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A Battery Swapping Service Management System Reliability-Based Design Concerning Station Information Delay

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***Abstract*—Since the long duration associated with traditional plug-in charging modes inevitably causes range anxiety to electric vehicle (EV) drivers, the battery swapping technology has emerged as a promising alternative. It thus becomes imperative to develop a reliable battery swapping service system, efficiently managing the large-scale energy replenishing demands from EVs. Firstly, this paper considers drivers' trip destination to minimize total trip duration, and the expense paid for battery swapping service to save users' service cost. By optimizing the requirement of battery swapping service during peak-price period, the expenditure for energy supplement can be reduced. Secondly, concerning in practice that the transmission delay is a crucial factor impacting the overall network and system reliability, this paper further investigates the impact of station information delay between the global controller and battery swapping stations (BSSs). By characterizing the delay into two types, namely, low and large delays, the scenario based on a known delay type are investigated. Thirdly, delay cases with multiple BSSs are also taken into account and a mixed decision-making method is developed. Finally, simulation results indicate the desirable performance of proposed scheme in satisfying user demand and alleviating impact of station information delay.**

***Index Terms*—Electric Vehicles, Battery Swapping Service, Station Recommendation, User Service Optimization.**

NOMENCLATURE

Notations

BSS_d	The BSS with station information delay
$\overline{C}$	The average servcie cost per kWh
C^{total}	The total expense for all EVs over network
$E_{i,d}^{fcon}$	The consuming energy from the destination to the farthest BSS
$E_{i,d}^{rem}$	The reamining energy arriving at the destination
N^0	The number of initial stock battery at BSS
N_B	The predicted number of availabe batteries
N_{slot}	The number of total charging slots at BSS
N_S	The predicted number of idle charging slots
ρ^{swap}	The duration of battery swapping operation
$T_{i,l}^{tra}$	The traveling time from current position to a BSS l
Δt	The value of information delay
EV_r	The EV falls below the SOC threshold and decides to refill its battery
$t_{i,l}^{cur}$	The current time slot
$t_{i,l}^{swap}$	The expected battery swapping time slot
$T_{l,des}^{min}$	The shortest time from selected BSS to destination
l^{opt}	The optimal BSS for battey swapping service
W	The overall service waiting time over network
$\bar{W}_l$	The average service waiting time at BSS l

Abbreviations

EV	Electric Vehicles
BSS	Battery Swapping Station
GC	Global Controller
ICT	Information Communication Technology
QoE	Quality of Experience
SOC	State of Charge

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I. INTRODUCTION

ELECTRIC Vehicles (EVs), as a new generation of consumer electronics, play a crucial role in achieving intelligent and green transportation [1]. Considering the numerous advantages of EVs, many governments and large organizations are actively engaged in the process of promoting EV industry development [2]. Although the superiority of EVs has attracted wide attention in the consumer electronics market, range anxiety remains a considerable barrier to their widespread adoption [3]–[5]. Unlike traditional Internal Combustion Engine (ICE) vehicles, EVs require more frequent charging due to limited battery capacity. The plug-in charging mode is the most fundamental EV energy supplement method. Effective guidance models and charging scheduling methods are proposed in several insightful studies [6]–[9] to optimize EV charging process. Even so, EVs still have to wait if no charging piles available, and suffer from dozens of minutes while recharging in process. These inconveniences inevitably affect the adoption rate of EVs [10].

Fortunately, the battery swapping service technology has been developed as an alternative energy supplement method to plug-in charging mode. NIO [11], as an advocate of battery swapping service, has built more than 2500 BSSs by September 2024. Unlike NIO, which only focuses on a specific brand of private EVs, Aulton [12] has cooperated with more than 16 automobile enterprises, providing battery swapping service for 30 types of EVs. Unlike the plug-in charging mode, EVs replace depleted batteries with a fully charged spare at Battery Swapping Stations (BSSs) under battery swapping service mode. Since batteries are readily available for upcoming battery swapping operation, EVs can be fully charged in a significantly shorter time [13]. Therefore, the battery swapping technology alleviates range anxiety and promotes the Quality of Experience (QoE) of EV drivers.

Within the realm of battery swapping service, previous studies investigate the optimization problem of *when/whether to swap* depleted batteries from a temporal perspective [14]–[16]. In this static temporal scenario, the primary focus is the interaction between BSSs and the power grid. However, the mobility characteristic of EVs has been ignored. Unlike temporal scenarios that concentrate on scheduling for battery charging, we investigate the battery swapping service management from a spatial perspective, which is defined as *where to swap* [17]–[22]. To be specific, the optimization problem focuses on recommending the optimal BSS for on-the-move EVs with requests to replace their batteries, thereby enhancing the QoE of battery swapping service.

The advent of Information and Communication Technology (ICT) has introduced new opportunities for demand-side management, revolutionizing the operation of traditional power grids [23]–[25]. With the help of ICT, a Global Controller (GC) can access the real-time local service status of BSSs in a centralized manner [17], [18], [21]. Besides, a reservation mechanism has been implemented to optimize battery swapping service management [21], [26], [27]. Through this reservation strategy for BSS selection, the service waiting time at BSSs can be predicted, enabling the selection of the BSS with the minimum queuing time as the optimal choice to alleviate service congestion.

Regarding service management performance, most existing studies on battery swapping service schemes primarily focus on minimizing service waiting time among all BSSs [21], [26], [27]. However, these studies often overlook the varying demands of EV drivers and may recommend BSSs that are far from the trip destination to optimize global waiting times, which can lead to an undesirable QoE for EV drivers. Besides, when an EV's State-of-Charge (SOC) falls below the set threshold, these studies assume that the EV will immediately head to a BSS for battery swapping. In practice, however, EV drivers prefer to postpone their battery swapping requests during peak-price electricity periods to save energy expenditure. Therefore, it is crucial to incorporate individual demand of EV drivers into battery swapping service management.

Regarding service management reliability, existing studies on battery swapping service management are based on the idealized assumption that BSS service status information is delivered to the GC in real time, without any time delays. [17], [18], [21]. Under the premise of real-time BSS local status monitoring, the optimal decision-making about BSS-selection is achieved. However, there is a potential risk of station [1] information transmitting delay in reality [28]. The Idaho National Laboratory [29], BankInfo Security [30] and SaiFlow [31] have demonstrated and highlighted the real-world Denial of Service (DoS) attack incidents on Electric Vehicle Supply Equipment (EVSE) through Open Charge Point Protocol (OCPP), causing substantial communication delay across stations.

In such cases, considering the inability of the GC to promptly monitor the states of BSSs over the network, the optimal decision on BSS-selection and battery swapping system reliability is hard to guarantee. Therefore, the information delay [2] becomes a critical factor in the process of BSS assignment for EVs, in order to achieve optimal decision-making. However, insufficient attention has been given to the impact of station information delay on the battery swapping service management reliability.

Motivated by the above issues, our technical contributions covering both performance improvement and management manners digitalization as follows:

1) *Integrating various user demand into battery swapping service:* To address the challenge of service management performance, we incorporate the individual trip destinations of EV drivers into battery swapping service management system. By recommending the most suitable BSS based on the EVs' trip plans and final destination, the total trip duration, comprising both service waiting time at BSSs and travelling time on the road, can be minimized. Furthermore, the service cost associated with battery swapping is another key concern for EV drivers. Based on Time-of-Use (TOU) electricity pricing and the remaining battery capacity, the proposed management scheme determines whether to postpone the demand for battery swapping services during peak-price periods, thereby allowing EV drivers to incur lower servicing costs.

2) *Investigating the impact of station information delay on system reliability:* To address the challenge of service management reliability, this paper initially investigates a scenario involving a single type of station information delay, where either low or large delays occur at a fixed BSS. Beyond this single type of delay, we further consider an uncertain delay situation, where low or large station information delays randomly occur at unknown BSSs across the network. To address this disadvantageous situation, a mixed decision-making method is proposed, combining solutions from both the low-delay and large-delay scenarios. Ultimately, based on the proposed management scheme, the reliability of the battery swapping service system can be enhanced.

To sum up, **our contributions are:** 1) Unlike prior works that focus solely on minimizing global waiting times while disregarding drivers' individual trip needs, this paper integrates personalized trip destinations and energy expenditure preferences into the BSS recommendation system, optimizing total trip duration and service costs through adaptive responses to TOU electricity pricing; 2) the study explores the impact of station information delays on service reliability. By modeling

[1]The station especially refers to battery swapping station (BSS) in this paper.

[2]The delay especially refers to station information delay in this paper.

both fixed and uncertain delay scenarios and proposing a mixed decision-making framework, the work enhances system robustness under varying station information delay conditions.

The remainder part of this paper is organized as follows. We briefly review related work in Section II. Section III presents the system model of proposed battery swapping service management scheme. Considering the impact of delay on decision-making, handling mechanisms regarding low and large station information delay are investigated in Section IV and Section V respectively. Moreover, a mixed decision-making method is proposed in Section VI, so as to deal with uncertain delay. Simulation results of the proposed scheme and other benchmarks are compared in Section VII. Finally, we conclude the paper in Section VIII.

