An Integrated Framework on Autonomous-EV Charging and Autonomous Valet Parking (AVP) Management System

Xu Zhang, Xu Xia, Shuohan Liu, Yue Cao, June Li, Weisi Guo

Abstract

Autonomous vehicles (AVs) transform traditional commuting by decreasing congestion, improving road safety, and naturally integrate better with electric controls for flexible implementation of autonomous driving technologies. Indeed, electric-powered AVs or autonomous electric vehicles (AEVs) are benefiting each other in many aspects. While autonomy brings great efficiency in driving as well as battery use, EVs require less maintenance and drastically cut fuel costs. With AVs, a pivotal concern is within the realm of long-range Autonomous Valet Parking (LAVP), such as diverse customer demands on parking (or drop-off / pick-up) for various journey planning. On the other hand, electric-powered AVs are typically with limited cruising range, and locating convenient charging services are also among the major impediments. As of yet, recent studies have started to investigate EV charging and LAVP in isolation as they rarely consider a joint optimization on user trip and energy refueling. Rather, we target in this work the integration of vehicle charging with autonomy in the sense of a systemic approach. Specifically, we propose an integrated AEV charging and LAVP management scheme, to resolve critical decision-making on convenient charging and parking management upon customer requirements during their journeys. The proposed scheme jointly considers charging reservations as well as parking duration at car parks (CPs), aiming to enable accurate predictions on future charging (and parking) states at CPs. Results show the advantage of our proposal

X.Zhang is with the Department of Computer Science and Engineering, Xi'an University of Technology, 710048, China. Email: zhangxu@xaut.edu.cn

X.Xia is with China Telecom Research Institute, 100190, China. Email: xiaxu@chinatelecom.cn

S.Liu is with School of Computing and Communications, Lancaster University, LA1 4YW, UK. Email: s.liu37@lancaster.ac.uk

Y.Cao (corresponding author) and J.Li are with School of Cyber Science and Engineering, Wuhan University, 430072, China; and Suzhou Research Institute of Wuhan University, Suzhou, 215123, China. Email: yue.cao@whu.edu.cn

J.Li is with School of Cyber Science and Engineering, Wuhan University, 430072, China. Email: jeli@whu.edu.cn

W.Guo is with Centre for Autonomous and Cyber-Physical Systems, SATM, Cranfield University. UK. Postal Code: MK43 0AL Email: weisi.guo@cranfield.ac.uk

This work is supported in part by the National Natural Science Foundation of China (62101437), Suzhou Municipal Key Industrial Technology Innovation Program (SYG202123), Hubei Province International Science and Technology Collaboration Program (2021EHB012).

over benchmarks, in terms of enhanced customer experiences in traveling period, as well as charging performances at both AEV and CP sides. Particularly, effective load balancing can be achieved across the network regarding the amount of charged as well as parked vehicles.

Index Terms

Autonomous vehicle, Autonomous valet parking, Charging management, Trip planning.

I. Introduction

FOLLOWING unprecedented development in automotive industry and computing technology, autonomous vehicle (AV) has drawn wide attention as a fully automated and technologically advanced means of transportation [1]. Essentially, vehicles are beyond the concept for commuting trips in a purely mechanical mode, and are starting to level up into smart transportation devices with richer infotainment computing capability. Ultimately, AVs tend to be electrically designed by adopting electronic controls to replace traditional mechanical operating systems. Hence, this creates the possibility of a flexible platform for autonomous technologies.

Fueled by sustainable energy development, electric vehicles (EVs) are transforming AVs in many ways that drive growth. Environmental impact is one immediate benefit, with integration of variable renewable energy sources into the power grid [2]. Greenhouse gas emissions can thus be reduced under electric AVs. Lower cost from electric engine also becomes easy to achieve in terms of fuel and maintenance, which promotes increased adoption rates, leading to considerably reduced cost on transportation. Besides, owing to the inherent drive-by-wire technology, EVs are better compatible with autonomy for feasible implementation [3].

With AVs, one likely precursor as the autonomous valet parking (AVP) provides the functionality for car navigation and parking autonomously without manual operations [4][5]. The basic concept of AVP is to allow a driver to be dropped off near their final destinations, where the vehicle then autonomously drives away to park. To get picked up, the customer We use “customer ” and “user” interchangeably in this work, referring to the passenger of an autonomous EV. could summon the vehicle by using a smartphone app. The parking problem in urban areas is always a great concern and needs to be optimized [6]. By leveraging AVP techniques, stress on car parking can thus be effectively relieved due to the automatic navigation and manoeuvre that could largely reduce parking space. Driven by the thrive in AV development, different vendors and research communities have developed many types of demos and prototype versions [7][8] based on AVP. Most literature on AVP management relates to constrained or low speed restricted environments, such as within car parks [9][10]. In this situation, the AVP functions start to work at the entrance and rely on vision and sensor system to locate a free space afterwards, and park the car autonomously. Such solutions are usually termed as the short-range AVP (SAVP). Towards a much larger scale, a few recent research efforts have shown attention on the long-range AVP (LAVP) [11][12], where AV traveling experiences are considered prior to car parking. In such a case, AV customers are dropped off (or picked up) concerning their location convenience, rather than tediously waiting at the garage entrance for the AV as SAVP. However, more issues have to be considered regarding challenging environment of road complexity with unpredictable interactions.

Considering the electric-powered AV typically with limited cruising range (i.e., range anxiety), vehicles require frequent stops for recharging during a long journey [13]. In the light of this, several solutions on how to optimally recharge EVs considering the factors of time and spatial dimensions have been studied in literature [14][15]. For charging facility improvement, fast chargers (i.e., level-3 chargers) and battery swapping technologies have been introduced [16][17]. While they are effective in greatly reducing charging period, there will be a huge cost on infrastructure deployment. Particularly, in the area where there is low EV penetration, it is hard to profit from costly investment on fast charging (or swapping) stations [18].

Additionally, finding convenient charging facilities are among the major concerns [19]. Challenges relating to charging efficiency have received wide research interests. Majority research works focus on simplified scenarios where EVs are seen as stationary loads (i.e., parked at home or charging stations (CSs)) [20][21][22]. In such cases, the main focus is on whether/when to charge while EVs are statically parked at home or CSs. High peak hours for charging are avoided and low electricity rates are encouraged following these solutions. Considering EV mobility feature in particular, a few efforts start to pay attention to a more realistic scenario, concerning the spatiotemporal dynamics of moving EV loads [23][24][25]. EVs are strategically navigated towards an optimal CS for energy refuelling, where crowded CSs can be effectively predicted and thus avoided [26]. Also, there have been a few works recently to show great interests in the mobile charging management, wherein recharging service is provided by mobile plug-in chargers [27]. With intelligent management on charging scheduling, mobile chargers can be efficiently scheduled towards parked EVs to provide on-site charging services.

AVs integrated with EVs could create many advantages including aspects from feasibility of technology integration to cost efficiency as well as eco-friendliness. Autonomous EVs (AEVs) leverage advanced computing technologies and next-generation batteries to provide passengers with more efficient transport solutions. By adopting advantages of cleaner energy resources, lower carbon emissions in the transport sector can be greatly reduced.

As of yet, recent studies just investigate EV charging and LAVP in isolation as they rarely consider a joint optimization on user trip and energy refueling [28]. Rather, we target in this work the integration of vehicle charging[1] with autonomy in the sense of a systemic approach. Specifically, the synergy of charging convenience and parking preferences is our focus for the intuitive consideration with AEVs concerning the overall journey experience.

Therefore, in order to promote the efficiency of AEVs coupling with autonomous nature, one imperative concern is thus *to efficiently plan the best route all the way from locating the most convenient charging service, to finding the best parking space at the destination*. Towards this end, our technical contributions are thus as follows.

1) *Integration of charging convenience and parking favor*: Considering the journey experience, the charging process is preferred to happen when customer not onboard, i.e., charging while AEV parked. Additionally, a drop-off/pick-up spot is typically selected based on user-friendly preferences close to customer final destinations. From the perspective of AEVs, where-to-park and charge give rise to concerns over trip duration and charging availability. Finding the optimal car park where AEV experience minimum waiting for charging, and reduced travel duration is thus challenging considering in a global picture.

2) *Reservation-enabled charging management*: By accounting for a joint concern on all of the key factors, including charging reservations as well as parking duration, charging (and parking) conditions can be precisely predicted for a future moment at car parks. Besides, load balancing across the network can be achieved, with regard to parked and charged AEVs in history.

3) *Integrating EV charging with LAVP management*: Essentially, LAVP focuses on optimization problem in spatial dimension, and where-to-park is the main concern within this realm. As for AEV charging, it is more related to a time dimension problem when parking place is determined already, and thus when-to-charge at car park selected is the major concern. In this work, we focus on such spatiotemporal perspective relating to both issues, by enabling well-coordinated fleets of AEVs based on the proposed joint scheme, so as to manage challenges around trip planning, including access to charging infrastructure, charging

[1]Please be noted that we consider healthy AEV batteries in this work that battery failure never happens.

time and parking management.

The paper is organized as follows. The overview of the proposed scheme including preliminary definitions and assumptions is provided in Section II. In Section III, we introduce the proposed scheme involving several critical logics of decision makings. A series of case studies are evaluated and discussed in Section IV and we conclude the article in Section V.

II. Integrated AEV Charging and LAVP Management

Within the context of AEV, intelligent charging scheduling and parking management would be essential to deliver efficient intra-city trips, so as to maximize parking occupancy as well as charging convenience.

A. System Overview

In Fig.1, an AEV (i.e., aev_r) is traveling within a city area. While on the move, the customer may request a parking near their final destinations (e.g., work place), and the vehicle (aev_r) starts to negotiate with the cloud global controller (GC) to find an appropriate parking area. Upon receiving parking requests from AEVs, the GC would suggest an appropriate selection of drop-off/pick-up (D/P) point to the vehicle concerning customer convenience, i.e., within walking distance to their final destinations. Once the decision on D/P-selected is confirmed by aev_r, the GC would recommend an optimized car park (CP) for the AEV, by accounting for the distance to the D/P-selected point. From that D/P-selected area, the customer's destination is within walking distance, and may request pick-up. Meanwhile, the AEV operates itself towards the CP-selected without human involvement, through autonomous navigation and parking. Upon arrival at the CP, the AEV would recharge itself depending on the charging availability at the parking lot. After recharging, aev_r continues being parked until departure deadline, in relation to the customer working/leisure period. Specifically, we define the following network entities involved in the proposed system.

