A Coordinated Battery Swapping Service Management Scheme Based on Battery Heterogeneity

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***Abstract*—The service management based on battery heterogeneity has become an increasingly important research problem in battery swapping technology. In this paper, with the method of bipartite matching, we first theoretically analyse the offline optimization problem of battery swapping service under battery heterogeneity. Nevertheless, the information of global view used in offline optimization solution cannot be known in advance during real-time operation. To address the disadvantage, an online framework comprising several sub-procedures is proposed for heterogeneous battery implementation. Firstly, by incorporating battery swapping station (BSS) local status such as charging and waiting queue of heterogeneous batteries, a charging slot allocation mechanism is designed. Utilizing the proposed allocation method, the charging priority is determined by the proportion of heterogeneous batteries demand, so as to guarantee charging fairness. Secondly, with the help of reservation information, the proposed allocation method can further be improved by predicting the future arrival distribution of heterogeneous types of electric vehicles. Thirdly, according to the service demand prediction based on long short-term memory neural network, joint optimization of BSS-selection and charging cost can be achieved by charging power adjustment. Simulation results indicate the desirable performance of proposed scheme in balancing the demands of multi-party participators.**

***Index Terms*—Electric Vehicle, Battery Swapping, E-Mobility, Coordinated Management.**

I. INTRODUCTION

IN recent years, the increased utilization of Electric Vehicles (EVs) has attracted much attention, among all solutions for improving the sustainability of transportation systems. EVs are increasingly becoming one of the most important transportation components due to their lower use-cost and elimination of carbon emissions. Apart from individual users' preferences, many countries and governments have also proposed favorable policies and regulations to encourage the development of EVs. These benefits promote EV registrations to increase by 41% in 2020, despite the pandemic-related worldwide downturn in car sales in which global car sales dropped 16% [1]. Compared to traditional internal combustion engine vehicles (ICEVs), the limited battery capacity of EVs could lead to frequent charging, lengthy charging time and range anxiety. Besides, locating a charging station with immediate service is also a primary concern of drivers when the EV needs energy supplement. These issues inevitably impact the EV drivers' experience and reduce acceptance for potential buyers.

It is thus necessary to improve the Quality of Experience (QoE) for EV charging considering the long-term development of EVs market. There has been substantial research on charging management considering the demands of EVs, charging stations (CSs) and electrical networks [2]–[4]. One of the main focuses related to charging management is "when/whether to charge" [2]. In such a scenario, the optimal charging-discharging planning is designed for the EVs parked at CSs or buildings. These situations are usually modeled as an optimization problem from the temporal dimension and EVs are usually regarded as static loads.

Considering the mobility feature of EVs, there is increasing concern over a more practical situation in locating the optimal CS for EVs during the driving phase. Compared with the "when/whether to charge" problem from temporal dimension, the above CS-selection problem is defined as "where to charge" from the spatial dimension. To further promote the QoE of charging, the EV reservations information has been applied to the CS-selection service [5], [6]. With the anticipated information, the service state of a certain CS can be predicated in advance. Meanwhile, potential charging hotspots can be effectively avoided. Furthermore, since EVs can be regarded as a load-balancing tool and transfer energy through EV charging activities, a novel CS-selection algorithm is proposed in [7], so as to alleviate the peak-valley difference in multi-microgrid systems.

Although many scheduling strategies have been integrated into the plug-in charging service mode, it still suffers from longer charging time, EV's low sustainability due to battery degradation and stress on the power grid during peak periods. Battery swapping, an alternative energy supplement service of plug-in charging mode, can efficiently cope with the above concerns [8]–[10]. The depleted battery can be replaced with a full battery at a battery swapping station (BSS) under 3-5 minutes, which costs a similar time to ICEVs filling the fuel tank. Then, depleted batteries removed from EVs are

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well managed by the BSS based on the power load and the real-time electricity price. Considering these benefits of battery swapping mode, researchers have recently focused more attention on the charging scheduling on BSSs [11]–[15]. The existing literature on battery swapping services has been becoming extensive, whereas the majority of them focus only on one type of battery.

In real-world applications, battery standards among various EVs are most likely heterogeneous. Besides, it is hard to guarantee the same size, shape and capacity for different types of batteries and EVs. Generally, each type of EV only matches a certain type of battery. Therefore, an effective battery swapping management scheme is important to meet swapping demand on various types of batteries at the same BSS. However, a few literature has focused on battery heterogeneity so far [15], [16].

The battery swapping service management based on heterogeneity is thus an important scheme but inadequately studied. Apart from the mobility characteristic of EVs, the service management scheme also incorporates the depleted battery charging management from temporal dimension. To be specific, it mainly consists of three parts: i) From the perspective of EV drivers, recommending the optimal BSS with minimal service waiting time; ii) From the perspective of EV companies and battery brands, allocating available charging slots for multi-types of depleted batteries with reasonable scheduling priority; iii) From the perspective of BSS operators, managing the charging process of depleted batteries charging considering time-of-use (TOU) electricity price. Our contributions thus can be summarized as follows:

1) Allocating available charging slots for depleted batteries based on battery heterogeneity: In our previous work [15], the basic battery swapping service framework based on battery heterogeneity is introduced. However, depleted batteries of all types are sorted only according to the Shortest Time Charge First (STCF) rule for recharging. This simplified charging scheduling method causes EV brands with shorter charging time to have higher priority than others, although their demand is not urgent. The charging order is unfair and disadvantageous to the long-term development of EV market. To address the disadvantage, we design an available charging slot allocation method, so as to ensure charging fairness and satisfy the fluctuant demand among heterogeneous battery types. Specifically, available charging slots are initially allocated according to the proportion of each type of EV waiting for the service. Then, the final allocation result is adjusted based on BSS local status, including the number of depleted batteries and current available charging slots. Moreover, by incorporating the EV reservation information (i.e. selected BSS, battery type and arrival time) to enable charging slot allocation process, the performance of charging priority scheduling can be improved based on the future arrival distribution of heterogeneous types of EVs.

2) An integrated battery swapping service framework based on battery heterogeneity: The offline solution is hard to deal with real-time service requirements, which causes it may not be suitable for practical applications. Considering the problem, we propose an online service implementation framework. Different from the work [15] only concerned with BSS-selection from the perspective of EV drivers, the proposed management scheme investigates the whole battery swapping process from various stakeholders, including benefits of EV drivers, EV/battery brands and the BSS operator. The service proposed scheme is devoted to solving both problems of BSS-selection (where to swap) and charging priority scheduling (when/whether to swap). Moreover, we have proposed a forecasting method based on LSTM (Long Short-Term Memory) neural network to predict the service demand during a particular time. Therefore, the operation cost of BSS can further be reduced with the charging power adjustment based on demand forecasting and real-time electricity price.

The remaining parts of this paper are organized as follows. Section II briefly reviews some related work. We introduce the system model of our scenario and give the problem definition in Section III. The offline theoretical analysis is presented in Section IV. In Section V, we propose the online implementation framework. The simulation results are shown in Section VI. Finally, we draw conclusions in Section VII.

II. Related Work

A. Selection of BSS for EVs On-the-move

The BSS-selection problem is a typical “where to swap” topic. In this case, if an EV on-the-move sends a swapping requirement, the optimal BSS is selected where the driver can complete battery replenishment. For EV drivers, the service convenience is one of the most important factors that they are concerned about. Therefore, the optimal BSS is usually selected to minimize the waiting/traveling/delay time for the sake of improving the battery swapping QoE.

Benefiting from the knowledge of convex optimization, both centralized [17] and distributed [18] solutions were proposed. In above works, the optimal BSS is determined to minimize the weighted sum of EV traveling distance and electricity cost. The difference is that global information is available in the centralized approach, and a solution based on second-order cone programming relaxation is accordingly proposed. Meanwhile, two distributed solutions based on the alternating direction method of multipliers and dual decomposition are derived aiming at individual BSS entities.

In a realistic BSS-selection scheme, an online scheduling strategy and service framework are necessary to deal with EVs with real-time battery swapping demand. Literature [19] proposed an online station assignment strategy achieving minimal service congestion and cost to EVs. Considering the BSS status with the number of available batteries and the charging time for depleted batteries, a communication framework was proposed to enable the EV battery swapping service [20]. Then, the potential service availability for a certain BSS can be further predicated based on the framework with the help of EV reservation information [13], [15], [20], [21]. Among these works, reservations and demand forecasting under battery swapping service have initially been considered in [20]. Based on mobile edge computing and vehicle-to-vehicle communication in a distributed manner, the optimal BSS is determined to minimize average waiting time, as in [13]. The work in [21] proposed a charging management framework for electric taxis (ETs) to select the best station where battery charging and swapping operation are integrated. Literature [15] investigated the impact of battery heterogeneity on BSS-selection, which mainly focused on improving the QoE of EV drivers and lacked coordinating service management. Besides, depleted batteries are charged only according to the STCF order without reasonable adjustment for various types. This causes the type of batteries with low capacity always have a high charging priority.

B. BSS Operation Scheduling

Considering the static load characteristic of batteries in the power grid, the BSS operator can minimize electricity costs and maximize operating revenues through an optimal operation scheduling. Besides, the desirable scheduling can also satisfy more EV service demands, which accords with the interest of BSS operator.

Based on BSS status, the operator usually achieves an optimal charging scheduling process by imposing different charging rates on depleted batteries [22]. Besides, the charging scheduling for depleted batteries at each time slot is also an important operation strategy. With that in mind, a scheduling scheme related to charging and discharging power for batteries at each period is studied. The scheme can minimize the operating costs for a BSS [23]. Moreover, the service admission for ETs and electric bus fleets is investigated based on the status of BSSs and vehicles. It aims to maximize service capacity for an integrated battery charging and swapping station [24]. Since the BSSs consume huge amounts of electricity, renewable energy sources (RESs) are of significant supplement to the traditional power grid and they can also efficiently reduce operating costs of BSSs [25]. Among RESs, photovoltaic (PV) and wind power are two representative methods. Since wind power is irregular and hard to capture, the joint consideration of PV and EV has attracted increasing attention [26], so as to optimize BSS operation. It should also be noticed that existing research literature on BSS operations is mainly based on a single type of battery where the battery heterogeneity is ignored.

C. Motivation

With the growing development of battery swapping service management, the research on service optimization is mainly based on a single participator, e.g., the optimal BSS-selection from the perspective of EV drivers and the BSS operation optimization from the perspective of BSS operators. By contrast, the coordinated battery swapping service management considering multi-party participators is an efficient significance for realistic BSS operations. However, majority of works related to coordinated battery swapping service management are based on homogeneous battery types. In comparison, the battery heterogeneity is with more practical application while not being thoroughly investigated. Specifically, to ensure the proper charging scheduling for heterogeneous batteries, it is necessary to design a charging slot allocation method in BSS management.

Therefore, this paper proposes a coordinated battery swapping service management framework based on battery heterogeneity involving multi-party participators. The coordinated managing scheme could improve the QoE of battery swapping service for EVs, ensure proper charging for various EV types and lower operating costs of BSSs.

