Towards Efficient Battery Swapping Service Operation Under Battery Heterogeneity

Xu Zhang, Yue Cao, Linyu Peng, Naveed Ahmad, and Lexi Xu

***Abstract*—The proliferation of electric vehicles (EVs) has posed significant challenges to the existing power grid infrastructure. It thus becomes of vital importance to efficiently manage the Electro-Mobility for large demand from EVs. Due to limited cruising range of EVs, vehicles have to make frequent stops for recharging, while long charging period is one major concern under plug-in charging. We herein leverage battery swapping (BS) technology to provide an alternative charging service, which substantially reduces the charging duration (from hours down to minutes). Concerning in practice that various battery is generally not compatible with each other, we thus introduce battery heterogeneity into the swapping service, concerning the case that different types of EVs co-exist. A battery heterogeneity-based swapping service framework is then proposed. Further with reservations for swapping service enabled, the demand load can be anticipated at BS stations as a guidance to alleviate service congestion. Therefore, potential hotspots can be avoided. Results show the performance gains under the proposed scheme by comparing to other benchmarks, in terms of service waiting time, etc. In particular, the diversity of battery stock across the network can be effectively managed.**

***Index Terms*—Electric Vehicle, Battery switch, Transportation planning, E-mobility.**

I. Introduction

FOLLOWING advances in sustainable energy development, Electric Vehicles (EVs) of electricity propulsion-based are starting to penetrate the transportation landscape. Fueled by the rapid development in green and intelligent transportation systems, various incentives from government or industries worldwide are promoting EVs to act as key enabler for the evolution of sustainable transport technology. Inevitably, EVs are gaining the popularity of general public, by an expansion of over 50% from 2016 according to [1].

As compared to traditional gasoline-powered vehicles, the main problem with EV transportation is long driving range. Limited cruising range requires EVs to charge frequently during a long journey, leading to the degradation of the travel efficiency as well as driving comfort. Besides, locating convenient charging services are also among the major obstacles [2].

It thus becomes imperative to tackle the challenges relating to Electro-Mobility (E-Mobility) for efficiency concerns. There have been many solutions toward the issue of charging management [3]–[5], [7]–[10]. One major focus is on "when/whether to charge" [3], when scenarios are simple and EVs are usually parked (e.g., at home or charging stations (CSs), etc.). In such cases, vehicles are seen as stationary loads with no spatiotemporal properties.

Considering the mobility nature of EVs, however, recent research efforts start to show great interests in a more practical scenario where EVs on-the-move. Consequently, "where to charge" (or E-Mobility) becomes a critical issue [4], [5]–[8]. In such cases, EVs are strategically assisted to drive toward an appropriate CS during their journey, e.g., by accounting for the waiting time for charging service [9], [10]. To avoid CS hotspots where EVs may be concentrated, charging reservations from EVs are suggested to be made in advance at the selected CS [11], [13], [14]. As such, congestions can be predicted at a specific time of a particular CS. Benefited from such intelligence on CS-selection, charging Quality of Experience (QoE) can be considerably improved.

While these plug-in charging solutions have shown their effectiveness, a near 100 percent charge still requires over 30 minutes based on fast charging power [15]. It is clear that it will be very challenging to overcome the disadvantages like longer time and battery degradation via existing fast charging technology. As such, it certainly appears that an alternative method of charging is needed. So, battery swapping (BS) could be a viable option that provides a promising option in a cost-effective way [17]. It takes only several minutes to replace a depleted battery with a fully-charged spare, comparable to a gas-powered vehicle. There have been a few works on the aspects of energy scheduling or battery swapping station (BSS) deployment [18]–[26]. As of yet, these research works are mainly based on a single type of battery running for all EVs, which is lack of practical application.

Nonetheless, considering many manufacturers in market, batteries are generally not compatible with each other. For instance, Nissan Leaf uses the proven lithium-manganese (LMO) battery,

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while other EVs like Tesla uses NCA (nickel, cobalt, aluminum) in the 18650 cell [7], where driving ranges and battery capacities differ from each other as well. Typically, each type of EV can only be switched with a certain type of battery. A practical concern thus requires further efforts put forth into diverse switching demand, such that EVs of different battery type can experience fast battery swapping. This has created a need to take efficiently account the distinct nature of *battery heterogeneity* into BS management, with regard to different EV types. Further integrated with the information and communication technology (ICT), the smart BSS-selection process could be enhanced by delivering critical context over the ubiquitous cellular networks [20]. Our contributions are thus as following.

1) *Introducing battery heterogeneity into swapping services:* We herein divide EV batteries into several groups depending on various associated type of EVs. As for each type, the BSS holds a stock for fully-charged spares and manages the charging process of depleted batteries removed from EVs. Such operations are independent among different battery groups. By maintaining the diversity of batteries at each BSS, the balance of BS demand involving various battery types can be achieved.

2) *Study of a heterogeneous-BS framework with reservations-enabled:* Upon the introduction of battery heterogeneity above, we further incorporate EV reservations for BS into the swapping service management, including EV battery type, expected EV arrival time and the charging duration for replaced battery. Along with local BSS battery charging and stock status, an efficient BS framework considering these key context is then proposed, so as to provide a viable guidance on optimal BSS-selection for EV users.

This paper is organized as follows. Related work is briefly reviewed in Section II. In Section III, we elucidate our proposed intelligent heterogeneous-BS framework. Key decision-making policies are presented in Section IV. The performance of the proposed framework is evaluated in Section V through extensive simulations and we conclude the paper in Section VI.

II. Related Work

Majority of existing research works investigate the charging scheduling relating to plug-in charging services [3]–[5], [7]–[10]. Concerning the conundrum with plugin charging of relatively long charging duration (typically at hours [27]), a few research efforts consider the battery swapping as a viable alternative [18]–[20], benefited from minutes-level replacement time comparable to gas filling time for a fuel-powered vehicle.

A. Plug-in Charging Service

Research efforts towards plug-in charging are generally of two-aspects: *when/whether to charge* and *where to charge*.

In the context of when/whether to charge, a simple scenario of parked EVs at homes or CSs is usually considered [3]. Vehicles are assumed as stationary loads with no spatiotemporal properties related to the mobility of the EVs. In comparison, the where to charge manages the CS-selection for EVs on-the-move [4], [5]–[8]. Usually, the CS with the minimum queueing time is recommended, by taking into account the local conditions of each CS [9], [10], e.g., the number of EVs along with their remaining charging time. Such charging recommendation is regarded as an effective solution especially in urban cities with insufficient charging infrastructures [7].

Even though, the same CS could be chosen by multiple EVs, wherein EVs can be left stranded by overcrowding [12]. Such issue mainly owns to the mobility uncertainty related to vehicles. Therefore, a few literature works additionally account for charging reservations [11], [13], [14], including expected EV arrival time and charging duration, etc. By doing so, charging status at each CS is able to be estimated for a future moment, thus eliminating heavy congestions at CSs.

