand of multiple parked EVs. In the other use case, the EV (with insufficient energy) moving on the road, needs to find a suitable CS to get charging service (CS-Selection).

A. Charging Scheduling

To efficiently manage parked EVs, most of previous charging scheduling works in [3], [4], [13] propose EVs charging scheduling policy via EVs' arrival time and apply FIFS policy to order EVs' charging priority. The work in [2] proposes a distributed charging scheduling policy based on the deduced approximation model of waiting time. The work in [14] manages the EVs' charging scheduling by a proposed dynamic programming-game theory based approach, which schedules EVs in a decentralized scheme. However, the above works do not consider EVs' departure time. Different from the FIFS policy, the work in [6] proposes two scheduling policies: Earliest Start Time (EST) and Earliest Finish Time (EFT). In EST, the order of charging depends on the time order of EV arrival. In EFT, the order of charging depends on how early the EV could finish its charging. However, the above works do not consider EVs' departure deadline. The work in [15] introduces parking duration and proposes deadline-driven charging optimization to allow more EVs get fully charged. Here, the parking duration is used to restore the time limitation that an EV would stay at a CS in practice. Meanwhile, to consider the EVs' type influence, the work in [16] optimizes the scheduling problem for EVs with multiple vehicle types in public transport. Here, EVs' charging time and energy consumption for different vehicle types are considered. The work in [12] proposes the scheduling policy for heterogeneous EVs, where those EVs with higher charging priority (in terms of vehicle type) is able to be preempted charged.

B. CS-Selection

By comparing the results based on two different CS-Selection schemes either on the closest distance or the minimum waiting time, the work in [10] shows that selecting the CS with the minimum waiting time performs better in the urban scenario. Meanwhile, the work in [17] simulates under highway scenario and selects the CS with the minimum waiting time estimation. The work in [18] combines waiting time estimation with charging intention detection. It is based on EV's historical CS preference and real-time location. To alleviate charging congestion at CSs, the work in [19] further models the CS-Selection as a multi-objective optimization problem. The optimal CS-Selection in this work is selected by jointly considering charging time, travel time, and charging cost. The works in [20], [21] also consider the charging cost and adopt pricing strategies depending on CSs congestion level, a CS with charging congestion would have a higher charging price. These pricing strategies prevent EVs from moving towards CSs with high congestion level and also maximize CSs profits.

The work in [22] considers energy demand response, which focuses on producing energy demand-supply balance. However, optimizing demand-supply cannot guarantee charging service quality. Therefore, estimating EVs' uncertainty is necessary to ensure the overall charging performance [23]. The work in [24] proposes a navigation system that allows EV drivers to communicate their intentions to other EV drivers, this improves the accuracy of estimation of CSs charging status. Furthermore, reservation-based schemes have been proposed, which anticipate EVs status (energy demand and current location). The work in [2] simulates EVs' reservations under highway scenario, and the work in [25] simulates under city scenario. The above reservation-based CS-Selection schemes adequately improve the overall charging performance (reducing the average waiting time and alleviating the charging congestion). To better restore the EV charging process, the work in [26] considers EV drivers' activities and the range anxiety. This work presents coverage location model for CS to minimize the missed trips. Furthermore, considering the charge anxiety, the works in [11], [12], [15] adopt the parking duration. Here, when allocating EVs, the GA needs to consider whether EVs could get charging service within the parking duration. Furthermore, the works in [11], [27] adopt traffic jam as an influence factor, EVs avoid selecting CS via a crowded path.

III. System Model

A. Urgency First Charging

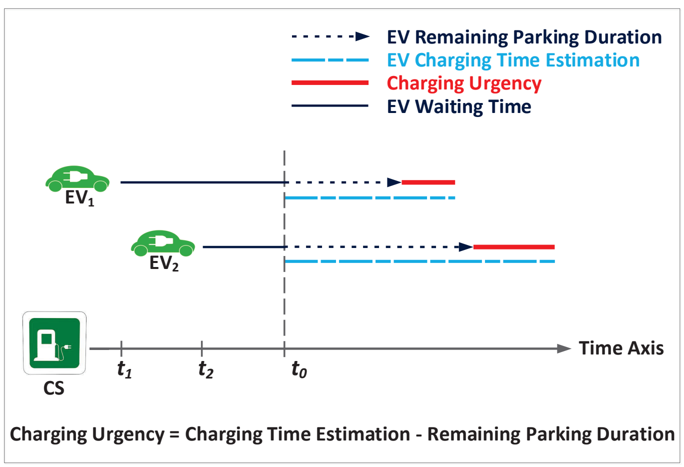


Fig. 1. Urgency First Charging

We propose a UFC policy as an underlying scheduling policy (concerning when to charge EVs). The UFC takes into account EVs' parking duration, charging energy demand and allows preempted charging for those EVs with higher "charging urgency". Here, the charging urgency is given by the difference that EV's remaining parking duration minus EV's charging time estimation.

In Fig.1, both EV_1 and EV_2 have been parked when a charging slot becomes available (t_0). Here, t_1 and t_2 refer to the arrival time of EV_1 and EV_2 respectively. As EV_1 arrives earlier than EV_2 and the parking duration is fixed, EV_1 has a shorter remaining parking duration. However, comparing the charging demand of EV_1 and EV_2 (the EV's full energy minus the EV's current energy), EV_2 requests a longer charging time. Although EV_2 has longer time left for departure than EV_1, its charging time is also much longer than EV_1. By formulation defined in Fig.1, EV_2 has a higher charging urgency. Therefore, EV_2 will get preemptive charging service although EV_1 arrives earlier.

If an EV is with higher charging demand and shorter remaining parking duration, the UFC policy scheduling will improve the possibility that the EV gets charging service. Meanwhile, the UFC policy can reduce the number of EVs miss fully charging (due to that some EVs may need to depart before being fully charged). It is worth mentioned that the preempted charging will only occur between EVs plan to be charged, the UFC policy will not interrupt EVs being charged.