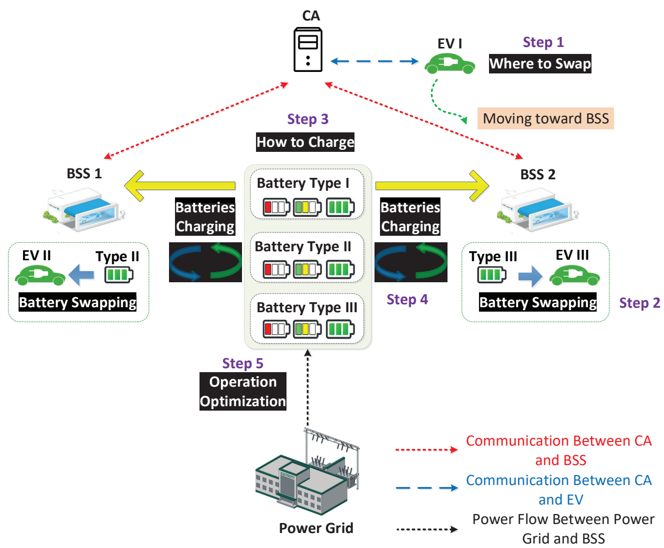


Fig. 1. An Illustration of Battery Swapping Service Management

III. System Model

A. Network Entity

A battery swapping service under battery heterogeneity is depicted in Fig. 1. Primary entities involved in the service management are elaborated as follows:

- **BSS:** EVs complete the battery swapping operation at BSS. There are a certain amount of available batteries for battery swapping in the stock at each BSS. Based on battery heterogeneity, batteries are accordingly classified into various types, defined as $\mathbb{X} = \{type-I, type-II, type-III, ..., type-X\}$. Depleted batteries of heterogeneous types are recharged at the BSS to meet the swapping demand from EVs concerning battery compatibility. Meanwhile, the BSS manages the charging scheduling for each type based on available charging slot allocation and spot pricing of electricity.
- **EV:** Each type of EV can only be driven by a specific type of battery. Besides, each EV has a SOC (State of Charge) value to depict the energy status.
- **CA (Central Aggregator):** It is a centralized entity that globally monitors the status of BSSs among the network. The CA manages the BSS-selection process for battery swapping service. Besides, it collects history service information of each BSS and predicates the potential demand during a particular period over the network.
- **Power Grid:** The power grid is connected with BSSs supplying electric energy for depleted batteries recharging. The BSS operator purchases electricity from the power grid according to the TOU electricity price.

B. Proposed Battery Swapping Service Management System

Moreover, the main procedures of battery swapping service management are introduced as follows:

- **Step 1 (Where to swap):** EVs travel along a planned course and monitor SOC constantly. When the SOC is below the default threshold, EVs will negotiate with CA to find a BSS for swapping a full recharged battery. Then, the CA recommends the optimal BSS for those EVs. EVs confirm the guidance by sending its reservation. The reservation information consists of the vehicle identification (ev_{id}), battery type ($x \in \mathbb{X}$), the arrival time (T_{ev}^{arr}) and expected charging duration of the depleted battery, etc. Finally, the EV drives to the optimal BSS to obtain a refilled battery.
- **Step 2 (Battery Swapping):** When EVs arrive at the selected BSS, the depleted battery will immediately be replaced with a refilled one if the matched type of battery is available. Otherwise, EVs have to wait until the matched type of battery becomes available.
- **Step 3 (How to Charge):** Allocating available charging slots for heterogeneous types of batteries is the key step in our system. Although types of batteries serviced in BSS are different, charging slots in BSS are homogeneous and can be shared by heterogeneous types of batteries. This is because the power of charging slots in BSSs are adjustable, so as to satisfy charging demand of heterogeneous battery. The similar charging mechanism has also been applied in [27].
- **Step 4 (Battery Charging):** Depleted batteries will be removed from EVs and added to the waiting queue. When there is enough available charging slot allocated for a certain type of battery, this type of depleted battery will be added to the charging slot immediately. These batteries are recharged at slots until they are full of capacity.
- **Step 5 (Operation Optimization):** Generally, the number of service demands at different periods can be predicted by the neural network. Thus, the BSS operator can manage the charging process based on demand forecasting and TOU electricity price achieving operation optimization.

C. Problem Formulation

To meet the benefits of participators in battery swapping service, we propose a coordinated service management scheme in this paper. It aims to: 1) minimize the service waiting time for EV drivers, 2) balance charging priority among heterogeneous types of batteries, 3) minimize the electric power cost while ensuring the QoE of EV drivers. These objectives can be formulated as the following optimization sub-problems.

1) Minimize the Service Waiting Time for EV Drivers: This problem is defined as the BSS-selection problem about "where to swap" for on-the-move EVs. It aims to find the optimal BSS with the minimum waiting time. The overall waiting time is defined as W and the optimization problem can thus be expressed as follows:

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

where $\mathbb{L}$:=$\{1, 2, ..., l, ..., L\}$ is the set of all BSSs over the network. I_l is the list of EVs under battery swapping service at BSS l, and $\bar{W}_l$ is the average service waiting time for swapping at station l. $\bar{W}_l$ is calculated as follows:

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

where T_i^{arr}, $T_i^{lea}$are arrival and departure time for EV_i respectively.

2) Minimize the Difference in Waiting Time for Various Types of Batteries: The charging fairness for heterogeneous types of batteries is important in battery swapping service management. According to the STCF rule, some types of batteries have a higher charging priority, e.g., the lower battery capacity, the higher charging priority they are. These batteries will be preferentially charged among all types. In that case, potential buyers will inevitably show more interest in the corresponding brands of EVs to obtain a higher charging priority. This causes vicious competition within the EV industry. Therefore, it is important to balance charging priority. The aim can be formulated as:

$$\text{minimize } D = \frac{\sum\limits_{x' \in (\mathbb{X} \backslash x)} \left| \bar{W}^x - \bar{W}^{x'} \right|}{|\mathbb{X}|} \tag{3}$$

where $\bar{W}^x$ is the average service waiting time for battery with type x, x' is each battery type except type x in set $\mathbb{X}$ and $|\mathbb{X}|$ is the amount of battery types.

3) Operation optimization of the BSS operator: The electric power cost is the main expense in BSS operation. Controlling the electric expenditure can maximize the profit of BSS operator. The electric power cost Pr can be described as:

$$Pr = \int_0^T \beta_t \alpha_t dt = \sum_{t=0}^{T} P_t \Delta t \alpha_t \tag{4}$$

where T is the total running time for the system, β_t is the consumption of electric energy, P_t is the total charging power, Δt is a uniform time interval during the running time and α_t is the real-time electric prices. As depicted in Eq. (4), the total electric power cost can be calculated on a time span summation.

Besides, the QoE of EV drivers is also an important impact on BSS operation. Therefore, the goal of BSS operation optimization can be formulated as follows:

$$\text{minimize } \overline{Pr} + \gamma \bar{W} \tag{5}$$

where $\overline{Pr}$ is average electricity cost, γ is the coefficient measuring the value of time and $\bar{W}$ is the average service waiting time for all EVs.

The above analysis shows that the battery swapping service management involves key stakeholders including EV drivers, EV industry and the BSS operator. The management scheme is usually addressed as a multi-objective optimization problem.

However, it is hard to solve for a large-scale and real-time decision. Therefore, we attempt to solve the optimization problem with a service framework manner [28], which will be introduced detailedly in Section V.

IV. The Offline Analysis of Battery Swapping Service

A. Problem Statement

Consider the battery swapping service over a time horizon $\mathbb{T} := [0, T]$ and the set of EVs of type x with battery swapping requirements is $\mathbb{I}^x$:= { 1^x, 2^x, ..., i^x,..., I^x } . We notice that the service waiting time is highly related to the available battery. If there is a matched type of available battery when an EV arrives, the waiting time will be zero. Based on this point, we define $N_l^x(t) > 0$ as the number of available batteries for type x at BSS l at time t. Accordingly, when there are non-available batteries, $-N_l^x(t)$ is the number of EVs waiting for batteries indicating BSS congestion. For all EVs, the BSS selection variables is $M := (M_{i^x}, i^x \in \mathbb{I}^x)$, where $M_{i^x} := (M_{i^x l}, i \in \mathbb{I}, l \in \mathbb{L})$ and $M_{i^x l}$ represents the matching between the certain station l and EV i^x,

$$M_{i^x l} = \begin{cases} 1, \text{ if } & EV_i \text{ of type } x \text{ selects BSS } l; \\ 0, \text{ if } & \text{otherwise.} \end{cases} \tag{6}$$

It is assumed that each EV only matches with one BSS during a particular time horizon $\mathbb{T}$, namely

$$M_{i^x l} \in \{0, 1\}, i^x \in \mathbb{I}^x, l \in \mathbb{L} \tag{7}$$

$$\sum_{l \in \mathbb{L}} M_{i^x l} = 1, i^x \in \mathbb{I}^x \tag{8}$$

As for BSS congestion, $N_l^x(t)$ will increase by one when there is a newly available battery. Accordingly, it decreases by one as an arrival EV finishes the battery swapping operation, depicted as:

$$\Delta N_l^x(t) = A_l^x(t) - \sum_{i^x \in \mathbb{I}^x} M_{i^x l} \cdot 1(t = T_{i^x l}^{arr}),\ l \in \mathbb{L}, t \in \mathbb{T} \tag{9}$$

where $A_l^x(t)$ is the number of newly available batteries at time t. $1(\cdot)$ is an indicator function and $T_{i^x l}^{arr}$ is the arrival time for EV i^x at BSS l. The second term of right-hand in Eq. (9) reflects the influence of BSS-selection on the number of available batteries. From this point, $N_l^x(t)$ is updated with

$$N_l^x(t)^+ = N_l^x(t)^- + \Delta N_l^x(t),\ l \in \mathbb{L}, t \in \mathbb{T} \tag{10}$$

where $N_l^x(t)^+ := \lim_{y \to t^+} N_l^x(y)$ and $N_l^x(t)^- := \lim_{y \to t^-} N_l^x(y)$. t^+ is the time instant at the end of time slot t, and t^- is the time instant at the beginning of time slot t. Therefore, based on above analyses, we can depict the change of available batteries during time slot t.

If there are no available batteries when an EV arrives, the EV will wait for depleted batteries to become available at BSSs. Meanwhile, the shortage of available batteries causes BSS congestion. Therefore, the problem of minimizing the service waiting time for EV drivers can be converted to minimize the total BSS congestion during a period. Accordingly, the BSS congestion is $< N_l^x(t) >^+$ and total congestion for BSS l over $\mathbb{T}$ is $\int_{t \in \mathbb{T}} < N_l^x(t) >^+ dt$, where $< y >^+ = \max\{y, 0\}$.

B. Offline Analysis

Let us consider the offline optimization theoretically, where global information, such as all service requirement during $\mathbb{T}$, is known. The offline optimization is formulated as

$$\min \quad \sum_{l \in \mathbb{L}} \int_{t \in \mathbb{T}} < -N_l^x(t) >^+ dt \tag{11a}$$

$$\text{s.t.} \quad (7)(8)(9)(10) \tag{11b}$$

The problem is hard to solve with known optimization theory concerning nonlinearity integrated with EV, BSS and time variables. However, we can alternatively analyze the solvability based on a bipartite matching method.