II. Related Work

A. BSS-selection for EVs

For EVs requiring energy supplementation, the service convenience is a key concern for users, closely tied to time expenditure, including additional travelling and waiting time for recharging. To address this, the battery swapping service management aims to enhance the QoE by optimizing BSS selection. Unlike traditional battery swapping service optimization problem focused on battery charging scheduling, the BSS selection decision-making process is typically defined as “where to swap”.

Although the BSS-selection scheme is a crucial component of battery swapping service management, there have been a limited number of studies on it. Since future service demand across network is unknown, an online station assignment strategy has been developed in [17] to minimize BSS congestion. Based on the convex optimization theory, the optimal BSS-selection problem has been addressed through centralized [18] and distributed [19] solutions, respectively. In these approaches, the weighted sum of EV travel distance and electricity cost is minimized. In this case, the BSS operation optimization and interaction with the power grid are achieved through battery charging control. Apart from a single type of battery, the work in [21] proposed a BSS-selection framework under battery heterogeneity, further improving the QoE for multi-type EVs. In contrast to the aforementioned works focused on enhancing EV drivers’ QoE, the study [22] comprehensively considers the demand from EV owners, BSS and distribution network. A desirable demand optimization is achieved through a real-time vehicle-to-station recommendation strategy.

B. Promotion of ICT on Battery Swapping Service

As the essential foundation of battery swapping service management, the ICT plays a significant role in promoting integration of EVs and energy network. Benefiting from the advancements in ICT, a communication link that supports the anticipated mobility information of EVs (i.e. service reservation) and station status monitoring is established [17], thereby enabling the BSS selection process. Leveraging this advantage, an optimal battery swapping service decision-making for EVs is investigated under urban city scenario [21], [26], [27].

To some extent, it is hard to coordinate the service scheduling for all EVs on a large-scale. However, the centralized management mechanism enables the edge devices (EV side) to be simple, and supports more sophisticated centralized optimizations at GC side, through global information aggregation [21], [27]. Considering the communication delay between EV side and cloud-unit, the literature [32] developed a general switched system model to address this issue. Two levels of cloud computing are designed in [33] to meet the different latency requirements between heterogeneous EVs and clouds while maintaining low communication costs. Although the communication delay from the service client (i.e., EV side) has been addressed in the aforementioned literature, there are few studies on the impact of information delays on the service supplier (i.e., BSS side).

C. Our Motivation

Existing works on battery swapping service management are limited to global optimization, in which individual users’ demands are often ignored. [21], [26]. Specifically, in the pursuit of minimizing global waiting time, EV drivers may be directed to BSSs far away from their destinations, which inevitably results in an undesirable QoE for the drivers. Furthermore, in previous works [17], [21], [27] that employ a centralized approach, it is assumed that the local status of stations is monitored by the GC in real time. However, the station information delay is a crucial factor that cannot be neglected in optimal decision-making. Although station information delay was considered in the previous work [26], it lacked effective methods for mitigating these delays. Building on this foundation, our paper delves deeper into the impact of station information delays on service reliability.

III. System Model

A. Network Structure

EV: EVs move on the road with a limited battery capacity. Once an EV falls below the set SOC threshold, it will send the requirement of battery swapping service to the GC. When an EV accepts the recommendation, a reservation confirmation is sent back to the GC, including EV identification, arrival time, and expected charging duration for the battery, etc. The format of EV reservation can be referred to Table I.

TABLE I
Format of EV Reservation

EV ID	ID of Selected BSS	Arrival Time	Expected Charging Time of Depleted Battery
EV_5	BSS_1	10760s	1730s

BSS: Each BSS owns a certain number of batteries and provides battery swapping service to EVs. After an EV is replaced with a fully charged battery, its depleted battery is charged in parallel at the BSS. The local status (the number of available batteries, the queue information of depleted and charging batteries) is monitored by the GC. The battery removed from the EV is first sorted according to Shortest Time Charge First (STCF) order and then added to charging slots. Once added, the battery is immediately charged.

GC: It is a centralized entity that manages the entire battery swapping service. The status of all BSSs and the requirement for battery swapping service are aggregated at GC to facilitate

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TABLE II
FORMAT OF BSS STATUS MONITORED BY GC

—BSS ID—		
BSS_3		
—Sensing Time—		
$t = 500s$		
—Number of Available Batteries—		
$N_B = 7$		
—Available Time For Swapping (ATS)—		
ATS = [1000s, 1400s, 1900s]		
—EVs' Reservations at The BSS—		
Entry	Arrival Time	Expected Charging Time of Depleted Battery
1	3500s	730s
2	4700s	700s

optimal BSS-selection decision. An example of BSS status information is presented in Table II.

For research on the impact of delay on the service demand side, the work in [34] investigated information delay between EVs and the GC. Although it is based on a charging management scenario, the proposed communication mechanism between EVs and the GC can still be applied to address EV information delay in battery swapping service. Therefore, benefited from the developed communication mechanism, the information transmission between EVs and the GC is regarded as real-time in this paper.

Since the delay from BSSs to GC is time-sensitive, this paper focuses on identifying the impact of information delay and compensating for its effects on green transportation performance. In light of this, we assume that EVs can report information to the GC in a timely manner when traffic conditions are ideal. This is because we consider the travel time includes both the driving time from current position to a specific BSS and the driving time from the selected BSS to the final destination, as introduced in Section III-D. The travel time defined in this paper encompasses the entire process of EVs traveling on the road. Although we do not consider road traffic congestion directly, road traffic congestion can still influence travel time and further reflect in optimal BSS decision-making. Moreover, literature [35] has focused on the impact of traffic congestion. It has been proven that traffic congestion does not significantly affect the overall tendencies and distribution of E-mobility service management schemes.

B. Proposed Service Management Procedure

The station information delay over the network is further classified into two categories: the *low* and *large* characteristics. In the low delay scenario, the GC has enough time to obtain the status information of a delayed BSS before an EV reaches the selected BSS, allowing the GC to decide whether to change the preselected BSS for the EV. In contrast, under the large delay scenario, the GC is unable to access the station status information before the EV arrives at the selected BSS.

Low station information delay case: Although there is a low information delay between BSSs and the GC, the information transmission between EVs and the GC is real-time in this paper. Therefore, the real-time location of EVs can be accurately tracked by the GC through GPS. The time sequences under low station information delay situation can be

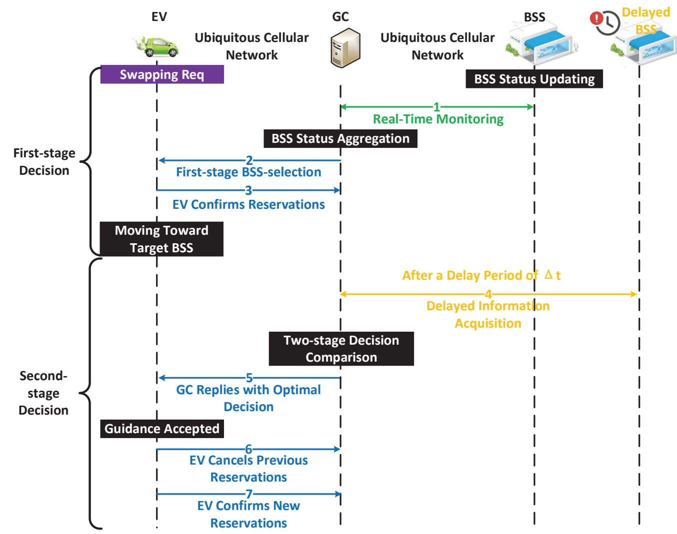

Fig. 1. Time sequences of two-stage method under low station information delay

summarized as Fig. 1. Based on a two-stage decision strategy, the system procedure for the proposed battery swapping service management under low information delay is introduced as follows:

1) When an EV_r falls below the SOC threshold and decides to refill its battery, it sends a request of battery swapping service.
2) Considering the station information delay of delayed station BSS_d, at time instant t, the GC initially aggregates all BSS status information except that of BSS_d. Since the station status of BSS_d is not included in decision-making process, a sub-optimal BSS is recommended to EV_r.
3) EV_r confirms the guidance from GC and further reports its reservation information such as its arrival time, expected charging duration for depleted batteries.
4) After a period of Δt, corresponding to the information delay, the GC successfully receives the status information of BSS_d. The GC can now check whether the previously recommended station (step 2) is still the optimal choice at current, by comparing the trip duration to BSS_d and previously selected sub-optimal BSS.
5) If the BSS_d is determined to be the optimal BSS, EV_r will cancel its previous reservation information at the selected BSS and re-report its reservation to BSS_d. After completing the two-stage decision-making process, EV_r will head to the optimal BSS for battery swapping service.

Large station information delay case: While the low station information delay scenario has been addressed, the proposed management scheme may not be effective in handling situations involving large delays. This is because EV_r will arrive at the previously determined sub-optimal BSS before receiving the delayed status information about BSS_d, which renders the second-stage decision in Fig. 1 ineffective.

