A Survey of Battery Swapping Stations for Electric Vehicles: Operation Modes and Decision Scenarios

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***Abstract*— The population of electric vehicles (EVs) has grown rapidly over the past decade due to the development of EV technologies, battery materials, charger facilities, and public charging services. Many governments have implemented plans to ban fossil fuel vehicles considering the significance of EVs in reducing greenhouse gas emissions. However, due to the battery material characteristics and charger power limitations, the EV charging process requires more time than is needed to fill a non-EV with fuel at a gasoline station, causing drivers to experience range anxiety and impeding the promotion of EVs. Hence, the battery swapping station (BSS) model has been proposed as an alternative method. Recently, researchers have studied the BSS approach by proposing various operation systems and optimization methods, and BSS service operators have successfully implemented swapping at commercial and private stations. This paper reviews the state-of-the-art BSS literature and business models, where the BSS offers a recharged battery to an incoming EV with a low state-of-charge. First, four operation modes are presented: a single BSS, multiple BSSs, an integrated BSS and battery charging station (BCS), and multiple BSSs and BCSs. Then, the BSS decision scenarios are surveyed in relation to five operational areas, i.e., charging schedule, service policy, construction and planning, dispatching and routing, and power management, where the scenarios are compared in terms of the BSS mode, decision maker, EV category, number of battery types, vehicle to grid, and focus and objective. Finally, the survey concludes with a discussion of several future research directions for EV BSSs.**

***Index Terms*— Battery swapping stations, electric vehicles, operation modes, decision scenarios, transportation.**

I. Introduction

ELECTRIC vehicles (EVs) have developed rapidly over the past decade, and by the end of 2019, the EV population had grown to 7.2 million globally, compared with only 17,000 in 2010 [1]. It is widely recognized that the planet is facing increasing risks from carbon emissions and oil supply shortages. Substituting EVs for internal combustion engine vehicles can enhance energy diversification, reduce greenhouse gas emissions, and significantly improve air quality.

From 2016 to 2018, the yearly growth in EVs was above 30%, but the growth rate in 2019 was only 6% given a contracted car market, a reduction in purchase subsidies, and consumer expectations regarding further technology improvements and new models. The promotion of EVs is restricted owing to the high purchase fees [2]–[4], battery degradation [5], long charging time [6], [7], inconvenient charging facilities [8], and limited traveling distance per charge [9], [10]. Hence, researchers have proposed battery charging station (BCS) models to optimize the charging process [11]–[13], improve operation services [14], and maximize business profits [15]. The material characteristics of batteries and the charging technologies mean that the above optimized BCS models cannot reduce the charging time, which also results in queuing for charging and range anxiety among EV drivers. Hence, the battery swapping station (BSS) model was proposed as an alternative method for providing energy to EVs. Using the BSS model, an EV owner can drive to a nearby BSS and swap out his/her battery with a low state-of-charge (SOC) for a fully recharged battery in a few minutes, which is comparable to filling a vehicle with fuel at a gasoline station.

Considering the benefits of the BSS model, many business providers worldwide are offering swapping services. In March 2011, the Better Place network deployed the first modern commercial BSS in Israel and Denmark, although the operator filed for bankruptcy in May 2013 due to business failure. Tesla is another provider that has offered battery swapping services since June 2013; Tesla deployed its first BSS along Interstate 5 in California between San Francisco and Los Angeles, which is the most common route taken by Model S sedan drivers. However, in June 2015, Elon Musk indicated that Tesla would abandon its BSS plan because only a few people were willing to use swapping services. The failures of Better Place and Tesla occurred for the following reasons.

- The number of battery-powered EVs in 2013 was 0.22 million, which is only 4.59% of the EV population in 2019 [1]. BSS services were not sustainable considering the low swapping demand and expensive construction costs.
- Most EV drivers in the USA install private charging piles at home, and they prefer to charge overnight at a lower electricity price [15]. Hence, the demand for BSSs is limited.
- Drivers' demand patterns in the USA and Israel show that they usually use EVs for traveling short distances and drive fossil fuel vehicles for long trips [16].
- From 2011 to 2015, the battery swapping services offered by Tesla and Better Place were immature, and the battery

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properties, swapping fees, charging schedules, and battery maintenance were not fully investigated [17].

Due to the development of EV technology over the past five years, two BSS service providers in China have successfully implemented swapping stations. NIO, a Chinese automobile manufacturer, opened its first BSS in May 2018, with the number of NIO BSSs in China reaching 190 by March 2021. In addition, NIO announced its second-generation BSS equipped with 13 battery packs, which can serve 312 battery swaps per day. Aulton, a Chinese BSS service provider, provides swapping services for typical automakers and commercial EV operators and has opened more than 300 BSSs in China. Collaborating with automakers, Aulton builds BSSs for specific types of EVs and batteries and performs the swapping service considering the construction cost, battery purchase fee, and operating profit. The major service target of Aulton is electric taxis, which are sensitive to the charging time and prefer the BSS model. Compared with Better Place and Tesla, the NIO and Aulton offer BSS models with the following features.

- The EV population in China increased to 4.92 million at the end of 2020, and most of the EVs are registered in core cities. Hence, the target groups are considerably larger than those in the USA and Israel from 2011 to 2015 [1].
- In China's core cities, most residents live in apartments without private parking lots. Hence, drivers must rely on public charging and swapping services for power supply [18].
- With the promotion of BSS modes, the BSS service network is maturing in the transportation system, and EV drivers can reach nearby BSSs within an acceptable traveling distance (e.g., 5-10 km) [19].
- Advanced battery swapping services, such as battery renting, discount swapping fees and battery upgrade policies, were introduced by NIO to entice drivers to use BSS services [20].

With continuing EV trends, the BSS model is becoming an important method for providing EV energy and is an essential substitution for the BCS model. First, the rapid growth in the EV population affects the quality of service (QoS) of BCSs, while the BSS model can help to reduce service pressure and provide an alternative method for supplying energy. Second, in some specific operating scenarios, such as electric taxis, buses, and trucks, BSSs can reduce the charging time and improve the operating revenue. Third, the battery packs are charged and managed in a centralized BSS, which can help to improve battery health and reduce the charging cost by allowing an optimal schedule. Last, with the help of diverse service policies, the BSS model can help drivers reduce acquisition costs by allowing them to rent a battery pack from a service operator.

However, many challenges have been emerged as a result of the growing EV population, expensive initial BSS construction cost, long charging time for swapped batteries, and unwise operation and service models.