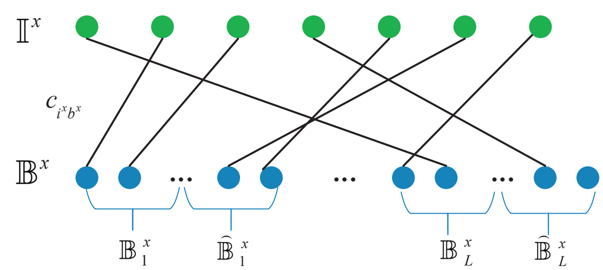


Fig. 2. A bipartite matching

We define a bipartite graph $\mathbb{G}^x$=($\mathbb{I}^x \cup \mathbb{B}^x$,$\mathbb{E}^x$) with the bipartition of vertex set $\mathbb{I}^x$ and $\mathbb{B}^x$. $\mathbb{I}^x$ is the set of EVs with type x and $\mathbb{B}^x$ is the set of matched type of battery. $\mathbb{E}^x$=$\mathbb{I}^x \times \mathbb{B}^x$ is the set of edges between $\mathbb{I}^x$ and $\mathbb{B}^x$ with weight coefficients $c^x := (c_{i^x b^x}, (i^x, b^x) \in \mathbb{E}^x)$, as shown in Fig. 2. The vertex in $\mathbb{I}^x$ is matched with an unmatched vertex in $\mathbb{B}^x$ to depict the matching process with EVs and batteries. The aim of match is to minimize the summation of each weight coefficients. Therefore, the matching optimization problem is defined as

$$\min \quad \sum_{(i^x, b^x) \in \mathbb{E}} c_{i^x b^x} a_{i^x b^x} \tag{12a}$$

$$\text{s.t.} \quad \sum_{b^x} a_{i^x b^x} = 1,\ i^x \in \mathbb{I}^x \tag{12b}$$

$$\sum_{i^x} a_{i^x b^x} \leq 1,\ b^x \in \mathbb{B}^x \tag{12c}$$

$$a_{i^x b^x} \in \{0, 1\}, (i^x, b^x) \in \mathbb{E}^x \tag{12d}$$

where $a^x = (a_{i^x b^x}, (i^x, b^x) \in \mathbb{E}^x)$. $a_{i^x b^x} = 1$ if vertex i^x matches with b^x, otherwise $a_{i^x b^x} = 0$.

$\mathbb{B}^x$ is the battery set of type x. It is derived from $(N_l^x(0), l \in \mathbb{L})$ and $(A_l^x(t),\ l \in \mathbb{L},\ t \in \mathbb{T})$. Define $\mathbb{B}^x := \cup_{l \in \mathbb{L}} (\mathbb{B}_l^x \cup \widehat{\mathbb{B}}_l^x)$. b^x in $\mathbb{B}_l^x$ is a real available battery at BSS l. Whereas, b^x in $\widehat{\mathbb{B}}_l^x$ is a dummy battery that an EV has to wait for a period until the charging battery becomes available by the end of $\mathbb{T}$, namely $N_l^x(T) < 0$. Besides, $T_{b^x}^{fin}$ is the time when the certain type of depleted battery becomes available and $T_{b^x}^{fin} = 0$ represents batteries have already been available at first.

Remark 1: Different from models in [17]–[19], we introduce the battery heterogeneity into the optimization model, and the characteristic is integrated into a matching problem. Besides, we adjust the optimization objective aiming at congestion management.

Remark 2: The construction of $\widehat{\mathbb{B}}_l^x$ in optimization problem (12) is to ensure consistency and feasibility with the optimization BSS-selection problem Eq. (11). $\widehat{\mathbb{B}}_l^x$ is the set of dummy battery of type x, which means the difference between the demand of swapping and the stock of real batteries. We can thus obtain $\left|\widehat{\mathbb{B}}_l^x\right| := \max\{|\mathbb{I}^x| - |\mathbb{B}_l^x|, 0\}$.

Proposition: The dummy battery set is convex, and the matching problem (12) is polynomial-time solvable.

Proof: According to the definition of dummy battery set $\left|\widehat{\mathbb{B}}_l^x\right| := \max\{|\mathbb{I}^x| - |\mathbb{B}_l^x|, 0\}$, we can derive $\left|\widehat{\mathbb{B}}_l^x\right| := \max\{|\mathbb{I}^x| - |\mathbb{B}_l^x|, 0\} \leq \max\{|\mathbb{I}^x| - |\mathbb{B}_l^x|\} + \max\{0\}$. Therefore, the dummy battery set is proven to be convex.

If an EV i^x matches with a battery b^x, the weight coefficient $c_{i^x b^x}$ is utilized to represent the system cost. Specifically, the service waiting time for arrival EV causes BSS congestion, which is defined as system cost in our scenario. We can obtain $c_{i^x b^x} := \max\{T_{b^x}^{fin} - T_{i^x b^x}^{arr}, 0\}$, where $T_{i^x b^x}^{arr}$ is the arrival time for EV i^x matched with battery b^x. From the definition of $c_{i^x b^x}$, we can know the match between EVs and batteries is to minimize the whole waiting time for all EVs requiring battery swapping.

For a certain offline optimization problem (11), $O(N^2)$ time is needed for the matching problem (12) to construct $\mathbb{G}$ and c, where $N := |\mathbb{B}^x|$. The optimal solution $\dot{a}^x$ is the optimal match between vertex i^x and b^x. Additionally, i^x represents the set of EV and b^x is the set of batteries. Therefore, $\dot{a}^x$ means the optimal match for a type of x EV with the battery. Since each battery belongs to a BSS, the optimal solution BSS-selection $\dot{M}$ is obvious if the optimal solution $\dot{a}^x$ is known. That is to say, each EV only needs to select the BSS where the matched battery exists:

$$\dot{M}_{i^x l} = \sum_{b^x \in \mathbb{B}_l^x \cup \widehat{\mathbb{B}}_l^x} \dot{a}_{i^x b^x}, \; i^x \in \mathbb{I}^x, \; l \in \mathbb{L} \tag{13}$$

The above can be solved in $O(N)$. Therefore, we have theoretically proven the optimization problem is solvable in polynomial-time.

V. The Online Implementation Protocol Framework

In the above section, the optimization problem has been proven with solvability in theory. However, the offline solution may not be implementable in practical scenario, concerning incomplete information and large scale demand. Therefore, it is necessary to propose an online strategy.

The online implementation framework consists of four functions: the BSS battery cycle, the allocation for available charging slots, the BSS operation optimization and the recommended BSS-Selection process. Fig. 3 illustrates the logic of proposed coordinated battery swapping service management scheme. Besides, a summarization of the computation logic is provided to depict the sequence between different algorithms.

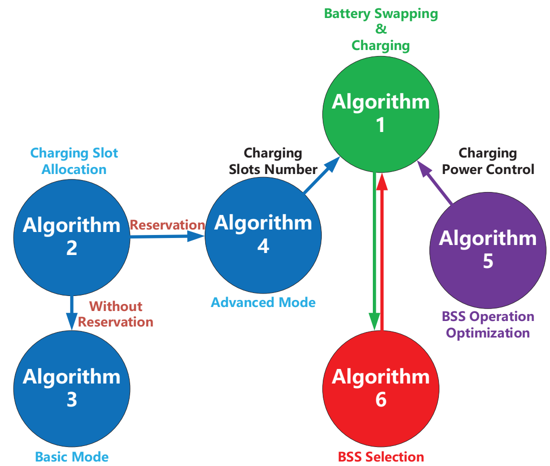


Fig. 3. Computation logic of battery swapping service management

Algorithm A summarization of the computation logic between different algorithms

for each EV with the requirement of battery swapping **do**
  move to the target BSS via **Algorithm 6**
end for
when EVs arrive at BSS
depleted batteries are swapped and battery status update via **Algorithm 1**
for each type of depleted batteries charging management at BSS **do**
  if enabled with reservation **then**
    charging slot is allocated via **Algorithm 4** and **Algorithm 2**
  else
    charging slot is allocated via **Algorithm 3** and **Algorithm 2**
  end if
  charging power is adjusted base on BSS operation optimization via **Algorithm 5**
end for

A. BSS Battery Cycle

The BSS battery cycle includes two main service management procedures: battery swapping for EVs parked at a BSS and charging for depleted battery.

1) Battery Swapping: EVs requiring battery swapping are serviced according to the following rules when arriving at a BSS.

- EVs at the BSS are serviced based on the first come first serve (FCFS). (line 1 in Algorithm 1).
- The serviced EV will be swapped with a fully charged battery immediately if the required battery type x is available $(N_l^x > 0)$. Otherwise, it will wait until a charging battery becomes available (line 2 to 7 in Algorithm 1).
- After the EV completes the battery swapping operation in a period τ_{ev}^{swap}, the number of available batteries N_l^x of type x will reduce by one. Meanwhile, the removed battery will be included into the depleted battery queue $N_{l,D}^x$ waiting for recharging. (line 8 to 11 in Algorithm 1).

Algorithm 1 Battery Swapping and Charging at BSS

1: sort the EV service queue parked at a BSS l according to FCFS
2: **for** each EV of type x **do**
3:   **if** $(N_l^x > 0)$ **then**
4:     swap the available battery of type x for the EV immediately
5:   **else**
6:     wait a depleted battery of type x accomplishes fully recharging
7:   **end if**
8:   **if** the EV complete swapping operation in duration τ_{ev}^{swap} **then**
9:     $N_l^x = N_l^x - 1$
10:     add the depleted battery into the queue of $N_{l,D}^x$
11:   **end if**
12: **end for**
13: **for** each interval $\dot{\tau}$ **do**
14:   **for** for each battery type $x \in \mathbb{X}$ **do**
15:     **while** $(N_{l,C} < \theta_l^s)$ **do**
16:       get the allocated slots θ_l^x of type x from Algorithm 3 or Algorithm 4 and $\theta_{l,fin}^x = N_{l,C}^x + \theta_l^x$
17:       **if** $(N_{l,C}^x < \theta_{l,fin}^x)$ **then**
18:         sort the queue of $N_{l,D}^x$ according to STCF
19:         schedule a depleted battery from the queue of $N_{l,D}^x$
20:       **end if**
21:     **end while**
22:     **for** $\left(i = 1; i \leq N_{l,C}^x; i++\right)$ **do**
23:       **while** $\left(E_{\mathcal{B}_{(i)}}^{cur} < E_{\mathcal{B}_{(i)}}^{max}\right)$ **do**
24:         $E_{\mathcal{B}_{(i)}}^{cur} = E_{\mathcal{B}_{(i)}}^{cur} + P_{cha}^x \times \dot{\tau}$
25:       **end while**
26:       remove this battery from the queue of $N_{l,D}^x$, $N_{l,C}^x$
27:       $N_l^x = N_l^x + 1$
28:     **end for**
29:   **end for**
30: **end for**

2) Battery Charging: Depleted batteries are charged in parallel with the constrain of charging slots, namely $N_{l,C} < \theta_l^s$ (line 15 in Algorithm 1). Especially, the allocation method for available charging slots regarding a certain battery type will be introduced in the next subsection. The depleted battery queue $N_{l,D}^x$ is sorted following the STCF order, which means the depleted battery with a shorter recharging time will have a higher priority. This charging scheduling order for depleted batteries has been proven with the best performance [12]. Then, the battery in $N_{l,D}^x$ will be scheduled into the recharging queue $N_{l,C}^x$ to recharge if $N_{l,C}^x < \theta_{l,fin}^x$ satisfies (line 16 to 21 in Algorithm 1).