The time sequences under large station information delay

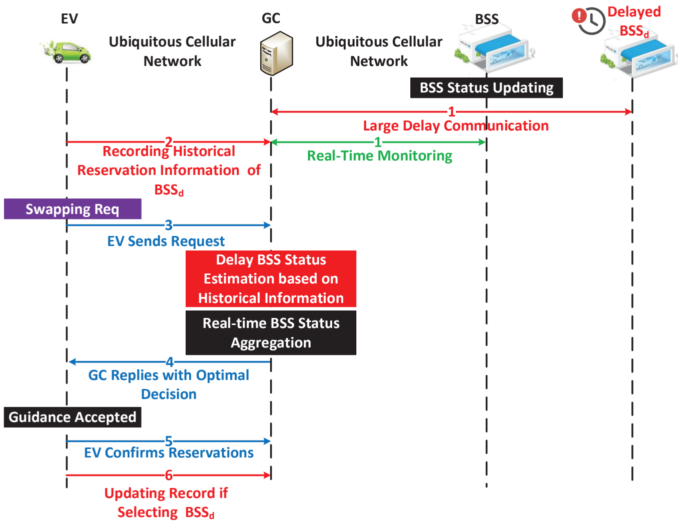

Fig. 2. Time sequences of recording and updating method under large station information delay

situation can be summarized in Fig. 2. Based on the recoding and updating strategy, the BSS-selection process under large station information delay situation is presented as follows:

1) Different from the two-stage decision-making mechanism in low station information delay scenario, the record and updating method is applied, so as to record historical reservation information of EVs and further predict service status across BSSs. Given the large delay in status updates and potential communication failures, the GC cannot obtain real-time BSS status information over an long period. Therefore, the GC records reservation information for each EV at BSS_d, and utilizes this information to predict future service status rather than relying on real-time monitoring.
2) When EV_r requires battery swapping service, the current status of BSS_d is inferred approximately based on the historical reservation data recorded at the GC. The optimal BSS is then determined and informed to EV_r by aggregating all available BSS status information.
3) EV_r confirms the optimal BSS recommendation from the GC, and reports its reservation details related to the selected BSS. Meanwhile, EV_r proceeds towards the decided BSS.

Given this paper's focus on service data and the impact of information delay, data privacy is a significant concern. Fortunately, several advanced technologies, such as blockchain [36], differential privacy [37], and federated learning [38], have been successfully applied to ensure data privacy in EV energy supplementation. These methods could also be incorporated into this paper to enhance private data protection.

C. Problem Formulation

In previous works [21], [26], [27] on optimal BSS recommendation, the service waiting time is the only concern. Under this criterion, the optimal BSS is assigned to EVs with battery swapping service requirement, so as to achieve the minimum service waiting time over system operation.

The service waiting time is measured from the EV's arrival at the BSS to the completion of battery replacement. Accordingly, the optimization problem for minimizing the overall service waiting time W across the network can be defined as:

$$\text{minimize } W = \sum_{l\in\mathbb{L}} (|I_l| \cdot \bar{W}_l), \tag{1}$$

where $\mathbb{L}$={1, 2, ..., l, ..., L} is the set of all BSSs. I_l indicates the set of EVs being serviced at BSS l, and $\bar{W}_l$ represents the average service waiting time for swapping at BSS l. $\bar{W}_l$ is obtained as:

$$\bar{W}_l = \frac{\sum\limits_{i\in I_l} (T_i^{arr} - T_i^{lea})}{|I_l|}, \tag{2}$$

where T_i^{arr} defines the arrival time and T_i^{lea} is departure time for EV_i, respectively.

By managing traffic flow, the service demand across BSSs can be balanced, thereby minimizing the global service waiting time. However, we should notice that these studies [21], [26], [27] focus solely on minimizing the global service waiting time at BSSs. By contrast, the individual requirement of EV drivers is neglected. To be specific, EVs may be assigned to the BSS far away from their trip destination, so as to achieve a minimum service waiting time among BSSs. Besides, the expense of battery swapping service is also not taken into account in above literature.

(1) Service expense: The cost of battery swapping is a significant factor for EV drivers [20]. Typically, drivers prefer a lower economic cost, which can be achieved by choosing a favorable service period. According to the charging standard for battery replacement of NIO Company [11], the optimization decision-making for EV_i concerning service expense C_i can be formulated as:

$$\text{minimize } C_i = (E_i^f - E_i^d) \cdot C^e, \tag{3}$$

where E_i^f represents the full battery capacity, E_i^d defines the initial energy of depleted battery removed from EVs, and C^e is the real-time electricity price.

Accordingly, the total expense for all EVs over network is expressed as:

$$C^{total} = \sum_{l\in\mathbb{L}} \sum_{i\in I_l} C_i. \tag{4}$$

Finally, the average service cost per kWh is derived as:

$$\overline{C} = \frac{C_{total}}{\sum\limits_{l\in\mathbb{L}} \sum\limits_{i\in I_l} E_i}, \tag{5}$$

where $E_i = E_i^f - E_i^d$ indicates the power consumption of EV_i.

(2) Service convenience: Apart from expense, the service convenience is another factor that EV drivers pay special attention to. Different from focusing on service waiting time, we further investigate the impact of EV final destination and traveling time. Thus, for EV_i, the total duration of whole trip $T_{i,l}^{total}$ is obtained:

$$T_{i,l}^{total} = T_{i,l}^{tra} + W_{i,l} + \rho^{swap} + T_{l,des}^{min}, \tag{6}$$

where $T_{i,l}^{tra}$ is the traveling time from current position to a specific BSS l. $W_{i,l}$ represents the service waiting time of EV_i at BSS l. ρ^{swap} defines the duration of battery swapping operation. $T_{l,des}^{min}$ indicates the shortest time driving from selected BSS to the final destination. Therefore, EVs prefer to select the optimal BSS that minimizes the total trip duration:

$$l^{opt} = \arg\min_{l \in \mathbb{L}} (T_{i,l}^{total}), \tag{7}$$

where l^{opt} is the optimal BSS decision-making that minimizes the total trip duration for EV_i.

IV. Battery Swapping Service Management Under Low Station Information Delay

As depicted in Fig. 3, the proposed management system aims to solve the joint concerns of "when/whether to swap" and "where to swap". Under the impact of station information delay, the interaction between these aforementioned two crucial service procedures is thoroughly investigated.

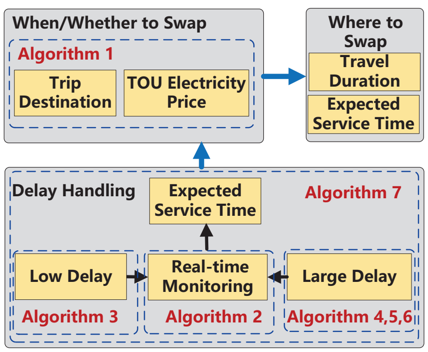

Fig. 3. Flow chart of computation logic

When/whether to swap: Considering the TOU electricity price, EV drivers typically prefer to postpone their battery swapping requests during peak-price periods. Unless the remaining battery capacity is unable to support the next trip, they will not move towards BSSs for energy supplements.

Where to swap: When EVs require battery swapping service, the optimal BSS is recommended based on the minimized trip duration. A crucial factor influencing trip duration is the service waiting time at the BSS, which can be estimated through real-time monitoring of the station's local status. However, caused by station information delay, the estimation accuracy will be affected. Fortunately, the impact of station information delay could be alleviated with system design.

Algorithm 1 Decision-making on When/whether to Swap

1: **for** each EV i below the set SOC threshold **do**
2: estimate the expected service time $t_{i,l}^{swap}$ at the optimal BSS
3: **if** $t_{i,l}^{swap}$ is within peak-price period **then**
4: calculate the remaining energy $E_{i,d}^{rem}$ arriving at the destination
5: calculate the consuming energy $E_{i,d}^{fcon}$ from the destination to the farthest BSS
6: **if** $(E_{i,d}^{rem} > E_{i,d}^{fcon})$ **then**
7: move to the destination and postpone the requirement of battery swapping service
8: **else**
9: move towards the recommended BSS
10: **end if**
11: **else**
12: move towards the recommended BSS
13: **end if**
14: **end for**

A. When/whether to Swap

As highlighted in lines 1 and 2 of Algorithm 1, for each EV requiring energy supplement, the expected battery swapping time $t_{i,l}^{swap}$ at a recommended BSS l can be estimated:

$$t_{i,l}^{swap} = t_i^{cur} + EWTS_l + \rho^{swap} + T_{i,l}^{tra}, \tag{8}$$

where t_i^{cur} is current time slot, ρ^{swap} indicates the fixed duration of battery swapping service operation and $T_{i,l}^{tra}$ represents the travel time to BSS. $EWTS_l$ represents the expected waiting time for battery swapping service at BSS.

Based on TOU electricity price, EV drivers will decide whether to postpone the requirement of battery swapping service, so as to reduce service expenses. Specifically, if $t_{i,l}^{swap}$ is within peak-price period, the remaining battery capacity $E_{i,d}^{rem}$ after arriving at the destination is compared with the consuming energy $E_{i,d}^{fcon}$ from the destination to the farthest BSS (line 3 to 5 in Algorithm 1). If $E_{i,d}^{rem} > E_{i,d}^{fcon}$, the EV will be able to support a trip to any BSS after reaching the destination. Otherwise, the EV will proceed to the recommended BSS, as the remaining battery capacity cannot support the next trip (line 6 to 10 in Algorithm 1). Moreover, if $t_{i,l}^{swap}$ is not within peak-price period, the EV will directly head to the optimal BSS for battery swapping service.