B. Battery Swapping Service

Undesired effects of plug-in charging include longer charging time, expensive batteries and battery degradation of fast charging, etc. They can be mitigated by using the BS services. By concept, the basic swapping approach enables the EV user to quickly replace a depleted battery with a fully-charged spare within minutes. Essentially, the immediate service in supplying power to EV can provide huge benefits to power system. On the other hand, the large-scale adoption of EVs are hindered due to costly ownership. By taking out of the battery the cost can be reduced. For instance, a third party will have the ownership of the battery and the liability for replacing the discharged batteries with fresh and charged ones [16]. Considering, separation of vehicle and battery pack might work better for all in price-conscious markets.

There have been a few works on BS study [18], [19], [21]–[26]. Authors in [24] decouples the charging of depleted batteries from BSS to remote charging stations, and proposed a matching solution to recycle depleted batteries. In [25], the scheduling of depleted batteries from EVs is based on minimization of charging cost power loss, and voltage deviations, where the price of battery swap depends on difference between the SOC and swapped fully charged spares. Also, there are research efforts put forth into charging load management [26]. However, most of these works focus on one BSS for BS management [19], [23], [24], and some assume EVs in limited motion [21], [22], [25], e.g., simple high way fashion or stationary EV loads. Considering a more realistic BS scenario where EVs on-the-move with multi-stations involved, relevant works are quite limited [20]. On the other hand, a homogeneous battery swapping scenario is usually assumed with majority of these existing research works, where a single type batteries assumed for all EVs. Concerning the practicality issue of heterogeneous EV batteries, research works are lacking.

C. Motivation

In the context of battery swapping, existing research works are basically based on an impracticable assumption of homogeneous battery type with all EVs. Within this assumption, a "one-to-one" matching is the major concern for pairing EV-BSS to facilitate optimal BS service. Under a heterogeneous BS system, however, the availability of battery stock at each BSS will not vary in the total numbers only, but also in the specific battery type,

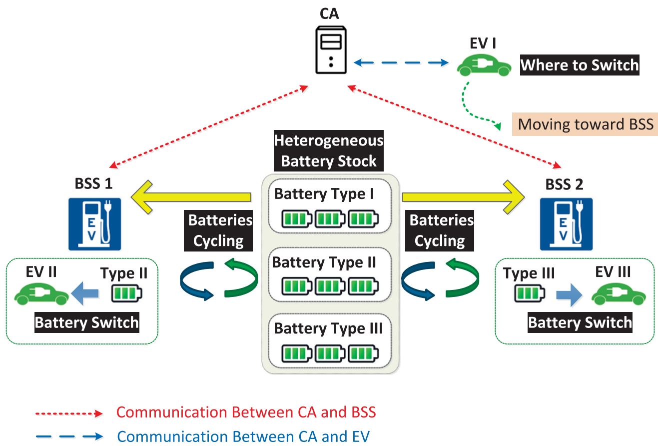


Fig. 1. An illustration of BS network scenario.

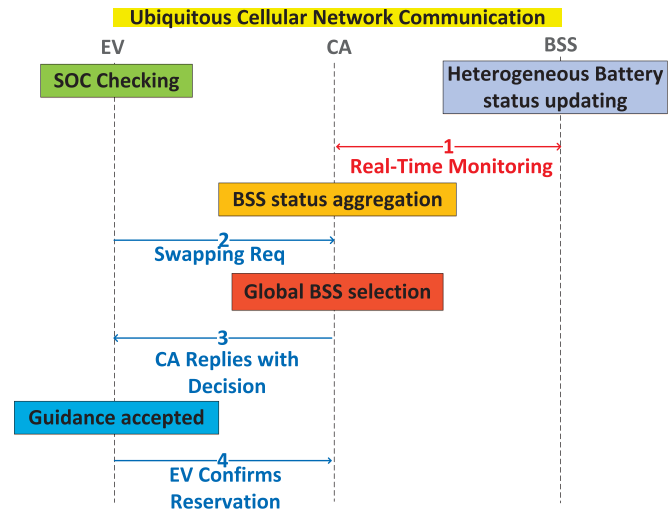


Fig. 2. The sequence chart for the BS service.

due to continuous arrivals of EVs of multi-types. As such, it becomes a more complicated "many-to-many" issue, which requires to take into account additional critical factors, such as EV battery type and battery stock of a specific type maintained at each BSS. Therefore, this has created a need to design a more effective framework that takes efficiently account the distinct nature of such battery heterogeneity, in order to provide efficient BS services concerning such diverse demand, which requires to maintain batteries based on a type-level.

III. Heterogeneity-Driven BS Service

Considering the high dynamics of EV swapping demand concerning vehicle mobility feature, the where to swap issue is our focus in this paper. By characterizing the multiple EV battery types, we propose a heterogeneous BS service framework to provide diverse BS services with efficiency concerns.

A. *Overview*

We consider a city scenario where fixed BSSs are geographically deployed. As depicted in Fig. 3-A, EVs are basically on-the-move and check their SOC constantly. Once a BS service is required, the vehicle user drives toward a BSS with the aid of a central aggregator (CA).[1] Essentially, there are three major network entities involved in our swapping process, as elaborated below.

- **BSS**: A battery stock is maintained by each BSS, filled with a limited number of fully charged batteries. These battery spares are grouped into different categories based on heterogeneous EV types, defined as a symbolic set $\Psi = \{type-I, type-II, type-III, \ldots, type-X\}$. Depleted batteries removed from EVs will be fully charged at the BSS. As such, batteries of various types can be cycled at each BSS for serving diverse swapping demand from EVs.
- **EV**: EVs are generally powered by batteries of specific types. Each EV is associated with a SOC threshold. Once the present SOC value is below a threshold value, a BS request will be sent to the CA for guidance on BSS selection. When a reply is received, the vehicle confirms the recommendation by reporting a BS reservation to the CA, including the vehicle identification (ev_id), its battery type (B_{ev}, $B_{ev} \in \Psi$), the arrival time (T_{ev}^{arr}) and expected charging duration (δ_{bat}^{cha}) for the drained battery, etc.
- **CA**: The CA globally monitors the BSS status and manages EV charging reservations. Such context information is aggregated and updated at CA periodically for effective BSS-selection decision making.

Generally, network entities like EVs are equipped with wireless devices so as to facilitate cellular communications, such as 3 G/LTE [28], etc. As such, the constant communication between CA and other network entities will be enabled by ubiquitous cellular networks, allowing for reliable exchange of critical context information.

B. *Protocol for Heterogeneous BS Service Process*

The process for the heterogeneous BS service system is illustrated in Fig. 3-B, and Table I lists the notations.