For each recharging battery of type x in the queue $N_{l,C}^x$, the battery energy will update per time interval $\dot{\tau}$ with the real-time charging power P_{cha}^x. When the battery reaches the rated capacity, it will be added to the available battery queue and removed from the queue of $N_{l,C}^x$ and $N_{l,D}^x$ (line 22 to 30 in Algorithm 1).

B. Allocation For Available Charging Slots

Although a certain type of EV is only compatible with the matched type of battery based on battery heterogeneity, various types of depleted batteries can be charged in generic charging slots at BSS. In our previous work [15], available charging slots are preferentially assigned to depleted batteries with shorter charging time. Whereas, a reasonable charging scheduling based on priority balance is ignored. That is to say, EVs with lower battery capacity will naturally have higher charging priority. Considering the impact, EVs with large capacity have to wait for available charging slots until all low-capacity batteries complete recharging. This happens even though there is no type of EV with low battery capacity waiting for service. It is no doubt that this kind of allocation method will influence the charging fairness of heterogeneous types of batteries. Besides, considering charging priority, this charging method may also further affect the brand choice of potential buyers of EVs. Therefore, the allocation mechanism for available charging slots should be carefully designed to ensure the QoE for EV drivers and the charging fairness for different EVs.

Algorithm 2 Charging slot allocation method

1: **for** each battery type $k \in \mathbb{K}$ **do**
2:   $\theta^k = floor(\frac{N^k}{N^{Sum}} \cdot \hat{\theta})$
3:   add (k, θ^k) into $SAHash$ and $N^{temp} = N^{temp} + \theta^k$
4:   add $(\frac{N^k}{N^{Sum}} - \frac{\theta^k}{\hat{\theta}})$ into $TArray$
5: **end for**
6: $diff = \hat{\theta} - N^{temp}$, define $count = 0$
7: sort $TArray$ according to descending order
8: **for** each battery type $k \in \mathbb{K}$ **do**
9:   **while** $(count <= diff)$ **do**
10:     **if** $(\frac{N^k}{N^{Sum}} - \frac{\theta^k}{\hat{\theta}}) >= TArray[diff]$ **then**
11:       $\theta^k = \theta^k + 1$, $count++$
12:       update $SAHash$ with (k, θ^k)
13:     **end if**
14:   **end while**
15: **end for**
16: **return** θ^k for each type of k

The allocation for available charging slots is defined as how to charge depleted batteries considering fairness among heterogeneity. The charging slot allocation method is introduced in Algorithm 2 as a basis in Fig. 3. The algorithm aims to allocate the available charging slots proportionally, making each value be an integer (as proportional as possible). Besides, the summation of each value should be equal to the total value of available slots. The primary idea is to keep integer part of the initial allocation value and discard the fractional part. Then, the round-down value will add back by one as compensation if there is a huge difference from the expected ratio. Next, we introduce Algorithm 2 in detail as follows.

Here, $\hat{\theta}$ is the number of allocated charging slots, N^k is the queue length of a certain battery type x and N^{Sum} is the summation of N^k for all types. These values are assigned by Algorithm 3 and 4. The result of calculation is added to the hash map $SAHash$ and the number of initially allocated charging slots N^{temp} is recorded. Besides, the difference between the actual proportion $\frac{\theta^k}{\hat{\theta}}$ and target allocation proportion $\frac{N^k}{N^{Sum}}$ is added into the array $TArray$ (line 1 to line 5). The difference between the number of available charging slots and the actual assignment is obtained (line 6). The array $TArray$ is sorted according to descending order (line 7). For each type of battery, if the difference between the actual proportion and target allocation proportion ranks in the top $diff$ of all batteries, we will add back allocated charging slots by one as compensation. Then, the $SAHash$ is updated with the new value (line 8 to 15).

Considering the actual queue information at BSSs, we further introduce two allocation methods in detail in Algorithm 3 as the basic mode (local BSS status concern only) and in Algorithm 4 as the advanced mode (global reservations concern).

Algorithm 3 Allocation for available Charging Slots - Basic Mode

1: obtain the number of current available charging slots θ_l^s
2: define $demandFlag = false$, $N_{l,E}^{Sum} = 0$, $N_{l,D}^{Sum} = 0$
3: **for** each battery type $x \in \mathbb{X}$ **do**
4: obtain local status information at BSS l: the queue of $N_{l,D}^x$ and $N_{l,E}^x$
5: $N_{l,D}^{Sum} = N_{l,D}^{Sum} + N_{l,D}^x$, $N_{l,E}^{Sum} = N_{l,E}^{Sum} + N_{l,E}^x$
6: **if** $(N_{l,E}^x! = 0)$ **then**
7: $demandFlag = true$
8: **end if**
9: **end for**
10: **if** $(demandFlag == true)$ **then**
11: let $\mathbb{K} = \mathbb{X}$, $N^k = N_{l,E}^x$ and $\hat{\theta} = \theta_l^s$
12: get θ_l^x of each type x return by Algorithm 2
13: **else**
14: let $\mathbb{K} = \mathbb{X}$, $N^k = N_{l,D}^x$ and $\hat{\theta} = \theta_l^s$
15: get θ_l^x of each type x return by Algorithm 2
16: **return** θ_l^x for each type of x
17: **end if**
18: define $\mathbb{X}' = \mathbb{X}$ and $N^{temp} = 0$
19: **for** each battery type $x \in \mathbb{X}$ **do**
20: **if** $(\theta_l^x > N_{l,D}^x)$ **then**
21: $\theta_l^x = N_{l,D}^x$, remove x from $\mathbb{X}'$
22: $N^{temp} = N^{temp} + \theta_l^x$
23: **end if**
24: **end for**
25: define $\theta^{re} = \theta_l^s - N^{temp}$
26: **if** $(\theta^{re}! = 0 \ \& \ \& \ N_{l,D}! = 0)$ **then**
27: let $\mathbb{K} = \mathbb{X}'$, $N^k = N_{l,D}^x$ and $\hat{\theta} = \theta^{re}$
28: get θ_l^x of each type x return by Algorithm 2
29: **end if**
30: **return** θ_l^x for each type of x

Algorithm 4 Allocation for available Charging Slots - Advanced Mode

1: obtain the number of current available charging slots θ_l^s
2: define $\mathbb{K}^1$, $N_{l,diff}^{Sum} = 0$, $N_{l,R}^{Sum} = 0$ and $N_{l,D}^{Sum} = 0$
3: **for** each battery type $x \in \mathbb{X}$ **do**
4: obtain local status and reservation information at BSS l: the queue of $N_{l,C}^x$, $N_{l,D}^x$, $N_{l,B}^x$ and $N_{l,R}^x$
5: define $N_{l,diff}^x = N_{l,R}^x - N_{l,C}^x - N_{l,B}^x$, $N_{l,R}^{Sum} = N_{l,R}^{Sum} + N_{l,R}^x$ and $N_{l,D}^{Sum} = N_{l,D}^{Sum} + N_{l,D}^x$
6: **if** $(N_{l,diff}^x > 0)$ **then**
7: $N_{l,diff}^{Sum} = N_{l,diff}^{Sum} + N_{l,diff}^x$
8: include the type of x into $\mathbb{K}^1$
9: **end if**
10: **end for**
11: **if** $(\mathbb{K}^1! = 0)$ **then**
12: let $\mathbb{K} = \mathbb{K}^1$, $N^k = N_{l,diff}^x$, $N^{Sum} = N_{l,diff}^{Sum}$ and $\hat{\theta} = \theta_l^s$
13: get θ_l^x of each type x return by Algorithm 2
14: **else**
15: **if** $(N_{l,R}^{Sum} == 0)$ **then**
16: let $\mathbb{K} = \mathbb{X}$, $N^k = N_{l,D}^x$, $N^{Sum} = N_{l,D}^{Sum}$ and $\hat{\theta} = \theta^s$
17: get θ_l^x of each type x return by Algorithm 2
18: **return** θ_l^x for each type of x
19: **else**
20: let $\mathbb{K} = \mathbb{X}$, $N^k = N_{l,R}^x$, $N^{Sum} = N_{l,R}^{Sum}$ and $\hat{\theta} = \theta^s$
21: get θ_l^x of each type x return by Algorithm 2
22: **end if**
23: **end if**
24: define $\mathbb{X}' = \mathbb{X}$ and $N^{temp} = 0$
25: **for** each battery type $x \in \mathbb{X}$ **do**
26: **if** $(\theta_l^x > N_{l,D}^x)$ **then**
27: $\theta^x = N_{l,D}^x$, remove x from $\mathbb{X}'$
28: $N^{temp} = N^{temp} + \theta^x$
29: **end if**
30: **end for**
31: define $\theta^{re} = \theta_l^x - N^{temp}$
32: **if** $(\theta^{re}! = 0 \ \& \ \& \ N_{l,D}! = 0)$ **then**
33: **if** $(N_{l,R}^{Sum} == 0)$ **then**
34: let $\mathbb{K} = \mathbb{X}'$, $N^k = N_{l,D}^x$, $N^{Sum} = N_{l,D}^{Sum}$ and $\hat{\theta} = \theta^{re}$
35: get θ^x of each type x return by Algorithm 2
36: **else**
37: let $\mathbb{K} = \mathbb{X}'$, $N^k = N_{l,R}^x$, $N^{Sum} = N_{l,R}^{Sum}$ and $\hat{\theta} = \theta^{re}$
38: get θ^x of each type x return by Algorithm 2
39: **for** each battery type $x \in \mathbb{X}$ **do**
40: **if** $(\theta_l^x > N_{l,D}^x)$ **then**
41: $\theta_l^x = N_{l,D}^x$, remove x from $\mathbb{X}'$
42: $N^{temp} = N^{temp} + \theta^x$
43: **end if**
44: **end for**
45: $\theta^{re} = \theta_l^x - N^{temp}$
46: let $\mathbb{K} = \mathbb{X}'$, $N^k = N_{l,D}^x$, $N^{Sum} = N_{l,D}^{Sum}$ and $\hat{\theta} = \theta^{re}$
47: get θ^x of each type x return by Algorithm 2
48: **end if**
49: **end if**
50: **return** θ_l^x for each type of x

1) Basic Mode for Slots Allocation: Algorithm 3 presents the available charging slot allocation mode solely considering the local status information at BSS: the depleted battery queue with respect to each type of x $(N_{l,D}^x)$ and the queue of EVs at BSS waiting for service $(N_{l,E}^x)$.