B. Assumption

In this paper, we distribute CSs in different locations over the city scenario. The GA globally manages EV charging and is equipped with communication module for wireless information exchange with CSs and EVs. EVs' on-board system can communicate with the GA with the equipped wireless devices such as 3G/Long Term Evolution (LTE). EVs request/reply to the GA for CS-Selection. Here, the GA processes the charging requests on the cloud in a centralized manner to optimize the distribution of charging facilities. When an EV is on-the-move and its SOC is lower than the preset threshold, the EV sends its charging request to the GA. The GA processes EV's charging request and starts ranking CSs through which the EV perceive the minimum trip duration (mainly influenced by waiting time). To fully recharge more EVs, the GA jointly considers EVs charging demand and CSs charging status. Here, the UFC scheduling policy is applied to provide preempted charging service for EVs with charging urgency. With this, the GA estimates total trip duration that the EV charges at each CS and selects the CS with the minimum total trip duration.

C. Problem Formulation

To alleviate potential charging congestion and achieve a better allocation of V2V charging among PLs, the CS-Selection optimization is formulated in this subsection, starting with the notations and following with the objective functions. To facilitate problem formulation, we have the notations as follows:

- $\delta_{l_{cs}}$: Number of EVs being fully charged at a CS.
- υl_{cs}: Average trip duration for each EV being fully charged at CS.
- N_{CS}: Queue of CSs.
- M: Total trip duration for all EVs being fully charged in the network.
- X: Total number of all EVs being fully charged in the network.

Then we have the objective functions:

$$\text{Maximize} \quad X = \sum_{l_{cs} \in N_{cs}} \delta_{l_{cs}} \tag{1}$$

$$\text{Minimize} \quad M = \sum_{l_{cs} \in N_{cs}} \delta_{l_{cs}} \times \upsilon l_{cs} \tag{2}$$

Here, the time an EV could stay at a CS is constrained by the parking duration. An EV has to depart from the CS after its departure deadline. The objective function (1) is set to maximize the total number of all EVs get fully charged, which could better reflects charging scheduling efficiency. To fully charge more EVs in the network, $\delta_{l_{cs}}$ at each CS needs to increase. The objective function (2) aims to minimize the total trip duration for all EVs being fully charged in the network. As $\delta_{l_{cs}}$ increases in objective function (1), υl_{cs} needs to decrease. υl_{cs} and $\delta_{l_{cs}}$ are related to N_{cs}, a larger N_{cs} enables a small υl_{cs}, this is because EVs could be distributed at more CSs. Since N_{cs} is immutable as it refers to number of total CSs, υl_{cs} can only be reduced by distributing EVs equally among the CSs as an ideal situation.

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}	Estimated charging time upon arrival of EV
T_{ev}^{sta}	Time EV has stayed at the CS after its arrival
T_{cur}	Current time in network
S_{ev}	Moving speed of EV
α	Electric energy consumed per meter
D_{ev}	Parking duration of EV
β	Charging power at CS
N_C	Queue of EVs under charging at CS
N_W	Queue of EVs waiting for charging at CS
N_R	Queue of EVs reserved for charging at CS
V_{ev}	Charging urgency of EV
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
EACT$_{cs}$	Estimated available charging time at CS
N_{cs}	Queue 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

Fig.2 illustrates T-variables in a timeline from EV$_r$'s original location to its destination with an intermediate charging at a CS.

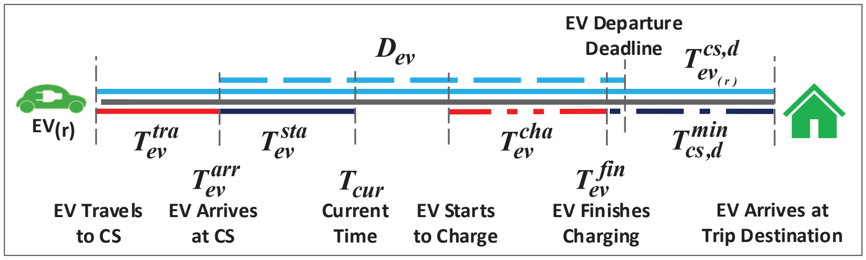


Fig. 2. T-variables on time axis

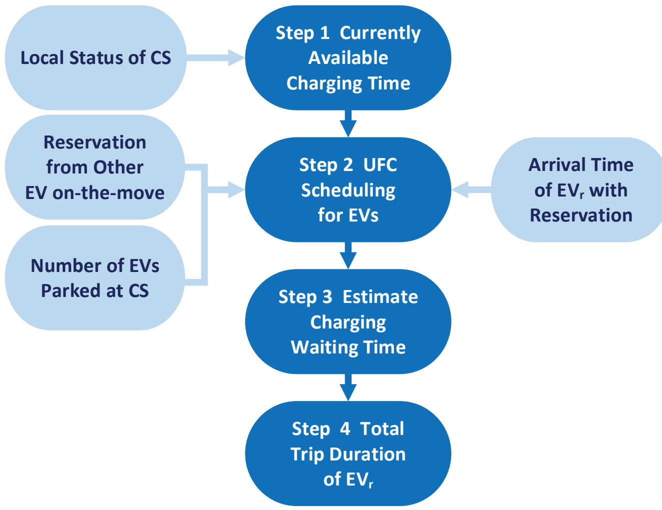


Fig. 3. Flow Chart of Computation Logic

IV. System Design

EV drivers want to shorten their trip durations. Therefore, the GA calculates EV's total trip duration at each CS with an intermediate charging and select the optimal CS. Referred to Fig.3, the total trip duration of an incoming EV with reservation (EV$_r$) is obtained through the follow steps:

Step 1: Through the local charging status, the GA estimates the available time at charging slots.

Step 2: When EV$_r$ requests, the output of **Step 1**, the queue of parked EVs and reservations of on-the-move EVs are aggregated to estimate the charging scheduling (via UFC policy) when EV$_r$ arrives.

Step 3: The GA calculates charging waiting time through the scheduling estimated by **Step 2**.

Step 4: Through the charging waiting time estimation by **Step 3** and the EV$_r$'s trip time drives to/departs from the CS, the total trip duration is estimated.