- **Step 1**: Periodically (with interval τ), the CA checks and aggregates updated conditions of all BSSs in the network, including battery stock availability (N_B^X), ongoing charging sessions (N_C^X), and the number depleted batteries (N_D^X), etc. Such information context is collected and recorded at battery-type level, e.g., $< BSS\_id, N_B^X, N_C^X, N_D^X >$, where $X \in \Psi$.
- **Step 2**: By regularly checking the SOC, the on-the-move EV (e.g., ev_r) informs the CA once a BS service is required, along with its battery type B_{ev}.
- **Step 3**: Once a BS demand is received, the CA ranks the BSSs with regard to charging load and waiting time, by compiling a list of BSSs concerning the aggregated

[1] A centralized fashion is applied in this paper to enable efficient BS selection, which has been widely adopted by relevant works. The centralized mode enables globalized and direct control as well as real-time monitoring over edge devices, further enhanced by sophisticated optimization at the global controller side.

TABLE I
LIST OF NOTATIONS

Symbol	Description
σ	Time interval of system resolution
N_B^X	Number of switchable batteries with type $X, X \in \Psi$
$N_{B(E)}^X$	Expected number of switchable batteries with type $X, X \in \Psi$
N_D^X	Number of depleted batteries removed from incoming EVs with type X $(X \in \Psi)$
N_R^X	Number of EVs that have made reservations for battery type $X, X \in \Psi$
N_C^X	Number of batteries with type X $(X \in \Psi)$ being charged
B_{ev}	Battery type of the EV
ρ_{sw}	Time duration to switch a battery
θ	Number of charging slots
E_X^{max}	Full volume of battery with type $X, X \in \Psi$
E_X^{cur}	Current volume of battery with type $X, X \in \Psi$
d	EV travelling distance
δ_{ev}^{tra}	EV traveling time duration
δ_{bat}^{cha}	Expected charging time
α	Charging power
T^{fin}	Charging finish time of an EV battery
γ	Energy consumption per meter
T_{ev}^{arr}	Expected EV arrival time
T_{cur}	Current network time
$ATSLIST_X$	Output list of ATS for battery type $X, X \in \Psi$

information relating to the required battery type. A best choice of BSS is then replied to the requestor ev_r.

- **Step 4**: The EV confirms the arrangement by reporting its reservation back to the CA, e.g., $< ev_{id}, B_{ev}, T_{ev}^{arr}, \delta_{bat}^{cha} >$.

Since the vehicle may need to travel to the selected BSS over an additional distance (d), extra energy can be consumed. As such, the expected charging time (δ_{bat}^{cha}) for the battery can be refined as below, given by α as the charging power.

$$\delta_{bat}^{cha} = (E_X^{max} - E_X^{cur} + d \cdot \gamma)/\alpha \tag{1}$$

where $X \in \Psi$, the term $(E_X^{max} - E_X^{cur})$ (Joules) refers to the energy already consumed by the vehicle with battery type X, while $(d \cdot \gamma)$ (Joules) corresponds to the additional energy consumption for the EV to travel to the reservation spot.

Similarly, the arrival time (T_{ev}^{arr}) of the vehicle will be approximated as $T_{ev}^{arr} = T_{cur} + \delta_{ev}^{tra}$ to additionally account for the travel time, where T_{cur} denotes the current time slot in the network and δ_{ev}^{tra} represents the extra traveling time period.

C. Problem Formulation

The problem we aim to solve is to find an efficient swapping scheduling scheme, which can minimize the average time for each particular type of EV that has to wait for BS during its trip. To facilitate such problem formulation, we have the following notations:

- ω_l: the average time for each vehicle to wait for swapping at BSS station l, including the time period that the vehicle has to wait for a battery to become available (termed as queuing time) and the time duration to switch a battery (defined as swapping time ρ_{sw}).
- Λ_{bss}: the set of BSS stations in the network.
- ν_l: flow of vehicles that arrive at station l.

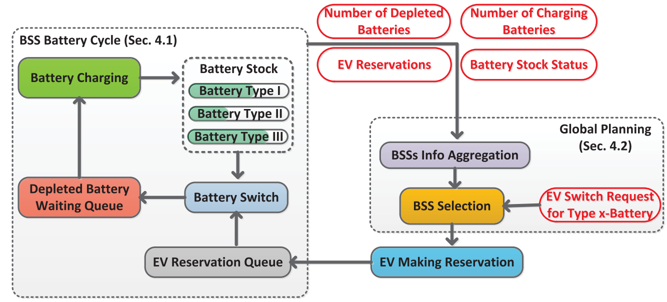


Fig. 3. Operational framework of the heterogeneous BS service.

- W: overall waiting time for BS of all vehicles in the network.

The problem is then formulated as follows:

$$\text{minimize } W = \sum_{l \in \Lambda_{bss}} \nu_l \cdot \omega_l \tag{2}$$

According to [12], the overall waiting time is minimized if plug-in charging demands are balanced among all charging stations. Similarly in a BS case, the value of (W) is minimized if swapping demands (ν_l) are balanced across all BSSs (Λ_{bss}). However, the uniform balancing is difficult or even impossible to achieve in practice considering the complex city scenario, which requires costly orchestration among all network entities. Hence, a more practical approach is to achieve local optimization for each system entity. Therefore, by accounting for swapping demand for each EV, the problem of Eq. (2) becomes

$$\arg\min_{l \in \Lambda_{bss}} \omega_l := \{l | l \in \Lambda_{bss} \wedge \forall i \in \Lambda_{bss} : \omega_i \geq \omega_l\} \tag{3}$$

Here, while the time to switch a battery (denoted as ρ_{sw}) plays a role in the waiting time ω_l, it is the queuing time that finally governs the value of ω_l. This is attributed to the fact that the swapping time only takes several minutes in general, which can be treated as a constant among all BSSs, compared to varied time for queuing at different BSSs that can take much longer time. Therefore, our focus is to find an optimal BSS to minimize the vehicles queuing time, which will be discussed in detail in the next section.

IV. HETEROGENEOUS BSS-SELECTION CONCERNING BS RESERVATIONS

Next we present our configuration logics toward this issue concerning the details of EV battery swapping management with heterogeneous BS demand. Fig. 4 depicts such operational framework with two main functions involved: the *BSS battery cycle* and the *global planning process*.

A. BSS Battery Cycle

Each BSS manages the cycling of EV batteries with multi-types as shown in Fig. 4. Typically, with batteries cycled from discharged state to charged state, the BS service can be effectively managed, which basically includes two phases: the **switch phase** (Algorithm 1) and the **charging phase** (Algorithm 2).

Algorithm 1: Battery Switch at BSS.

1: **for** each EV parked at BSS **do**
2:   **if** ($N_B^X > 0 \&\& X \in B_{ev}$) **then**
3:     start to switch a battery of type (B_{ev}) for EV
4:   **else**
5:     wait until a battery of type (B_{ev}) becomes available
6:   **end if**
7:   **if** a fully recharged battery is switched in duration ρ_{sw} **then**
8:     $N_B^X = N_B^X - 1$, where $X \in B_{ev}$
9:     included depleted battery from EV into the queue of N_D^X, $X \in B_{ev}$
10:   **end if**
11: **end for**

Algorithm 2: Battery Charging at BSS.