- **Autonomous Electric Vehicle (AEV)**: Each AEV is with a State of Charge (SOC) threshold, and recharging is needed once the energy ratio (current energy versus maximum energy) is below the SOC threshold. Considering the journey experience, the charging process here always happens while an AEV is parked at a CP, where charging facilities are available. Note the charging process happens after dropping off the customer at the selected D/P point (determined by GC), when the LAVP mode starts to work all the way towards the CP. With each AEV, a parking duration (D_{aev}) is applied for recording the time duration relating to customer working/leisure period. Therefore, the charging process could

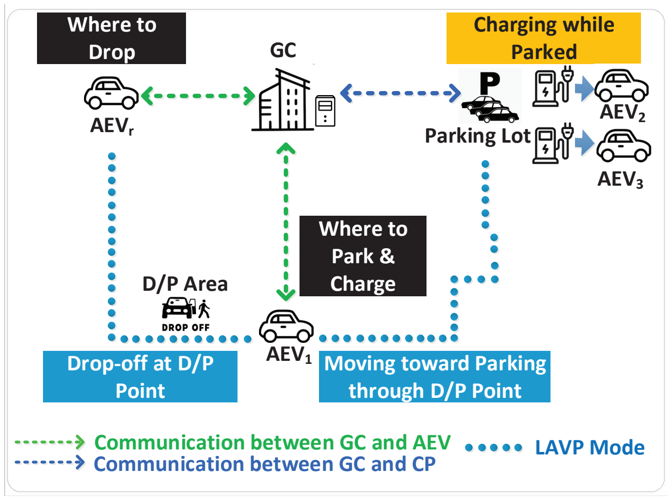


Fig. 1. Big picture of proposed Integrated AEV charging and parking management aided by a cloud server GC

be terminated before fully charged. Further, the AEV also reports its charging reservation to the GC, including the context information of its arrival time (T_{aev}^{arr}) and expected charging period (δ_{aev}^{cha}), along with the parking deadline (D_{aev}) in the form of $\langle T_{aev}^{arr}, \delta_{aev}^{cha}, D_{aev}\rangle$ (notations defined in Table I).

- **Car Park (CP)**: In mega cities, CPs are usually with large parking capacity owing to their vast space located at suburbs. As such, a CP is large enough for hundreds of vehicles. Commonly, CPs are installed with multiple charging points (π_{cp}) into some parking space to provide charging services to a number of AEVs while they are parked. Charging conditions are also monitored by GC, including the number of charging AEVs (charging or waiting for charging) and their charging time.
- **Global Controller (GC)**: It is a centralized server to manage all parking and charging demands in the network. With D/P-selection, the distance from customer final destination is one major concern. Upon receiving the confirmation on the D/P-selected from the vehicle, the GC would then perform the decision-making on CP-selection, concerning the charging conditions at individual CPs, as well as energy consumption of AEVs towards CPs.

B. Assumption

A city scenario is considered in this paper. Here, CPs are geographically deployed. Considering the dense traffic as well as high land cost in urban areas, CPs are usually sited outside city centre [31]. From this perspective, it is practical to assume that CPs are assumed with sufficient parking space, indicating that an AEV will always find a parking space at the selected CP.

D/P points are usually located within or near city centre concerning the convenience of customers [32]. Practically, the location of drop-off-selected could be different from pick-up spot for a customer, due to

TABLE I
LIST OF NOTATIONS

Symbol	Description
T_{cur}	Current time in network
T_{aev}^{arr}	AEV's arrival time at CP
δ_{aev}^{cha}	Expected charging time upon arrival at CP
T_{aev}^{tra}	AEV's traveling time to reach CP
θ_{av}^{pk}	Expected AV parking period at CP
D_{aev}	Parking duration of AEV at CP
π_{cp}	Number of charging slots at CP
T_{cx}^{trip}	The outbound/inbound trip duration of AEV customer
l_{dp}	Location of D/P spot
$T_{cx}^{aev,l_{dp}}$	The traveling time of AEV from current location to D/P point
$T_{cx}^{l_{dp},dst}$	Customer walk time from D/P spot towards the final destination
$T_{aev}^{l_{dp},cp}$	The traveling time of AEV from D/P spot to CP
N_C	Number of AEVs under charging at CP
N_W	Number of AEVs waiting for charging at CP
N_R	Number of AEVs reserved for charging at CP
E_{aev}^{max}	Full energy volume of AEV
E_{aev}^{cur}	Current energy volume of AEV
v_{aev}	Moving speed of AEV
ρ	Electric energy consumed per meter
β	Charging power at CP
$EWTC_{cp}$	Expected waiting time for charging of AEV at CP

varied customer requirements. To simplify the analysis, the same location of D/P-selected is assumed. However, we believe the proposed scheme in this paper can perform well in situations when selected D/P points are deployed geographically.

Here AEVs are considered to be private and thus, pickup and parking requests are sent to the user's own vehicle. After dropping off the customer, an AEV will drive toward an appropriate CP (CP-selected) for parking. While being parked, the AEV would recharge its battery[2]. By doing so, customer experience quality can be assured since charge replenishment can be done without taking up time while customer onboard. At the CP side, the underlying AEV charging scheduling is based on the First Come First Serve (FCFS) order. As we target at shared transport service, thus the earlier arrived AEV should be recharged, in order to meet upcoming demand from potential users. Thereby, parking AEV that arrives earlier will have a higher charging priority in scheduling.

[2]The same battery type is assumed with all AEVs in this work. However, our schemes applies well in the case where battery types vary with different AEVs.

Each CP is deployed with multiple charging slots. Since these charging capacity can be limited in quantity, AEVs would have to wait when charging slots are fully occupied. In particular, each AEV is with a certain period of parking duration. As such, the vehicle may depart from the CP to pick up customers without fully charged. The GC globally manages charging and parking plans for all AEVs in the network. By leveraging the communication techniques, information broadcasting between network entities can be efficiently enabled to facilitate charging and parking services.

C. System Cycle of Proposed Integrated AEV Charging and LAVP Management

Fig. 2 shows the system cycle.

Driving Phase: The AEV is traveling towards its trip destination, including the outbound trip (e.g., customer is heading towards the workplace) and the inbound trip (e.g., customer is heading back home).

Parking Planning Phase: During the driving phase, AEV customer requires a parking service allocated from GC near the final trip destination. Based on locally recorded information related to D/P points and CPs, the GC returns the most appropriate D/P spot and optimal CP to the AEV.

Drop-off Phase: Once the AEV is notified by GC in terms of the D/P point-selection decision, the AEV accepts the suggestion and drops off the customer at that area, where the customer takes a few minutes of walk towards the final trip destination.

LAVP Phase: On the basis of the D/P spot-selected, the decision on an optimal CP will be replied from GC by executing the CP-selection procedure, depending on the traveling from the D/P-selected spot, along with charging conditions at the CP. Then, the AEV sends its charging reservation $\langle T_{aev}^{arr}, \delta_{aev}^{cha}, D_{aev} \rangle$ to the GC, and continually drives towards the CP-selected in fully autonomous mode, and operates parking without human involvement .

Parking and Charging Phase: While parking at the CP, the AEV would charge itself if charging facility is available. Concerning the parking duration (D_{aev}), the vehicle may or may not get fully charged upon the parking deadline. In this case, the vehicle leaves and starts **LAVP Phase**, which then turns to **Pick-Up Phase**. Otherwise, the vehicle stays parked and continues recharging process until fully charged.

Pick-up Phase: Upon the pick-up request from GC sent by the customer, the AEV turns back to LAVP mode and drives towards the pick-up point, which can be notified by GC based on the D/P-selection logic. Namely, the AEV then begins the **LAVP Phase** to autonomously drive towards the pick-up spot, where the vehicle turns back to **Driving Phase** after customer getting aboard.

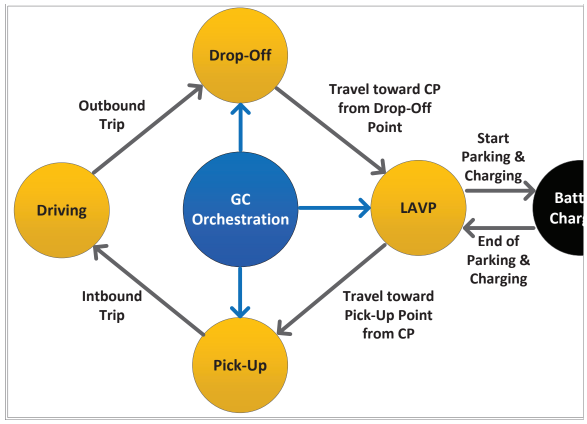
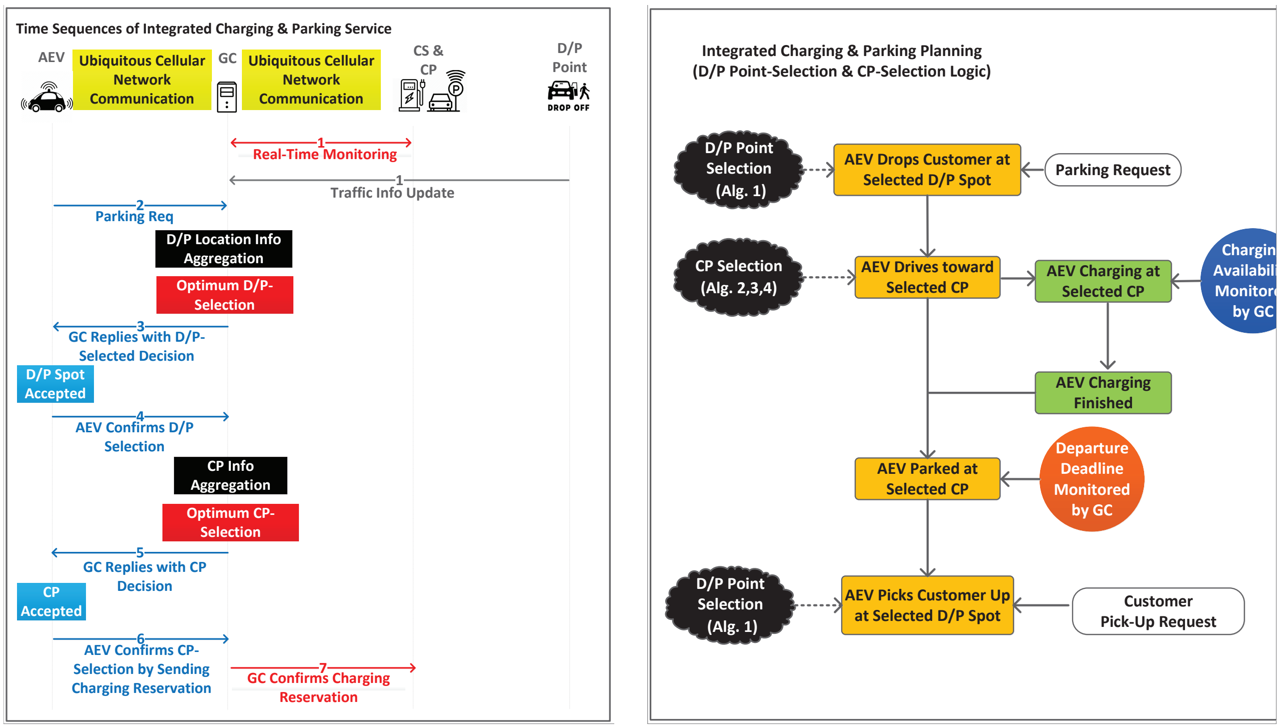


Fig. 2. System cycle of proposed integrated charging & parking management



(a) (b)

Fig. 3. Operational logic relating to on-the-move AEV LAVP & charging management: (a) Time Sequences (b) Operational Logic

III. System Design

This section presents the procedure regarding decision-making of D/P spot-selection together with CP-selection logics. Fig. 3 depicts critical system-level decision-makings relating to the overall trip cycles.