A. Estimation of CS Charging Status

Considering that CS has several charging slots to charge multiple EVs in parallel, the EVs under charging is characterized in the queue of N_C. The current time in the network is denoted as T_{cur}. If no EV currently parking at the CS for charging, T_{cur} will be added into the LIST (available charging time list of the charging slots) with δ (number of charging slots) times to indicate the CS is available, and

Algorithm 1 Estimation of CS Charging Status

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** $(n = 1; n \leq N_C; n++)$ **do**
6: **if** $((T_{cur} - T_{ev_{(n)}}^{arr} + \frac{E_{ev_{(n)}}^{max} - E_{ev_{(n)}}^{cur}}{\beta}) \leq (T_{ev_{(n)}}^{arr} + D_{ev_{(n)}}))$ **then**
7: LIST.ADD($\frac{E_{ev_{(n)}}^{max} - E_{ev_{(n)}}^{cur}}{\beta} + T_{cur}$)
8: **else**
9: LIST.ADD($T_{ev_{(n)}}^{arr} + D_{ev_{(n)}}$)
10: **end if**
11: **end for**
12: **if** $(N_C < \delta)$ **then**
13: **for** $(m = 1; m \leq (\delta - N_C); m++)$ **do**
14: LIST.ADD(T_{cur})
15: **end for**
16: **end if**
17: sort LIST with ascending order
18: **return** LIST

the available charging time of all charging slots is T_{cur}, as line 2 in Algorithm 1 demonstrated. Lines from 5 to 11 present the charging process of EV$_n$ (EVs in the queue of N_C). Line 6 compares parking duration $D_{ev_{(n)}}$ and time $(\frac{E_{ev_{(n)}}^{max} - E_{ev_{(n)}}^{cur}}{\beta})$ to fully charge EV$_n$. If EV$_n$ could get fully charged before its departure, given by the condition $((T_{cur} - T_{ev_{(n)}}^{arr} + \frac{E_{ev_{(n)}}^{max} - E_{ev_{(n)}}^{cur}}{\beta}) \leq (T_{ev_{(n)}}^{arr} + D_{ev_{(n)}}))$, its charging finish time $(\frac{E_{ev_{(n)}}^{max} - E_{ev_{(n)}}^{cur}}{\beta} + T_{cur})$ will be added to the LIST. Otherwise, the charging finish time will be given by $(T_{ev_{(n)}}^{arr} + D_{ev_{(n)}})$ instead, which indicates that EV$_n$ has to leave after the departure deadline.

The lines between 12 and 16 consider the situation that not all charging slots are occupied, T_{cur} will be added to the LIST with $(\delta - N_C)$ times (number of available charging slots). Here, T_{cur} will be the available charging time for these unoccupied charging slots. Followed by lines 17 and 18, Algorithm 1 returns the LIST with ascending order. The LIST indicates the charging status for each charging slot in the order of their available time.

B. Estimation of Available Charging Time

To alleviate charging congestion at CSs, the CS-Selection scheme attempts to allocate EVs evenly across CSs. In practice, EVs have different charging urgency requirements and some EVs may need to be preempted charged. Therefore, the GA estimates charging status of CSs when the on-the-move EV that sends charging request (EV$_r$) arrives. Algorithm 2 and Algorithm 3 calculate the Estimated Available Charging Time (EACT) at the CS underlying the UFC policy charging scheduling. There are two cases separately introduced in Algorithm 2 and Algorithm 3:

- **Case-1:** Algorithm 2 considers the incoming EVs (EV$_r$ and other EVs made reservations) have chance to be preempted charged upon their arrival (only with high charging urgency), comparing with EVs in the queue of N_W.

- **Case-2:** Algorithm 3 considers the incoming EVs will be charged, in which case, all EVs in the queue of N_W have been charged or the CS has no parked EV.

Algorithm 2 EACT Case-1$\langle$LIST, $N_R\rangle$

1: sort the queue of N_W according to UFC order
2: add EV$_r$ into the queue of N_R
3: sort the queue of N_R according to UFC order
4: **if** no EV is waiting for charging **then**
5:     **return** EACT Case-2$\langle$LIST, $N_R\rangle$
6: **else**
7:     **for** $(i = 1; i \leq N_W; i++)$ **do**
8:         **for** $(j = 1; j \leq N_R; j++)$ **do**
9:             **if** (LIST.GET(0) $> T^{arr}_{ev_{(j)}}) \cap (V_{ev_{(j)}} > V_{ev_{(i)}})$ **then**
10:                 **if** (EV$_j$ equals to EV$_r$) **then**
11:                     **return** LIST.GET(0)
12:                 **else**
13:                     **if** $((T^{cha}_{ev_{(j)}}$ + LIST.GET(0)) $< (D_{ev_{(j)}} + T^{arr}_{ev_{(j)}}))$ **then**
14:                         $T^{fin}_{ev_{(j)}} =$ LIST.GET(0) $+ T^{cha}_{ev_{(j)}}$
15:                     **else**
16:                         $T^{fin}_{ev_{(j)}} = D_{ev_{(j)}} + T^{arr}_{ev_{(j)}}$
17:                     **end if**
18:                     replace the LIST.GET(0) with $T^{fin}_{ev_{(j)}}$
19:                     sort LIST with ascending order
20:                     record EV$_j$ into DELETESET
21:                 **end if**
22:             **end if**
23:         **end for**
24:         remove EVs recorded in DELETESET, from the queue of N_R
25:         **if** $((T^{cha}_{ev_{(i)}}$ + LIST.GET(0)) $< (D_{ev_{(i)}} + T^{arr}_{ev_{(i)}}))$ **then**
26:             $T^{fin}_{ev_{(i)}} =$ LIST.GET(0) $+ T^{cha}_{ev_{(i)}}$
27:         **else**
28:             $T^{fin}_{ev_{(i)}} = D_{ev_{(i)}} + T^{arr}_{ev_{(i)}}$
29:         **end if**
30:         replace the LIST.GET(0) with $T^{fin}_{ev_{(i)}}$
31:         sort LIST with ascending order
32:     **end for**
33: **end if**
34: **return** EACT Case-2$\langle$LIST, $N_R\rangle$