1: **for** each interval σ **do**
2:   **while** ($N_C < \theta$) **do**
3:     sort the queue of N_D according to STCF
4:     schedule a depleted battery from the queue of N_D
5:   **end while**
6:   **for** ($i = 1; i \leq N_C; i++$) **do**
7:     **while** ($E^{cur}_{X_{(i)}} < E^{max}_{X_{(i)}}$) **do**
8:       $E^{cur}_{X_{(i)}} = E^{cur}_{X_{(i)}} + \alpha \cdot \sigma$
9:     **end while**
10:     remove this battery from the queue of N_D, N_C
11:     $N_B^X = N_B^X + 1$
12:   **end for**
13: **end for**

1) Switch Phase: Upon arrival at the BSS, the incoming flow of EVs in need of BS is managed as the following process.

- If the required battery type is readily available at the selected BSS, given by ($N_B^X > 0$, $X \in B_{ev}$), the vehicle will be switched straightaway with a fully-charged spare (line 2 to 3 in Algorithm 1).
- Often, the vehicle may have to wait at the BSS until a recharging battery of the specific type is finished, due to non-available batteries ($N_B^X = 0$, $X \in B_{ev}$), as presented in Algorithm 1 from line 4 to 6. In this case, the switch service discipline follows the first come first serve (FCFS) order to regulate the switch behaviors of the vehicles.

Here after the switch duration of ρ_{sw}, the number N_B^X is reduced by 1 for battery type $X \in B_{ev}$ (line 7 to 8 in Algorithm 1), while the drained battery is included into the depleted battery queue (N_D^X) waiting for recharging (line 9 in Algorithm 1).

2) Charging Phase: All depleted batteries removed from vehicles will be recharged in parallel via a number of charging slots (θ), depending on the condition $N_C < \theta$ (line 2 in Algorithm 2). Once a battery is fully charged, the switchable batteries (N_B^X) will be added by one depending on different battery types. Meanwhile, a drained battery will be scheduled from the line of drained batteries (N_D) into recharging queue (N_C) (line 4 in Algorithm 2). The charging service discipline follows the Shortest Time Charge First (STCF) order, whereby the drained battery with the shortest charging time will be associated with the highest priority. The STCF is proved to achieve the best performance gains according to [20].

From line 6 in Algorithm 2, for each battery in the recharging queue of N_C^X, it will be charged with per time interval σ at the charging power of α (line 8). Once a depleted battery is recharged depending on if $E^{cur}_{X_{(i)}} = E^{max}_{X_{(i)}}$, it is added to the battery stock, and corresponding information is removed from the queue of N_D and N_C (line 10).

B. Global Planning Phase

Here, the BSS-selection logics are performed at the CA side, by accounting for EV reservations as well as BS service availability across the network. The *Expected Waiting time for Switch* (EWS) (i.e., ω_l) at a BSS is estimated by following conclusions from Eq. (3), so as to reduce the service time for individual drivers.

Further considering the issues of load balancing across BSSs, we thus have the following

- Upon a switch request from a vehicle EV (e.g., ev_r) with the battery type of B_{ev}, the CA first considers the BSS with the maximum number of $N_B^X > 0$, $X \in B_{ev}$ from all BSSs.
- If none of BSSs holds the type of batteries readily available, the one with the minimum value of EWS is selected following Eq. (3).

A key factor that contributes to the computation of EWS is the *available time for switch* (ATS) of batteries maintained at a BSS. A simple way to achieve ATS is executed as below.

- Based on the charging status at *local* BSS, i.e., on-going charging sessions and the queue of depleted batteries in the waiting zone, the ATS can be obtained. Such estimation is easy to achieve.

However, since estimations are generally made while EVs on-the-move, the actual situation at a station could become quite different upon the arrivals of vehicles. Therefore, the accuracy of the estimation on ATS requires more sophisticated executions. As such, the estimation on ATS can thus be refined as below.

- By additionally accounting for EV swapping *reservations*, including context like $< ev_{id}, B_{ev}, T^{arr}_{ev}, \delta^{cha}_{bat} >$, the future state at a BSS can be accurately approximated.

The process for the above estimation is detailed in Algorithm 3 as the **basic mode** (local concerns only) and in Algorithm 4 as the **advanced mode**(reservation concerns), respectively.

1) Basic Mode of Estimation on ATS: Algorithm 3 details the prediction of ATS in a basic mode solely based on local conditions: the charging queue (N_C^X) and the waiting queue (N_D^X) of discharged battery. Considering the battery heterogeneity, the available time is estimated based on different types X ($X \in \Psi$).

For each type of battery (line 1 in Algorithm 3), i.e., $X \in \Psi$, Algorithm 3 starts from the on-going charging queue of N_C^X, wherein the charging duration $\frac{E^{max}_{X_{(i)}} - E^{cur}_{X_{(i)}}}{\alpha}$ is summated to the current network time T_{cur} (line 3). The summation is considered

Algorithm 3: Estimation of ATS - Basic Mode.

1: **for** each battery type $X \in \Psi$ **do**
2:   **for** $(i = 1; i \le N_c^X; i++)$ **do**
3:     add $\left(\frac{E^{max}_{X_{(i)}} - E^{cur}_{X_{(i)}}}{\alpha} + T_{cur}\right)$ into list $ATSLIST_X$
4:     add $\left(\frac{E^{max}_{X_{(i)}} - E^{cur}_{X_{(i)}}}{\alpha} + T_{cur}\right)$ into temp list $TLIST_X$
5:   **end for**
6:   sort $ATSLIST_X$ with ascending order
7:   **if** $(N_D^X = 0)$ **then**
8:     **return** $ATSLIST_X$
9:   **else**
10:     sort the queue of N_D^X according to STCF
11:     **for** $(j = 1; j \le N_D^X; j++)$ **do**
12:       sort $TLIST_X$ with ascending order
13:       $T_j^{fin} = \left(TLIST_x.get(0) + \frac{E^{max}_{X_{(j)}} - E^{cur}_{X_{(j)}}}{\alpha}\right)$
14:       replace $TLIST_X.get(0)$ with T_j^{fin}
15:       add T_j^{fin} into $ATSLIST_X$
16:     **end for**
17:     **return** $ATSLIST_X$
18:   **end if**
19: **end for**

as the charging finish time for a battery, which is then included into the $ATSLIST_X$ and the $TLIST_X$.

Here the values added to the list of $ATSLIST_X$ is yet to be taken as the complete available times for switchable batteries, depending on the condition of N_D^X.

- If there are no batteries with type $X \in \Psi$ waiting for charging, in terms of $N_D^X = 0$ (line 7 in Algorithm 3), the $ATSLIST_X$ will be returned right away.
- Otherwise, the waiting queue (N_D^X) needs to be taken into account to complete list $ATSLIST_X$.