- Compared with the EV charging model, the BSS model has several drawbacks that impede its promotion. First, the battery pack should be designed for swapping purposes, which increases manufacturing costs and commonality. Second, battery heterogeneity should be considered in both the planning and operation stages to satisfy the diverse demands of EV drivers. Third, battery ownership is an important issue, as drivers want to know the state of health and capacity of different swapped batteries. Fourth, the construction cost of a BSS is much higher than that of a charging station, which affects large-scale BSS promotion. Last, there are no international standards on swapping stations and battery packs, which means that the current BSSs cannot be regularly used by EVs with different battery brands/types.
- From the perspective of the EV industry and transportation, the proportion of electric vehicles was only 1% of the global vehicle stock in 2019, and the EV population is still unquestionably increasing due to maturing technologies and governmental promotion policies [1], [21]. Hence, the number of swapping and charging stations will increase concurrently with the EV population, and optimal operation and service models are urgently needed.
- From the perspective of EV drivers, how to reach a nearby BSS to swap for a fully recharged battery is an important matter. In this case, the density of BSSs should be comparable to that of gasoline stations assuming that vehicles continue to transition from fuel oil to electric [22]. Additionally, the number of batteries at a BSS should be sufficient for swapping [23] to avoid driver queuing and limit the waiting time considering the long charging time required for swapped batteries.
- From the perspective of BSS operators, three optimization directions are considered: initial construction planning, charging process management, and EV swapping service response. First, the optimal location should be determined after considering the traffic flow, swapping demand, power load, etc. [24]. Due to the expensive purchase price of EV battery packages, the number of initial batteries for a new BSS is another important decision in construction planning [25]. Second, optimized charging process management models should be studied to adjust the amount of charging power used, which can balance the demand for recharged batteries and charging damages [23]. Third, considering the limited number of batteries at BSSs and the long charging time, some operators should use optimal service response systems to handle driver swapping requests [26].
- From the perspective of the power grid, the BSS is a crucial part of balancing the power load and optimizing the power sale profit. Considering the vehicle-to-grid (V2G) model, swapped batteries are owned by the BSS, and the grid can buy energy from the fully recharged batteries if the grid power load is low [27]. In the BSS operation model, each BSS must buy a large amount of energy from the power grid. The grid can also formulate corresponding policies for BSSs, including the varied/time-of-use electricity price [28], instant power limit [29], and accumulated electricity quantity [30], [31].

Therefore, optimization models for the power grid should be studied to support the BSS model.

Faced with these challenges, researchers have conducted several studies to address the research issue in BSS optimization models. However, to the best of our knowledge, few papers have reviewed research in the field of BSSs [32], [33]. Reference [32] presents an overview of the BSS system in terms of battery swapping techniques, followed by the benefits and challenges of BSS models. Compared with [32], this paper further systematically reviews the state-of-the-art BSS studies and classifies them based on the operation modes and decision scenarios. The detailed comparisons between [32] and this paper are illustrated as follows. First, reference [32] reviews the functioning of BSSs and their role in public transportation, but this paper focuses on how to define and build operation models. Second, reference [32] discusses how BSSs benefit public transportation, customers and power systems, which is discussed in Section I as the background in this paper. Third, this paper reviews recent works and classifies them into four operation modes and five decision scenarios, and it is the first paper in this area. Finally, reference [32] proposes a smart swapping station for xEV architecture as a cloud-integrated big-data-driven model, which includes the hybrid cloud, smart BSS and xEVs. In this paper, some new decision architectures are also discussed in Section IV, where a collaborative decision and flexible decision structure are suggested for future studies. In another BSS survey [33], the authors conducted an online survey to investigate the preferences and expectations of EV owners regarding BSS models. In contrast, this study first proposes a comprehensive survey of BSS models by studying the business mode and operation models of BSSs and BCSs.

Because of the limited BSS model surveys, the swapping models are analogized by reviewing the EV charging models in [27], [34]–[41]. Reference [27] proposed a survey of EV network deployment and management considering the energy flow, data communication, and computational aspects, with EV aggregators, charging scheduling, and V2G being deployed in the framework. In [34]–[36], the EV charging operation and schedule models are reviewed. Reference [34] reviews the scheduling algorithms for charging EVs in a smart grid, which are divided into unidirectional and bidirectional charging. The review also considers centralized and distributed charging, as well as mobility aspects. In [35], EV control charging strategies are reviewed using real-world data by classifying them into scheduling, clustering, and forecasting strategies. The mathematical modeling-based literature on EV operation is reviewed in [36], which classifies EV operation by recurring themes such as infrastructure planning, charging operations, and public policy and business models. Two surveys study the EV charging problem in terms of the algorithms for distributed charging control [37] and smart charging control [38]. In [39], a survey of economy-driven approaches for EV charging is proposed to consider unidirectional energy flows and bidirectional energy flows. Last, considering the innovative developments of the EV industry, a technological review of the EV standards, charging infrastructure, and grid impacts is presented in [40]. A comprehensive review of V2G technology is introduced in [41], which discusses the actors, business models, and innovation activity systems. Thus, compared with the plentiful EV charging model surveys, a thorough review of BSS models is urgently needed.

The contributions of this survey paper are summarized as follows.

- First, to the best of our knowledge, the number of survey papers on BSS systems is limited compared with those on the BCS system. Regarded as an important alternative method for providing energy to EVs, the BSS model has attracted the attention of scholars who propose various operation systems and optimization methods. Hence, this paper is the first to review the state-of-the-art EV BSS in terms of the mode definition and model formulation.
- Second, in BSS mode definition, most of the papers optimize the operation of a single BSS by maximizing the operation profit and minimizing the energy cost. However, with the development of BSS systems and EV technology, more complicated modes have been proposed by integrating multiple BSSs and BCSs. Hence, this paper first categorizes four modes of BSS operation systems in terms of different combinations of BSSs and BCSs, which cover most of the operation modes in the BSS literature.
- Third, some key characteristics of BSS and BCS operation models are summarized and compared in this paper. After that, this paper summarizes the BSS literature as encapsulated in five decision scenarios, and some of the specific focuses and objectives are discussed. By classifying the BSS scenarios, this survey helps readers and researchers understand the underlying decision scenarios, and the comparisons of model characteristics are illustrated in tables.
- Finally, based on a comprehensive survey of the BSS operation models and decision scenarios, four research directions are given considering the research gaps in this area. Specifically, twelve detailed directions are illustrated in terms of the extended BSS models, multiple scenarios, collaborative decisions, and flexible decision structure. Hence, the research directions could inspire researchers to further develop BSS operations.

This paper is organized as follows. Section II presents four BSS operation modes, and Section III describes five decision scenarios. Section IV summarizes several future research directions, and it is followed by the conclusions in Section V.