Step 1 *Monitoring in real-time*: The charging states of CPs are kept track of by the GC, regarding the amount of parked AEVs, the expected charging time as well as charging reservations.

Step 2 *Reporting request for parking*: A parking request could be sent by aev_r on-the-move to GC for suggestion on appropriate D/P and CP locations.

Step 3 *Selection on best D/P spot*: Once a parking demand is received, the GC computes the most appropriate D/P location by executing the D/P spot-selection procedure (according to Alg. 1 in latter section), and the best D/P area is selected (in terms of minimized outbound/inbound trip duration for the customer). The decision is then sent back to requestor aev_r.

Step 4 *D/P-selected confirmation*: The decision on D/P-selected is confirmed with requestor aev_r by sending back its reply to GC.

Step 5 *Selection on optimal CP*: Upon receiving the reply from aev_r of the D/P-selection, the GC starts to compile and select the most appropriate CP, in terms of minimized charging waiting time along with shortest travel distance (according to Alg. 4 in latter section). The decision is then replied to requestor aev_r.

Step 6 *Confirmation on CP-selected*: aev_r confirms the decision on CP-selection by sending back its charging reservation $\langle T^{arr}_{aev}, \delta^{cha}_{aev}, D_{aev} \rangle$ to GC.

While parking at CP, aev_r would charge itself when charging slots are available. Considering the parking deadline (triggered by the pick-up request from customer), the aev_r would drop any ongoing charging sessions or finish parking, and return to the on-the move-mode to pick up the customer at the D/P point-selected.

A. D/P Point-Selection Procedure

In order to obtain the most appropriate D/P point, the outbound (or inbound) trip duration of the customer (denoted as T^{trip}_{cx}) needs to be minimized, which can be computed with the following inputs:

- The traveling time of aev_r from current location to a D/P point (with location l_{dp}), given by $T^{aev,l_{dp}}_{cx}$.
- The traveling time for the customer (by walk or other forms of transportation) from that D/P spot towards the final destination, given by $T^{l_{dp},dst}_{cx}$.

Based on above, the traveling time (T^{trip}_{cx}) for the customer through an intermediate D/P point can be obtained as follows.

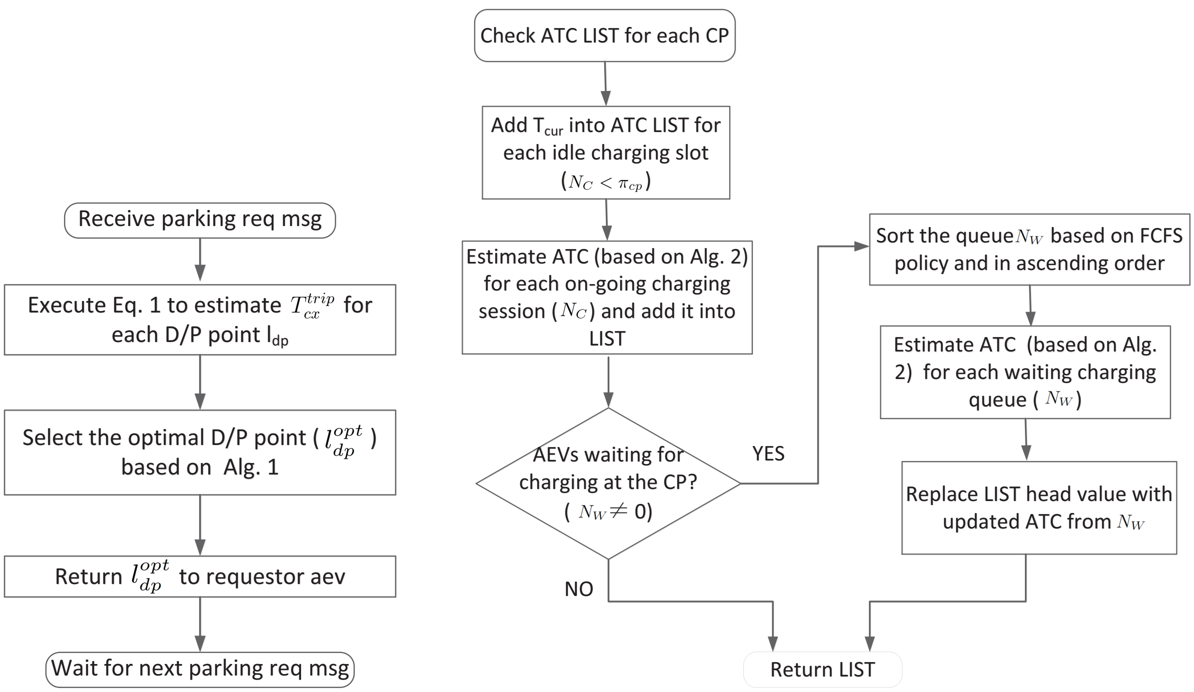
$$T^{trip}_{cx} = T^{aev,l_{dp}}_{cx} + T^{l_{dp},dst}_{cx} \tag{1}$$

Given the location of a D/P spot indexed as l_{dp}, $l_{dp} \in \Lambda_{dp}$, wherein Λ_{dp} represents the set of D/P locations within a range of the final customer destination, the most appropriate D/P point can be determined by running T^{trip}_{cx} for each l_{dp} (as elaborated in Alg. 1, line 1 to 5), and the one meets the minimum value is

Algorithm 1 Decision Making on D/P Point-Selection

1: **for** $\forall l_{dp} \in \Lambda_{dp}$ **do**
2: estimate $T_{cx}^{aev,l_{dp}}$
3: estimate $T_{cx}^{l_{dp},dst}$
4: calculate $T_{cx}^{trip} = T_{cx}^{aev,l_{dp}} + T_{cx}^{l_{dp},dst}$
5: **end for**
6: $l_{dp}^{opt} \leftarrow \arg\min(T_{cx}^{trip})$ (based on Eq. (1))
7: **return** l_{dp}^{opt}

selected, given by l_{dp}^{opt} (line 6 in Alg. 1). The GC then returns the decision back to aev_r. The flowchart related to Alg. 1 is also described in Fig. 4(a).



(a) (b)

Fig. 4. Flowcharts relating to algorithms: (a) Alg. 1 (b) Alg. 2

B. CP-Selection Procedure

Once the best D/P spot is obtained based on Alg. 1, the GC is able to determine the optimal CP by accounting for the following context information.

- *The traveling time* of aev_r from that D/P spot to each CP (l_{cp}), denoted as $T_{aev}^{l_{dp},cp}$.
- *The Expected Waiting Time for Charging* (EWTC) at individual CPs.

While the calculation on $T_{aev}^{l_{dp},cp}$ is easy to achieve, the value of EWTC requires predictions on the charging state with each CP for a future moment. In order to achieve this, one key concern is thus on the availability of charging service across the network. Considering the accuracy with such estimations, charging reservations at individual CPs have a key role to play. As such, we have the following key factors that contribute to EWTC.

- *Available time for charging* (ATC) at a CP indicating that a charging slot becomes idle to use.
- *Charging reservation* at a CP, including context information such as $\langle T^{arr}_{aev}, \delta^{cha}_{aev}, D_{aev}\rangle$.

Here the ATC implies the local charging status at a CP, which can be obtained by accounting for on-going charging sessions and the queue of AEVs waiting for charging, which can be characterized into two types of queues, the on-going charging queue (N_C) and the waiting queue for charging (N_W), respectively. Due to the spatiotemporal dynamics of AEVs constantly on-the-move, a CP with currently desirable local value of ATC could become a hotspot and ultimately becomes saturated concentrated with in-coming AEVs. Hence, an additional consideration of charging reservations (N_R) at CPs would provide a more accurate estimation on the future state of EWTC at a CP.

Meanwhile, an AEV could consume extra energy to reach the selected CP, owing to the extra trip travel after it made its parking request. The expected arrival time (T^{arr}_{aev}) can thus be approximated as below, wherein T^{tra}_{aev} represents the additional travel period from current AEV location to the selected CP via the shortest path.

$$T^{arr}_{aev} = T_{cur} + T^{tra}_{aev} \tag{2}$$

As such, the expected charging period (δ^{cha}_{aev}) can be refined as the following, given by $(v_{aev} \cdot T^{tra}_{aev} \cdot \rho)$ as the extra energy consumption given a consumption rate at ρ per meter.

$$\delta^{cha}_{aev} = (E^{max}_{aev} - E^{cur}_{aev} + v_{aev} \cdot T^{tra}_{aev} \cdot \rho)/\beta \tag{3}$$

Details of such estimation processes on ATC as well as EWTC are elaborated in Alg. 2 and Alg. 3, respectively.

In Alg. 2, as for cases that there are still available charging slots at a CP ($N_C < \pi_{cp}$), the current time in network (denoted as T_{cur}) is seen as the ATC for each idle charging slot and added to LIST (line 1 to 5 in Alg. 2). Otherwise, of each AEV_j (in the queue of N_C), the time duration $\Big(\frac{E^{max}_{aev(j)} - E^{cur}_{aev(j)}}{\beta}\Big)$ to fully charge a battery will be compared with the parking deadline $D_{aev(j)}$.

- In the case that this AEV_j can be fully charged before departure (line 7 in Alg. 2), characterized by the condition $\Big((T_{cur} - T^{arr}_{aev(j)} + \frac{E^{max}_{aev(j)} - E^{cur}_{aev(j)}}{\beta}) \leq D_{aev(j)}\Big)$, wherein $(T_{cur} - T^{arr}_{aev(j)})$ implies the waiting time since the arrival of AEV_j, the charging finish time of AEV_j can be given by $\Big(\frac{E^{max}_{aev(j)} - E^{cur}_{aev(j)}}{\beta} + T_{cur}$

Algorithm 2 Estimation of ATC

1: **if** $(N_C < \pi_{cp})$ **then**
2:     **for** $(i = 1; i \leq (\pi_{cp} - N_C); i++)$ **do**
3:         LIST.ADD(T_{cur})
4:     **end for**
5: **end if**
6: **for** $(j = 1; j \leq N_C; j++)$ **do**
7:     **if** $\left(\left(T_{cur} - T^{arr}_{aev(j)} + \frac{E^{max}_{aev(j)} - E^{cur}_{aev(j)}}{\beta}\right) \leq D_{aev(j)}\right)$ **then**
8:         LIST.ADD $\left(\frac{E^{max}_{aev(j)} - E^{cur}_{aev(j)}}{\beta} + T_{cur}\right)$
9:     **else**
10:         LIST.ADD $\left(T^{arr}_{aev(j)} + D_{aev(j)}\right)$
11:     **end if**
12: **end for**
13: **if** $N_W = 0$ **then**
14:     **return** LIST
15: **else**
16:     prioritize the queue of N_W based on FCFS policy
17:     prioritize LIST with ascending order
18:     **for** $(k = 1; k \leq N_W; k++)$ **do**
19:         **if** $\left(\left(\text{LIST.GET(0)} - T^{arr}_{aev(k)} + \frac{E^{max}_{aev(k)} - E^{cur}_{aev(k)}}{\beta}\right) \leq D_{aev(k)}\right)$ **then**
20:             $T^{fin}_{aev(k)} = \left(\text{LIST.GET(0)} + \frac{E^{max}_{aev(k)} - E^{cur}_{aev(k)}}{\beta}\right)$
21:         **else**
22:             $T^{fin}_{aev(k)} = \left(T^{arr}_{aev(k)} + D_{aev(k)}\right)$
23:         **end if**
24:         replace LIST.GET(0) with $T^{fin}_{aev(k)}$ in LIST
25:         prioritize LIST in ascending order
26:     **end for**
27:     **return** LIST
28: **end if**

).