Algorithm 3 begins with the number of available charging slots (line 1). The Boolean variable $demandFlag$, the current number of EVs $N_{l,E}^{Sum}$ and the total number of depleted batteries $N_{l,D}^{Sum}$ are defined for calculation (line 2). These variables are updated with the queue information of each battery type (line 3 to 9). $demangFlag == true$ means there are EVs waiting for battery swapping service at the BSS. Accordingly, available charging slots are initially determined by the proportion of each type of EV waiting for the service (line 10 to 13). Otherwise, if there is no EVs waiting for the service, available charging slots are allocated only based on the depleted battery queue information $N_{l,D}^{Sum}$ (line 14 to 17). For each battery type x, if the number of allocated slots is larger than the number of depleted batteries, the allocated slots for this type will be revised to the number of depleted batteries. Then, the type x will be removed from the temp set $\mathbb{X}'$ and the number of already allocated charging slots is recounted with N^{temp} (line 18 to 24). Accordingly, the subsequently reallocated number of charging slots is derived (line 25). It is assumed that both the number of reallocated charging slots and the queue of depleted batteries are not empty. In that case, the remaining battery type set $\mathbb{X}'$ will be reallocated to charging slots according to the proportion of depleted batteries (line 26 to 30).

2) Advanced Mode for Slots Allocation: Different from Algorithm 3 that only considers local information, Algorithm 4 further considers the global reservation queue information $N_{l,R}^x$. Under this design, the information of upcoming EVs can be obtained in advance through reservation, so as to adjust the allocation of charging slots depending on battery type.

Similar to Algorithm 3, Algorithm 4 firstly obtains the number of available charging slots and then defines initial parameter values for calculation. These variables are updated according to the queue information with respect to each battery type. Specifically, the charging battery queue $(N_{l,C}^x)$, the depleted battery queue ($N_{l,D}^{x}$), the available battery queue ($N_{l,B}^{x}$) and the reservation queue ($N_{l,R}^{x}$) at a certain BSS l are obtained (line 1 to line 2). Then, based on the above queue information, $N_{l,diff}^{x}$ is defined as the reservation queue subtracting the summation of available and charging battery queue. $N_{l,R}^{sum}$ and $N_{l,D}^{sum}$ are the total number of reservation information and depleted batteries for all types of battery, respectively. If $N_{l,diff}^{x} > 0$, it means the demand battery of type x is larger than the summation of charging and available batteries. Then, these types are included into the temp set $\mathbb{K}^1$. $N_{l,diff}^{Sum}$ is the sum of $N_{l,diff}^{x}$ that satisfies the above condition (line 3 to 10).

If the set of $\mathbb{K}^1$ is not empty, the available charging slots are allocated initially based on the set of $\mathbb{K}^1$ (line 11 to 13). Otherwise, the charging slot allocation will be derived based on the reservation queue (line 14 to 23):

- If the reservation queue is empty, charging slots are ultimately allocated based on the proportion of depleted batteries at the BSS.
- If the reservation queue is not empty, the charging slots are initially allocated based on the proportions of heterogeneous battery types in the queue.

The initial allocation procedure for available charging slots is presented from line 11 to 23 in Algorithm 4. However, the initially allocated charging slots may exceed the number of depleted batteries because the depleted battery queue is ignored. Therefore, we will further adjust the allocation considering depleted battery queue information from line 24 to 50 in Algorithm 4.

If the initially allocated value for type x exceeds depleted battery, the value will be reset to the amount of depleted batteries. Accordingly, the number of above reset slots is recorded in N^{temp} and the corresponding battery type is deleted from the temp type set $\mathbb{X}'$ (line 24 to 30 in Algorithm 4). Moreover, the further reallocated number is calculated at line 31. If both the number of reallocated charging slots and the queue of depleted batteries are not empty, the allocation will continue further combine the reservation information:

- Notice that the slots allocation is ultimately determined according to the proportion of depleted batteries when the entire reservation queue is empty (line 32 to 35).
- Otherwise, it will consider the battery type proportion in the reservation queue and the number of depleted batteries. Finally, the remained type of batteries is allocated based on the proportion of depleted batteries (line 36 to 49).

C. BSS Operation Optimization Control

An effective BSS operation method based on network demand forecasting is important in reducing power costs while ensuring the QoE of EV drivers. Specifically, considering both TOU electricity price and battery demand forecasting, the BSS operator controls the battery charging through power on/off. In this part, we give the forecasting method based on long short-term memory (LSTM) neural network.

The LSTM structure included a memory cell is first proposed by Hochreiter and Schmidhuber [29], and it is further enhanced by Gers et al. [30] with an extra forget gate. It has been proven the effectiveness on overcoming the disadvantage of long-term dependencies and gradient vanishing/exploding in recurrent neural networks (RNN). Then, we briefly introduce the workflow. The forecasting system is with input of historical service information sequence $\{d_{1,x}, d_{2,x}, ..., d_{\tau,x}\}$. $d_{\tau,x}$ is the demanded number of batteries with respect to each type x during a given time segment τ over time horizon $\mathbb{T}$. The outcome $h_{\tau,x}$ is the predicated battery demand. The LSTM consists of the memory cell state $C_{\tau,x}$ and three gates, as shown in Fig. 4. As the most characteristic part of LSTM, three gates are composed of input $j_{\tau,x}$, output $o_{\tau,x}$ and forgetting gates $f_{\tau,x}$. These gates are utilized to control the update and ignorance of information. The formulations of all nodes in the model are expressed as follows:

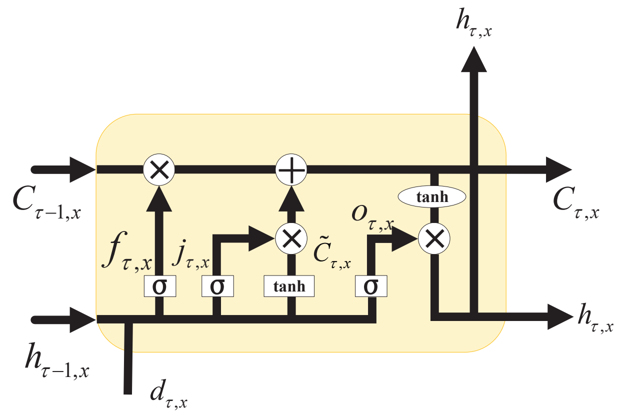


Fig. 4. The structure of forecasting system based on LSTM

$$f_{\tau,x} = \sigma\left(W_{f,x}\left[h_{\tau-1,x}, d_{\tau,x}\right] + b_{f,x}\right) \tag{14}$$

$$j_{\tau,x} = \sigma\left(W_{j,x}\left[h_{\tau-1,x}, d_{\tau,x}\right] + b_{j,x}\right) \tag{15}$$

$$\tilde{C}_{\tau,x} = tanh\left(W_{C}\left[h_{\tau-1,x}, d_{\tau,x}\right] + b_{C,x}\right) \tag{16}$$

$$C_{\tau,x} = f_{\tau,x} * C_{\tau-1,x} + j_{\tau,x} * \tilde{C}_{\tau,x} \tag{17}$$

$$o_{\tau,x} = \sigma\left(W_{o,x}\left[h_{\tau-1,x}, d_{\tau,x}\right] + b_{o,x}\right) \tag{18}$$

$$h_{\tau,x} = o_{\tau,x} * tanh\left(C_{\tau,x}\right) \tag{19}$$

where $W_{f,x}, W_{j,x}, W_{C,x}$ and are weight coefficients; $b_{f,x}, b_{j,x}, b_{C,x}, b_{o,x}$ are residuals; $\sigma\left(.\right)$ is sigmoid activation function; $tanh\left(.\right)$ is the hyperbolic tangent activation function; $*$ represents element-wise multiplication. Based on above analysis, the forecast output at the current time step ($h_{\tau,x}$) can be eventually obtained.

Considering the predicted result, the BSS operator can control the depleted battery charging process based on TOU electricity price to achieve BSS operation optimization, presented in Algorithm 5.

For each time segment τ, the service quantity of type x can be predicated on the above LSTM-enabled forecasting system. Besides, the number of totally serviced EVs of type x can also be obtained with real-time monitoring BSSs (line 1 to 2 in Algorithm 5). If the current time segment τ is with a peak price period and the number of serviced EVs of a certain

Algorithm 5 BSS Operation Optimization Control Based on Forecasting

1: **for** each time segment τ **do**
2: obtain the forecasting service number of type x ($h_{\tau,x}$) and total serviced EV number of type x over networks from the beginning of time segment (N^x_{ser}).
3: **if** (τ in peak price period & & $N^x_{ser} \geq h_{\tau,x}$) **then**
4: Set current charging power $P^x_{cha} = 0$
5: **else if** (τ in basic price period & & $\tau + 1$ in valley price & & $N^x_{ser} \geq h_{\tau,x}$) **then**
6: Set current charging power $P^x_{cha} = 0$
7: **else**
8: Set current charging power $P^x_{cha} = P_0$
9: **end if**
10: **end for**

type (N^x_{ser}) reaches the predicated number ($h_{\tau,x}$), the current charging power of type x will be set to zero (line 3 to 4). In addition to this, if the current time segment τ is with a peak price period and the next time segment $\tau + 1$ is with a valley price period while $N^x_{ser} \geq h_{\tau,x}$, the current charging power of type x battery will also be set to zero (line 5 to 6). Otherwise, the charging power will keep at the rated power P_0 (line 7 to 8).

On the one hand, stopping charging will inevitably increase the service waiting time and reduce the QoE of battery swapping. On the other hand, depleted batteries charging without planning will increase the cost of BSS operator. Therefore, the proposed BSS operation optimization control strategy can achieve a trade-off between charging QoE and electric power cost.

Algorithm 6 Recommended BSS-Selection

1: **for** each BSS station in network **do**
2: **for** each battery type x **do**
3: obtain $< N^x_{l,C}, N^x_{l,D}, N^x_{l,B}, N^x_{l,R} >$
4: **for** each battery of type x under (and waiting for) charging **do**
5: add charge finish time to list $ATSLIST_x$
6: **if** the reservations list $N^x_{l,R}$ is not empty **then**
7: **for** each charing reservation earlier than $T^{arr}_{ev(i^x)}$ **do**
8: refine list $ATSLIST_x$
9: **end for**
10: **end if**
11: sort $ATSLIST_x$ with ascending order
12: obtain ATS^x_1 from list $ATSLIST_x$
13: **if** ($N^x_B > 0$) **then**
14: $EWTS^x_l = 0$
15: **else**
16: $EWTS^x_l = ATS^x_1 - T^{arr}_{ev(i^x)}$
17: **end if**
18: **end for**
19: **end for**
20: **end for**
21: **if** the charging list $N^x_{l,C}$ or the available battery list $N^x_{l,B}$ is not empty **then**
22: $l^{opt}_{bss} \leftarrow \arg\min(EWTS^x_l)$
23: **else**
24: $l^{opt}_{bss} \leftarrow \arg\min(d_l)$
25: **end if**
26: **return**

D. Recommended BSS-Selection process

Among all BSSs, the optimal BSS will be determined by the CA (as shown in Algorithm 6). Thus, a desirable service can be experienced for the EV driver from spatial dimension with a carefully designed BSS-selection method. The expected waiting time for swapping (EWTS) as the metric to measure the QoE of EV drivers can be formulated as:

$$EWTS^x_l = \begin{cases} 0, & \text{if } N^x_B > 0; \\ ATS^x_1 - T^{arr}_{ev(i^x)}, & \text{if } N^x_B = 0. \end{cases} \tag{20}$$

where ATS^x_1 is the earliest time for the availability of a battery with type x. The detailed derivation of ATS^x_1 has been introduced in our previous work [15]. Then, we present the recommended BSS-Selection process in Algorithm 6 as follows:

Once receiving a battery swapping demand from $EV(i^x)$, the CA would query the service status of each BSS about the matched battery type x, including information such as $< N^x_{l,C}, N^x_{l,D}, N^x_{l,B}, N^x_{l,R} >$, as shown at line 3 of Algorithm 6. By aggregating the local status information (i.e., $N^x_{l,C}, N^x_{l,D}$) from all BSSs, a list of $ATSLIST_x$ is initially calculated for each BSS (line 4 to 5) to obtain the available time for swapping (ATS). Moreover, we further consider reservation information from EVs with the matched type ($N^x_{l,R}$) to refine and update the list $ATSLIST_x$. Therefore, the predicted time of an available battery at each BSS can be eventually obtained (line 6 to 10). Finally, $EWTS$ is derived based on Eq. (20) (line 13 to 17).