II. BSS Modes

In state-of-the-art EV charging studies, battery charging station and battery swapping station models are included to supplement energy for EVs. In BCS mode, EV drivers plug into the charging pile and recharge their battery for several hours. In BSS mode, EV drivers unload the used battery and replace it with a fully charged battery, which takes a shorter time (a few minutes). To understand the BSS operation models, the present investigation first focuses on the two types of stations (BSS/BCS) and the number of BSSs and BCSs in the business models; these can be classified into four modes considering different BSS and BCS combinations, i.e., a single BSS, multiple BSSs, an integrated BSS and BCS, and multiple BSSs and BCSs.

In this section, the procedure for each mode is introduced by explaining the EV flow, battery flow, and charging status with four flowcharts. Then, the operational challenges are discussed considering the mode characteristics. Finally, the modes are further investigated and compared in terms of the operation models in the next section.

A. Single BSS

Fig. 1 illustrates the basic operation mode of a single BSS, which is the most common business mode of existing commercial BSSs. The workflow is described as follows. First, when the state-of-charge (SOC) of a battery decreases, the EV driver sends a request to the BSS; if the request is accepted, the driver proceeds to the BSS. Second, the battery is swapped at the BSS and aggregated to the swapped battery batch. Third, if charging piles are available in the recharging center, the swapped battery is assigned to a charger for charging. Fourth, when the battery is fully charged or the termination criterion is satisfied, the battery is moved to the fully recharged battery batch to await future swapping. Last, the fully recharged battery is swapped for the battery of an incoming EV and leaves the BSS.

EV drivers can send a swapping request or walk into a nearby BSS, unload their used battery, receive a fully recharged battery, and leave the BSS. The whole swapping process takes only a few minutes, which is comparable to filling a vehicle up with fuel at a gasoline station. From the BSS perspective, there are two operating tasks involved: handling swapping requests from EV drivers and managing the charging process of the swapped batteries. Here, the BSS operation procedure requires the following problems to be solved:

1) Swapping Requests: In realistic BSS operations, there are two types of swapping requests based on whether the driver arrives with an appointment set in advance:

- Walk-in request: If an EV driver arrives at a BSS for swapping, the information (the actual arrival time, remaining SOC and battery type) is obtained by the BSS operator.
- Advance request: To optimize the swapping process and improve the quality of service (QoS), the BSS often asks EVs to send appointment requests prior to arrival. The request information often includes the expected arrival time, current SOC, distance to the BSS, and battery type.

Advanced requests can help a BSS optimize charging and swapping scheduling. Thus, incentive mechanisms are usually applied to the BSS service model, and BSS operators should be able to handle stochastic swapping requests.

2) Request Response: Given the swapping request information, the BSS operator can make an optimal decision regarding whether to accept or reject a request considering the subsequent swapping demands and the numbers of fully recharged batteries, queuing batteries, and recharging batteries.

3) Dynamic Decision: Even when advanced swapping requests are sent by EV drivers, their actual arrival times cannot be guaranteed. Therefore, a dynamic decision strategy is proposed to update the actual demand features and to determine the dynamic optimal decisions. In addition, some advanced technologies can help to increase demand accuracy, including global positioning systems and real-time communication in intelligent vehicles.

4) Charging Management: Compared with the BCS model, the battery charging time is transferred only from the EV side to the BSS side. In other words, the swapped batteries still need to be recharged for hours at the BSS. Charging management is crucial to the BSS mode for the following reasons.

- The batch of fully recharged batteries shown in Fig. 1 indicates the service availability of the BSS, which can be managed by adjusting the charging rate at the recharging center if an optimal charging schedule is obtained.
- The BSS operator has to manage the charging process considering the swapping demands from EV drivers, power constraints from the grid, operating costs, including the purchase of batteries and electricity from the grid, and battery degradation.
- Because the charging power of a lithium-ion battery follows nonlinear characteristics, it is difficult to estimate the exact final charging time. Some researchers have built nonlinear mathematical models to simulate the constant-current constant-voltage characteristics [42], and these can estimate the electricity quantity for each time slot and the time required to complete charging for different chargers.

5) Flexible SOC: In realistic BSS operation, a flexible SOC in battery swapping is viable under optimal charging management. First, the battery's target SOC can be specified by the driver in their personal request. Second, during busy service times, the BSS can serve batteries that are not fully recharged to minimize the waiting time, and drivers can obtain a discount as compensation [43]. Third, battery charging characteristics allow a constant current to be used to quickly recharge the battery from 0% to approximately 80%, and the charging power in the remaining stage is significantly lower [42]. Thus, a flexible SOC can help the BSS maximize its quality of service under optimal charging management.

6) Stock Battery Number: The most significant difference between the EV BCS and BSS models is the number of batteries. In the BCS model, the number of batteries is equivalent to the number of EVs, and the batteries themselves belong to the EV drivers. In the BSS model, the BSS needs to purchase initial batteries (stock batteries) for managing daily operation (15 batteries in Fig. 1), which is a high investment cost in the BSS construction and planning stage [23], [25].

7) Battery Heterogeneity: Another difference between the BCS and BSS models is the charging standard (charger facility and battery type). In the BCS model, there are mature international standards for charging ports and chargers, and all of the EVs can use the same chargers regardless of the vehicle brand and type. Thus, in most BCS models, the heterogeneity of EV/battery types is not considered. However, in the BSS model, there is no battery standard for different brands or even different types of EVs within the same brand. If a BSS aims to serve more than one type of EV, battery heterogeneity must be considered in the construction stage and scheduled

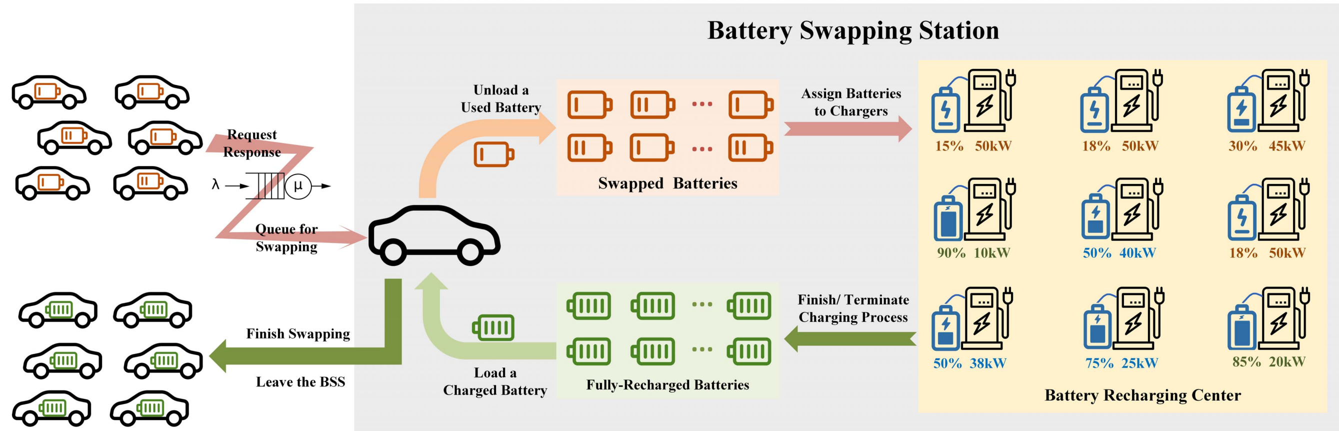

Fig. 1. Mode of Single BSS.

in the operating stage. Considering the high purchase cost and limited charging facilities, battery heterogeneity is another crucial factor to be investigated.