- In the other case when the AEV_j reaches its parking deadline and has to leave without being fully charged at this CP (line 9 in Alg. 2), the charging finish time is given by $(T^{arr}_{aev(j)} + D_{aev(j)})$.

Upon above processing for AEVs under charging, the waiting charging queue (N_W) of AEVs at a CP further complete the list of ATC, depending on the following conditions.

- If there are no AEVs waiting for charging ($N_W = 0$), the LIST will be returned (lines 13 and 14 in Alg. 2).
- Otherwise, the queue of N_W needs to be processed for each waiting AEV (line 15 in Alg. 2).

In the latter case (starting from line 16 in Alg. 2), the queue of N_W is sorted according to the discipline of FCFS following the underlying charging scheduling policy in Section II. Meanwhile, the LIST is sorted in ascending order related to all AEVs under charging, thereby the head value (denoted by LIST.GET(0)) implies the earliest available time for charging out of every charging slot at a CP. Therefore, in order to update the charging finish time ($T^{fin}_{aev(k)}$) in LIST by further considering each waiting AEV_k, the earliest charging available time needs to be taken into account.

- Given by (LIST.GET(0)$-T^{arr}_{aev(k)}$) as the waiting time duration prior to charging (line 19 in Alg. 2), the charging finish time ($T^{fin}_{aev(k)}$) can be calculated either as $\big($LIST.GET(0)$+\frac{E^{max}_{aev(k)}-E^{cur}_{aev(k)}}{\beta}\big)$, or ($T^{arr}_{aev(k)} + D_{aev(k)}$) in line 20 and 22 of Alg. 2, respectively.
- Further, the head value (LIST.GET(0)) from LIST will be updated by $T^{fin}_{aev(k)}$ (line 24 in Alg. 2), and the LIST is then sorted in ascending order (line 25 in Alg. 2) by processing each waiting AEV_k in the queue of N_W.

The process of estimating ATC is also depicted in flowchart as shown in Fig. 4(b), related to Alg. 2. Intuitively, the estimation of ATC based on Alg. 2 is majorly determined by the local charging status, including calculations of two operational loops (N_C and N_W). In fact, many existing researches adopt ATC directly for the selection of CP [13][22]. As discussed previously, one potential risk here is heavy overcrowding happening at some CPs, due to the blindness of charging state for a future moment (after reserved AEVs arrive). Therefore, in order to effectively predict and avoid crowded CPs, charging reservations (i.e., N_R) are further considered in the estimation of EWTC in our work.

Therefore, on the basis of Alg. 2, along with reported charging reservations (N_R), the GC can then estimate the EWTC value for requestor AEV_r at individual CPs, as presented in Alg. 3. The charging queue (N_R) is sorted according to FCFS (line 1 in Alg. 3) by following the underlying charging scheduling policy, and AEV_i thus represents the i^{th} AEV in the queue of N_R.

Algorithm 3 Estimation of EWTC

1: prioritize the queue of N_R based on FCFS policy
2: prioritize LIST (returned by Alg. 2) with ascending order
3: **for** $(i = 1; i \leq N_R; i++)$ **do**
4:     **if** $(T^{arr}_{aev(i)} < T^{arr}_{aev(r)})$ **then**
5:         **if** (LIST.GET(0)$> T^{arr}_{aev(i)}$) **then**
6:             **if** (LIST.GET(0)$-T^{arr}_{aev(i)} + \delta^{cha}_{aev(i)} \leq D_{aev(i)}$) **then**
7:                 $T^{fin}_{aev(i)} =$ (LIST.GET(0)$+\delta^{cha}_{aev(i)}$)
8:             **else**
9:                 $T^{fin}_{aev(i)} = (T^{arr}_{aev(i)} + D_{aev(i)})$
10:             **end if**
11:         **else**
12:             **if** $(\delta^{cha}_{aev(i)} \leq D_{aev(i)})$ **then**
13:                 $T^{fin}_{aev(i)} = (T^{arr}_{aev(i)} + \delta^{cha}_{aev(i)})$
14:             **else**
15:                 $T^{fin}_{aev(i)} = (T^{arr}_{aev(i)} + D_{aev(i)})$
16:             **end if**
17:             replace the LIST.GET(0) with $T^{fin}_{aev(i)}$
18:             prioritize LIST with ascending order
19:         **end if**
20:     **end if**
21: **end for**
22: **if** (LIST.GET(0)$> T^{arr}_{aev(r)}$) **then**
23:     **return** $EWTC =$ (LIST.GET(0)$-T^{arr}_{aev(r)}$)
24: **else**
25:     return $EWTC = 0$
26: **end if**

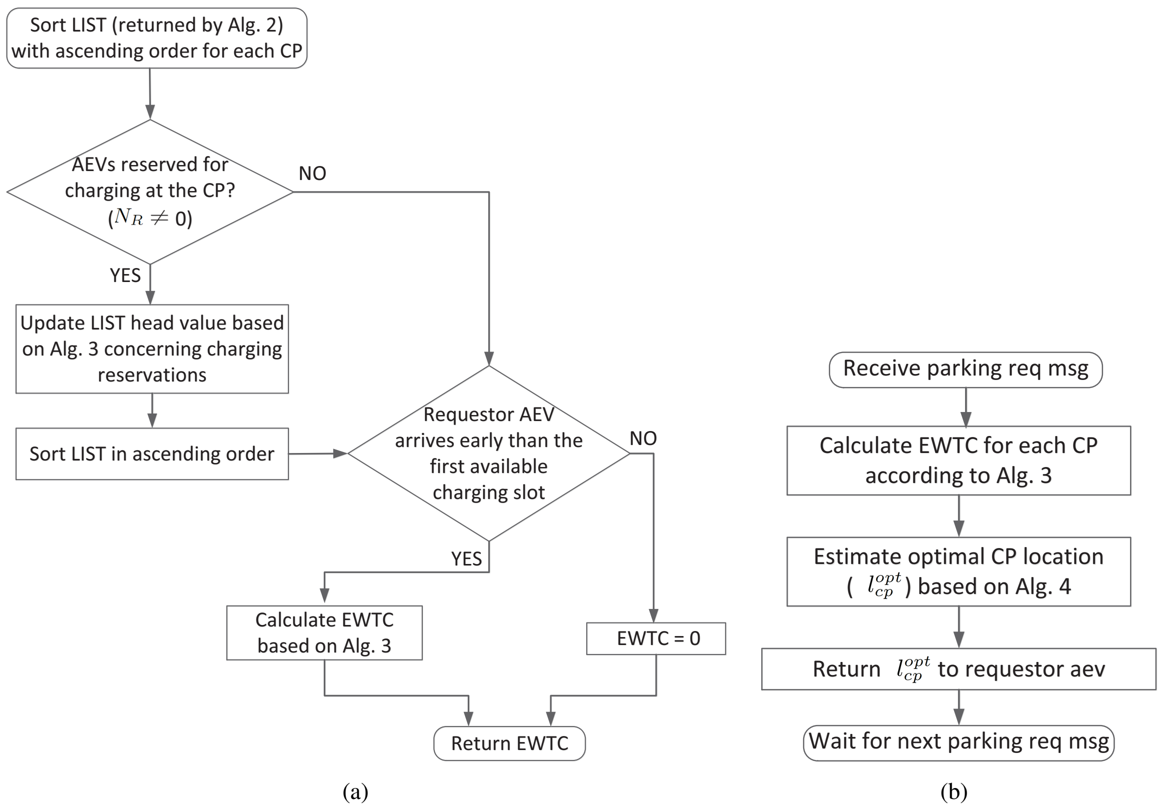


Fig. 5. Flowcharts relating to algorithms: (a) Alg. 3 (b) Alg. 4

As observed in line 4 of Alg. 3, AEVs (AEV_i) among the reservation queue at a CP with an earlier arrival time than AEV_r will get involved in the dynamic update process of LIST returned by Alg. 2. To predict the EWTC value for AEV_r, the LIST is updated. Specifically, the head value from LIST corresponds to the earliest available charging time, given by the following operational loop:

- If AEV_i ($i \in N_R$) arrives later than the earliest available charging time at the CP (given by (LIST.GET(0) $> T^{arr}_{aev(i)}$) in line 5 of Alg. 3), the AEV has to wait (approximated as the duration of (LIST.GET(0) $- T^{arr}_{aev(i)}$) before getting charged, and thus the charging finish time is calculated by considering this charging availability as well as the charging duration ($\delta^{cha}_{aev(i)}$).
  Particularly, if the vehicle (AEV_i) can get fully charged before its departure from CP, given by the condition (LIST.GET(0) $- T^{arr}_{aev(i)} + \delta^{cha}_{aev(i)} \leq D_{aev(i)}$) in line 6, $T^{fin}_{aev(i)}$ can then be calculated as presented in line 7. Otherwise, $T^{fin}_{aev(i)}$ will be computed by aggregating the parking deadline $D_{aev(i)}$ in line 9.
- In another case when charging is already available upon the arrival of AEV_i (in line 11), the vehicle does not need to wait and can be charged right away. Therefore, $T^{fin}_{aev(i)}$ can be calculated by considering $T^{arr}_{aev(i)}$, $\delta^{cha}_{aev(i)}$ and $D_{aev(i)}$ following line 13 and 15.

For each charging finish time ($T_{aev(i)}^{fin}$) of AEV_i in the queue of N_R, the earliest charging available time from LIST (LIST.GET(0)) is replaced (line 17 in Alg. 3). With all AEV_i processed in the queue of N_R, the available charging time at charging slot is continuously updated.

After the update of LIST by completing all charging reservations prior to the arrival of requestor AEV_r, its EWTC value can thus be approximated by comparing the arrival time to the head value from LIST (as presented between line 22 and 24 in Alg. 3). When AEV_r arrives late (given by (LIST.GET(0) $> T_{aev(r)}^{arr}$)), the AEV has to await the duration of (LIST.GET(0) $- T_{aev(r)}^{arr}$) as presented in line 22. Note flowchart depicted in Fig. 5(a) describes the execution process of Alg. 3.