1) Case-1: Initially, the queue of N_W is sorted with the UFC policy, EV$_r$ is added into the queue of N_R (sorted with the UFC order). Lines between 4 and 6 refer to the condition that EV$_r$ arrives at a CS with no other EVs waiting for charging, then the EACT will be further calculated in Algorithm 3. The LIST has been sorted in Algorithm 1 with the earliest available order of charging slots. Thus, LIST.GET(0) represents the first available charging time. When the first charging slot is available, EV$_i$ (the EV in the queue of N_W) and EV$_j$ (the EV in the queue of N_R) will be compared to decide their charging priority. The comparison is indicated in loop operation starts from line 7. Here, the charging urgency (V_{ev}) will be the indicator to determine the charging order among the EVs, given by:

$$V_{ev} = T_{ev}^{cha} - (T_{ev}^{arr} + D_{ev} - T_{ev}^{sta}) \tag{3}$$

In this equation, T_{ev}^{arr} reflects the time slot an EV arrives at CS, T_{ev}^{cha} reflects the charging time. T_{ev}^{sta} reflects the time that the EV has stayed at the CS after its arrival, calculated by $(T_{cur} - T_{ev}^{arr})$. Here, $(T_{ev}^{arr} + D_{ev} - T_{ev}^{sta})$ refers to the remaining parking duration of a EV. Line 9 refers to the condition that EV$_j$'s charging urgency $V_{ev_{(j)}}$ is higher than EV$_i$'s charging urgency $V_{ev_{(i)}}$, and EV$_j$ has arrived at the CS when the first charging slot is available $(\text{LIST.GET(0)} > T_{ev_{(j)}}^{arr})$, then EV$_j$ can preempt charging before EV$_i$. However at line 10, there are two different conditions.

On the one hand, if EV$_j$ (the EV in the queue of N_R being processed in current loop operation) is the EV$_r$. This implies that EV$_r$ is able to be preempted charged upon its arrival, Algorithm 2 will return the EACT as LIST.GET(0) at line 11.

On the other hand, lines from 13 to 18 consider the other condition that EV$_j$ could preempt charging prior to EV$_i$, but EV$_j$ is other than EV$_r$. EV$_j$'s charging finish time $T_{ev_{(j)}}^{fin}$ will take place LIST.GET(0). As EV$_j$ is currently travelling and has not yet arrived the CS, its charging time $T_{ev_{(j)}}^{cha}$ is estimated by:

$$T_{ev_{(j)}}^{cha} = \frac{E_{ev_{(j)}}^{max} - E_{ev_{(j)}}^{cur} + (S_{ev} \times T_{ev_{(j)}}^{tra} \times \alpha)}{\beta} \tag{4}$$

Here, extra energy is consumed due to EV$_j$'s travelling from its current location to the CS, which is calculated as $(S_{ev} \times T_{ev_{(j)}}^{tra} \times \alpha)$. Under the condition that meets line 13, EV$_j$ can get fully charged within its parking duration ($D_{ev_{(j)}}$ + $T_{ev_{(j)}}^{arr}$), then $T_{ev_{(j)}}^{fin}$ is estimated as (LIST.GET(0) + $T_{ev_{(j)}}^{cha}$). If EV$_j$ can not get fully charged, line 16 estimates $T_{ev_{(j)}}^{fin}$ as EV$_j$'s departure deadline ($D_{ev_{(j)}}$ + $T_{ev_{(j)}}^{arr}$).

Because the charging slot is occupied by EV$_j$, the LIST will be updated in the ascending order so that LIST.GET(0) will still be the earliest available charging time. Since EV$_j$ has been scheduled, it will be removed from the queue of N_R which is given at line 24. EV$_j$ will not be scheduled to get preempted charged when it does not meet the preempt charging condition ($V_{ev_{(j)}}$ is higher than $V_{ev_{(i)}}$ and there is an available slot when EV$_j$ arrives). Therefore, only EV$_i$ could get charged. Lines from 25 to 28 calculate EV$_i$'s charging finish time $T_{ev_{(i)}}^{fin}$. Considering the parking duration, If EV$_i$ could be fully charged (($T_{ev_{(i)}}^{cha}$ + LIST.GET(0)) $<$ ($D_{ev_{(i)}}$ + $T_{ev_{(i)}}^{arr}$)), $T_{ev_{(i)}}^{fin}$ will be calculated as (LIST.GET(0) + $T_{ev_{(i)}}^{cha}$). Otherwise, $T_{ev_{(i)}}^{fin}$ will be calculated as ($D_{ev_{(i)}}$ + $T_{ev_{(i)}}^{arr}$). Lines 30 and 31 update the LIST to ensure that LIST.GET(0) is the first available charging time. Eventually, if EV$_r$ is still not scheduled for charging within the loop operation, Algorithm 3 is applied to schedule the rest EVs in the queue of N_R at line 34.

Algorithm 3 EACT Case-2$\langle$LIST, $N_R\rangle$

1: insert all EVs (in the queue of N_R) into N_R^f
2: sort the queue of N_R^f according to FIFS order
3: **for** $(k = 1;\ k \leq N_R;\ k++)$ **do**
4: **for** $(l = 1;\ l \leq N_R^f;\ l++)$ **do**
5: **if** $(($LIST.GET(0) $> T_{ev_{(l)}}^{arr}) \cap ($LIST.GET(0) $> T_{ev_{(k)}}^{arr}) \cap (V_{ev_{(l)}} > V_{ev_{(k)}}))$ **then**
6: **if** (EV$_l$ equals to EV$_r$) **then**
7: **return** LIST.GET(0)
8: **else**
9: **if** $((T_{ev_{(l)}}^{cha}$ + LIST.GET(0)) $< (D_{ev_{(l)}} + T_{ev_{(l)}}^{arr}))$ **then**
10: $T_{ev_{(l)}}^{fin} =$ LIST.GET(0) $+ T_{ev_{(l)}}^{cha}$
11: **else**
12: $T_{ev_{(l)}}^{fin} = D_{ev_{(l)}} + T_{ev_{(l)}}^{arr}$
13: **end if**
14: replace the LIST.GET(0) with $T_{ev_{(l)}}^{fin}$
15: sort LIST with ascending order
16: record EV$_l$ into DELETESET
17: **end if**
18: **end if**
19: **end for**
20: remove EVs recorded in DELETESET, from the queues of N_R and N_R^f
21: **if** (EV$_k$ is not EV$_r$) **then**
22: **if** (LIST.GET(0) $> T_{ev_{(k)}}^{arr}$) **then**
23: **if** $((T_{ev_{(k)}}^{cha}$ + LIST.GET(0)) $< (D_{ev_{(k)}} + T_{ev_{(k)}}^{arr}))$ **then**
24: $T_{ev_{(k)}}^{fin} =$ LIST.GET(0) $+ T_{ev_{(k)}}^{cha}$
25: **else**
26: $T_{ev_{(k)}}^{fin} = D_{ev_{(k)}} + T_{ev_{(k)}}^{arr}$
27: **end if**
28: **else**
29: **if** $((T_{ev_{(k)}}^{arr} + T_{ev_{(k)}}^{cha}) < (D_{ev_{(k)}} + T_{ev_{(k)}}^{arr}))$ **then**
30: $T_{ev_{(k)}}^{fin} = T_{ev_{(k)}}^{arr} + T_{ev_{(k)}}^{cha}$
31: **else**
32: $T_{ev_{(k)}}^{fin} = D_{ev_{(k)}} + T_{ev_{(k)}}^{arr}$
33: **end if**
34: **end if**
35: replace the LIST.GET(0) with $T_{ev_{(k)}}^{fin}$
36: sort LIST with ascending order
37: **else**
38: **if** (LIST.GET(0) $> T_{ev_{(r)}}^{arr}$) **then**
39: **return** LIST.GET(0)
40: **else**
41: **return** $T_{ev_{(r)}}^{arr}$
42: **end if**
43: **end if**
44: **end for**