In the latter case, the queue (N_D^X) is sorted according to the STCF charging discipline (line 10). The STCF policy has been investigated as solution to fast feed depleted battery [20], and maintain a fast operation loop for charging and switch. A loop then operates to sort the $TLIST_X$ in an ascending order (line 12). Since the $TLIST_X$ is initiated with charging finish times of (N_C^X), the first value from the sorted list refers to the earliest time that a charging slot becomes available. As such, the charging start time to recharge a depleted battery from the queue N_D^X is obtained as $TLIST_X.get(0)$. Along with the charging duration, the summation of ($TLIST_X.get(0) + \frac{E^{max}_{X_{(j)}} - E^{cur}_{X_{(j)}}}{\alpha}$) is computed as the time T_j^{fin} to finish charging a drained battery from the queue (N_D^X) (line 13). Within each loop (line 11 to line 16), $TLIST_X.get(0)$ will be replaced by T_j^{fin} to update the on-going charging sessions ($TLIST_X$). Meanwhile, T_j^{fin} is included into the $ATSLIST_X$ (line 15). And the loop continues until all batteries from (N_D^X) is processed, and the $ATSLIST_X$ is then returned for each battery type X.

Algorithm 4: Estimation of ATS - Advanced Mode.

1: **for** each battery type $X \in \Psi$ **do**
2:   sort $ATSLIST_X$ returned by Algorithm 3, with ascending order
3:   define $TLIST_X$, $N^X_{B_{(E)}} = N^X_B$
4:   sort the queue of N_R^X according to FCFS
5:   **for** $(k = 1; k \le N_R^X; k++)$ **do**
6:     **if** $(T_k^{arr} < T^{arr}_{ev_{(r)}})$ **then**
7:       **for** $(i = 1; i \le |ATSLIST_X|; i++)$ **do**
8:         **if** $(T_i^{fin} < T_k^{arr})$ **then**
9:         $N^X_{B_{(E)}} = N^X_{B_{(E)}} + 1$
10:         delete T_i^{fin} from $ATSLIST_X$ and $TLIST_X$
11:         **end if**
12:       **end for**
13:       **if** $(|ATSLIST_X| \ge \theta)$ **then**
14:         **if** $(|TLIST_X| = 0)$ **then**
15:         include first θ elements T_i^{fin} into $TLIST_X$
16:         **end if**
17:         sort $TLIST_X$ with ascending order
18:         $T_k^{fin} = \left(TLIST_X.get(0) + \delta^{cha}_{bat_{(k)}} + \rho_{sw}\right)$
19:         replace the $TLIST_X.get(0)$ with T_k^{fin}
20:       **else**
21:         $T_k^{fin} = \left(T_k^{arr} + \delta^{cha}_{bat_{(k)}} + \rho_{sw}\right)$
22:         include T_k^{fin} into $TLIST_X$
23:         $N^X_{B_{(E)}} = N^X_{B_{(E)}} - 1$
24:       **end if**
25:       include T_k^{fin} into $ATSLIST_X$
26:     **end if**
27:   **end for**
28:   **for** $(j = 1; j \le |ATSLIST_X|; j++)$ **do**
29:     **if** $(T_j^{fin} < T^{arr}_{ev_{(r)}})$ **then**
30:       $N^X_{B_{(E)}} = N^X_{B_{(E)}} + 1$
31:     **end if**
32:   **end for**
33:   **return** $ATSLIST_X$
34: **end for**

2) Advanced Mode of Estimation on ATS: Upon Algorithm 3, Algorithm 4 further considers the BS reservation queue as defined by N_R^X, $X \in \Psi$. Given the vehicle requesting for BS, e.g., ev_r, any reservations made earlier than ev_r will be taken into account before computing the ATS upon the arrival of ev_r at a BSS. Further, the estimation on the number of switchable batteries for each type at a BSS can be obtained as well, as denoted by $N^X_{B_{(E)}}$.

For each type of battery, Algorithm 4 initially sorts the reservation queue (N_R^X) at line 4 according to FCFS order as discussed previously in the charging phase. Within the queue of N_R^X, the expected arrival time (T_k^{arr}) of each EV will be compared with the arrival time ($T_{ev_{(r)}} arr$) of ev_r. For each vehicle (EV_k) that arrives arrivals earlier than ev_r ($T_k^{arr} < T^{arr}_{ev_{(r)}}$), the $ATSLIST_X$ will be updated from line 7 in the following cases.

- The charging finish time (T_i^{fin}) of each battery from $ATSLIST_X$ is compared to the arrival time T_k^{arr}. If the charging finishes early ($T_i^{fin} < T_k^{arr}$), it implies that a battery will become switchable before the arrival of EV_k, leading to the increment of $N_{B_{(E)}}^X$ at line 9. As a result, the number of batteries being charged or waiting to be charged (as included in the $ATSLIST_X$) decreases, and the given value (T_i^{fin}) is then removed from $ATSLIST_X$ directly at line 10 (and also $TLIST_X$ initialized from line 15).
- Given by the condition ($|ATSLIST_X| \geq \theta$) at line 13, meaning the number of batteries being charged or waiting to be charged exceeds the number of charging slots (θ) at the BSS. In this case, the vehicle EV_k has to wait an additional time for a switchable battery. And the charging finish time (T_k^{fin}) of the battery from EV_k is thus given by at line 18 as the following.

$$T_k^{fin} = TLIST_X.get(0) + \delta_{bat_{(k)}}^{cha} + \rho_{sw} \tag{4}$$

  where the head value ($TLIST_X.get(0)$) from the sorted list $TLIST_X$ refers to the earliest time available for charging, $\delta_{bat_{(k)}}^{cha}$ is the charging duration to fully charge the battery according to Eq. 1, and ρ_{sw} implies the battery replacement duration.
- Otherwise if there are idle charging slots available (line 20), the EV_k will be directly switched with a fully charged battery without waiting, and T_k^{fin} then is given as

$$T_k^{fin} = T_k^{arr} + \delta_{bat_{(k)}}^{cha} + \rho_{sw} \tag{5}$$

Therefore, the availability in switchable batteries decreases by one at line 23 due to the replacement. Toward this end, the updated charging finish time (T_k^{fin}) will be included into $ATSLIST_X$ at line 25.

Note the loop repeats for each type of battery until all vehicles (EV_k) from $N_R^X, X \in \Psi$ is processed given by the condition $T_k^{arr} < T_{ev_{(r)}}^{arr}$, and then the $ATSLIST_X$ is updated. Then, $T_{ev_{(r)}}^{arr}$ is compared to T_j^{fin} from $ATSLIST_X$ (line 28). If the condition ($T_j^{fin} < T_{ev_{(r)}}^{arr}$) holds, one more battery will become switchable before the arrival of ev_r (line 30). Finally, the updated list $ATSLIST_X$ is returned. In addition, the temporary list $TLIST_X$ helps to update charging times for batteries under charging in the whole process.

3) Estimation on Expected Waiting Time for Switch (EWS): Based on Algorithm 4, we can finally estimate the waiting time for switch at a BSS upon the arrival of vehicle ev_r, which is illustrated in Algorithm 5.