Once the EV decides to swap its depleted battery, the following procedures within the battery swapping service management system are carried out to determine the optimal BSS.

B. Real-time Status Monitoring

The GC monitors real-time local status of BSSs. Then, the decision-making about optimal BSS-selection is based on the aggregated BSS status information. The monitoring and estimation process are presented in Algorithm 2.

Algorithm 2 Real-time Monitoring and Status Estimation

1: **for** each BSS l in the network **do**
2: real-time monitoring BSS local status N_B, N_C, N_D
3: **for** each battery in the queue of N_C, N_D **do**
4: update battery available time list ATS
5: **end for**
6: **for** each EV servcie reservation earlier than $T_{ev_r}^{arr}$ **do**
7: update its depleted battery available time in list ATS
8: $N_B = N_B - 1$
9: **end for**
10: **for** each element in list ATS **do**
11: **if** the value is earlier than $T_{ev_r}^{arr}$ **then**
12: $N_B = N_B + 1$
13: **end if**
14: **end for**
15: sort list ATS based on ascending order
16: obtain the first value ATS_0
17: **if** $(N_B > 0)$ **then**
18: $EWTS_l = 0$
19: **else**
20: $EWTS_l = ATS_0 - T_{ev_r}^{arr}$
21: **end if**
22: **end for**

Supported by ICT, the GC can timely obtain the BSS local status, such as number of available batteries N_B, charging batteries N_C and depleted batteries waiting for charging N_D (line 2 in Algorithm 2). For batteries in N_C, N_D and depleted batteries swapped by EVs in reservation queue, the charging completion times are calculated similarly to previous work

[27]. Meanwhile, a list ATS is defined to store the battery availability time, and the finish time of charging is added to it. For each time instant in list ATS, if the battery's availability time is earlier than the expected arrival time ($T_{ev_r}^{arr}$) of the service-requesting EV (ev_r), it indicates that a battery will be available before ev_r arrives. In this case, the number of available batteries, N_B, is incremented by one. By contrast, if other EV arrives earlier than ev_r, the earlier-arriving EV will be prioritized for battery swapping, and N_B will be decremented by one. These steps are detailed in lines 3–14 of Algorithm 2.

Based on this analysis, when ev_r arrives at a BSS, the number of available batteries N_B is eventually derived. Intuitively, if there are available batteries, the EV can immediately proceed with the battery swapping operation, and the expected waiting time for swapping $EWTS_l$ is zero (lines 15 to 18 in Algorithm 2). However, if there are no available batteries, ev_r has to wait for the charging batteries becoming available. Accordingly, $EWTS_l$ is estimated through the earliest battery available time ATS_0 and ev_r arrival time, as shown from lines 19 to 22 in Algorithm 2.

In Section IV-A, the optimization problem for "when/whether to swap" was addressed, balancing service demand and expenditure. Building upon that, Section IV-B presents the real-time status monitoring method for determining "where to swap." In subsequent contents, we investigate the impact of low (Section IV-C) and large station information delay (Section V) on decision-making, respectively. Eventually, a mixed decision-making method (Section VI) is developed to handle uncertain delay scenario, where low or large station information delays occur randomly at unknown BSSs.

C. Handling Low Station Information Delay

In preceding sections, we introduced the estimation method of BSS service waiting time based on real-time monitoring. However, due to the existence of station information delay, the status information about BSSs may become outdated. This delay can lead to inaccuracies in estimating the battery swapping service waiting time, which in turn may mislead the optimal BSS selection process.

To mitigate the adverse effect of low station information delay, a two-stage decision-making method is applied, as shown in Fig. 1. The detail regarding this is presented in Algorithm 3. In the first stage, as shown from lines 1 to 8 in Algorithm 3, the optimal BSS is determined based on real-time status monitoring. If ev_r requires battery swapping service while traveling towards a certain destination, the travel duration to each BSS $T_{ev_r,l}^{tra}$ and the travel duration from a BSS to the destination $T_{bss,des}^{min}$ are obtained. Additionally, the $EWTS_l$ can be estimated based on real-time BSS local status via Algorithm 2. The total trip duration $T_{ev_r,l}^{total}$, including an intermediate energy supplement, is then calculated according to Equ. (6). Therefore, the BSS with minimum total trip duration is determined, and ev_r is directed to the BSS l_{bss}^{sel}.

Since station bss_d experiences an information delay of Δt, the status of bss_d is not included for BSS-selection in the first-stage. In the second stage (lines 9 to 17 in Algorithm 3), after the delay period Δt, the GC obtains the updated local status of bss_d. At this point, the total trip duration through bss_d, denoted as $\widehat{T}_{evr,l}^{total}$, is recalculated. If $\widehat{T}_{ev_r,l}^{total} < T_{evr,l}^{total}$, it indicates that ev_r would experience a shorter total trip duration at bss_d. In this case, ev_r will be redirected to bss_d, and its reservation will be updated. Meanwhile, the reservation at previously selected BSS l_{bss}^{sel} is canceled. Otherwise, if the previously selected BSS l_{bss}^{sel} remains optimal, ev_r will continue its planned route to l_{bss}^{sel}.

Algorithm 3 Two-stage Decision-making Method under Low Station Information Delay

1: **for** each BSS in the network without station information delay **do**
2: obtain $T_{ev_r,l}^{tra}$, $T_{bss,des}^{min}$
3: estimate $EWTS_l$ via Algorithm 2
4: calculate $T_{ev_r,l}^{total}$
5: **end for**
6: $l_{bss}^{sel} \leftarrow \arg\ \min(T_{ev_r,l}^{total})$
7: Reply to requester ev_r with the optimal decision of selected BSS l_{bss}^{sel}
8: move towards the selected BSS l_{bss}^{sel}
9: make reservation at the selected BSS l_{bss}^{sel}
10: after a period of Δt
11: receive estimation status $EWTS_l$ of bss_d
12: calculate trip duration $\widehat{T}_{ev_r,l}^{total}$
13: **if** ($\widehat{T}_{ev_r,l}^{total} < T_{ev_r,l}^{total}$) **then**
14: cancel reservation at previously selected BSS l_{bss}^{sel}
15: move towards bss_d and make reservation at bss_d
16: **else**
17: keep moving towards the optimal BSS l_{bss}^{sel}
18: **end if**

V. Battery Swapping Service Management Under Large Station Information Delay

A. Record and Updating Method

In the preceding analysis, the two-stage decision-making method was proposed to mitigate the adverse effects of low station information delay. Under this scenario, before an EV arrives at the preselected BSS l_{bss}^{sel} determined in the first-stage decision-making, the GC can obtain the status information of a delayed BSS. By comparing the total trip durations for the preselected BSS and the delayed BSS in the second-stage decision-making, the optimal BSS is ultimately determined. In fact, it is because the GC can have enough time to obtain all BSS status information before an EV arriving the preselected BSS, thus the two-stage decision-making method is effective.

However, for large station information delay situation, the two-stage decision-making method is no longer applicable. The primary issue is that the GC cannot obtain the status information of the delayed BSS within a reasonable timeframe due to the large transmission delay. As a result, EVs are unable to modify their initial decision during the trip.

Given large station information delay, the battery swapping service is developed based on an information record and updating method, as depicted in Fig. 2. With the stored historical reservation data at GC, the local status of delayed BSS is estimated to guide the optimal BSS decision-making. The record and updating procedure at the GC is detailed in Algorithm 4.

For the reservation queue of a BSS with information delay, Algorithm 4 first sorts it according to FCFS (First Come First Serve) rule (line 1 in Algorithm 4). Two lists List_B^d (recording

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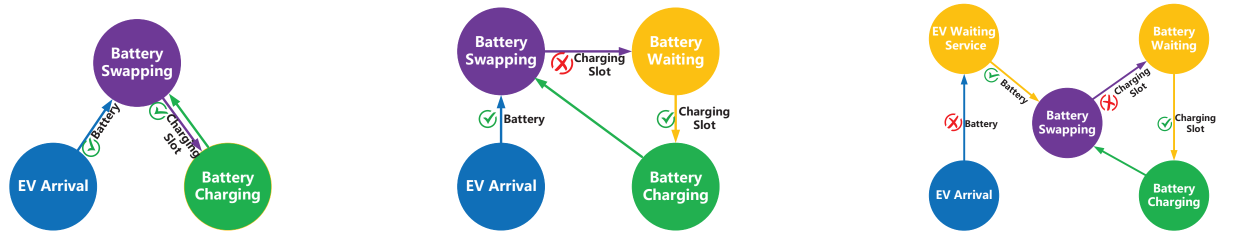