The above analysis is based on the assumption that the charging list $N^x_{l,C}$ and $N^x_{l,B}$ are not empty. This means the available charging slots and batteries are adequate compared with the swapping demand. The optimal BSS is recommended with the minimum $EWTS^x_l$, calculated according to the information on swappable and charging batteries (line 21 to 22). However, considering the extreme case where there are no available batteries and charging slots for the certain battery type x, it is hard to estimate $EWTS^x_l$. Once facing such a dilemma, EV drivers will choose the closest BSS (line 23 to 24).

The travel time on the road and the waiting time at BSS are both important factors for the EV drivers' QoE. Differing from directly integrating the travel time into EV drivers' QoE, the proposed management scheme has investigated the impact of travel time (calculated by summation of travel time and current time in network), so as to improve EV drivers' QoE. To be specific, when an EV requires battery swapping service, the travel time from current position to each BSS will be calculated. Then, the arrival time of EV to each BSS can be obtained. By comparing the arrival time and the time when depleted batteries become available, the service waiting time at each BSS can thus be predicated. Finally, the optimal BSS with minimum service waiting time is recommended for EV drivers. To sum up, we do not directly consider the travel time, but we consider the arrival time related to travel time.

E. The theoretical analysis of optimization problem

Inspired by the classic work [6], [31], [32], we theoretically analyze the performance of online implementation protocol framework, so as to derive a performance upper bound for solutions. It is different from the optimization algorithms that obtain the optimal solution when the system reaches a steady state through iteration. By contrast, the online implementation protocol framework is a classical one-shot decision optimization problem.

The optimal BSS-selection aims to recommend the BSS for EV drivers that can minimize the overall service waiting time. To facilitate problem analysis, we mainly focus on one type of battery to obtain performance bound. Actually, the service waiting time of all types also consists of each type. Thus, the simplification does not affect the effectiveness of theoretical analysis. The system goal can be formulated as follows:

Objective:

$$\text{Find } \Omega \text{ to minimize } W = \sum_{l \in \mathbb{L}} \Psi\left(r_l\right), \tag{21}$$

where $\Omega = \{\varphi_{s,l} | \forall (s,l) \in \mathbb{L}^2\}$ is a swapping scheduling from last BSS s to next BSS l, and $\varphi_{s,l}$ is the arrival rate of EV flow from the BSS s to the next service BSS l. We denote $\Psi\left(r_l\right) = \nu_l \cdot w_l$ to reflect the service waiting time at BSS l. ν_l is the expected number of EV that arrive at BSS l, and w_l is the expected service waiting time that an EV spends at BSS l for battery swapping service. Through the summation of waiting time at each BSS, the total service waiting time can thus be derived. Moreover, considering the energy constraint over network and queuing service capability, the optimal scheduling is achieved based on following constraints:

s.t.,

$$\sum_{l \in \mathbb{L}} \sum_{s \in \mathbb{L}} \left(\varphi_{s,l} \cdot E_{s,l}\right) = \phi, \tag{22}$$

$$r_l = \frac{\lambda_l}{\rho_l} = \frac{\sum_{s \in \mathbb{L}} \varphi_{s,l}}{P_0}, \tag{23}$$

$$\Psi\left(r_l\right) = \frac{\theta r_l^{\theta+1}}{\theta!(\theta - r_l)^2 \cdot \left(\frac{\theta r_l^{\theta}}{\theta!(c - r_l)} + \sum_{n=0}^{\theta-1} \frac{r_l^n}{n!}\right)} + r_l, \tag{24}$$

$$0 \le r_l / \theta < 1, \forall l \in \mathbb{L}, \tag{25}$$

Eq. (22) is the constraint of electric energy over network, and it means the energy consumed at all BSSs should be in accord with the sum of charging demand input for depleted batteries at all BSSs. The left-side of Eq. (22) indicates the electric energy consumption for depleted batteries recharging over all BSSs. For an EV on the vehicle flow from the BSS s to the next service BSS l, the expected energy demand of depleted battery charging can be expressed as:

$$E_{s,l} = e_{max} - P^{-} \cdot d_{s,l}, \tag{26}$$

where e_{max} represents the full capacity of battery, P^{-} is the energy consumption per unit distance for an EV and $d_{s,l}$ is the travel distance. For the right-side of Eq. (22), $\phi \in \Phi\left(\lambda_{s,l}, \Omega_{s,l}\right)$, and Φ is a function to reflect the charging energy demand for depleted batteries from EV arrival with respect to $\lambda_{s,l}, \Omega_{s,l}$.

In Eq. (23), $\lambda_l = \sum_{s \in \mathbb{L}} \varphi_{s,l}$ denotes the arrival rate, ρ_l represents the service rate and P_0 is charging power. The battery swapping service process can be modeled as a $M/M/\theta$ queue, where θ is the number of allocated charging slots. Based on above information, the service waiting time at BSS l can be derived with queuing theory in Ref. [33], which is given in Eq.(24). r_l/θ is server utilization. Meanwhile, Eq. (25) guarantees the queue length of BSSs will stay in a finite range and not grow indefinitely.

Moreover, we conduct the theoretical performance with respect to waiting time. It is assumed that all EVs run out of the full energy of battery when they arrive at BSSs, the maximum value ϕ_{min} can thus be derived:

$$\phi_{min} = \sum_{(s,l) \in \mathbb{L}^2} \lambda_{s,l} \left[P^{-} \cdot d_{s,l} - e_{max}\right]. \tag{27}$$

Considering $\Psi\left(r_l\right)$ is monotonically increasing with respect to r_l and ϕ_{min} is the minimum value, we can get $\Psi\left(\frac{\phi}{|\mathbb{L}| \cdot P_0}\right) \ge \Psi\left(\frac{\phi_{min}}{|\mathbb{L}| \cdot P_0}\right)$. Then, we can get the upper of battery swapping service waiting time for online implementation:

$$W \ge |\mathbb{L}| \cdot \Psi\left(\frac{\phi_{min}}{|\mathbb{L}| \cdot P_0}\right), \tag{28}$$

which is consequently a performance upper bound for the optimization problem.

Based on above analysis, the theoretical analysis of optimization problem has been obtained.

F. The discussion of gap between the online solution and the offline solution

The concept of competitive ratio, defined as $r_M := sup \frac{Cost(M^{on})}{Cost(M^{*})}$ is commonly adopted to measure the worst possible ratio between online implementation and the offline optimum over all input instances. To discuss the gap between the online solution in Section V and the offline solution in Section IV, a network of a line topology with L stations is modelled, as shown in Fig. 5. We assume that there are L battery swapping demand sorted by time-sequence. Each edge represent the system cost for each assignment between an EV and a BSS. We suppose EV i_1^x at the node in between BSSs l_1 and l_L, with closer to BSS l_1 by $\frac{\mu T}{S}$, where S and μ are constant. The online implementation is a greedy strategy, which aims to assign an EV to the BSS with least cost locally, i.e., BSS l_k is assigned to EV i_k^x, $k = 1, 2, \ldots, L$, as depicted in Fig. 5. Therefore, the total system cost is $\frac{(2^L - 1 + \mu)T}{S}$. By contrast, the offline solution is with optimal system cost of $\frac{(1+\mu)T}{S}$. Therefore, considering the specific case, the competitive ratio is $r_M = \frac{Cost(M^{on})}{Cost(M^{*})} = \frac{2^L - 1 + \mu}{1 + \mu} \to 2^L - 1$ with $\mu \to 0$.

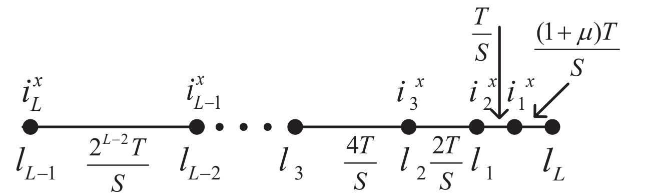


Fig. 5. An analysis of online implementation and offline solution

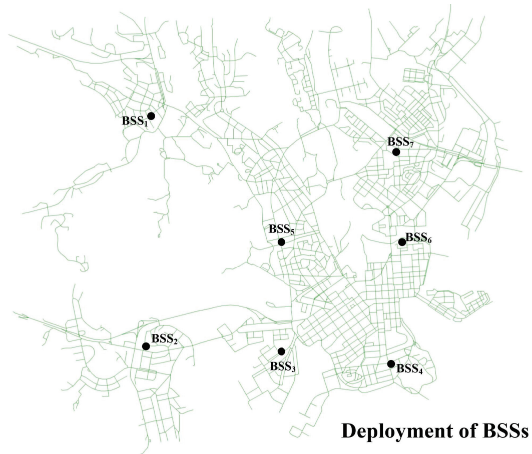


Fig. 6. Simulation scenario of Helsinki city

VI. Performance evaluation

A. Simulation Configuration

The EV battery swapping system based on the Opportunistic Network Environment (ONE) [34] is developed to evaluate the performance of related algorithms. As presented in Fig. 6, the default simulation scenario is established from the district of Helsinki city in Finland with 8300×7300 m^2 area. In this simulation scenario, the main road information is abstracted from the map to determine EV route.

There are an initial number of 300 EVs with a fluctuating speed of $[30 \sim 50]$ km/h moving along the road in the network. A target position is randomly selected from the map for each EV trip. Then, the EV drives to the destination with the shortest path considering the practical map road. When the EV arrives at the destination, a new destination emerges once again. The above procedure is repeated until the EV reaches the SOC threshold and then a battery swapping service will be required. All EVs are set according to the charging specification {Maximum Capacity, Max Traveling Distance, SOC threshold}. Considering battery heterogeneity, three types of EVs (or batteries) are studied with the following configuration [15]. Each type of EV has the same number of entities.

- Type I: Coda Automotive [35] {33.8 kWh, 193 km, 30%}
- Type II: Wheego whip [36] {30 kWh, 161 km, 40%}
- Type III:Hyundai BlueOn [37] {16.4 kWh, 140 km, 50%}

When the battery level is below the set threshold value, the intelligent in-vehicle system will remind EV drivers to replenish energy. On the one hand, EV drivers may immediately move towards BSSs for battery swapping service. On the other hand, EV drivers may postpone their demand of battery swapping service and drive to BSSs at their convenience. Both two situations are consistent with the actual drivers' behavior.