Towards this end, the decision-making on the selection of an optimal CP can thus be determined based on following inputs.

- The traveling time for AEV to drive from D/P point towards CP ($T_{aev}^{l_{dp},cp}$).
- The EWTC value at CP given by the calculation in Alg. 3.

As elaborated in Alg. 4, by running Alg. 3 for each CP within the network, the CP with the minimum aggregation of $T_{aev}^{l_{dp},cp}$ and EWTC is selected as the optimal one (l_{cp}^{opt}), which is then sent back to requestor AEV_r. Such process is also presented in flowchart as depicted in Fig. 5(b).

Algorithm 4 CP-Selection Decision Making

```
for ∀l_cp ∈ Λ_cp do
    calculate T_aev^{l_dp,cp}
    calculate EWTC_cp based on Alg. 3
end for
l_cp^opt ← arg min(T_aev^{l_dp,cp} + EWTC_cp)
return l_cp^opt
```

C. Discussion

1) It is worth noting the concern over the trade-off between increased energy use and driving autonomy. Obviously, autonomy brings great efficiency in driving as well as battery usage, while EVs require less maintenance and drastically reduce fuel costs. Meanwhile, AVs could use more power than traditional mechanical vehicles, in order to power electronic devices for smart navigation, such as sensors and computers. Some analysts suggest that these increased power needs will have a serious impact on an EV's range and degrade batteries. At the same time, optimists also believe that electric power can supply enough energy for an AEV without a significant decrease in driving range [3], by advocating improvements in energy-efficiency technology that is likely to mitigate such trade-offs between the two.

2) Traffic condition on the road can exert AEV mobility uncertainty, representatively such as traffic jams. As a result, AEVs may not be able to arrive at CP-selected on previously reserved time. From a more practical perspective, it is important to further enable the update on CP reservations constantly, including any modifications or cancellations. In this work, decision-making logics are based on charging reservations of non-modifications and thus, our future work could be extended to additionally account for such practical consideration. Also, the rising number of AEVs on-the-move would intensify such road congestion and hence, the overall travel experiences can be greatly degraded in terms of traveling period. Therefore, it would be interesting to see how traffic congestions affect the selection over optimal CPs and ultimately, the experience quality of AEV customers. This traffic impact could be our future work focus within the charging and LAVP realm.

3) Ultimately, AEVs are moving toward shared mobility services (e.g., taxicabs) involved in transit and active transportation. Many positive impacts have already been shown by several studies [33], such as low carbon-emissions and enhanced vehicle performance. On the other hand, shared mobility services relate to demand-driven sharing among passengers, which could easily be saturated with massive pickup requests if services are not wisely scheduled. As such, the availability regarding the shared AEV would become a major issue when customer demand for pickups becomes huge. Besides, high security and privacy protection at system level are also among the major concerns. Therefore, AEVs of shared mode requires more complex and careful designs in order to guarantee users' travel experience, which would be our future work.

4) The health of the AEV's battery is also one of the concerns on the development of the vehicle [34]. Due to the battery degradation over time in nature, it is hard to maintain the original range. As such, it is difficult for the initial battery of the vehicle to reach a full charge state in practice. In this paper, the initial battery state is set to be fully charged, in order to ensure a guaranteed traveling experience (non-stops for recharging) before dropping off customers. Nevertheless, a medium (or other level) battery state would incur frequent recharging while customer onboard, leading to poor customer travel experience quality. Besides, recharging with customer onboard introduces complexity into the system, with regard to concerns over availability of charging stations within city centres, the customers tolerance to charging duration and limited parking space, etc. Many important issues arise such as long queueing problems at hotspot charging stations and ultimately, great complexity of efficient scheduling of AEVs. It relates to more careful designs and decision-makings. However, it could be our future work to extend our proposed

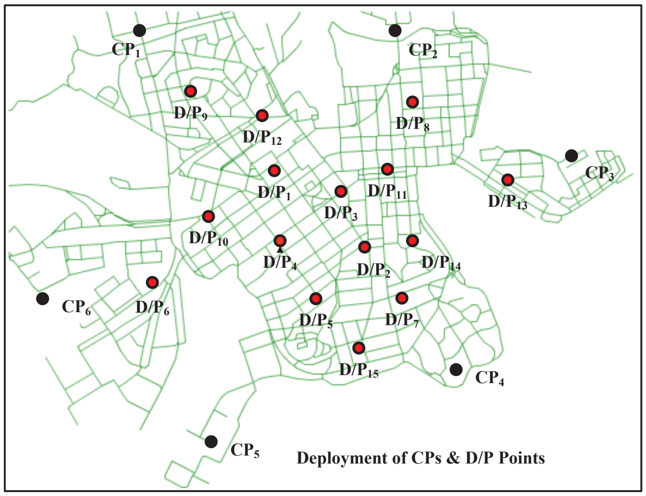


Fig. 6. Simulation scenario of Helsinki City

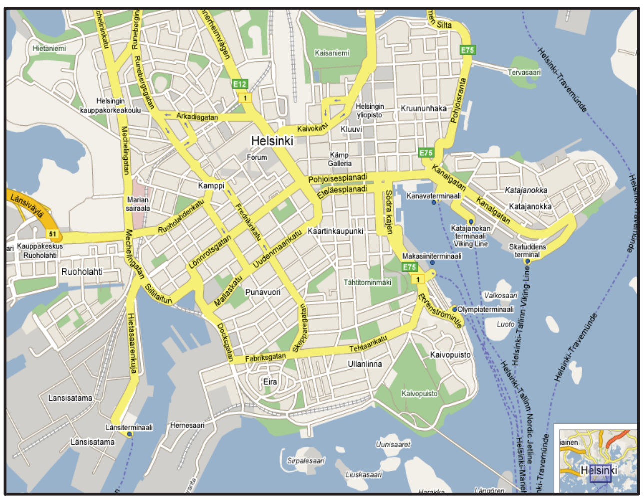


Fig. 7. Google map of Helsinki city

designs to a more practical case, where recharging happens anytime with a relatively varied initial charging state.

IV. Case Study

The integration of AEV charging and LAVP system has been built under Opportunistic Network Environment (ONE) [29]. In Fig.6, the simulation scenario refers to the downtown area of Helsinki city with $4500 \times 3400m^2$ area abstracted from Google map in Finland (Fig. 7). Here, 300 AEVs are initiated in the network with moving speed varied within the range of [30∼50] km/h. Each AEV customer's destination is randomly chosen from a location in the map. AEV drivers request for parking at 3600s, and 7200 is set as the parking duration at CPs. Note the communication cost is linearly increased with AEV density (N_{aev}), calculated as $O(N_{aev})$.

The configuration of AEVs follows the charging specification Maximum Electricity Capacity (MEC), Max Traveling Distance (MTD), Status Of Charge (SOC) threshold. The electricity consumption for the Traveled Distance (TD) is calculated based on (MEC$\times$ TD) / MTD as widely adopted in literatures such as [24]. All AEVs' batteries are with full volume initially in the network. 6 CPs are deployed providing sufficient electric energy, and each CP is installed with 40 charging slots, providing a constant charging power of 10 kW. Constant charging power is commonly used in many relevant works [24][27]. Besides, each CP is provided with suffice parking spots, indicating all arriving AEVs at the selected CP can be parked. Besides, 15 D/P points are installed in the network. Note the shortest path is applied for AEVs traveling considering the Helsinki road topology. Once parked at the selected CP, AEVs start charging right away when charging slots are readily available. When summoned by a customer, the AEV would take the shortest route back to the D/P spot, where it picks up the customer and continues to drive towards the next destination. In reality, the GC is believed to be with super power as well as super computation capability to make charging/parking plans for all AEVs in largescale network.

The following schemes are evaluated for comparison:

- **LAVP-CHARGE-RES**: The proposed integrated AEV charging and LAVP management scheme, considering A-EV charging reservations at CPs. The CP-selection is based on the one with the minimum EWTC, along with distance concerns between the D/P-selected and individual CPs (according to Alg. 4).
- **LAVP-CHARGE-WAI**: The proposed integrated AEV charging and LAVP management scheme without considering charging reservations. The CP-selection is based on local CP charging states where AEVs are already parked (being charged or waiting to be charged), according to Alg. 2.
- **LAVP-CHARGE-DST**: The integrated AEV charging and LAVP management scheme selects CP simply based on the distance between the D/P-selected and individual CPs, according to detail in [11]

Note the procedure for D/P-selection follows the same algorithm based on Alg. 1 with all of the above schemes, due to the inherent optimality based on Euclidean geometry.

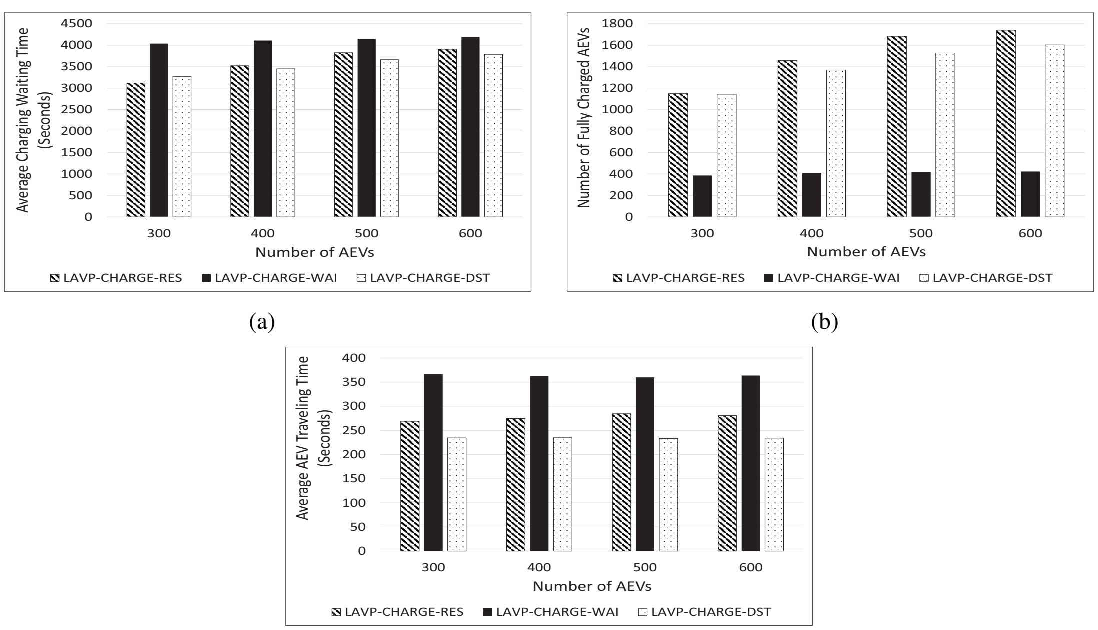
A 12 hours duration experiment is shown in the simulation, with a 0.1s resolution, indicating that AEVs locations, speeds and energies are updated every 0.1s. Performance metrics are given as follows:

- **Average Charging Waiting Time**: As the performance metric at AEV side, it measures the average period between the arrival time of AEV at selected CP, and charging finish time.