(a) Case 1: Batteries available and charging slots idle

(b) Case 2: Batteries available but charging slots occupied

(c) Case 3: Fully charged battery not available

Fig. 4. The situation when an EV arrives BSS

Algorithm 4 Record & Updating Method to Large Station Information Delay

1: sort the queue of $N_R^{bss_d}$ according to FCFS
2: **for** $(k = 1; k \leq N_R^{bss_d}; k++)$ **do**
3: **if** $(T_k^{arr} < T_{ev_r}^{arr})$ **then**
4: count value in List$_B^d$ and List$_B^u$ earlier than T_k^{arr} as N_B^d, N_B^u
5: count value in List$_S^d$ and List$_S^u$ earlier than T_k^{arr} as N_S^d, N_S^u
6: **if** $(N_B > 0 \&\& N_S > 0)$ **then**
7: add $(T_k^{arr} + \rho_{sw})$ into List$_B^d$
8: add $(T_k^{arr} + \rho_{sw})$ into List$_S^d$
9: add $(T_k^{arr} + \rho_{sw} + \delta_{bat(k)}^{cha})$ into List$_S^u$ and List$_B^u$
10: **end if**
11: **if** $(N_B > 0 \&\& N_S \leq 0)$ **then**
12: add $(T_k^{arr} + \rho_{sw})$ into List$_B^d$
13: add $(T_k^{arr} + \rho_{sw})$ into List$_W^u$
14: count value in List$_W^d$ and List$_W^u$ earlier than $(T_k^{arr} + \rho_{sw})$ as N_W^d, N_W^u
15: obtain the N^{ord}-th value T_k^{cha} later than $(T_k^{arr} + \rho_{sw})$ in List$_S^u$
16: add T_k^{cha} into List$_S^d$, List$_W^d$
17: add $(T_k^{cha} + \delta_{bat(k)}^{cha})$ into List$_S^u$ and List$_B^u$
18: sort List$_S^u$ with ascending order
19: **end if**
20: **if** $(N_B \leq 0)$ **then**
21: add T_k^{arr} into List$_E^u$
22: count value in List$_E^d$ and List$_E^u$ earlier than T_k^{arr} as N_E^d, N_E^u
23: obtain the N^E-th value T_k^{swap} in List$_B^u$ later than T_k^{arr}
24: add T_k^{swap} into List$_B^d$ and List$_E^d$
25: add $(T_k^{swap} + \rho_{sw})$ into List$_W^u$
26: count the value in List$_W^u$ and List$_W^d$ earlier than $(T_k^{swap} + \rho_{sw})$ as N_W^d, N_W^u
27: obtain the N^{ord}-th value T_k^{cha} later than T_k^{swap} in List$_S^u$
28: add T_k^{cha} into List$_W^d$ and List$_S^d$
29: add $(T_k^{cha} + \delta_{bat(k)}^{cha})$ into List$_S^u$ and List$_B^u$
30: sort List$_B^u$ with ascending order
31: **end if**
32: **end if**
33: **end for**
34: **return** List$_B^d$, List$_B^u$ and List$_E^d$, List$_E^u$

time slots of available batteries with variation in decrease trend) and List$_B^u$ (recording time slots of available batteries with variation in increase trend) are initialized as empty lists and updated to reflect the time variation of available batteries. Similarly, two additional lists List$_S^d$ and List$_S^u$ are utilized to record the time of idle charging slots with variation. These lists are also initially empty and are updated as the battery swapping service progresses.

For each EV k in the reservation queue, its arrival time is defined as T_k^{arr}. If EV k arrives earlier than EV ev_r (lines 2 and 3 in Algorithm 4), the values in List$_B^d$ and List$_B^u$ less than T_k^{arr} are accordingly counted as N_B^d and N_B^u (line 4 in Algorithm 4). Similarly, N_S^d and N_S^u are defined to reflect the change process of charging slots (line 5 in Algorithm 4). Based on these statistics, the predicted number of available batteries when EV k arrives is calculated as:

$$N_B = N^0 - N_B^d + N_B^u, \tag{9}$$

where N^0 is the initial number of stock batteries at BSS. If the value of N_B is less than zero, it means there are other EVs that arrived earlier than EV k and are waiting for service. When these earlier arriving vehicles complete battery swapping operation, it is the turn of EV k.

The predicted number of idle charging slots when the EV k arrives is obtained as:

$$N_S = N^{slot} - N_S^d + N_S^u, \tag{10}$$

where N^{slot} is the number of total charging slots at the BSS. If the value of N_S is less than zero, it means there are other EVs that arrived earlier than EV k have been replaced with full batteries, but these removed depleted batteries are waiting to be placed on the charging slots. Therefore, the battery removed from EV k will not be immediately charged due to the lack of available charging slots.

When EV k arrives at a BSS, one of the following conditions will be experienced:

1) Case 1: Fully charged batteries are available and charging slots are idle ($N_B > 0 \&\& N_S > 0$)

As shown in Fig. 4(a), the EV k will complete the battery swapping operation immediately without waiting (line 6 in Algorithm 4). After the battery swapping operation at time $T_k^{arr} + \rho^{swap}$, the number of available batteries and idle charging slots decreases. Then, the charging duration $\delta_{bat(k)}^{cha}$ is expressed as:

$$\delta_{bat(k)}^{cha} = (E^{max} - E_k^{cur} + d \cdot \gamma)/P_0, \tag{11}$$

where $E^{max} - E_k^{cur}$ represents the currently consumed energy and $d \cdot \gamma$ indicates the additional energy traveling to a target BSS. After the charging duration $\delta_{bat(k)}^{cha}$, the depleted battery from EV k will be fully recharged, and the occupied charging slot will be released. Meanwhile, these time slots are recorded in the corresponding lists (lines 7 to 9 in Algorithm 4).

2) Case 2: Fully charged batteries are available but charging slots are occupied ($N_B > 0 \&\& N_S \leq 0$)

In this case, there are available batteries but all charging slots are occupied by charging batteries (line 11 in Algorithm 4). As shown in Fig. 4(b), the EV accomplishes battery swapping operation immediately, but depleted batteries will wait for recharging. To reflect the time variation of depleted batteries waiting for recharging, the list List$_W^u$ (recording time slots of waiting charging batteries with variation in increase trend) and List^d_W (recording time slots of waiting charging batteries with variation in decrease trend) are defined. Accordingly, the time slot of battery swapping operation $(T^{arr}_k + \rho_{sw})$ is thus recored in List^d_B and List^u_W (line 12 and 13 in Algorithm 4). Then, the value in List^u_W and List^d_W earlier than its battery swapping time $(T^{arr}_k + \rho_{sw})$ is counted as N^d_W and N^u_W respectively (line 14 in Algorithm 4). Utilizing above count result, the charging beginning time of depleted battery removed from EV k (T^{cha}_k) is the N^{ord}-th value in List^u_S after the battery swapping operation (line 15 in Algorithm 4). The List^u_S records each time slot that an occupied charging slot becomes idle again and is initialized as a empty value. N^{ord} is calculated:

$$N^{ord} = N^u_W - N^d_W. \tag{12}$$

The charging beginning time T^{cha}_k is added in List^d_S, List^d_W (line 16 in Algorithm 4). Then, at time $(T^{cha}_k + \delta^{cha}_{bat(k)})$, the depleted battery will finish charging and become available. Accordingly, the occupied charging slot will be idle again. Finally, the time slot of charging finishing is recorded in List^u_S and List^u_B (line 17 in Algorithm 4). List^u_S is sorted according to ascending order for subsequent calculation (line 18 in Algorithm 4).

3) Case 3: Fully charged batteries are not available ($N_B \le 0$)

If there are no available batteries ($N_B \le 0$), charging slots must be already occupied by charging batteries (line 21 in Algorithm 4). As shown in Fig. 4(c), since there are not available batteries, EV k has to wait until a depleted battery fully charged. The arrival time T^{arr}_k is also the time of an EV waiting for service and added into List^u_E (line 20 in Algorithm 4). The value in List^d_E and List^u_E earlier than its arrival time (T^{arr}_k) is counted as N^d_E and N^u_E respectively (line 22 in Algorithm 4). The List^u_B is initialized as a empty list and records each time slot that a battery finishes charging becoming available. The battery swapping service time for EV k (T^{swap}_k) is the N^E-th value in List^u_B after arriving (line 23 in Algorithm 4), where N^E is calculated as follows:

$$N^E = N^u_E - N^d_E. \tag{13}$$

Then, the battery swapping service time T^{swap}_k is added in List^d_B and List^d_E (line 24 in Algorithm 4). List^d_B records the time slot when available batteries decrease. Similarly, List^d_E records the time slot when service waiting EVs increase. From line 25 to 30 in Algorithm 4, the depleted battery removed for EV k waiting for recharging is similar to the procedure from lines 14 to 18 in Algorithm 4 explained above. Finally, lists related to the variation of batteries and EVs are returned for subsequent status estimation.

B. Estimation of Expected Waiting Time for Swapping

According to ascending order, Algorithm 5 sorts lists related to the variation of batteries and EVs, as returned by Algorithm 4 (line 1 in Algorithm 5). Then, the number of available batteries that increase N^u_{tot} and decrease N^d_{tot} are counted (line 2 in Algorithm 5). The number of available batteries when service requesting EV ev_r arrives is denoted as $N_{B(E)}$, which is calculated as:

$$N_{B(E)} = N^0 - N^d_{tot} + N^u_{tot}. \tag{14}$$

Algorithm 5 Estimation of Expected Waiting Time for Swapping

1: sort List^d_B, List^u_B and List^d_E, List^u_E returned by Algorithm 4, with ascending order
2: count value in List^d_B and List^u_B earlier than $T^{arr}_{ev_r}$ as N^d_{tot}, N^u_{tot}
3: $N_{B(E)} = N^0 - N^d_{tot} + N^u_{tot}$
4: **if** $N_{B(E)} > 0$ **then**
5: **return** $EWTS = 0$
6: **else**
7: count the value in List^d_E and List^u_E earlier than $T^{arr}_{ev(r)}$ as N^d_E, N^u_E
8: $N^{ev}_w = N^u_E - N^d_E$
9: obtain the N^{ev}_w-th value $T^{swap}_{ev_r}$ in List^u_B later than $T^{arr}_{ev_r}$
10: **return** $EWTS_l = T^{swap}_{ev_r} - T^{arr}_{ev_r}$
11: **end if**

- If there are available batteries, the EV will complete battery swapping service immediately. Thus, $EWTS_l = 0$ (line 4 to 5 in Algorithm 5).
- Otherwise, the service time $T^{swap}_{ev_r}$ is estimated through the service order. Specifically, for an EV waiting at the BSS, ev_r will be the $N_{B(E)}$-th service in the queue. If the $N_{B(E)}$-th battery finishes recharging, ev_r will be next in line for service. Therefore, the waiting time is calculated as the difference value between arrival time and service time. (line 6 to 10 in Algorithm 5).