8) Dynamic Balance: As shown in Fig. 1, the BSS operation model aims to obtain a balanced decision regarding the batteries in the swapped batch, recharging center and fully recharged batch. The ideal scenario for a balanced BSS model is recharge-and-swap: when an EV arrives at the BSS, a battery is fully recharged concurrently and swapped for the battery in the EV directly without waiting for the fully recharged batch to have adequate resources, and then the swapped battery is assigned directly to an available charger. In this case, the swapped batch and fully recharged batches are always null. However, in real-world operation, achieving this balance is impractical considering the variation in EV swapping demands, which are subject to hours, traffic flow, and grid power constraints. Therefore, the majority of studies on single BSS optimization achieve a dynamic balance by suggesting reservations, forecasting uncertain demand, and optimizing the charging schedule at recharging centers.

The challenges of the BSS model are discussed and compared with those of the BCS model. The BSS model is not only a new operational problem but also a novel scheduling and optimization research topic considering uncertain swapping requests, optimal charging management, diverse battery types, and dynamic operational balance. Therefore, the single BSS mode is the basic module in the BSS operation system, and the subsequent modes in this section are integrations of multiple BSSs and BCSs.

B. Multiple BSSs

Fig. 2 shows the multiple BSS operation mode, which involves a control center, 11 swapping demands from EV drivers, and N candidate BSSs to be assigned. The multiple BSS mode workflow is described as follows. First, the drivers have three methods for starting a swapping order: request before arrival (one hour in advance), reserve (daily schedule), and walk in without an appointment. Second, after receiving the swapping orders from the EV driver and monitoring the battery condition at each BSS in real time, the control center determines a candidate BSS for the EV under predefined objective values and constraints. Then, the EV driver accepts the assignment and proceeds to the BSS for swapping or rejects the suggested BSS. Last, the BSSs and control center should communicate in real time to update the dynamic availability and battery queuing in each BSS. Some crucial problems should be emphasized in this multiple BSS mode.

1) Battery Availability: Fig. 2 illustrates an example of N swapping stations with different battery availability states. In BSS-1, the swapped batch and the fully charged batch are both full, and two chargers are available for the incoming swapped batteries. Therefore, BSS-1 has the highest availability for the next swapping order. In contrast, BSS-2 has no fully charged batteries for swapping, and there are many swapped batteries waiting to be recharged. Therefore, BSS-2 has the lowest availability compared with the other BSSs. In BSS-3, the swapped batch and fully charged batch are both empty, and 7 of 9 chargers are in use. In this case, the incoming EV needs to wait at the BSS until a battery is fully recharged. Last, the swapped batch and fully charged batch are both full in BSS-N, which means that the incoming EV can load a battery immediately, but the swapped battery needs to queue for recharging. Hence, the swapping orders in BSS-N can be satisfied, but the battery utilization is lower than that at the other stations.

2) Localization of BSSs: In the real-world multiple BSS mode, the BSSs are placed at different locations within a service region. Hence, determining the locations of the BSSs should be defined as an optimization problem, and some considerations should be investigated.

- First, in the construction and planning stage, the locations of multiple BSSs should be optimized based on the swapping demand, population density, and power system limits.
- Second, to support long-distance traveling, some BSSs can be located along the highway network, and the distance between two stations should be subject to the traveling distance per charge.
- Third, to establish a new BSS in a region, the swapping loads of the existing BSSs should be considered, with

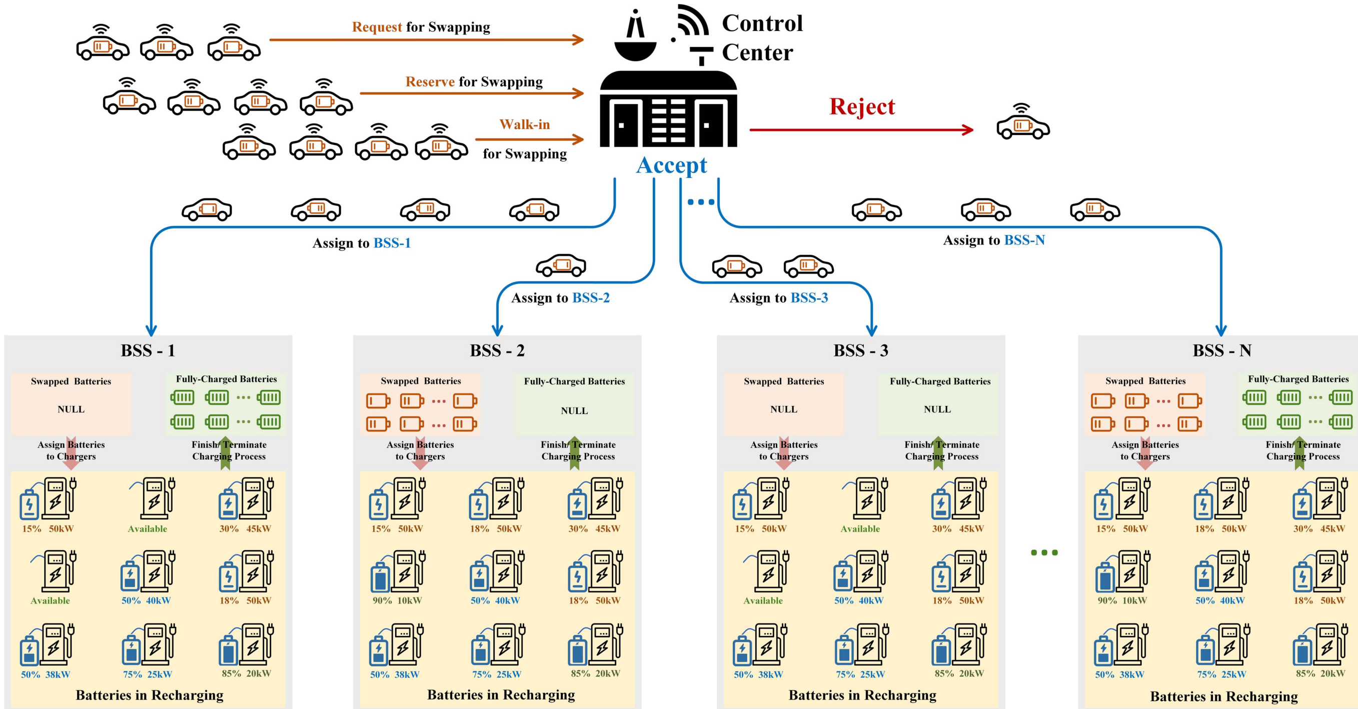

Fig. 2. Mode of Multiple BSSs.

the aim being to satisfy drivers' swapping demands and reduce the queuing problems in nearby BSSs.