- **Number of Fully Charged AEVs**: As the performance metric at operator side, it measures the total number of fully charged AEVs. Ideally, it is appreciated that AEVs can finish recharging within the limited parking duration. Otherwise, user Quality of Experience (QoE) would be certainly degraded especially when AEV travels to a CP and finds no chance for recharging (due to charging slots unavailable or vehicle reaching parking deadline). In such cases, the AEV would have to continuously search for charging service even when customer onboard.
- **Average AEV Traveling Time**: As the performance metric at AEV side, it measures the average travel time that an AEV experiences (e.g., outbound trip), which refers to the overall journey through a D/P spot towards CP.
- **Average Customer Trip Duration**: As the performance metric at AEV side, it measures the average time duration for an AEV customer to experience, e.g., for the outbound trip, from when requesting a drop-off till the time reaching the final destination (e.g., workplace).

Here, the inbound trip follows a similar route as the outbound trip route based on the shortest path. As such, the A-EV or customer experiences quite similar trip duration as the outbound trip. Therefore, the above performance regarding the average AEV/customer trip duration mainly consider the outbound trip.

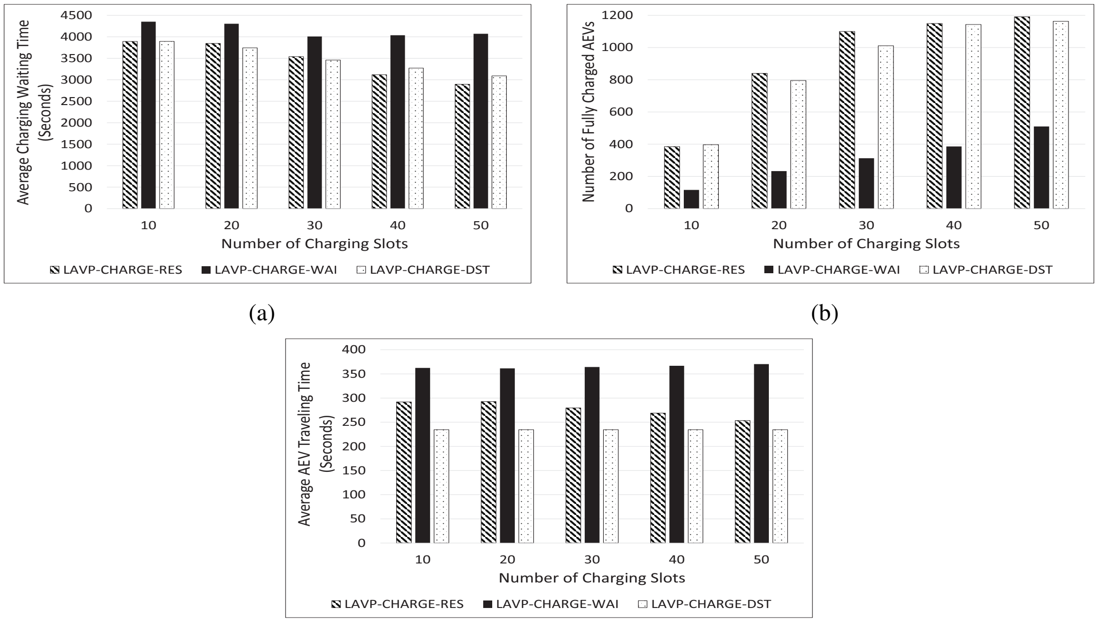
A. *Influence of AEV Density*



(a) (b)

(c)

Fig. 8. Impact of AEV Density: (a) Average Charging Waiting Time (b) Number of Fully Charged AEVs (c) Average AEV Traveling Time



(a) (b)

(c)

Fig. 9. Impact of Charging Slots: (a) Average Charging Waiting Time (b) Number of Fully Charged AEVs (c) Average AEV Traveling Time

With increment in the number of AEVs on the move in the network, waiting time for charging at individual CPs can be greatly increased as shown in Fig. 8 (a). Particularly, the proposed LAVP-CHARGE-RES enables great performance gains compared to other schemes. This is mainly benefited from the capability for predicting charging states across the entire charging network for a future moment. As observed, the LAVP-CHARGE-WAI suffers from much longer waiting time for charging. Because of limited charging slots installed, hotspot for charging can easily happen if many AEVs choose the same CP, especially if such choices are made under the blindness of charging states for a future moment. For example, a number of 100 AEVs may travel towards the same empty CP (0 waiting time with 40 charging slots unoccupied at the moment), since they just decide based on current status rather than predicted conditions like RES. It is also interesting to notice in Fig. 8 (a) that the LAVP-CHARGE-DST achieves similar performance gains as the LAVP-CHARGE-RES. When individual AEV customer destinations vary in diversity across the network, the CP-selected based on distance (in geographical proximity to D/P spot under LAVP-CHARGE-DST) could be well scattered and hence, congestions at CPs could be well alleviated.

In Fig. 8 (b), the proposed LAVP-CHARGE-RES outperforms other schemes by charging more AEVs. Meanwhile, the LAVP-CHARGE-DST achieves desirable performance as well. Since CPs are more likely to suffer from AEV congestions under LAVP-CHARGE-WAI, the amount of fully charged vehicles tend to be much less due to the long wait for limited charging slots becoming available.

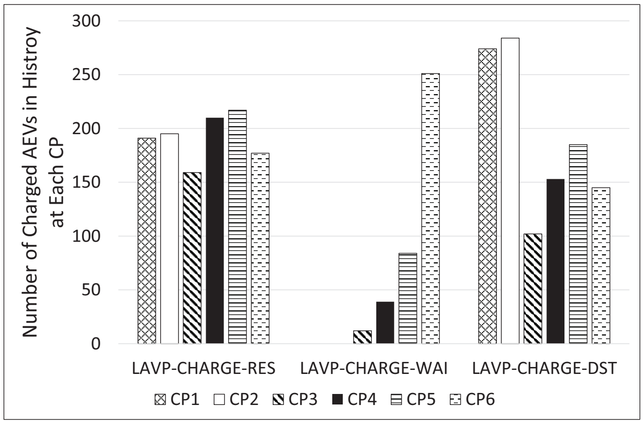
Regards the AEV travel/customer trip duration with varied AEV numbers, performances are shown in Fig. 8 (c) and Fig. 16 (a). As expected, the AEV travel duration can be substantially reduced by the proposed LAVP-CHARGE-RES (and LAVP-CHARGE-DST), mainly due to the travel distance concern, while the LAVP-CHARGE-WAI endures much longer travel period. As observed, the performance trend tends to be not influenced by varied AEV density as shown in Fig. 8 (c) and Fig. 16 (a). This indicates that AEV density has minor effect on AEV/customer trip duration as there is no congestion happening at D/P points. As will be shown in latter section, the two performance metrics are largely dominated by the installation of D/P points as well as CPs. In particular, comparable customer trip duration can be achieved by all schemes as shown in Fig. 16 (a), owing to the same D/P selection policy (following Alg. 1) applied to all schemes in this case study.

B. Influence of Charging Slots

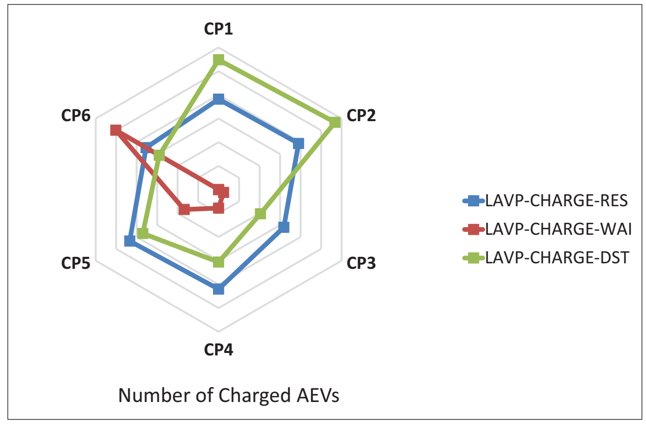
When the number of charging slots are increased at CPs, all metrics perform better in Fig. 9 (a) and (b). Here, the proposed LAVP-CHARGE-RES (and LAVP-CHARGE-DST) achieve shorter charging waiting time comparing with LAVP-CHARGE-WAI, even with a small number of 10 charging slots more likely to overload CP for charging services. In particular, LAVP-CHARGE-WAI suffers from long waiting time for charging, which implies that the consideration for only local conditions of CPs is not suggested to achieve an optimal charging performance, especially when CPs are potentially in congestion. Besides, the number of fully charged AEVs is remarkably increased under LAVP-CHARGE-RES and LAVP-CHARGE-DST as shown in Fig. 9 (b), with an optimality of the proposed LAVP-CHARGE-RES compared to others.

Due to similar reasons as discussed previously, the performance trend in Fig. 9 (c) and Fig. 16 (b) is less affected with all schemes with varied charging slots. While LAVP-CHARGE-RES and LAVP-CHARGE-DST are benefited from the concern on travel distance as shown in Fig. 9 (c), all schemes experience similar performances over the customer travel period as observed in Fig. 16 (b), mainly due to the same selection policy on D/P spots applied.

Fig. 10 and Fig. 11 further show the distribution of AEVs charged (or parked) in history at each CP. Noticeably, the AEV load across the network can be effectively balanced with the proposed LAVP-CHARGE-RES, while LAVP-CHARGE-WAI behaves in a quite skewed distribution. As compared, a moderate skewed distribution is achieved based on LAVP-CHARGE-DST against LAVP-CHARGE-WAI, owing to the CP-selection potentially scattered over the network. Essentially, load balancing has direct correlation with the QoE, and a system that achieves balanced load is able to minimize the overall charging waiting time across the network [30].