2) Case-2: If the queue of N_W is empty or EV$_r$ fails to get preempted charged, the GA only needs to consider charging priority among EV$_r$ and the other EVs in the queue of N_R. The inputs of Algorithm 3 (the LIST and the queue of N_R) have been updated by Algorithm 2. All EVs in the queue of N_R are added into the queue of N_R^f at line 1. The queue of N_R^f is then sorted as a queue scheduled in FIFS order. The loop operation from line 3 goes through EV$_l$ (the EV in the queue of N_R^f), meanwhile loop operation from line 4 goes through EV$_k$ (the EV in the queue of N_R). If EV$_l$ has arrived at the CS before LIST.GET(0), EV$_k$ has arrived at the CS before LIST.GET(0) and EV$_l$ is with a higher charging urgency ($V_{ev_{(l)}} > V_{ev_{(k)}}$), EV$_l$ is allowed to be charged prior to EV$_k$. Under the condition meets line 5, we have:

- At lines 6 and 7, if the EV$_l$ in the current loop is EV$_r$, the EACT will be returned as LIST.GET(0).
- Lines 8 to 16 refer that EV$_l$ could get charged before EV$_k$, however EV$_l$ is other than EV$_r$. LIST.GET(0) will be replaced with EV$_l$'s charging finish time $T^{fin}_{ev_{(l)}}$. Note that if EV$_l$ could get fully charged before its departure, $T^{fin}_{ev_{(l)}}$ will be calculated as (LIST.GET(0)+$T^{cha}_{ev_{(l)}}$). If EV$_l$ could not get fully charged, $T^{fin}_{ev_{(l)}}$ will be calculated as ($D_{ev_{(l)}}$ + $T^{arr}_{ev_{(l)}}$). Then line 15 sorts the LIST to ensure the LIST is with available time order.

As EV$_l$ has been scheduled for charging, it will be removed from the queues of N_R and N^f_R at line 20. It should be mentioned that EV$_l$ and EV$_k$ are EVs in the initial queue of N_R, the queues of N_R and N^f_R have same EVs but sorted with two different scheduling policy. Any EV$_l$ mapping to EV$_k$ that is excluded at line 20, will no longer appear in subsequent loop operations. After EV$_l$ that meets the above condition has been scheduled, Algorithm 3 only needs to schedule the rest EV$_k$. There are two different cases depends on whether EV$_k$ is EV$_r$:

- Lines from 21 to 36 process the condition that EV$_k$ is other than EV$_r$. Depending on whether EV$_k$ arrives before LIST.GET(0) and whether EV$_k$ could be fully charged, there are four different sub-cases. Firstly, if EV$_k$ arrives before LIST.GET(0) and could be fully charged within its parking duration (($T^{cha}_{ev_{(k)}}$ + LIST.GET(k)) $<$ ($D_{ev_{(k)}}$ + $T^{arr}_{ev_{(k)}}$)), $T^{fin}_{ev_{(k)}}$ will be calculated as (LIST.GET(0)+$T^{cha}_{ev_{(k)}}$) at line 24. Secondly, if EV$_k$ arrives before LIST.GET(0) but could not be fully charged within its parking duration, $T^{fin}_{ev_{(k)}}$ will be calculated as ($D_{ev_{(k)}} + T^{arr}_{ev_{(k)}}$) at line 26. Thirdly, if EV$_k$ arrives later than LIST.GET(0) but could be fully charged within its parking duration, $T^{fin}_{ev_{(k)}}$ will be calculated as ($T^{arr}_{ev_{(k)}} + T^{cha}_{ev_{(k)}}$). In the last sub-cases, if EV$_k$ arrives later than LIST.GET(0) and could not be fully charged within its parking duration, $T^{fin}_{ev_{(k)}}$ will be returned as ($D_{ev_{(k)}} + T^{arr}_{ev_{(k)}}$). Then $T^{fin}_{ev_{(k)}}$ will take place LIST.GET(0) at line 35 and the LIST will be sorted with ascending order at line 36.
- Lines from 37 to 43 consider the final condition that EV$_k$ in current loop is EV$_r$. EV$_r$'s arrival time will be compared with LIST.GET(0) concerning when EV$_r$ could get charged. LIST.GET(0) is returned as the EACT at lines 39 if EV$_r$ arrives before the first available charging slot. In the other condition under line 41, its arrival time ($T^{arr}_{ev_{(r)}}$) is returned as the EACT.