3) Routes for the EV to the BSS: When EV drivers send swapping requests to the control center, the distances and travel times between the driver's current location and the BSS should be obtained. Due to traffic flow and traveling patterns, the uncertainty of appointment information should also be investigated as input to the decision model. In addition, the remaining SOC of an EV and the distance to the target BSSs are correlated because the EVs must reach the target BSS without exhausting their remaining energy. Hence, the remaining EV SOC and the distance to each BSS should be considered to be important constraints in the dispatching and routing problem.

4) Coordinated Decision: Different from the single BSS mode, the control center in the multiple BSS mode should optimize the decision by coordinating the demands from EV drivers and the battery statuses of the distributed BSSs. On the EV driver side, the control center can make a decision based on the current information and reply to the drivers for confirmation. If the assignment is not accepted, some coordination procedures should be negotiated by revising the expected arrival time or changing to another BSS. On the BSS side, the control center should monitor the battery status of each BSS and dynamically adjust the charging processes. Hence, in an intelligent BSS system, coordinated decisions are crucial to obtaining the optimal decision. In conclusion, the multiple BSS mode can be defined as a series of optimization problems, including a localization problem for planning multiple BSSs, a placement problem for new BSSs in a service region, a routing problem from the EV to the target BSS, and a scheduling problem for operating the charging process. To establish a novel multiple BSS mode, the previous problems can be considered and combined by building integrated multiobjective optimization models.

C. Integrated BSS and BCS

Fig. 3 presents the integrated mode with a BSS and a BCS operated by a control center. Different from the previous two BSS modes, a charging section is included, with 10 parking ports, 8 EVs in recharging mode, and 9 EVs in queuing mode. In this example, two types of chargers are presented: 6 fast chargers with a maximum power of 50 kW and 4 slow chargers with a maximum power of 25 kW. The BSS operation model is described in Section II-A with a fully recharged batch, a swapped batch, and a recharging batch. The control center is responsible for receiving demands from EV drivers, monitoring the BSS and BCS statuses in real time, determining a proper method (swap/charge) for EVs, and determining an optimal charging schedule for both BSSs and BCSs. In this section, the decision strategy of an integrated BSS and BCS station is defined as the combination of decentralized and centralized models: the decentralized models address swapping or charging requests separately; the centralized models obtain the decision (to swap or to charge) for an incoming EV based on the drivers' preferences and lower load in the integrated station. Some detailed features of the integrated BSS and BCS modes are presented in the following.

1) Decentralized Decision Models: The integrated BSS and BCS modes can be defined as two decentralized decision models that serve both swapping and charging orders, respectively. When an EV driver sends a request, they can specify whether they want to swap or recharge the battery. From the

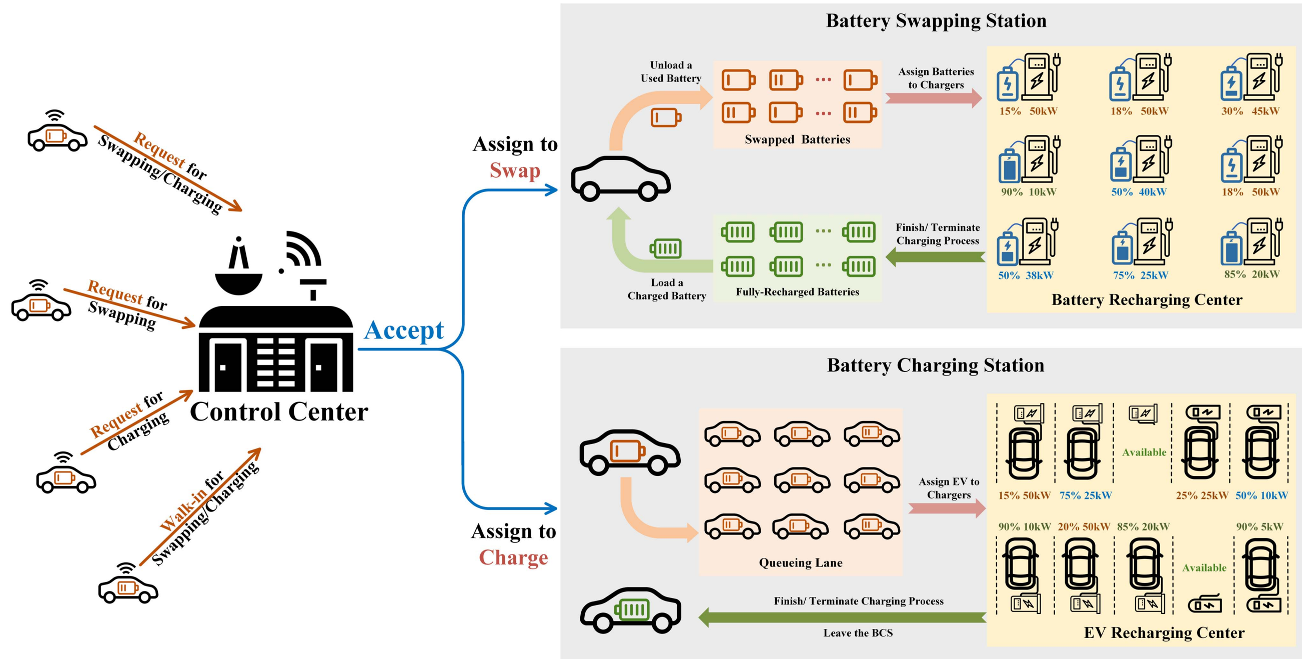

Fig. 3. Mode of Integrated BSS and BCS.

control center's perspective, two isolated decision models are defined to handle the swapping and charging requests, and they determine whether to accept or reject each request based on the dynamic loads at the BSS and BCS.

2) Centralized Decision Models: In contrast to the decentralized model, the integrated BSS and BCS station can also be defined as a centralized decision model, where the BSS and BCS are complementary, considering the order demands from EV drivers and the status of each station. There are two operating strategies in this centralized model.

- If an EV driver does not indicate the charging or swapping intent, the assignment is determined by the control center. Then, the dynamic number of batteries at the BSS and BCS are monitored by the control center, and the decision can be optimized based on the global condition.
- If the BSS is under a high load (the number of fully recharged batteries is low), some batteries can be recharged in EVs at the BCS and sent to the BSS after being fully recharged. Then, the interaction can be optimized based on the EVs' parking time at the BCS and the swapping load at the BSS.