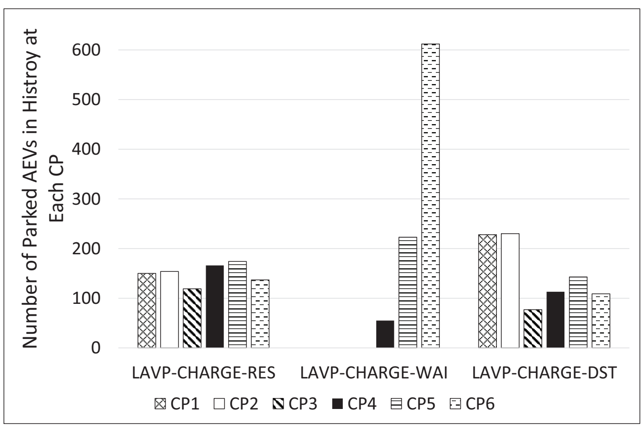


(a)

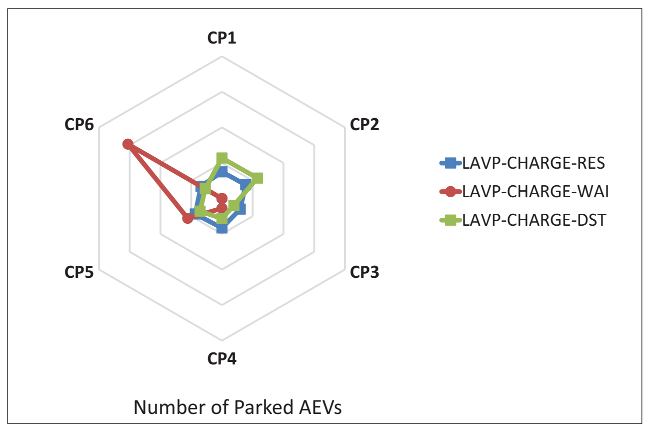


(b)

Fig. 10. Distribution of Number of Charged AEVs at Each CP



(a)



(b)

Fig. 11. Distribution of Number of Parked AEVs in History at Each CP

C. Influence of Charging Power

As observed in Fig. 12 (a), a reduced charging power leads to more AEVs got stranded at CPs, resulting in longer waiting time for charging. Such case becomes even worse for LAVP-CHARGE-WAI. Clearly, the proposed LAVP-CHARGE-RES shows its advantage with the capability to estimate waiting period for a future moment. As for the number of charged AEVs at CPs, a low charging rate exerts a reduced amount as shown in Fig. 12 (b). With increased charging power, more AEVs (or ideally all arriving AEVs) would be able to be charged up. Results from Fig. 12 (c) and Fig. 16 (c) reflect the negligible role of charging power in AEV/customer travel duration.

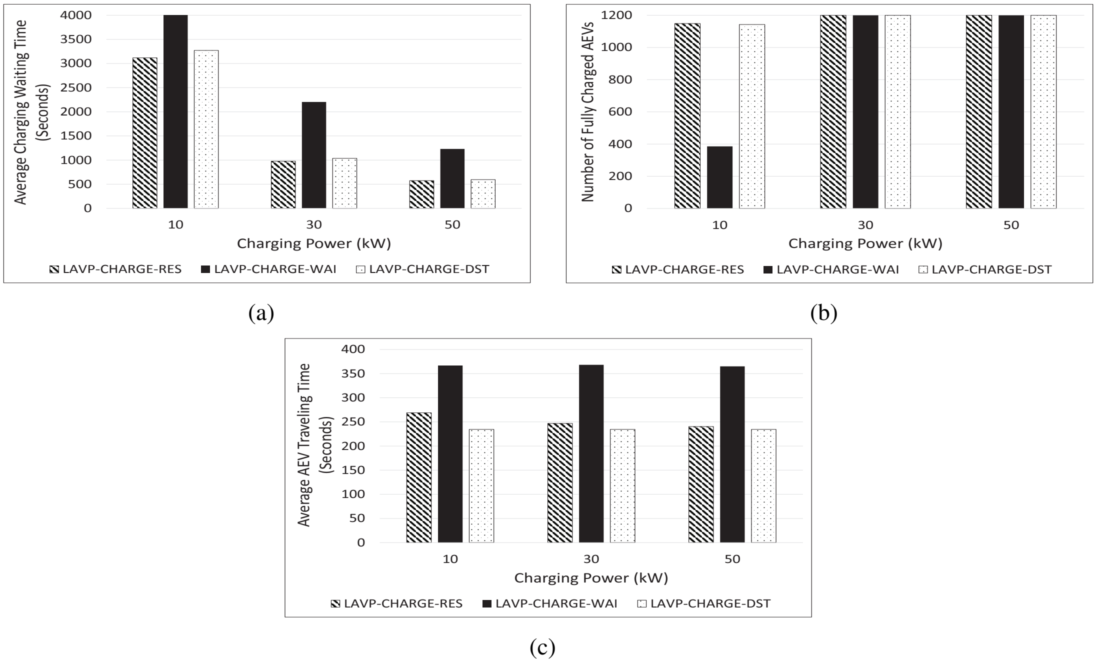
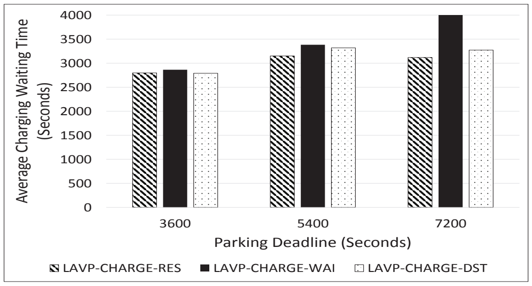


Fig. 12. Impact of Charging Power: (a) Average Charging Waiting Time (b) Number of Fully Charged AEVs (c) Average AEV Traveling Time

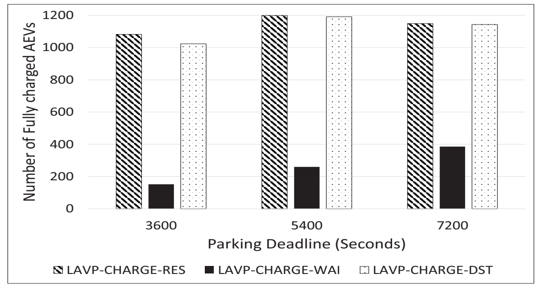
D. Influence of Parking Duration

As shown in Fig. 13 (a), the increment of parking duration leads to a longer average charging waiting time. Since this metric includes the on-going charging duration, such results indicate that AEVs can be charged for relatively longer time upon parking deadline. In addition, more AEVs can be fully charged at CPs (as shown in Fig. 13 (b)), leading to the increment of the waiting time for charging of other parked AEVs as well. Benefitted from a synergy consideration on charging waiting time as well as travel distance, the LAVP-CHARGE-RES achieves the most performance gains as observed in Fig. 13 (a) and (b). In particular, with short parking duration, only a handful of AEVs could be fully charged under LAVP-CHARGE-WAI. While a longer parking period can increase the amount of charged vehicles, LAVP-CHARGE-WAI incurs much longer waiting time.

Note that with a shorter parking duration, e.g., around 3600 sec, a great amount of AEVs can never be fully charged under LAVP-CHARGE-WAI. As compared, LAVP-CHARGE-RES and LAVP-CHARGE-DST are able to charge considerable AEVs even within a short parking period. As observed in Fig. 13 (c) and Fig. 17 (a), the average AEV traveling duration is reduced with both LAVP-CHARGE-RES and LAVP-CHARGE-DST, due to the consideration of the travel distance. Still, the performance trend is not affected much with varied parking duration, indicating that varied parking deadline has little effect on these two performance metrics.



(a)



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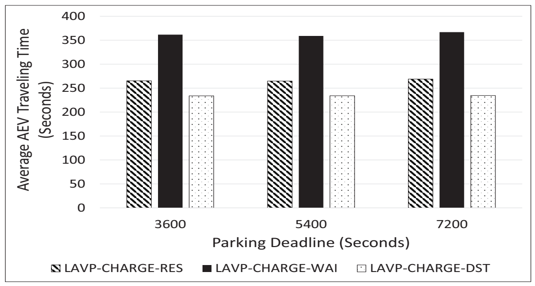


(c)

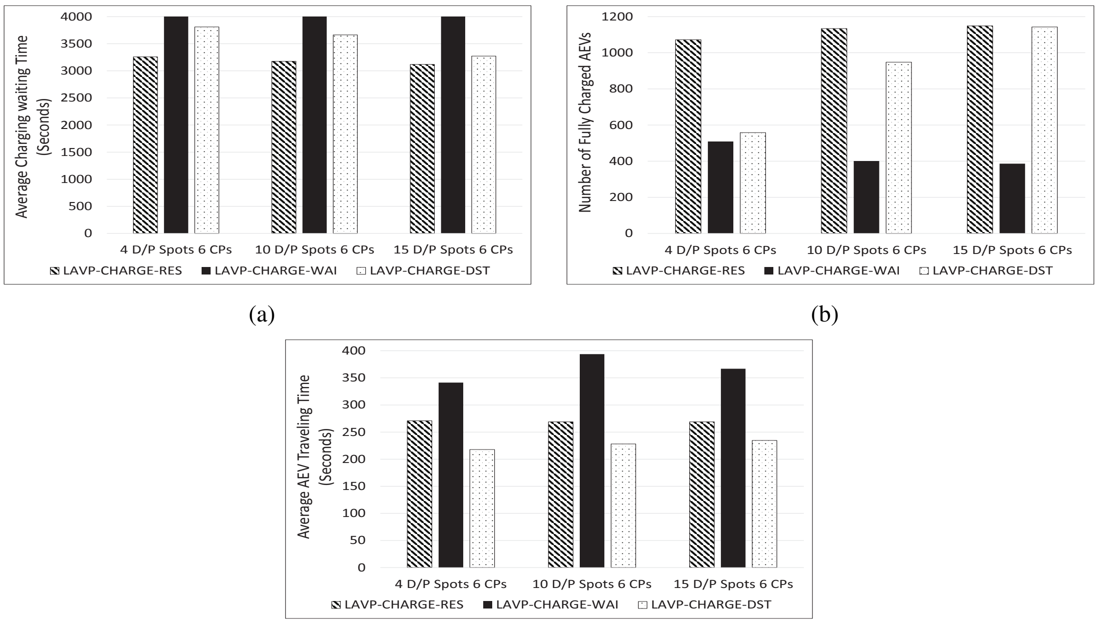
Fig. 13. Impact of Parking Duration: (a) Average Charging Waiting Time (b) Number of Fully Charged AEVs (c) Average AEV Traveling Time

E. Influence of D/P Spots

Here, we examine the impact of different numbers of D/P spots with a fixed amount of CPs in the system. As observed in Fig. 14 (a), the waiting time for charging is not influenced much by different deployment of D/P points. Clearly, since charging conditions remains unchanged throughout the experiment, charging performances tend to be not affected. As noticed, the waiting time under LAVP-CHARGE-DST is reduced with more D/P spots deployed, however. The rationale is that less D/P spots limit the choices on CPs under a distance-driven CP-selection scheme. As such, AEVs could be concentrated at a few CPs that leads to the increase of charging waiting time. With more D/P spots installed, the LAVP-CHARGE-DST is able to select CPs well scattered over the network, thereby reducing the charging waiting time.

Due to the same reason, the number of fully charged A-EVs rises with expanding D/P points under LAVP-CHARGE-DST, as shown in Fig. 14 (b). Not surprisingly, the proposed LAVP-CHARGE-RES shows its optimality against all other schemes as shown in Fig. 14 (b). As compared, the amount of charged AEVs under LAVP-CHARGE-WAI becomes even less with more D/P points deployed. The reason could be owing to the blindness of future charging status at CP-selected and consequently, and many AEVs are never fully charged since the CP becomes overcrowding.

Results from Fig. 14 (c) indicate that the D/P deployment has limited effect on AEV traveling period, especially under LAVP-CHARGE-RES and LAVP-CHARGE-DST. Since travel distance is never the concern with LAVP-CHARGE-WAI, the traveling period could thus become longer against other schemes. However, the customer trip duration can be substantially reduced under all schemes as shown in Fig. 17 (b), due to more D/P options to drop customers off much closer to their final destinations. Results from Fig. 17 (b) indicate that customer QoE could be greatly benefited by deploying more D/P spots especially in crowded city centers.