C. CS-Selection Decision Making

As to select the CS with the minimum time spent through an entire charging process (total trip duration $T^{cs,d}_{ev_{(r)}}$), the CS-Selection scheme calculates total trip duration ($T^{cs,d}_{ev_{(r)}}$) at each CS. Here, $T^{cs,d}_{ev_{(r)}}$ is calculated

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 EACT_{cs} via Algorithm 3
5: **if** $((T^{cha}_{ev_{(r)}} + \text{EACT}_{cs}) \leq (D_{ev_{(r)}} + T^{arr}_{ev_{(r)}}))$ **then**
6: $T^{cs,d}_{ev_{(r)}} = T^{tra}_{ev_{(r)}} + T^{cha}_{ev_{(r)}} + \text{EACT}_{cs} + T^{min}_{cs,d}$
7: **else**
8: $T^{cs,d}_{ev_{(r)}} = T^{tra}_{ev_{(r)}} + T^{arr}_{ev_{(r)}} + D_{ev_{(r)}} + T^{min}_{cs,d}$
9: **end if**
10: **end for**
11: $l^{min}_{cs} \leftarrow \arg\min(T^{cs,d}_{ev_{(r)}})$
12: **return** l^{min}_{cs}

with the following three inputs:

1) The travelling time from EV_r's current location to the selected CS, given by $T^{tra}_{ev_{(r)}}$.
2) The duration EV_r spends at the selected CS, which is given by the lines between 6 and 8 in Algorithm 4. It refers to the EV's charging and waiting time (duration before the EV gets charging service). Here, the EACT at CS (with location l_{cs}) has been estimated by the Algorithm 3.
3) The travelling time from the selected CS to EV_r's trip destination, given by $T^{min}_{cs,d}$.

Considering the parking duration, $T^{cs,d}_{ev_{(r)}}$ is calculated in two cases to refer that EV_r to be fully/not fully charged respectively. Firstly, if EV_r could get a fully charged service before it departure deadline $((T^{cha}_{ev_{(r)}} + \text{EACT}_{cs}) \leq (D_{ev_{(r)}} + T^{arr}_{ev_{(r)}}))$, $T^{cs,d}_{ev_{(r)}}$ is given by:

$$T^{cs,d}_{ev_{(r)}} = T^{tra}_{ev_{(r)}} + T^{cha}_{ev_{(r)}} + \text{EACT}_{cs} + T^{min}_{cs,d} \tag{5}$$

In the other case, EV_r could not get a fully charged because it has to depart at its departure deadline $(T^{arr}_{ev_{(r)}} + D_{ev_{(r)}})$, $T^{cs,d}_{ev_{(r)}}$ is calculated by the following calculation at line 8:

$$T^{cs,d}_{ev_{(r)}} = T^{tra}_{ev_{(r)}} + T^{arr}_{ev_{(r)}} + D_{ev_{(r)}} + T^{min}_{cs,d} \tag{6}$$

When loop operation finished at line 10, $T^{cs,d}_{ev_{(r)}}$ for each CS is obtained. The GA will select the CS with the minimum $T^{cs,d}_{ev_{(r)}}$ together with its location l^{min}_{cs} back to EV_r as the CS-Selection decision.

V. Performance Evaluation

We use Opportunistic Network Environment (ONE) [28] to build a city charging system simulation scenario. In Fig.4, a 4500×3400 m^2 area scenario demonstrates the urban area of Helsinki city in Finland. EVs are configured using Coda Automotive [29] with 33.8 kWh maximum electricity capacity, 193 km max travelling distance and average energy consumption of 0.1751 kWh/km. All EVs' batteries are with

Fig. 4. Simulation Scenario of Helsinki City

full volume at the beginning of the simulation.

To classify different EVs types, three SOC thresholds 30%, 40% and 50% are set. EVs are initialized in the scenario with variable moving speed from $30km/h$ to $50km/h$. The speed of EVs change upon each path to reflect the impact of traffic. Each EV would randomly select its destination. Whenever the destination is reached, a new destination will be randomly selected again, until its SOC reaches the preset threshold.

Besides, 7 CSs are deployed in the city scenario and provide fast charging. CSs are equipped with 5 charging slots. We apply the centre manner for communication between EVs, CSs and the GA. The GA processes all charging requests from all EVs and make CS-Selection decision to EVs whenever EVs request CS-Selection. The EV with request then would travel towards the decided CS for charging with the shortest road path underlying the Helsinki road topology.

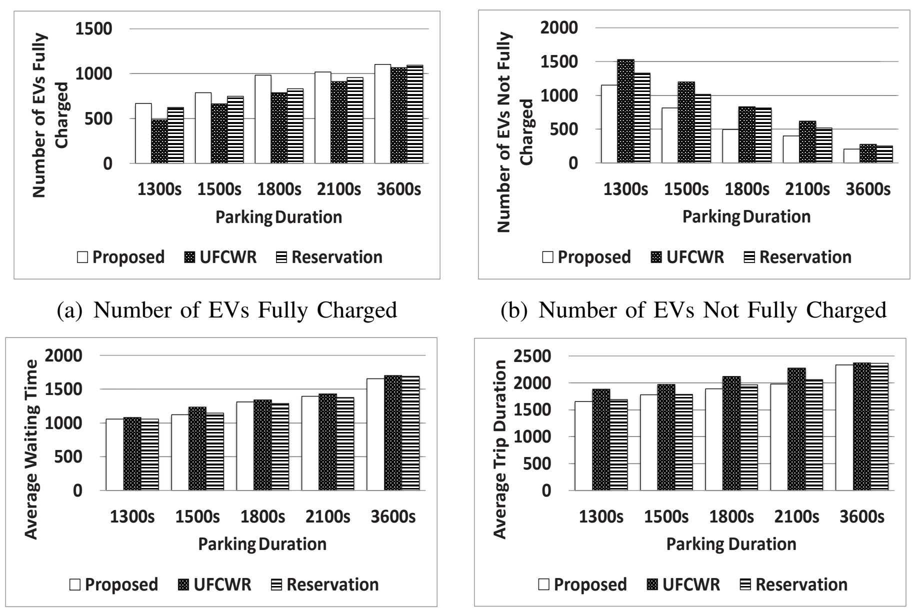
The simulation lasts for a 12 hours' duration with updating per 0.1s, where EVs' positions, speeds and energies are updated every 0.1s, no matter EVs are on the road or parked at CSs. Unless mentioned, incoming EVs are scheduled underlying the UFC policy, as detailed in Section III-A. The following CS-Selection schemes are evaluated for comparison:

- **Proposed**: The GA returns the decided CS with the minimum total trip duration by the Algorithm 4.
- **Urgency First Charging Without Reservation (UFCWR) [30]**: Literature work that the GA selects the CS with the EACT which is detailed in Algorithm 2, but does not ask EVs making reservations to CSs. The EVs' charging scheduling in simulation is based on the UFC policy.
- **Reservation**: The reservation scheme is based on FIFS charging scheduling [25]. The GA returns the CS-Selection decision by the EACT which considers both parked EVs and EVs made reservations.