Algorithm 6 Global Planning under Large Station Information Delay

1: upon receiving an EV battery swapping service request
2: **for** each BSS l in the network **do**
3: calculate $T^{tra}_{ev_r,l}$, $T^{min}_{l,des}$
4: **if** the transmission is with large station information delay **then**
5: estimate $EWTS_l$ via Algorithm 4 and Algorithm 5
6: **else**
7: estimate $EWTS_l$ via Algorithm 2
8: **end if**
9: **end for**
10: $T^{total}_{ev_r,l} = T^{tra}_{ev_r,l} + EWTS_l + \rho^{swap} + T^{min}_{l,des}$
11: $l^{sel}_{bss} \leftarrow$ argmin$(T^{total}_{ev_r,l})$

C. Global Planning Process

Algorithm 6 demonstrates the global planning process for optimal BSS-selection at the GC side. Upon receiving the service request from ev_r, $T^{tra}_{ev_r,l}$ and $T^{total}_{ev_r,l}$ are calculated (line 3 in Algorithm 6). For each BSS in the network, the real-time status of BSSs without station information delay is monitored by Algorithm 2 (line 7 in Algorithm 6). In contrast, Algorithm 4 and 5 are executed to alleviate the impact of large information delay (lines 4 to 5 in Algorithm 6). Based on $EWTS_l$, the total trip duration through an intermediate battery swapping service is derived (line 10 in Algorithm 6). Finally, the optimal BSS with minimum trip duration is recommended (line 11 in Algorithm 6).

VI. Mixed Decision-making Method With Uncertain Delay

In previous sections, we investigated the effect of different station information delays and proposed algorithms to address their impact. However, a crucial assumption in the cases discussed above is that the type of station information delay

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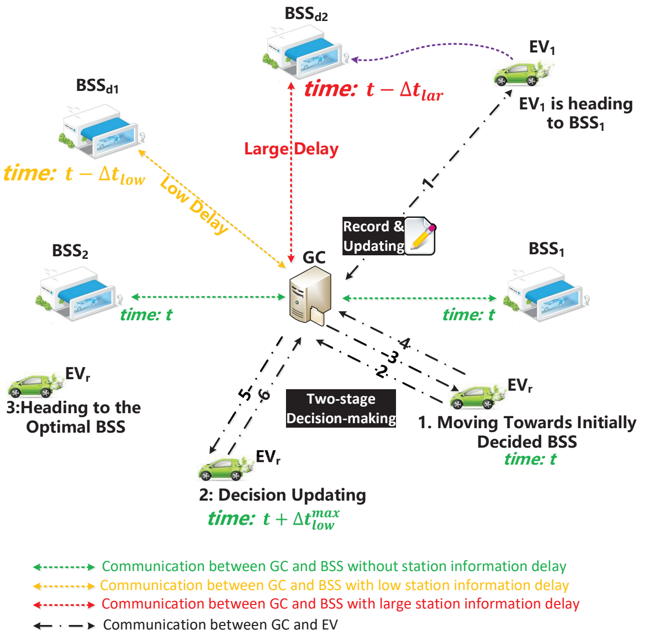

Fig. 5. Overview of proposed EV battery swapping service management under uncertain delay

(either low or large) is known and fixed for each BSS. To broaden the scope of the analysis, we now relax this assumption and consider a more comprehensive scenario, where the delayed BSSs are unknown and station information delay is uncertain. The overview of proposed battery swapping service management method under this uncertain delay scenario is shown in Fig. 5, while the overall operation framework is depicted in Fig. 6. The mixed decision-making method integrates the characteristic of both large and low delay management mechanisms. The detailed procedure is presented in Algorithm 7.

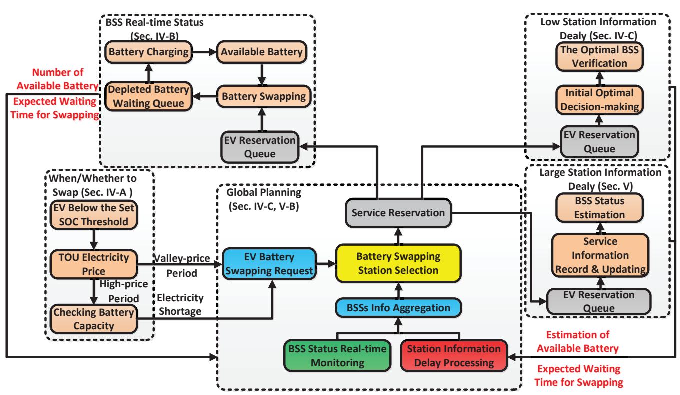

Fig. 6. Operation framework of proposed EV battery swapping service management system to uncertain delay

The value of Δt_{low}^{max} represents the maximal value of station information delay among low delay BSSs, and is initially set as 0 (line 1 in Algorithm 7). For an EV with the requirement of battery swapping service, BSSs are classified according to the type of station information delay in terms of low or large

Algorithm 7 Mixed Decision-making Method under Uncertain Delay

1: $\Delta t_{low}^{max} \leftarrow 0$
2: upon receiving an EV(ev_r) battery swapping service request
3: **for** each BSS l in the network **do**
4:     **if** $(\Delta t_l > T_{ev_r,l}^{min})$ **then**
5:         LIST$_{\mathrm{lar}}$.ADD(l)
6:     **else if** $(0 < \Delta t_l \leq T_{ev_r,l}^{min})$ **then**
7:         LIST$_{\mathrm{low}}$.ADD(l)
8:         **if** $(\Delta t_l > \Delta t_{low}^{max})$ **then**
9:             $\Delta t_{low}^{max} \leftarrow \Delta t_l$
10:         **end if**
11:     **else**
12:         LIST$_{\mathrm{rt}}$.ADD(l)
13:     **end if**
14: **end for**
15: **for** each BSS l_1 in LIST$_{\mathrm{lar}}$ and LIST$_{\mathrm{rt}}$ **do**
16:     calculate trip duration T_{ev_r,l_1}^{total} of BSS l_1 via Algorithm 4, 5 and 6
17: **end for**
18: obtain the optimal BSS l_{bss}^{sel}
19: make reservation and move towards the selected BSS l_{bss}^{sel}
20: after a period of Δt_{low}^{max}
21: **for** each BSS l_2 in LIST$_{\mathrm{low}}$ **do**
22:     calculate T_{ev_r,l_2}^{total} of BSS l_2
23: **end for**
24: $l_{bss}^{sel'} \leftarrow$ argmin(T_{ev_r,l_2}^{total})
25: **if** $(T_{ev_r,l_2}^{total} < T_{ev_r,l_1}^{total})$ **then**
26:     cancel previous reservation at l_{bss}^{sel}
27:     make reservation and move towards $l_{bss}^{sel'}$
28: **else**
29:     keep moving towards the optimal BSS l_{bss}^{sel}
30: **end if**

cases (line 2 to 14 in Algorithm 7). To be specific, if the station information delay Δt_l exceeds the shortest travel time $T_{ev_r,l}^{min}$ that the EV drivers to a BSS, the target BSS will be added into LIST$_{\mathrm{lar}}$. Similarly, if the station information delay Δt_l exists but is below the shortest travel time $T_{ev_r,l}^{min}$, the BSS is regarded as low delay station and added into LIST$_{\mathrm{low}}$. Meanwhile, the current BSS delay Δt_l is compared with Δt_{low}^{max}, so as to obtain the maximal delay among low delay BSSs. The value of Δt_{low}^{max} is utilized to determine subsequent decision updating intervals. Otherwise, if a BSS is without information delay and transmits real-time data to the GC, the BSS is appended to LIST$_{\mathrm{rt}}$.

Inspired by the two-stage decision-making method in Algorithm 3, Algorithm 7 initially selects the optimal BSS in the first stage. For BSSs with large station information delay and real-time status monitoring, the optimal BSS l_{bss}^{sel} among them is determined via Algorithm 4, 5 and 6 (line 15 to 18 in Algorithm 7). Then, the EV will make reservation at l_{bss}^{sel}, and move toward it for battery swapping service (line 19 in Algorithm 7).