- If there are batteries of the required type available ($X \in B_{ev}$) at BSS, given by $N_{B_{(E)}}^X > 0$, the vehicle ev_r can be switched to a fully charged battery directly without waiting. Therefore, EWS can be obtained as 0;
- Otherwise, the vehicle has to wait a duration of ($ATSLISTX.get(0) - T_{ev_{(r)}}^{arr}$) for a switchable battery. And thus the EWS is returned as $ATSLISTX.get(0) - T_{ev_{(r)}}^{arr} + \rho_{sw}$, with a time duration of ρ_{sw} for battery switch.

Algorithm 5: Estimation of Expected Waiting Time for Switch.

sort $ATSLIST_X$ returned by Algorithm 4, with ascending order
obtain $N_{B_{(E)}}^X$, $X \in B_{ev}$ from Algorithm 4
if ($N_{B_{(E)}}^X > 0$ && $X \in B_{ev}$) **then**
  return $EWS = 0$
else
  return $EWS = (ATSLISTX.get(0) - T_{ev_{(r)}}^{arr} + \rho_{sw})$
end if

C. Discussion

1) Reservation Randomness Concern: As discussed previously, when a BSS-selection decision is made, the EV will confirm the recommendation by reporting a reservation to the CA, which includes information such as $< ev_{id}, B_{ev}, T_{ev}^{arr}, \delta_{bat}^{cha} >$. However, compared to static context like vehicle ids or battery types, the expected arrival times can be quite random. Considering dynamics on road traffic situations [14], e.g., traffic jams, EVs arrivals at a BSS can be unpredictable subject to the EV mobility uncertainty. As such, it is imperative to update EVs reservations at the CA periodically, such that a cancellation or revision on a swap reservation can be predicted. This way, the accuracy on the available time for switch can be greatly improved.

2) Privacy Concern: In a centralized mode, the BSS-selection is performed by a global controller CA as presented in Section III-A. Since EVs have to release their status information (e.g., IDs and locations) to CA for BSS-selection decision making, this can raise the privacy issue, however. One solution is to find a trustworthy third party by both sides (EVs and BSSs) to play the role of CA, which can be implemented as a cloud server from a reliable platform. Furthermore, the privacy-sensitive information can be encrypted by leveraging related techniques, such as pseudonym, to hide the EV locations and IDs. On the other hand, a decentralized manner requires less privacy-concerned information, by encouraging BSS-selection at EV side. Nevertheless, the accuracy regarding key information (e.g., BSS status and BS demand load) will become the concerned issue with such distributed approach. One possible solution is to enable a constant information exchange between network entities to improve the preciseness, which raises the communication cost concern, however.

3) Integration of BS and Plug-in Charging: Due to practicality concern, there could be the coexistence of BSSs as well as plug-in charging stations at current stage. As for EVs that require constant travelling (e.g., public transportation or taxies), they would like to choose the BS management due to short service time. With EVs belonging to private owners, a concern may arise that a brand new battery could be replaced by a used spare at a BSS. As such, plug-in charging is preferred in this case. The proposed communication framework (i.e., centralized mode) can be utilized by both services. For efficiency concern,

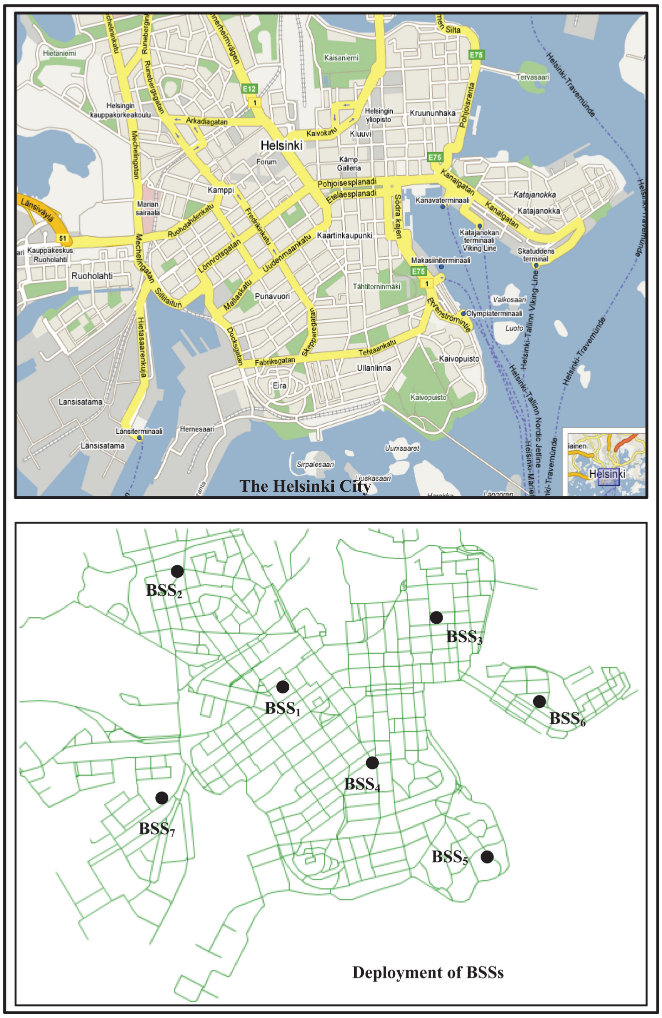


Fig. 4. Simulation Scenario of Helsinki city.

it requires to strategically provision services depending on various service preferences. Additionally, profiles related to travel history collected from practice are also important to manage the inter-play of these two different charging services. The research work regarding this issue will be left to our future work.

V. Performance Evaluation

A. Simulation Configuration

We have built up an EV battery swapping system in Opportunistic Network Environment (ONE) [29]. As shown in Fig. 5-A, the scenario is with 4500×3400 m^2 area based on the downtown area of Helsinki city in Finland abstracted from Google map.

There are 300 EVs on-the-move initialized in the network, with variable speed ranging from [30∼50] km/h. The destination of each EV route is randomly selected from the map, and a new spot is chosen once the current destination is reached. An EV will require a BS service once the SOC reaches the threshold. All routes are formed based on the shortest path feature considering the actual Helsinki road topology. The setting of EVs follows the charging specification {Maximum Electricity Capacity, Max Traveling Distance, SOC threshold}. Three types of EVs (or types of batteries) are configured in this work as below, each of which is allocated with equalized amount of vehicles.

- Type I: Coda Automotive [30] {33.8 kWh, 193 km, 30%}
- Type II: Wheego whip [31] {30 kWh, 161 km, 40%}
- Type III: Hyundai BlueOn [32] {16.4 kWh, 140 km, 50%}

A total of 7 BSSs are deployed with sufficient electricity energy. Each BSS maintains three types of batteries, i.e., $\Psi = \{I, II, III\}$, and initially holds $N_B^X = 10$ batteries (fully charged) for each type, i.e., $X \in \Psi$. Up to $\theta = 30$ of depleted batteries (removed from EVs) are able to be charged in a row at a BSS, by a charging power of $\alpha = 10$ kW. Battery switch time is set to $\rho_{sw} = 5$ minutes. The simulation time represents a duration of 12 hours, with $\sigma = 0.1$ seconds of resolution for network update interval.