To compare different simulation results, the following performance metrics are evaluated:

- **Number of EVs Fully Charged**: It is a performance metric at the CS side, which refers to the total number counting of EVs get fully charged service in the network within the simulation duration (each EV can be fully charged and counted for several times).
- **Number of EVs Not Fully Charged**: Number of EVs not fully charged although they have arrived at a CS. In the extreme case, an EV could not get charging service within its parking duration, which degrades user QoE, and the EV needs to continuously find a new CS for charging.
- **Average Waiting Time**: It is a performance metric at the EV side, which represents the average time costs that an EV get fully charged after it arrives at a selected CS.
- **Average Trip Duration**: The average trip duration sums the travelling time that an EV travels through the decided CS and its charging time the EV spends at the CS.

A. *Influence of Parking Duration*



(a) Number of EVs Fully Charged (b) Number of EVs Not Fully Charged

(c) Average Waiting Time (d) Average Trip Duration

Fig. 5. Influence of Parking Duration (EV Density: 330 EVs & Charging Power: 62kWh)

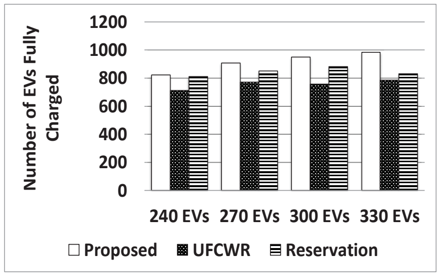
In the first group of simulations, we fix EV density and charging power. Here, we set parking duration to 1300s, 1500s, 1800s, and 2100s respectively. In 1800s, an EV could complete a fully charging from empty battery volume to full battery volume. Here, charging slots would terminate EVs' charging service after their departure deadline. We observe that with a higher parking duration, all of the three CS-Selection schemes achieve a higher number of EVs get fully charged in Fig. 5(a). However, as both the proposed scheme and the reservation scheme allow EVs making reservations, they have more accuracy in the EACT than the UFCWR scheme. Thus the GA can allocate EVs towards a CS with lower congestion level. Since the proposed scheme takes into account the charging urgency and would allow preempted charging, it avoids some EVs having to leave CS when the parking duration expires after a long wait but not getting fully charged. With the benefit of the UFC policy, more EVs could get fully charged comparing with the reservation scheme.

In Fig.5(b), the proposed scheme has an obvious advantage over the reservation scheme and the UFCWR scheme. Especially when the parking duration is the primary constrain, congestion would occur at CSs, EVs with higher charging urgency would require preempted charging, thus charging scheduling becomes significant. In Fig.5(c), the UFCWR scheme suffers from the longest average waiting time among the three schemes, no matter how parking duration changes. The average waiting time of the proposed scheme and the reservation scheme are at a similar level. Because both the reservation scheme and the proposed scheme enable the GA to estimate CSs charging status more accurate, it can prevent EVs from driving to a CS with a high level of congestion. However the proposed scheme has certain advantages as the proposed scheme achieves a larger number of EVs fully charged (in Fig.5(a)). The proposed scheme achieves a shorter average trip duration than the UFCWR scheme and the reservation scheme in Fig.5(d). With the increasing parking duration, the advantage of the proposed scheme becomes more significant. Because in Algorithm 4 the proposed CS-Selection scheme jointly considers the time from the EV's current location to the CS and the time from the CS to EV's destination, so the proposed scheme performs better than the other two schemes in average trip duration.

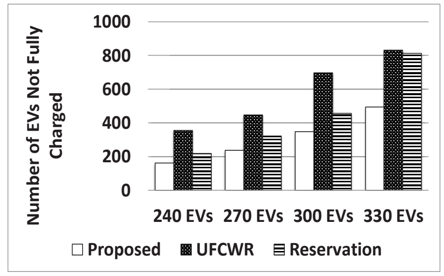
We set the parking duration to 3600s in the last set of simulations. As there are not many EVs in the network, most EVs can be fully charged in Fig.5(a) and only a few EVs can not fully charged in Fig.5(b). Meanwhile, the average waiting time and trip duration fail to reflect the difference between the three schemes. This is because the advantages of schemes can be better reflected when congestion occurs.

B. Influence of EV Density

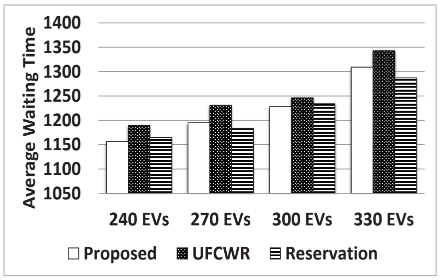
In the second group of simulations, we fix EV's parking duration to 1800s and charging power to 62kW. Then we observe the results of three different CS-Selection schemes when changing number of EVs. In Fig.6(a), the result shows that the proposed scheme achieves the highest number of EVs fully charged. Especially when the total number of EVs increases, the proposed scheme performs much better than the reservation scheme and the UFCWR scheme. Here, the proposed scheme achieves the higher number of EVs fully charged because it considers the charging urgency of EVs and allows preempted charging.