The advantages of the integrated BSS and BCS models are discussed as follows. First, the control center handles the swapping and charging demands concurrently, which improves the quality of service for EV drivers. Second, the decision is optimized by assigning the swapping and charging processes, and then the global optimization objective can be obtained. Third, the control schedule for the recharging process in the BSS and BCS is optimized based on the demand and station status. Fourth, the control center is assumed to follow a decentralized decision model for handling incoming orders and can ask EV drivers to specify the preferred process, i.e., swap or charge. Last, with the use of the centralized strategies proposed in Section II-C2, the service capacity can be improved by coordinating the EVs in the BCS and the batteries in the BSS, which will improve the global QoS in the BSS and BCS modes.

D. Multiple BSSs and BCSs

Fig. 4 shows a comprehensive BSS operation mode with N BSSs and M BCSs with different swapping and charging loads. The control center acts as an aggregator, receiving demands from EV drivers and, knowing the status of each station, assigning drivers to the optimal BSS or BCS. In this mode, the BSSs and BCSs are distributed within a geographical region, such as downtown in a city or at a rest area on a freeway. Thus, the operation and localization models are comparable with the multiple BSS mode in Section II-B and the integrated BSS and BCS mode in Section II-C. Additional specific features of multiple BSSs and BCSs are discussed in the following.

1) Charging Availability: Fig. 4 illustrates an example with three BSSs with different charging loads. In BCS-1, the queuing lane is empty, and two charging piles are available for assignment. In BCS-2, all of the charging piles are occupied, and three EVs are in the waiting lanes. However, four EVs are charged beyond 90% SOC and will finish charging upon reaching their target SOCs. In contrast, in BCS-M, all piles are occupied, and the queuing lane has 8 EVs waiting to be recharged. When inquiring about the chargers' statuses, only 2 of the 10 EVs are almost recharged, and thus, the incoming EVs must wait for a longer time until the recharging processes are finished. Hence, BCS-1 has the highest availability for charging, while BCS-M has the lowest availability. Then, the control center assigns EVs to BCS-1 and BCS-2, and BCS-M is assigned when the queuing condition no longer exists.

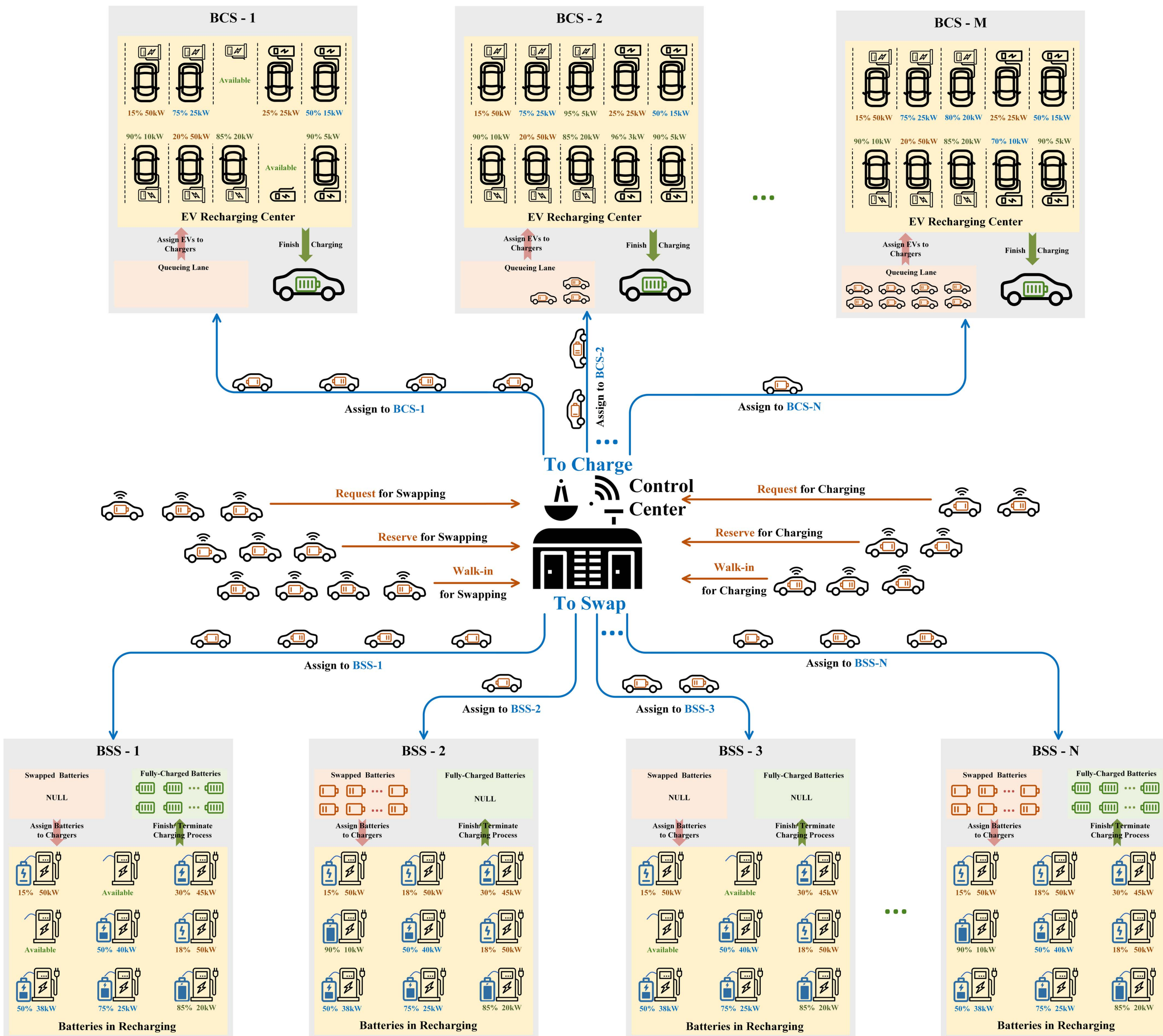

Fig. 4. Mode of Multiple BSSs and BCSs.

2) BSS and BCS Planning: Faced with the explosive growth in the EV population, BSS and BCS planning now draw more attention to urban planning, power grids, and business operators.