(a) (b) (c)

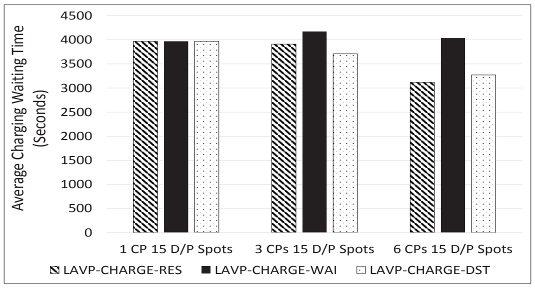
Fig. 14. Impact of D/P Spots: (a) Average Charging Waiting Time (b) Number of Fully Charged AEVs (c) Average AEV Traveling Time

F. Influence of CP Number

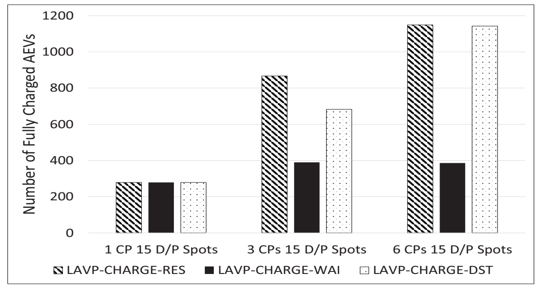
Results of Fig. 15 (and Fig. 17 (c)) show the impact of different scales of CP deployment in performances. As shown in Fig. 15 (a), limited options of CPs (e.g., less than 3 CPs) result in long waiting time under all schemes. With more CPs deployed, LAVP-CHARGE-RES and LAVP-CHARGE-DST are able to achieve desirable performances as noticed in Fig. 15 (a) and (b). Obviously, LAVP-CHARGE-WAI experiences the worst performances as in accordance with previous results.

Not surprisingly, all schemes (except for LAVP-CHARGE-WAI) experience reduced AEV traveling period when more CPs deployed, as shown in Fig. 15 (c). The undesired effect under LAVP-CHARGE-WAI is mainly attributed to highly concentrated AEVs at certain CPs-selected, whereby CP-selection based on local charging conditions only, regardless of any future charging states. As a result, CP-selected under LAVP-CHARGE-WAI could become seriously overcrowding when large amount of AEVs head towards the same CP. Obviously, the customer travel is not affected by different scales of CP deployment.

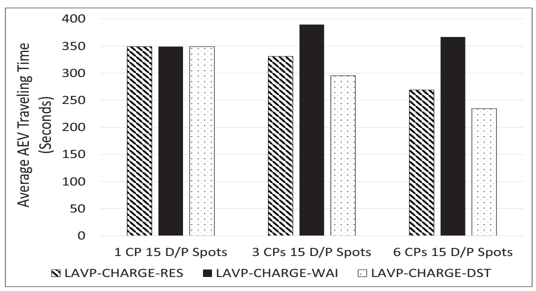
As observed, the CP number has a pivotal role in charging performances as well as vehicle traveling period. In particular, it can be highly effective when distance is one of the concerns with respect to CP-selection, i.e., under LAVP-CHARGE-RES and LAVP-CHARGE-DST. Yet, the CP number seems not having a critical play when LAVP-CHARGE-WAI applied. This is mainly due to the inefficiency of such local waiting time-based scheme, which has been discussed in many ways in previous sections.



(a)

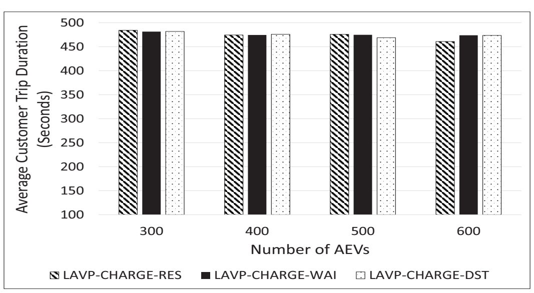


(b)

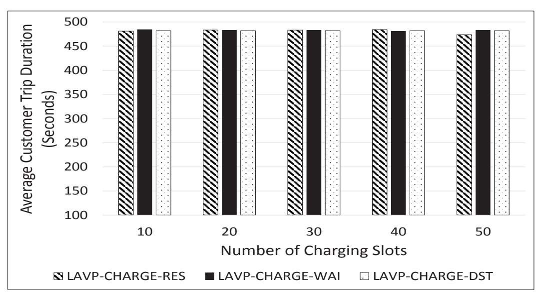


(c)

Fig. 15. Impact of CP Number: (a) Average Charging Waiting Time (b) Number of Fully Charged AEVs (c) Average AEV Traveling Time



(a)



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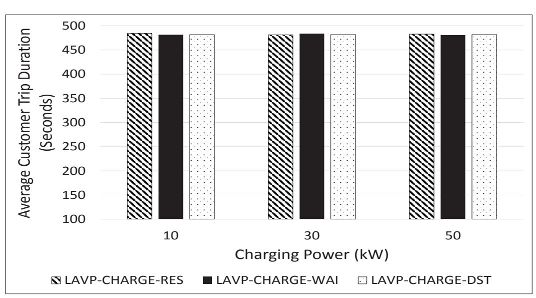
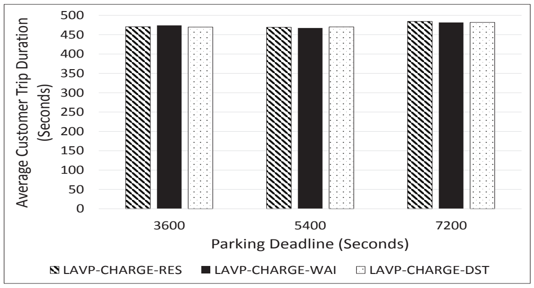
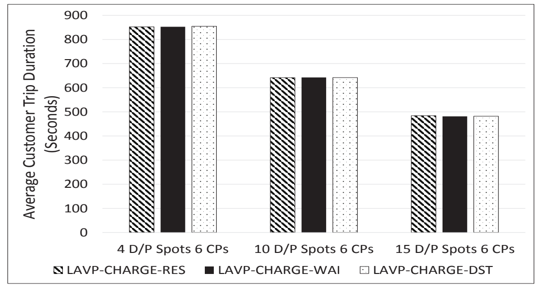


(c)

Fig. 16. Average Customer Trip Duration: (a) Impact of AEV Density (b) Impact of Charging Slots (c) Impact of Charging Power



(a)



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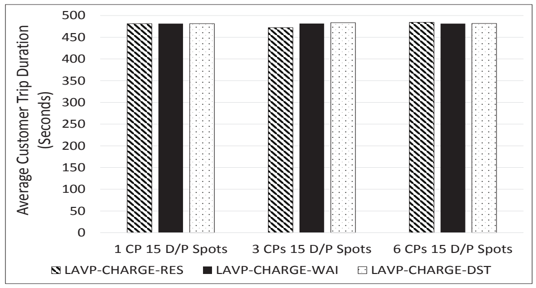

(c)

Fig. 17. Average Customer Trip Duration: (a) Impact of Parking Duration (b) Impact of D/P Spots (c) Impact of CP Number

V. Conclusion

In this work, we propose an integrated framework of AEV charging with LAVP management, aiming to provide a joint concern regarding charging convenience as well as parking favor for AEVs. Specifically, we target major concerns of where-to-park & charge in the sense of a systematic approach. The CP selection computation takes into account AEV parking duration and their charging reservations, so as to facilitate the accurate estimation on CP charging states as well as anticipated AEV mobility. Since charging and parking conditions at individual CPs in a future moment can be precisely predicted, hotspots for AEV arrivals can be effectively avoided in the network. Comprehensive simulation studies under the Helsinki city scenario are executed to show the efficiency of our proposed framework. By comparing with other counterparts, results show the viability of the proposed scheme, with respect to an improved customer journey experience as well as AEV charging convenience. Besides, the proposed framework is able to achieve effective load balancing across the network, regarding the amount of charging and parking AEVs.

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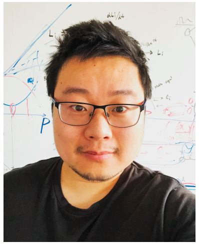
Xu Zhang received the B.Eng. degree in telecommunication engineering from the Xidian University, Xi'an, China, in 2007, and the M.Sc. and Ph.D. degrees from the University of Science and Technology, Beijing, China, and the University of Surrey, Surrey, U.K., in 2010 and 2015, respectively. She is currently a Lecturer with the Department of Computer Science, Xi'an University of Technology, Xi'an, China. Her research interests include networking and network management, including aspects such as content delivery networks, information-centric networking and E-mobility.

Xu Xia (M'21) graduated in 2005 from Chonbuk National University, South Korea, with a Master of Science degree in Information and Communications. He has been with China Telecom since 2012 and his activities mainly focus on the mobile core network and evolution. Now he holds the position of Director of Standards in China Telecom Research Institute. He was elected as 3GPP SA1 Vice-Chair in 2019. He is also serving the vice Chairman of IMT-2020 (5G) application group and vice Chairman of CCSA TC5 WG12 group, both of which are key standard organizations in China. He is also acknowledged as a pioneer member of 5G enabled vertical industries, and recently mainly focused on 5G/6G for identifying industry trends and transforming them into technical requirements, and creating of business contacts within standardization bodies, especial played a key role on 5G Smart Grid.

Shuohan Liu has being working towards his PhD degree at School of Computing and Communications, Lancaster University, Lancaster, UK since 2019. Further to his PhD study, he had conducted external research assistant at Research Institute of Beihang University in Shenzhen and School of Cyber Science and Engineering, Wuhan University, China. His research interests focus on the intersection of Information, Transportation and Energy, including Electric Vehicle Charging Optimization, Electric Vehicle Charging Scenario Iteration.

Yue Cao (M'16, SM'21) received his PhD degree from the Institute for Communication Systems (ICS) formerly known as Centre for Communication Systems Research, at University of Surrey, Guildford, UK in 2013. Further to his PhD study, he had conducted research fellow at University of Surrey, and academic faculty at Northumbria University, Lancaster University, UK and Beihang University, China; and he is currently the Professor at School of Cyber Science and Engineering, Wuhan University, China. His research interests focus on Intelligent Transport Systems, including E-Mobility, V2X, Edge Computing.

June Li received her PhD degree from the School of Computer, Wuhan University, Wuhan, China in 2004. She is currently the Professor at School of Cyber Science and Engineering, Wuhan University, China. Her research interests focus on Cyber Security, Industrial Control System Security and Power Grid Cyber-Physical System Security.



Weisi Guo (M’11, SM’16) received his PhD degree from the University of Cambridge, UK in 2011. He was an Ass. Professor at the University of Warwick (2012-19) and Turing Fellow (2017-19). He is currently a full Professor and head of the Human Machine Intelligence Group at Cranfield University, UK. He was a winner of the IET Innovation Award. His research interests focus on networks, data science, and autonomy.