The following schemes are implemented for comparisons:

- *Basic-BS:* The proposed heterogeneous BSS-selection scheme without bringing EV reservations. The estimation on waiting time is computed according to the basic mode from Algorithm 3, and the battery availability can be estimated based on local conditions as presented in [20].
- *Reservation-BS:* The proposed heterogeneous BSS-selection scheme based on Algorithm 4, with EV reservations enabled.
- *MQT-Plug-in:* The CS-selection scheme under plug-in charging mode [9], based on minimum queuing time.
- *Reservation-Plug-in:* The plug-in charging based CS-selection with reservations enabled, as presented in [11].

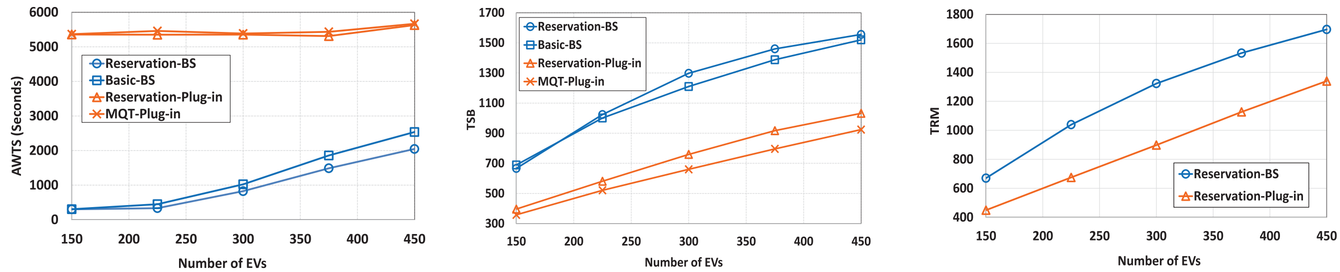
The performance metrics below are evaluated:

- *Average waiting time for switch (AWTS):* The average time duration for an EV to spend at the selected BSS, including the waiting time for switch and the switch duration.
- *Totally switched batteries (TSB):* The total number of EVs that have been replaced with fully-charged batteries at BSSs.
- *Total reservations making (TRM):* The communication cost over cellular network for BS service booking.

B. Impact of EV Density

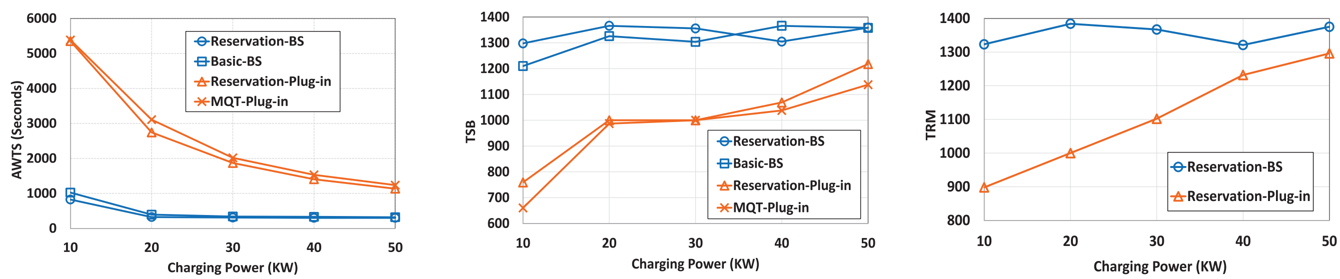
As shown in Fig. 5(a) and (b), the BS scheme outperforms the plug-in charging scheme significantly. For the vehicle density at 150 initially, the AWTS can be reduced by more than 90% under the Reservation-BS, as compared to traditional MQT-Plug-in. As observed, an increased AWTS is experienced by all schemes, with the increment on EV density. The rational is basically due to potential congestions that happen at local stations. As such, vehicles have to queue up and wait longer time, while the availability of a battery (or charging slot) is becoming less.

In particular, the trend under the plugin charging mode seems to be less affected by the increased EV density, in comparison to the rising pattern under the BS mode. This is because of the battery variety with BS services as concerned in this work. While EVs in plugin-charging mode are charged up regardless of EV (or battery) types, an vehicle needs to be swapped with a particular type of battery under the heterogeneous BS mode. With limited battery stock for each type, the AWTS would



(a) (b) (c)

Fig. 5. Impact of EV density: (a) AWTS (b) TSB (c) TRM.



(a) (b) (c)

Fig. 6. Impact of charging power: (a) AWTS (b) TSB (c) TRM

be influenced more, especially with the dynamically moving patterns of EVs.

As shown in Fig. 5(a), due to limited charging slots at BSSs, there is a slight increase of AWTS under the BS mode with more EV arrivals. With the increment of EVs, more depleted batteries are removed from vehicles and readily available batteries are running out at BSSs. The cycling of batteries is then triggered at stations. And thus the average waiting time for a switchable battery continues to increase with EVs constantly arriving. As noticed, performances are especially improved (in terms of short AWTS and TSB) if reservations enabled, further enhanced by enabling a joint concern on estimations of available batteries as well as time to wait for switchable spares.

Intuitively, the totally switched batteries are growing with more vehicles requiring BS services. And the number will be improved more if a short AWTS can be achieved. As such, similar trends and performance gains are shown in Fig. 5(b) in comparison to Fig. 5(a).

In Fig. 5(c), the TRM continues to grow with the density of EVs. This is mainly owing to the centralized mode fashion, since all queries and reservations from vehicles are reported to the central controller for BSS-selection decision-making. As observed, there are slightly more frequent communications under the Reservation-BS scheme against the Reservation-Plug-in scheme. The rational is that EVs can be quickly swapped to fully-charged battery spares under a BS scenario, and begin on-the-move again. As such, more vehicles will return to road and continue their journey under the BS mode. Again, these EVs will report reservations for BS (or recharging) services, which would surpass the number of reports under a plug-in case. However, such communication overhead could be alleviated if partial queries could be offloaded, e.g., onto road side unites or neighboring vehicles.