After a period of Δt_{low}^{max}, all low delay BSSs local status at service requirement moment can be sensed by GC (line 20 in Algorithm 7). For BSSs with low station information delay, the total trip duration T_{ev_r,l_2}^{total} that ev_r moves toward is calculated. Accordingly, the BSS $l_{bss}^{sel'}$ with the minimal value of T_{ev_r,l_2}^{total} is obtained (line 21 to 24 in Algorithm 7).

Eventually, the optimal BSS l_{bss}^{sel} determined in the first-stage is compared with the second-stage decision $l_{bss}^{sel'}$. If the latter trip duration T_{ev_r,l_2}^{total} is lower than T_{ev_r,l_1}^{total}, ev_r will cancel previous reservation at l_{bss}^{sel}. By contrast, ev_r makes reservation

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at the latter optimal BSS $l_{bss}^{sel'}$, and moves towards it (line 25 to 27 in Algorithm 7). Otherwise, the previously selected BSS l_{bss}^{sel} is still the global optimal BSS. Thus, ev_r keeps its planning of battery swapping service, and drives to l_{bss}^{sel} (line 28 to 30 in Algorithm 7).

Considering the impact of user demand and station information delay, Fig. 6 illustrates the detailed operation framework. We define the number of BSSs over network is l, and the number of EVs is m. Each BSS is equipped with n batteries. Thus, through algorithm analysis, the computation complexity of mixed decision-making algorithm presented in this paper can be obtained as $O(lmn)$.

It is worth noting that, while the proposed record and update method is primarily designed for large delay scenarios, it also remains effective in low delay situations. However, the two-stage method, specifically tailored for low station information delays, delivers more accurate predictions while incurring lower communication, storage, and system costs compared to the approach designed for large delays. Therefore, when considering both cost and accuracy, the methodology intended for large delays is not employed in low delay cases.

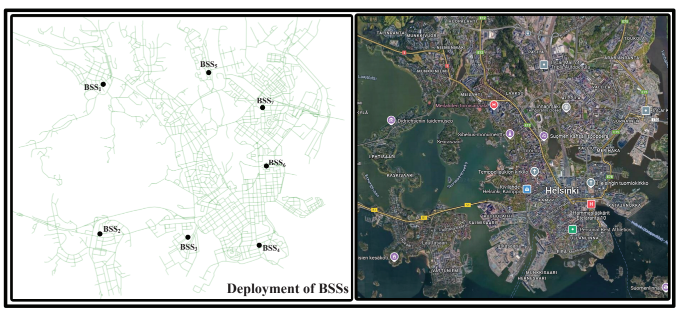


Fig. 7. Simulation scenario of Helsinki city

VII. Performance Evaluation

A. Simulation Configuration

Based on the opportunistic network environment (ONE) [39], we have developed an EV battery swapping system to depict service behavior across a whole region. The simulator is an open-source software based on Java (JDK 11.0.8) created by the University of Helsinki in Finland. Leveraging the characteristics of different e-mobility service scenarios, our team has developed a real-time simulation platform based on ONE to depict the traffic flow, power grid, and EV service procedure. In Fig. 7, the default scenario is abstracted from Helsinki city in Finland with 8300×7300 m^2 area. Meanwhile, the main route information is retained according to actual Helsinki road.

Considering a practical traffic flow scenario, a total number of 300 EVs with a fluctuating speed of $[30 \sim 50]$ km/h are initialized in the network. Each EV randomly selects a trip destination on the city map. Once an EV reaches its current destination, a new target location is generated. When the SOC drops below the set threshold, the EV requests battery swapping service. All EVs are configured with the following charging specification {Maximum Capacity, Max Traveling Distance, SOC threshold}. In particular, 300 EVs are initialized with configuration {30 kWh, 161 km, 30%}.

Additionally, 7 BSSs are deployed across the city district, providing battery swapping service to EVs. Referring to [21], [26], each BSS is initially equipped with 30 fully charged batteries ($N^0 = 30$), and 30 depleted batteries are available to be charged in parallel with a fast-charging power of 62 kW. The battery swapping operation time at a BSS is set to $\rho^{swap} =$ 5 minutes. The simulation is performed to represent a 12 hours experiment, with $\sigma = 0.1$ seconds network update interval. The TOU electricity price is referred from [40]. The above simulation setup is consistent with classical studies about EV battery swapping and charging services based on Helsinki city [21], [26], [27], [34], [35], [41], so as to reflect the practical realities of such an environment.

The following schemes on battery swapping service management are conducted for comparison:

- **R-Trip**: The proposed battery swapping service management scheme considers trip destination, and incorporates the total trip duration into optimal BSS decision-making.
- **P-RTrip**: The proposed battery swapping service management scheme is based on R-trip, and further considers whether to postpone battery swapping service on the basis of service expenditure.
- **Cloud** [26]: This approach enables BSSs and EVs to communicate with GC via a centralized cloud system, so as to minimize average service waiting time over network. It is based on BSS status prediction bounded by time window.
- **R-BS** [27]: This scheme aims at minimizing average service waiting time over network, with BSSs transmitting their status to the GC in real time..

The following metrics are adopted for performance evaluation:

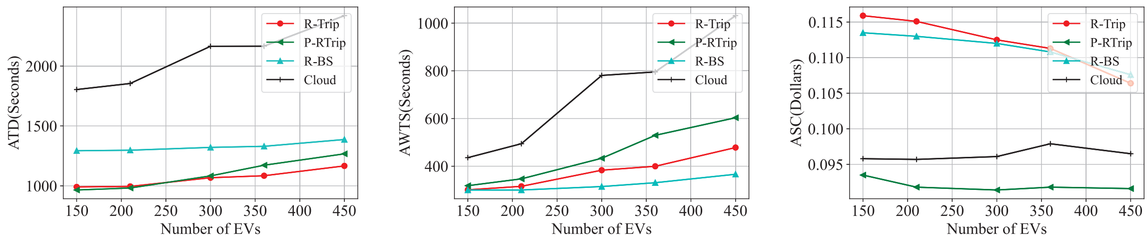
- **Average Trip Duration (ATD)**: The average time duration for an EV trip, through battery swapping service at an intermediate BSS.
- **Average Waiting Time for Swapping (AWTS)**: The average period an EV spends at the selected BSS, lasting from the time it arrives until finishing battery swapping service.
- **Average Service Cost (ASC)**: For EV drivers, the average service expenditure per kWh electricity. The metric is calculated based on Equ. (5).

B. Scenario I: Research on User Demand

In this subsection, we investigate the impact of user demand, considering both the EV scale and BSS charging power. To assess the effects of incorporating total trip duration and the option to postpone service demand, we first perform the simulation without accounting for information delay. The results of this analysis on user demand will serve as a foundation for further exploring the influence of station information delay on battery swapping service management in Section VII-C.

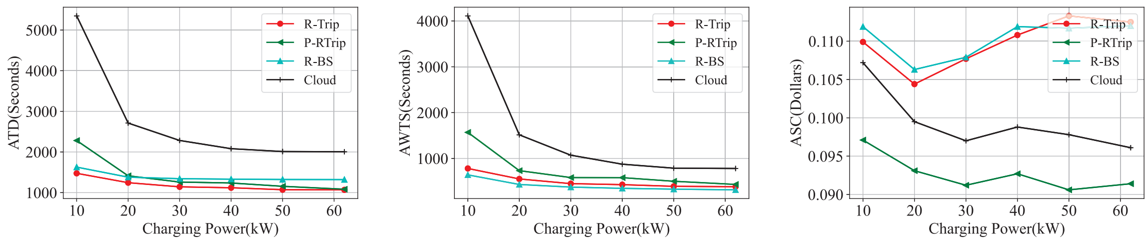
1) Impact of EV Density

As shown in Fig. 8(a), proposed schemes based on total trip duration (i.e. R-Trip and P-RTrip) always achieves the



(a) ATD (b) AWTS (c) ASC

Fig. 8. User demand: Impact of EVs density



(a) ATD (b) AWTS (c) ASC

Fig. 9. User demand: Impact of charging power

shortest ATD compared to the other related schemes. This is because the R-BS scheme prioritizes selecting the BSS with the minimum average service waiting time, as illustrated in Fig. 8(b). However, even though this BSS may be farther from the EV's final destination, EVs are still directed towards it, resulting in longer ATD. In contrast, while the Cloud scheme aims to minimize average service waiting time, it exhibits suboptimal performance in terms of both AWTS and ATD. The issue arises because the Cloud scheme relies on time window-based information transmission. When concurrent service demands occur, since the most recent BSS status information is not available until the next time window, a large number of EVs are directed to the same BSS, leading to congestion. As noticed, in Fig. 8(c), the proposed P-RTrip scheme presents a remarkable service expenditure optimization for EV drivers.

Combining Fig. 8(a) and Fig. 8(b), we observe that an increased ATD and AWTS are suffered by all schemes with the increment of EVs. The reason is that BSSs are with limited charging power and charging slots. As the number of EVs requiring battery swapping increases, congestion inevitably occurs, forcing EVs to wait for depleted batteries to become available. Since AWTS is a component of ATD, the increase in AWTS directly contributes to the rise in ATD.