Considering the behavior of human intervention without following the system prompt in the latter service scenario, we mainly focus on the former service scenario in this paper. In this realistic service scenario, EV drivers will ensure enough battery level so that they can arrive BSSs for energy supplements. Compared with a small-capacity battery, EVs with a larger battery capacity can move further at an identical SOC threshold. This leads to EVs with larger battery capacity having a lower SOC threshold value. In our research, the setting of SOC threshold value can guarantee EVs arrive at any BSSs over city map, but meanwhile reflect service congestion caused by battery charging.

Besides, 7 BSSs are placed over the city map equipped with the above three types of batteries $\mathbb{X} = \{type-I, type-II, type-III\}$. We consider another special scenario where specific types of batteries are at a specific BSS. For example, batteries with type I, II and III are serviced at BSS1, while batteries with type IV, V, and VI are provided at BSS2. Actually, although such scenario is a slight variation of our research, the crucial problem is similar to what our paper targets, by guiding EVs to swap batteries at those BSSs with compatible batteries available. Also, such special scenario also shares the same heterogeneous battery charging scheduling as proposed in this paper.

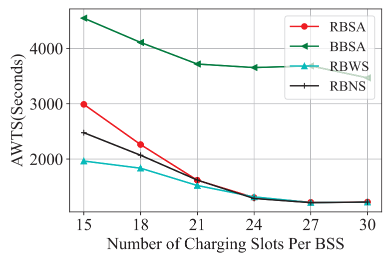
Inspired by the classical distributed BSS model defined in [38], the charging inside BSS have limited capacity. For each type, the initial number of fully charged battery at BSSs is 10 ($N_B^x = 10$). There are $\theta = 15$ charging slots that can charge depleted batteries in parallel with a rated power $P_0 = 10kW$. The duration for battery swapping operation is $\tau_{ev}^{swap} = 5$ minutes. The simulation depicts a period of 12 hours with $\dot{\tau} = 0.1$ seconds network update interval. Besides, the charging time is estimated based on proposed algorithms in this paper.

The following related schemes are all developed based on battery heterogeneity and preformed for evaluation:

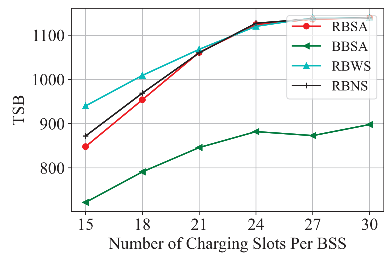
- **Reservation battery swapping without slot allocation (RBWS):** The heterogeneous BSS-selection scheme with EV reservations enabled, as presented in [15]. All depleted batteries are directly sorted according to STCF without slots allocation based on battery heterogeneity.
- **Basic battery swapping with slot allocation (BBSA):** The proposed heterogeneous battery swapping scheme without considering EV reservations. The available charging slots are allocated based on Algorithm 3.
- **Reservation battery swapping based on slot allocation (RBSA):** The heterogeneous battery swapping service framework based on reservation information. Available charging slots are allocated considering battery heterogeneity according to the advanced mode in Algorithm 4.
- **Reservation battery swapping based on native slot allocation (RBNS):** All charging slots are allocated evenly according to the number of battery types. That is to say, for each type of battery, the allocated charging slots is the total of charging slots divided by the number of battery types. Then, the number of allocated charging slots remains constant all the time. Besides, the heterogeneous BSS-selection scheme is also driven by EV reservations.

The performance metrics are:

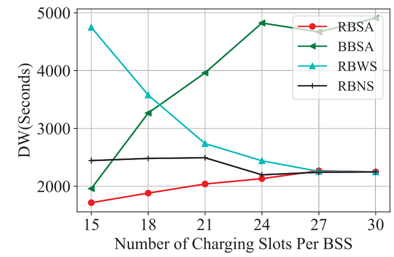
- **Average waiting time for switch (AWTS):** The average time an EV spends at a BSS from the EV arrival until leaving.
- **Difference in waiting time for various types of batteries (DW):** The waiting time difference among various



(a) AWTS

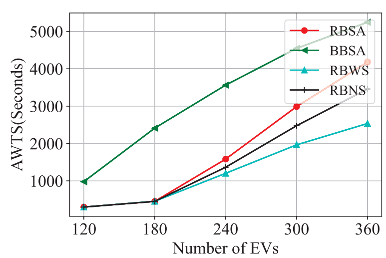


(b) TSB

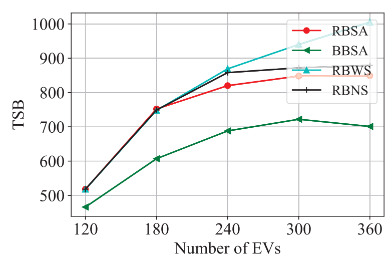


(c) DW

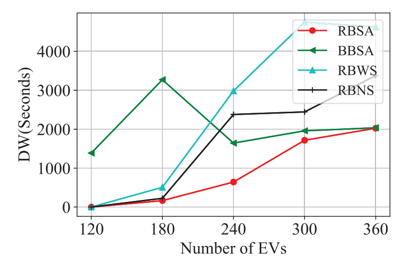
Fig. 7. Influence of charging slots at BSS



(a) AWTS

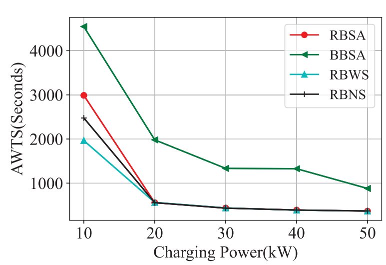


(b) TSB

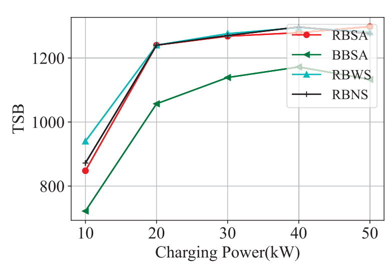


(c) DW

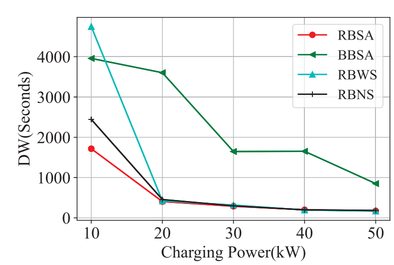
Fig. 8. Influence of EVs density



(a) AWTS

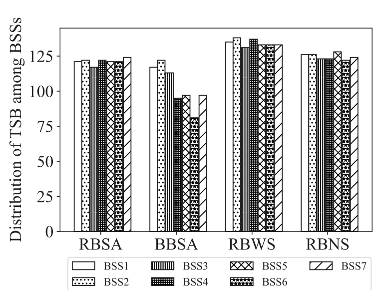


(b) TSB

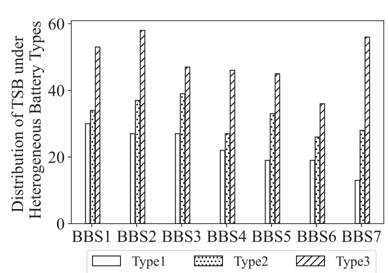


(c) DW

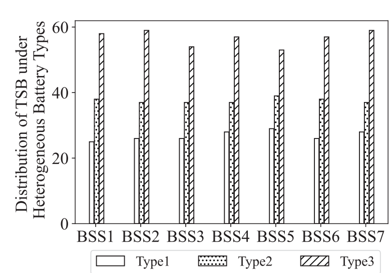
Fig. 9. Influence of charging power



(a) under different algorithms



(b) heterogeneous battery distribution under basic slots allocation mode



(c) heterogeneous battery distribution under advanced slots allocation mode

Fig. 10. Distribution of TSB among BSSs

types of batteries. The metric is calculated according to Eq. (3).
- **Totally swapped batteries (TSB):** The total number of serviced EVs at all BSSs.

B. Influence of charging slots at BSS

As shown in Fig. 7(a) and 7(b), the RBWS algorithm is with desirable performance. The reason is it schedules depleted batteries charging order only according to STCF rule without considering battery types. That is to say, it always accelerates the recycling of low-capacity batteries with higher priority. The low-capacity battery is certainly with short charging time and thus leads to shorter AWTS. Intuitively, the number of TSB is improved with a short AWTS. Thus, there is a correlation trend and performance gain between Fig. 7(a) and 7(b).Besides, Fig. 7(a) also shows the BSS-selection scheme without EV reservation costing longer waiting time. Additionally, if the number of charging slots at BSS increases, the performance will be improved because more batteries can be charged in parallel.

Another important metric we concerned is DW. As depicted in Fig. 7(c), the proposed allocation schemes can significantly reduce the difference in service waiting time of multi-type EVs, especially facing the limited charging slots. Besides, the proposed RBSA algorithm can always keep the minimum DW despite of the variation in charging slots amount. In comparison to Fig. 7(a), the RBSA algorithm can reduce the DW with a slightly higher cost of AWTS.

We observe that the performance metrics under three reservation-driven schemes are gradually close. Besides, these algorithms eventually converge to a similar value with the increment of charging slots. The reason is that each battery can be added to the charging slots immediately without waiting based on adequate charging slots. Therefore, the effect of available charging slot allocation is not so remarkable.

C. Influence of EVs density

We herein vary the number of EVs to study the impact of EVs density. As depicted in Fig. 8(a), the AWTS increases with a higher EV density. Intuitively, the TSB grows with more EVs requiring battery swapping service. Then, the result in Fig. 8(b) verifies the deduction. Besides, EVs have to wait for the depleted batteries becoming available due to the limited charging ability at BSSs. Therefore, the TSB keeps slightly stable with EVs increment when the number of EVs exceeds a certain value. In Fig. 8(c), we observe that the charging slot allocation schemes based on EVs reservation always exhibit superiority in comparison of the RBWS scheme. Although there is no EV reservation applied in the BBSA scheme, this scheme can also allocate the charging slots with local status information at BBSs. The reason is that the local waiting queue with an increasing number of EVs can accurately reflect the demand distribution of battery types. Thus, the BBSA scheme can eventually achieve desirable performance in terms of shorter DW.

D. Influence of charging power

Here, the impact of charging power on performance metrics is shown in Fig. 9. If the charging power increases, the performance is improved. It is obvious that depleted batteries can be fully charged with shorter time under a higher charging power. Therefore, the waiting time at BSSs for EVs is accordingly reduced and the recycling of batteries is accelerated. Besides, the shorter waiting time will further reduce the DW.

E. Distribution of TSB among BSSs

In Fig. 10(a), we compare the distribution of TSB (or charged EVs) among each BSS for different algorithms. We observe that the algorithms based on reservation information can improve load balancing. In comparison, the algorithm only utilizing local status information causes a skewed distribution. According to the analysis on Eq. (1), the load balancing leads to desirable QoE concerning waiting time. Fig. 10(a) also explains why the reservation-enabled scheme is always with better performance with the above conditions changing. Heterogeneous battery distribution results under charging slot allocation schemes proposed in this work are shown in Fig. 10(b) and 10(c), respectively. In basic mode, the local hotspot at a certain BSS leads to congestion and eventually causes degraded performance.