- From the perspective of urban planning, the demand for charging/swapping utility should be investigated by considering the EV distribution, road transportation, traffic conditions, and commercial/residential zones. Then, a new charging station can be constructed or upgraded from a traditional parking lot by installing charging facilities. New BSSs can also be planned in a region for serving commercial EVs, e.g., electric taxis, buses, and trucks, which have high-energy demand and rapid charging requirements.
- From the perspective of the power grid, the charging and swapping stations act as high-energy consumption units affecting voltage stability. Hence, when planning BSS or BCS locations, the power grid constraints should be considered. In addition, in terms of electricity trading, the BSS/BCS purchases electricity from the grid, charges batteries and EVs, and sells electricity to the drivers for profit. Therefore, electricity policy can be negotiated between the power grid and the station operator. Last, owing to V2G and battery-to-grid (B2G) technology, the BCS/BSS can sell electricity back to the grid, which results in earned profits for the BCS/BSS resulting from price variance and helps the grid maintain voltage stability.
- From the perspective of BSS/BCS operators, the aim is to make a profit by providing swapping/charging services to EV drivers. In the planning stage, the operators aim to find a place with high swapping/charging demand so that

they can maximize their operating profit. In contrast, their operating cost includes the station construction/building, charging facilities, and initial stock of batteries at the BSS, which can be minimized with intelligent optimization decision models. The station's operating profit can be maximized by increasing the charging demand and reducing planning costs.

3) Optimization Problems: Once the locations and facilities are determined (Section II-D2), the multiple BSS and BCS operation model can be defined as three types of optimization problems: a charge/swap assignment problem, a routing problem and a charging schedule problem.

- The first type of optimization problem assigns either the charge or swap service to the incoming EV based on its demand and station conditions. In Fig. 4, the availability of BSSs follows the order BSS-1, BSS-N, BSS-3, and BSS-2, considering the fully recharged and swapped battery batches. In the BCSs, the availability follows the order BCS-1, BCS-2, and BCS-M, knowing the EVs' SOCs at the charging center and the queuing lanes at the station. Hence, a metric can be defined by evaluating the availability of each BSS and BCS and then the incoming EVs can be assigned to the appropriate station for charging or swapping.
- The second optimization problem determines the route from the EV's current position to the target BCS/BSS. The arrival SOC of the EV can be estimated by the current SOC of the EV, the traveling distance from the EV to the station, and the power consumption rate (in Wh/km), which is a crucial factor for determining the charging schedule in both BSSs and BCSs. Hence, both geographic information and electric conditions are considered when formulating routing problem models.
- The most complex problem is dynamically determining a charging schedule for each BSS and BCS. Two schedule targets are mentioned for this mode: scheduling and assigning the EVs and batteries to specific chargers and scheduling the process throughout the whole charging period. In BSSs, considering the different remaining SOCs of swapped batteries and the incoming swapping orders from EVs, the first target is to select a battery from the swapped batch and assign it to an optimized charger. In BCSs, the first target is to assign the arriving EV to the optimal charger, where two types of chargers are used with different maximum charging rates. Hence, the optimal schedule can be determined by considering the EV parking time and remaining SOC. The second target is to determine an optimal schedule for changing the charging rate in BCSs and BSSs. The dynamic charging schedule can help adjust the total charging time, which will change the statuses of BCS queuing lanes and BSS swapped battery batches. Combining the first and second schedule targets, a series of optimization objectives can be obtained, such as maximizing profit, minimizing electricity cost, reducing voltage stability, and improving the quality of service.

Above all, the multiple BSS and BCS mode is the most complicated case in the BSS operation system, as it incorporates the challenges discussed in the single BSS, multiple BSS, and integrated BSS and BCS modes. As discussed in Section II-D3, the problems are usually defined as three subproblems, which are solved by separate optimal models. However, the decisions among the three subproblems are correlated; thus, a global decision is formulated as a multiobjective optimization problem by combining the charge/swap assignment, the routes from the current location to the target BSS/BCS, and the dynamic charging schedules in the BSSs and BCSs. Hence, the mentioned multiobjective problem is an NP-hard problem for determining an optimal solution, which can be solved by defining it as a complex operation system and proposing intelligent models. The BSS decision scenarios are reviewed in Section III.

III. BSS Decision Scenarios

In terms of the decision variables and objective values of the BSS, the existing literature can be broadly summarized into five scenarios: **charging schedule**, **service policy**, **construction and planning**, **dispatching and routing**, and **power management**. Among the different decision scenarios, seven key features for BSS model formulation are clarified.

- **BSS Mode:** Four BSS modes are introduced in Section II, including a single BSS, multiple BSSs, an integrated BSS and BCS, and multiple BSSs and BCSs. Here, the literature's operation mode is presented for comparison in the decision scenarios.
- **Decision Maker:** The literature on BSS optimization usually defines the decision makers as the BSS operator, EV driver, and power grid, where the model definitions and object formulations are discrepancies. For example, the objectives of the BSS operator are to maximize the profit or minimize the construction investment, while the objectives of the EV drivers are to minimize the queuing time or reduce the swapping cost.
- **EV Category:** There are two categories of EVs: private EVs and commercial EVs, where commercial EVs include electric buses, taxis and trucks. When investigating BSS decision scenarios, different categories of EVs indicate different types of traveling features, demand patterns, charging/swapping preferences, and optimization directions. Hence, the EV category is an important aspect of EV and BSS/BCS research.
- **Number of Battery Types:** As discussed in Section II-A7, battery heterogeneity is a crucial factor in the BSS decision scenarios considering the nonuniform battery types of swapped batteries. Hence, BSSs need to purchase more types of batteries for swapping and manage the service and charging schedule for each type. In recent literature, only a few papers consider the diverse types of batteries in BSS and BCS systems.
- **Vehicle-to-Grid:** Considering the rapid growth of the EV population and large capacity of lithium-ion batteries, feedback of the electrical energy in EV batteries to the

power grid is considered to play an important role, as it can improve the stability and reliability of the grid [27]. Thus, V2G and B2G are widely adopted in BSS decision models from the perspective of the operator and power grid.

- **Focus & Objective:** Based on the above aspects, different aspects of the BSS decision scenarios have been studied in recent literature, e.g., microgrid, photovoltaic BSS, battery degradation, demand uncertainty, pricing policy, and number of initial batteries. The corresponding objectives are defined in the optimization models, e.g., maximize the operating profit, service capacity, and quality of service and minimize the electricity cost, charging damage to batteries, construction costs, and average waiting time.

In this section, the existing works on BSS operation systems are reviewed in terms of five decision scenarios. As such, the above seven features are analyzed and compared in the literature. It is worth noting that some papers involve multiple scenarios in their decision models, as noted by the superscripts used in Table I to Table IV.

A. Charging Schedule

In this section, the charging schedule approaches are reviewed in terms of the four focuses, i.e., BSS operation [23], [25], [44]–[46], photovoltaic (PV) BSS [47]–[50], microgrid [51], [52], and power system [53]–[56], as shown in Table I.