2) Impact of Charging Power

Fig. 9 illustrates the impact of charging power on various performance metrics. As shown in 9(a) and 9(b), increasing charging power can significantly reduce both ATD and AWTS. Thus, an improvement on charging power can lead to a more desirable QoE for EV drivers. While charging powers between 20 kW and 60 kW can both substantially alleviate service congestion, a BSS configured with 60 kW charging power offers faster battery charging compared to one with 20 kW. As a result, battery swapping can be performed immediately upon EV arrival, without the need to wait for a battery to be fully charged. In the ideal case, EVs only need to wait for the fixed battery swapping operation time, $\rho^{swap} = 5$ minutes, which results in less service congestion.

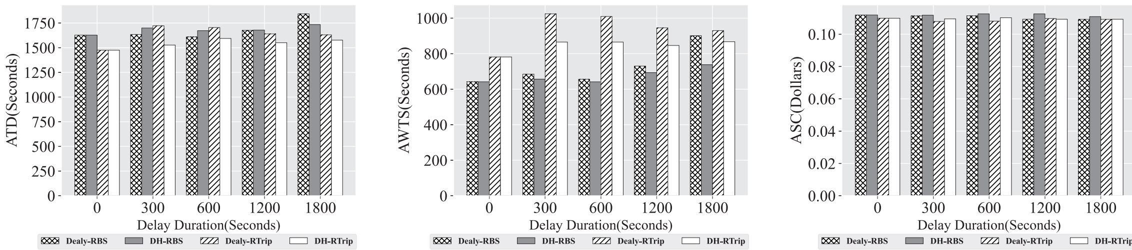
In Fig. 9(c), it can be seen that R-Trip and R-BS incur higher costs than P-RTrip. In the R-Trip and R-BS schemes, when an EV's battery state falls below the SOC threshold, the EV will immediately communicate with the GC and head towards the nearest BSS for battery swapping. In contrast, the P-RTrip scheme evaluates whether to postpone the battery swapping service based on the peak-price period, as outlined in Algorithm 1. This approach encourages EVs to perform battery swapping during the valley-price period. As shown in Equations (3) and (5), both battery swapping service expenses and ASC are closely related to real-time electricity prices. Therefore, the P-RTrip scheme results in lower costs compared to the R-Trip and R-BS schemes.

C. Scenario II: Research on Station Information Delay

To further investigate the influence of station information delay on battery swapping service management, the following schemes are further presented:

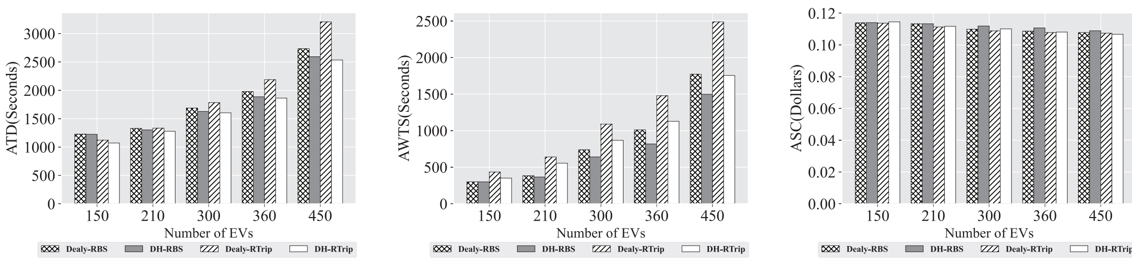
- **Delay-RBS:** The R-BS scheme [27] under interference of station information delay.
- **Delay Handling-RBS (DH-RBS):** To alleviate the adverse effects of station information delay, an enhanced version of the R-BS scheme, developed within the mixed decision-making framework of Algorithm 7. The difference is DH-RBS scheme aims to minimize service waiting time at BSSs rather than total trip duration.
- **Delay-RTrip:** The R-Trip scheme under interference of station information delay.
- **Delay Handling-RTrip (DH-RTrip):** To alleviate the adverse effects of station information delay, the DH-RTrip scheme is proposed based on Algorithm 7.

Meanwhile, the default charging power at BSSs is adjusted to 10 kW, so as to obviously demonstrate the impact of station



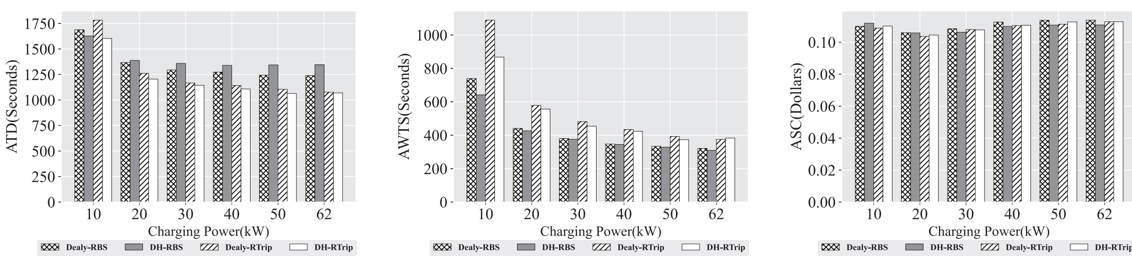
(a) ATD (b) AWTS (c) ASC

Fig. 10. Station information delay: Impact of delay duration



(a) ATD (b) AWTS (c) ASC

Fig. 11. Station information delay: Impact of EVs density



(a) ATD (b) AWTS (c) ASC

Fig. 12. Station information delay: Impact of charging power

information delay.

1) Impact of Station Information Delay Duration

For performances considering station information delay, Fig. 10 shows ATD, AWTS and ASC on the basis of delay duration. As shown in Fig. 10(a), although schemes based on R-BS method (i.e. Delay-RBS, DH-RBS) show a distinct advantageous performance on AWTS in Fig. 10(b), the superiority does not maintain in ATD. Considering AWTS is the component of ATD, it also proved the effectiveness of R-Trip schemes (i.e. Delay-RTrip, DH-RTrip) in reducing travel time on road for battery swapping service. As presented in Fig. 10(c), all schemes show similar ASC under different delay.

As for the proposed DH-RTrip scheme in Fig. 10(a), compared with no delay scenario, we can observe that it achieves a relatively close performance on AWTS. Similarly, from Fig. 10(b), we can observe the DH-RTrip scheme also shows a desirable performance in optimizing ATD. Therefore, the effectiveness of proposed schemes in eliminating adverse effects of station information delay can be proven.

2) Impact of EV Density

According to the middle value of above information delay duration, we set the maximum time delay over network as 900s for subsequent experiments. Then, the effectiveness is verified under different EV densities. In Fig.11(a), following the increased EVs' amount, an increased ATD is experienced by all schemes. This is because AWTS is a component of ATD. Thus, the increased AWTS in Fig. 11(b) further leads to an increment on ATD. Fortunately, the proposed delay handling schemes can alleviate the disadvantage to an extent. As shown in Fig. 11(a), the proposed DH-RTrip scheme achieves the lowest ATD. Meanwhile, the proposed DH-RBS scheme is with the lowest AWTS in Fig. 11(a).

Besides, the ASC shows a slightly decrease with the increment of EVs in Fig. 11(c). The rational is that EVs will obtain an immediate battery swapping service with a small-scale EV, causing the service period is mostly concentrated at peak-price period. By contrast, facing a large quantity, EVs may be serviced within valley-price period due to waiting for energy supplement at BSS.

3) Impact of Charging Power

Regardless of the variation of charging power, the delay handling schemes (i.e. DH-RBS, DH-RTrip) can still achieve a relatively lower ATD and AWTS in Fig. 12(a) and 12(b). It also verifies the effectiveness of the proposed delay-handling scheme. Since the DH-RBS scheme alleviates the impact of delay, the BSS status information can be obtained timely. Thus, although the recommended BSS is far from the final destination of an EV's trip, EVs still move towards it for battery swapping service to minimize service waiting time. This explains why the DH-RBS scheme has lower AWTS in Fig. 12(b) but a longer ATD in Fig. 12(a). By contrast, apart from alleviating the impact of delay, the DH-RTrip scheme jointly considers the AWTS and travel time, leading to lower ATD and AWTS.

It is worth noting that the increased charging power can significantly reduce the impact of delay. This is because high charging power can effectively recover BSSs to a leisure status, thus without service waiting. Although the optimal decision-making may mislead EVs to an undesirable BSS under the interference of delay, the powerful charging ability still supports depleted batteries achieving refilling in a short duration. Fig. 12(c) indicates that charging power is not the determinant of ASC, and all schemes have relatively close ASC among different charging power. Compared with Fig. 9(c), it also proves that optimizing service demand within a peak-price period can remarkably reduce the ASC.

VIII. CONCLUSION

In this paper, we propose a battery swapping service management system that accounts for station information delay to ensure system reliability. Based on TOU electricity price and trip planning, the proposed scheme determines whether to postpone battery swapping request during peak-price periods. This approach effectively balances the need for energy supplementation with the goal of reducing service expenditure. Additionally, by incorporating trip destination into the optimal BSS decision-making process, EV drivers benefit from a reduced total trip duration. Recognizing that the station information delay is a risky factor in real-world applications, this paper also investigates their impact on the reliability of the battery swapping service system. Drawing from the analysis of both low and high delay scenarios, we introduce a mixed decision-making method to address the uncertainty associated with station information delays. Finally, the effectiveness of the proposed management system in ensuring a high QoE for EV drivers is validated through comprehensive simulation results.

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