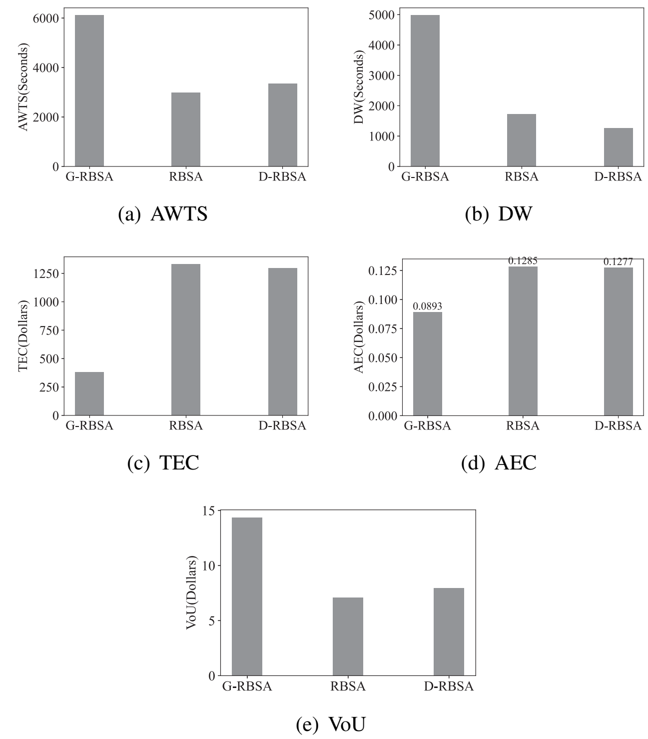
TABLE I
RETAIL ELECTRICITY PRICE (USD/KWH)

User type	TOU price		
	Peak price	Basic price	Valley price
Commercial	0.17	0.13	0.05

F. Charging control based on real-time price

In this subsection, we investigate the effect of proposed BBS operation optimization control scheme. In Table I, we provide the TOU electricity price according to [39]. The coefficient γ in Eq.(5) is set with 8.4 \$/h according to the survey [40]. Apart from the RBSA method proposed in Algorithm 4, the following variant schemes are also evaluated:

- **Electricity cost greedy strategy (G-RBSA):** The G-RBSA scheme is derived from the proposed RBSA scheme. However, the electric cost is the only factor the G-RBSA scheme concerns. Therefore, it will only charge depleted batteries at the basic and valley price periods.
- **Electricity cost control strategy based on demand forecasting (D-RBSA):** The D-RBSA scheme is based on the BSS operation optimization control strategy in Algorithm 5. In this scheme, the electricity cost and the QoE are both taken into account. For the predicting model training process, the data set comes from the EV battery swapping simulation system in Opportunistic Network Environment (ONE). The simulation system generates 300 days of network operation data. Each record includes the served number of multiple types of EVs with a 2 hours time segment. The data are split into three subsets for different purposes, namely training set, validation set



(a) AWTS (b) DW (c) TEC (d) AEC (e) VoU

Fig. 11. The results of BSS operation optimization.

and testing set. Besides, the data split is 0.6/0.2/0.2. During the training phase, the PyTorch framework is adapted. Adam is served as the optimizer and the loss is with mean-squared-error. The learning rate is 0.0002, and the batch size is 5. The training process is executed on NVIDIA GeForce RTX 2080Ti GPU.

The following performance metrics related to electricity cost are conducted:

- **Total electricity cost (TEC):** The total electricity cost is the summation of all BSSs purchasing electricity from the power grid during the whole operation process.
- **Average electricity cost (AEC):** The average electricity cost is obtained by TEC dividing the total electricity consumption. It reflects the average cost per kWh of electricity.
- **Value of utility (VoU):** The value of utility is the summation of average electricity cost and average waiting time, which is derived based on Eq. (5).

As shown in Fig. 11, we observe that the G-RBSA scheme is with the longest AWTS due to ignoring the service requirements from EVs. Although the G-RBSA indeed reduces the TEC and AEC than other schemes, the AWTS is tremendously increased, causing undesirable QoE for EV drivers. Besides, the D-RBSA can achieve better performance in other metrics at the cost of a slightly longer AWTS. This is because the D-RBSA can optimize the battery charging phase according to demand forecasting results. Furthermore, as depicted in Fig. 11(e), we can observe that the RBSA achieve similar performance with D-RBSA on VoU.

G. The impact of congestion

The insightful literature [41] presents the impact of congestion on the battery swapping service. Inspired by the excellent work, we investigate the impact of congestion on battery swapping service performance. The traffic congestion is stochastically generated from every 300 s, and the radius is 300 m. That is to say, an EV will slow the moving speed when the distance between its location and congestion is smaller than 300 m. Besides, the duration of congestion is set with 100 s. Performance metrics are evaluated under different numbers of traffic congestion. As shown in Fig. 12, AWTS and TSB are reduced with the increasement of congestion. This is because more EVs have to reduce speed and even stop under the impact of congestion, when they are moving towards BSSs. Furthermore, the decrease in AWTS will reduce the DW to an extent.

H. The verification on larger test case

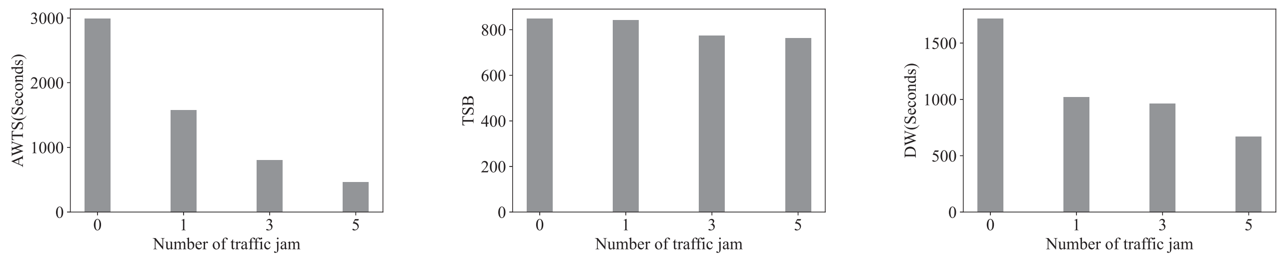
Based on the city map with an area of 8300×7300 m^2, we have further conducted a larger test case with more EVs, charging slots and stock batteries, so as to verify the scalability of the proposed framework. To be specific, the extended experiments consider a much higher demand from EVs as well as a higher service capability of BSSs. The number of EVs increases from 300 to 450. For the default parameter setting of BSS operation, the configuration of charging slots and stock batteries is expanded to 21 and 45, respectively. As shown in Fig. 13, the proposed RBSA scheme remarkably reduces DW, even though it is at the cost of a subtle increment on AWTS. Therefore, the proposed battery swapping service management framework still exhibits superior performance on the large test case.

I. The comparison between offline and online solutions on service waiting time

Considering the solvability of offline algorithms, the simulation is performed based on a test case that is more small-scale than above practical simulation scenario. The test case is based on 4500×3400 m^2 downtown area of Helsinki city, and 3 BSSs are deployed over the area. The number of each type of EV is 24. For the default configuration of BSS, there are 5 initial available batteries and 15 charging slots at each BSS. Other configurations of EVs and BSSs are in accord with the setting in Section VI.A.

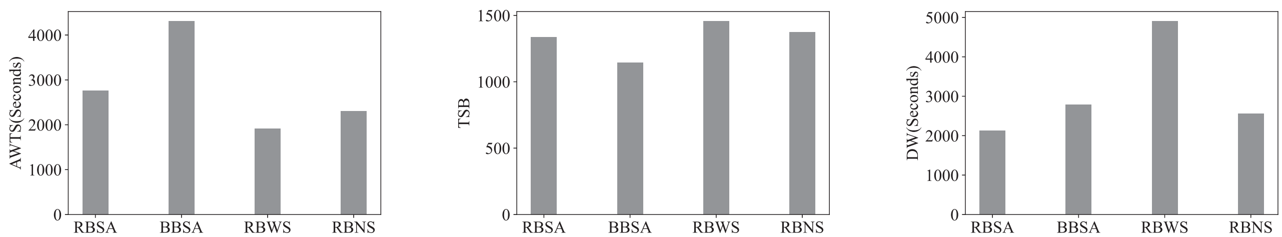
Since the offline algorithms in [31], [42] mainly are developed based on service waiting time, we thus focus on the same metric of offline and online solutions. The comparison of service waiting time is presented in Fig. 14(a).

From Fig. 14(a), we can observe that the offline algorithm achieves a 31.40% improvement in AWTS over the online method in the situation, which is in accord with the theoretical analysis in Subsection V.F. This is because the prior information is necessary for the implementation of offline algorithm. In other words, for the offline algorithm, the requirement of battery swapping can be known in advance, so as to well match EVs with BSSs in an optimized manner.



(a) AWTS (b) TSB (c) DW

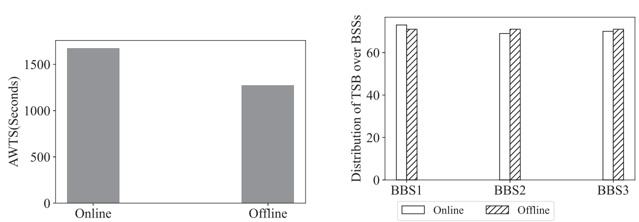
Fig. 12. Influence of traffic congestion.



(a) AWTS (b) TSB (c) DW

Fig. 13. The verification on larger test case.

The same conclusion can be drawn from Fig. 14(b). The offline algorithm achieves a much balanced demand distribution among BSSs, while the online method is with fluctuation.



(a) AWTS (b) TSB

Fig. 14. The performance comparison between offline and online solutions.

J. Future work

From the perspective of BSS operator, reducing the maintenance cost of heterogeneous batteries caused by degradation is significant. Whereas, based on different properties of heterogeneous batteries, the same charging rate results in different degradation. Therefore, for BSS operation under battery heterogeneity, it is worthwhile to further investigate the charging management based on battery degradation.

Also, considering the remarkable economic benefit brought by RESs, the joint optimization of renewable energy and EV should be taken into account for battery charging management. Based on the characteristic of power generation in city scenario, PV has been regarded as a promising method among RESs. However, since solar power is with high uncertainty due to weather, climate and district, the modeling about power generation is of importance to recharge batteries at BSSs, which is our future directions.

VII. Conclusion

In this paper, we develop a coordinated battery swapping service management framework involving multi-party participators. In order to balance the charging priority of various types of batteries (or EVs), an available charging slot allocation scheme is proposed. The proposed scheme is with further extension towards EV reservations for more efficient services. The demand information about heterogeneous types of batteries at a certain BSS can thus be predicated. Besides, a BSS operation optimization control strategy based on the LSTM neural network is introduced to balance the BSS operation cost and QoE of EV drivers. Simulation experiments verify the performance of proposed scheme in balancing the charging priority compared with other benchmarks. Meanwhile, the simulation result further validates the operation optimization scheme's viability concerning demands from EV drivers and the BSS operator.

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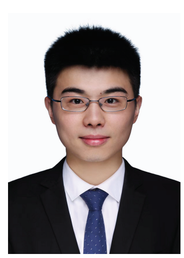

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