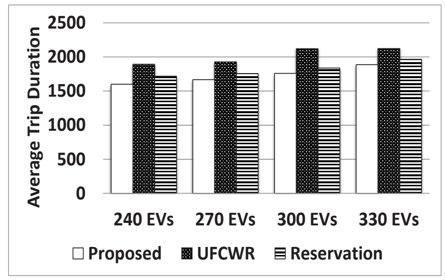
(a) Number of EVs Fully Charged



(b) Number of EVs Not Fully Charged



(c) Average Waiting Time



(d) Average Trip Duration

Fig. 6. Influence of EV Density (Parking Duration: 1800s & Charging Power: 62kWh)

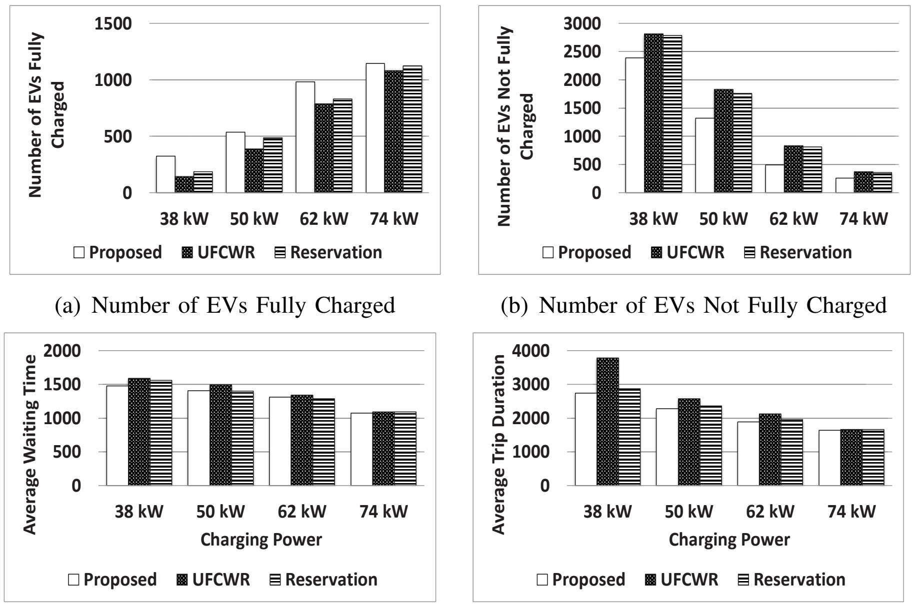
Performance Metrics\CS-Selection Schemes	Proposed	UFCWR	Reservation
Number of EVs Fully Charged	1401	883	870
Number of EVs Not Fully Charged	1844	2973	2922
Average Waiting Time (s)	2031	2377	2242
Average Trip Duration (s)	4288	4883	4743

TABLE II
INFLUENCE OF EV DENSITY (EV DENSITY: 660 & PARKING DURATION: 3600S & CHARGING POWER: 62KWH)

The result in Fig.6(b) also proves the advantage of the proposed scheme. It is worth mentioning that when the number of EVs increased by 330, the difference between the proposed scheme and the reservation scheme has a huge increase, this is because more congestion occurs when the number of EV increases and charging scheduling becomes significant. As the total number of EVs increases, the average waiting time and the average trip duration in Fig.6(c) and Fig.6(d) increase as well. This is due to the more charging congestion happens. The average waiting time of the proposed scheme and the reservation scheme are at a similar level as shown in Fig.6(c), shorter than the UFCWR scheme. This is because the UFCWR scheme calculates the EACT without considering EVs' reservations, thus the CSs charging status are not able to be accurately predicted and the GA may select a CS with charging congestion. Due to the difference of number of EVs fully charged, the proposed scheme has an advantage over the reservation scheme as it allows more EVs get fully charged (in Fig.6(a)). In Fig.6(d), the proposed scheme achieves the shortest average trip duration among the three schemes. This is because Algorithm 4 jointly considers travelling time and charging time, which is different from the reservation scheme and the UFCWR scheme.

In Table II, we further increase the number of EVs and the parking duration to 3600s (otherwise most EVs cannot be fully charged). This setting reflects that when the number of vehicles increases and congestion occurs, the proposed scheme increases the probability of EV get fully charged within the limited parking duration. This scheme also reduces the total trip time as it considers the charging urgency.

C. Influence of Charging Power



(a) Number of EVs Fully Charged (b) Number of EVs Not Fully Charged

(c) Average Waiting Time (d) Average Trip Duration

Fig. 7. Influence of Charging Power (EV Density: 330 EVs & Parking Duration: 1800s)

In the third group of simulations, we fix the parking duration to 1800s and EV density to 330 EVs to observe the influence of charging power. In this paper, we use DC charging (fast charging technology) to supplement EV energy. Fast charging reduces the charging time of EVs, which is more convenient for drivers to travel. In Fig.7(a), the proposed scheme achieves the highest number of EVs get fully charged. Especially when the charging power is at 38kW, the proposed scheme has an obvious advantage over the other CS-Selection schemes. This is because the proposed scheme allows preempted charging and sends reservations to the GA, which benefits overall EVs charging allocation. The result in Fig.7(a) also shows that, with the increase of charging power, more EVs get fully charged in all three schemes. The proposed scheme achieves the least number of EVs not fully charged in Fig.7(b). Because the proposed scheme considers the charging urgency of EVs, it prevents EVs from waiting at one CS without charging before its departure. When the charging power increases by 74kW, EV's charging time is shortened at all CSs, and all the three schemes decrease the number of EVs not fully charged.

The UFCWR scheme suffers from the longest average waiting time in Fig.7(c), this is because the UFCWR scheme does not ask EVs to send their reservations. Thus estimation of CSs charging status are uncertain, and it causes CS hotpots. Both the proposed scheme and the reservation scheme achieve shorter average waiting time comparing with the UFCWR scheme, however the proposed scheme allows more EVs get fully charged (Fig.7(a)) and thus it proves the importance of considering charging urgency. In Fig.7(d), the average trip duration decreases when the charging power increases. Here, the result shows that if charging power at CSs is increased, EVs would adequately avoid charging congestion, thereby reducing the overall trip duration. Among the three CS-Selection schemes, the proposed scheme considers the influence of the trip time in Algorithm 4, and thus achieves the shortest average trip duration.

VI. Conclusion

In this paper, we proposed a UFC charging scheduling policy that orders EVs charging priority by their charging urgency (jointly considering their charging demand and parking duration). Based on the UFC scheduling policy, we further proposed a reservation-based CS-Selection scheme to minimize the EVs' trip duration, which also guarantees more EVs to get fully charged within the parking duration. Results show the proposed CS-Selection scheme achieves a shorter EVs' trip duration through an intermediate charging, higher number of EVs get fully charged as well as a shorter average waiting time.

VII. Acknowledgements

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