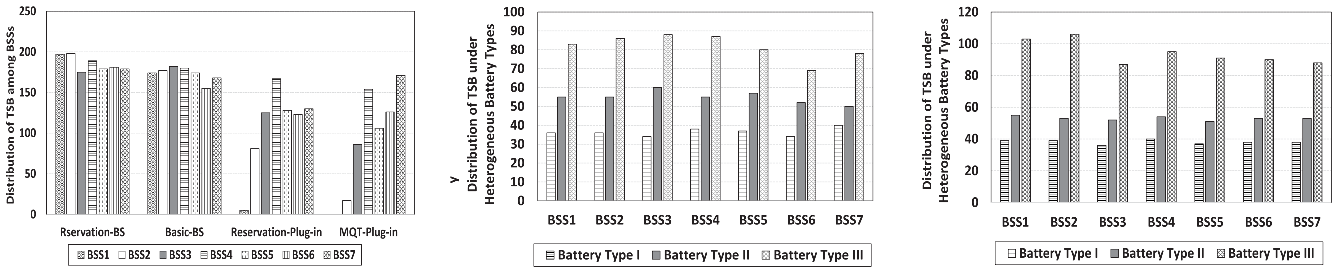
C. *Impact of Charging Power*

Here, the influence of charging power on specific performance metric is shown in Fig. 6. One immediate advantage is to enable reservations, in terms of reduced AWTS and increased TSB as shown in Fig. 6(a) and (b), especially when charging power is low, i.e., under 30 kW. If the charging power is high enough (e.g., more than 30 kW in our settings), the benefits of reservations are not obvious. This implies that a fast charging service is able to serve EVs with desirable QoE, even without reservations-enabled. And for a BS case in particular, it is the swapping time that dominates AWTS (or TSB) under high charging powers, resulting in relatively stable AWTS trends.

From Fig. 6(c), we can see that the impact of charging power on TRM is subtle under a BS mode, while the influence is much more under a plug-in case. This indicates that under a BS scenario, the communication overhead will not be affected much over varied charging powers. It is an interesting observation, which can help to tackle the cost for frequent communications while the charging power does not have a play.

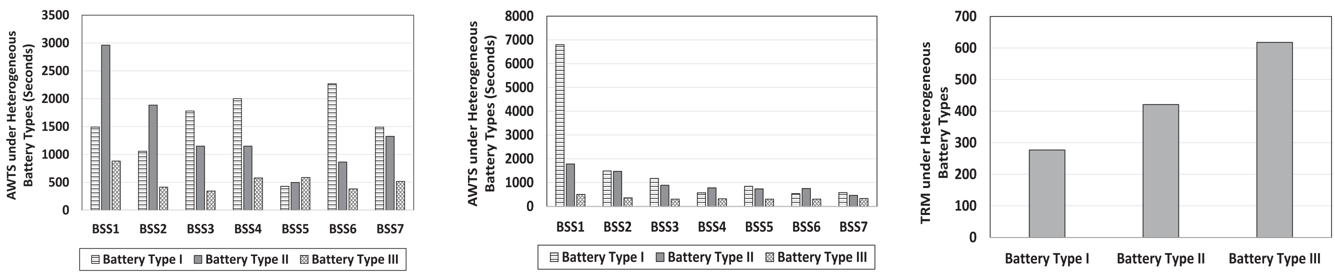
D. *Distribution of TSB among BSSs*

Fig. 5-D(a) shows the distribution of TSB (or charged EVs) among all stations under various schemes for comparison. Noticeably, the BS mode achieves the best load balancing, while the plug-in mode behaves in a skewed distribution over the network. According to the analysis as given in Eq. (3), there is a direct correlation between the load balancing and service experiences



(a) (b) (c)

Fig. 7. Distribution of TSB among BSSs: (a) under different schemes, (b) heterogeneous battery distribution under Basic-BS mode, and (c) heterogeneous battery distribution under Reservation-BS mode.



(a) (b) (c)

Fig. 8. Performances under Battery Type Level: (a) AWTS under Basic-BS mode, (b) AWTS under Reservation-BS mode, and (c) TRM under Reservation-BS mode

in terms of waiting times. And results from Fig. 5-D(a) provides a more direct explanation of such relationship, along with previous evaluations of Fig. 5(a) and Fig. 6(a).

As for the TSB distribution related to battery heterogeneity, Fig. 5-D(b) further shows the distribution of TSB for each battery type at every BSS under a basic-BS scheme. As observed, the TSB values for each type of battery achieves a relatively balanced distribution among the network. This implies that the diversity of battery stock across the network can be effectively managed. As noticed, at each BSS, the TSB values are different for each battery type, with battery type III accounts for the most demand. Such differences are closely associated with various SOC values. EVs assigned with high SOC values generally suffer from short driving ranges and thus, they require more frequent BS services.

Further considering BS reservations, Fig. 5-D(c) shows the distribution of TSB for each battery type over the network. Similarly to Fig. 5-D(b), a desirable balancing is achieved, while more readily switchable batteries can be maintained at each station. This is mainly benefitted from the joint concern on AWTS and TSB for BSS selection.

E. Performances Under Battery Type Level

As for performances considering battery heterogeneity, Fig. 5-E further shows AWTS and TRM on the basis of battery type-level. Not surprisingly, with reservation-enabled, each type of EVs suffers from less waiting times at BSSs as compared to the Basic-BS mode in Fig. 5-E(a). As noticed, EVs of type I still have to wait relatively long period especially at BSS 1 as shown in Fig. 5-E(b), which implies that BSS 1 is highly concentrated with type-I vehicles. However, for the rest of BSSs, each type of EVs enjoys relatively balanced AWTS under the Reservation-BS mode. As observed from Fig. 5-E(a) and (b), EVs of type I suffer from longer waiting times, while type III EVs enjoy the least. This implies that more EVs of type III can receive BS services, which is in accordance with the results in Fig. 5-D(b) and (c), where more EVs of type III can be replaced with full-charged batteries. Such relationship further proves the effectiveness of the proposed scheme.

Fig. 5-E(c) shows the TRM for each battery type under the Reservation-BS mode. Intuitively, EVs of type-III make more frequent reservations for BS services as compared to other types, while type-III EVs report the least BS reservations. Based on previous evaluations, EVs of type-III receives the most BS services while enjoying the least AWTS, and thus more vehicles of this type will become in motion again. In other words, they are more likely to run out of energy once more. Therefore, a new round of BS services is in demand, which would incur more frequent reports for BS service reservations.

VI. Conclusion

In this paper, we introduce battery heterogeneity into the swapping service, in terms of various EV battery types. In order to facilitate the intelligent BS station-selection concerning such practical concern, a battery heterogeneity-based swapping service framework is then proposed. The proposed scheme is further enhanced with reservations for efficient swapping services, such that the demand load for a particular battery type can be anticipated at a particular BS station. A series of simulation studies are executed to evaluate the viability of the proposed framework. By comparing to other benchmarks, results show the viability of the proposed scheme for determining an optimal BSS-selection. In particular, the swapping load can be well balanced over the network based on the proposed framework. Meanwhile, the diversity of battery stock across the network is able to be effectively maintained for achieving an optimal E-Mobility system.

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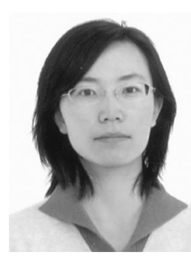

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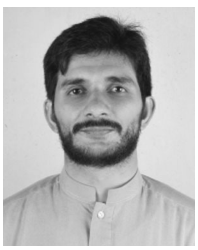

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