1) BSS Operation Schedule: Considering the battery condition and swapping/charging demand, the BSS operator can determine an optimal charging schedule for the batteries and EVs, which helps the station maximize the operating profit [25] and minimize the electricity costs [23], [44], [45]. Additionally, an optimal schedule for the charging process can help the BSS to satisfy more EV swapping and charging requests such that its QoS [44] and service capacity [46] are maximized.

The first charging process approach is to assign a type of charger to the batteries in a BSS, knowing that different types of chargers have different charging rates and impose different charging damage on batteries. Then, the BSS can determine an optimal schedule for chargers and batteries based on the operation conditions, e.g., swapping demand, electricity prices, and battery purchase costs. Reference [23] defined a charging scheme model to determine an optimal charging schedule for batteries in BSSs, which aims to minimize the initial number of batteries and charging damage to batteries. In their model, four types of candidate chargers are used, and an estimation model is defined to quantify the charging damage of different chargers. A similar charger decision model is also used in [25] with the aim of maximizing the overall operating profit, including three components with monetary value: normalized battery purchase cost per charge, charging damage related to the charging rate, and electricity cost. This model considers the charging process (constant-current/constant-voltage, CC/CV) for lithium-ion batteries, which is comparable to the actual charging process but is nonlinear. Finally, the proposed models in [23], [25] are evaluated by hundreds of swapping requests over a time duration of one day.

The second charging process approach is to determine the specific charging schedule for the batteries at the BSS, which indicates the charging quantity/energy assigned to each battery at each time slot. Given the battery charging demand (start time, deadline, maximum charging rate, target SOC, current SOC, etc.), a battery charging scheduler is proposed to find the optimal charging rate for all batteries at all time slots [44]. In this model, an online BSS control problem is defined to minimize the energy cost with a QoS guarantee, and an offline BSS design problem is proposed to determine the optimal number of stored batteries. Faced with the random customer request problem, reference [45] develops a mathematical model for an uncertainty-constrained BSS optimal operation system that can forecast the electricity price and demand based on historical data. Different from [44], this charging schedule includes the charging and discharging power of each battery at each time slot, which can result in profit from selling power to the grid with the V2G strategy. Therefore, the objective is to minimize the operating costs, including the purchasing power and battery degradation costs.

The third approach to the charging process is to determine whether to accept or reject the swapping/charging demand from EV drivers based on the current workload in the BSS/BCS. An integrated battery charging and swapping station model (introduced in Section II-D) is proposed in [46] to evaluate the stations' service capacity. The model is evaluated by considering electric taxi fleets and electric bus fleets with various swap lanes and charging stations. The schedule is developed to determine the acceptance of swapping and charging requests based on the service policy. Some impacts of service capacity are investigated based on the size of the battery, vehicle moving speed, BCS power, and swapping price. Thus, the charging process schedule of this approach is described in a table with binary decisions (1/0 values), where 1 denotes acceptance of the request and 0 denotes rejection of the request.

This section gives three approaches to setting the charging schedule in BSS operation systems; these can be applied to integrated models such as PV-based BSSs, microgrids with BSSs, and power system operations.

2) PV-BSS Schedule: Considering the massive electricity consumption of BSSs for recharging batteries, renewable energy sources (RESs) are widely adopted for constructing BSSs, including solar PVs and wind energy. Because the photoperiod of solar energy fits the need for recharging energy, the PV-BSS is considered to be an efficient and less expensive approach for combining swapping and power-generation functions. However, due to the uncertainty of solar energy under different weather conditions and the uncertainty of driver swapping demand, forecasting PV energy and the demand from EVs is a major challenge in renewable energy operation systems. Here, some typical works on PV-BSSs are reviewed.

Owing to the uncertainties in PV-BSSs (e.g., swapping demand, PV generation, weather conditions, and traffic load), some forecasting models that use statistics and machine learning techniques have been proposed [47], [48]. A day-ahead scheduling model is proposed in [47] to use the chance-constrained programming method, which describes the

TABLE I
CHARACTERISTICS OF OPERATION MODELS (SCENARIO 1): CHARGING SCHEDULE

Scenario	Ref.	Mode	Decision Maker			EV Category	#. Type Battery	V2G	Focus	Objective
			BSS Operator	EV Driver	Power Grid					
Charging Schedule	[23]	Single BSS	✓	✗	✗	Private EV	1	✗	Initial Num. of Batteries Charging Damage Battery Degradation	Min. Operation Cost
	[25]	Single BSS	✓	✗	✗	Private EV	1	✗	Initial Num. of Batteries Charging Damage Real Charging Process	Max. Operation Profit
	[44]	Single BSS	✓	✗	✗	Private EV	1	✗	Quality of Service Optimal Num. of Batteries Energy Pricing	Min. Energy Cost
	[45]	Single BSS	✓	✗	✗	Private EV	1	✓	Demand Uncertainty Random Requests Battery Degradation	Min. Operation Cost
	[46][a]	Multiple BSSs & BCSs	✓	✗	✗	EV Taxi & EV Bus	2	✗	Service Capacity EV's Moving Speed Price Policy	Max. Service Capacity
	[47]	Single BSS	✓	✗	✗	Private EV	1	✗	PV-BSS Day-ahead Schedule PV&Demand Uncertainty	Min. Electricity Cost
	[48]	Single BSS	✓	✗	✓	EV Taxi	1	✗	PV-BSS Weather/Traffic Forecasts Battery Degradation	Max. Annual Benefit
	[49]	Single BSS	✓	✗	✓	EV Taxi	1	✗	PV-BSS Service Availability	Max. Operation Performance
	[50]	Single BSS & BCS	✓	✗	✓	EV Bus	1	✓	PV-BSS Renewable Energy Battery Degradation	Min. Total Cost Increase Bus Usage Reduce Construct Cost
	[51]	Single BSS	✓	✗	✗	Private EV	1	✓	Microgrids Bi-level programming Real-time Pricing	Min. Microgrid's Cost (Upper Level) Max. BSS's Profits (Lower Level)
	[52]	Multiple BSSs	✓	✗	✓	Private EV	1	✓	Microgrid Bi-level Schedule Battery Degradation PV&Demand Uncertainty	Min. Total Cost (Upper Level) Min. Cost of BSS (Lower Level)
	[53][b]	Single BSS	✓	✗	✓	Private EV	1	✗	Power System Station or Bus Node Centralized Charging	Min. Charging Cost & Min. Power Loss & Min. Voltage Deviation
	[54]	Single BSS	✓	✗	✗	Private EV	1	✓	Power System Day-ahead Schedule Demand/Price Uncertainty Battery Degradation	Max. BSS Profit
	[55]	Single BSS	✓	✗	✗	Private EV	1	✗	Power System Day-ahead Schedule Battery Degradation	Max. BSS Profit
	[56][c]	Multiple BSSs	✓	✗	✗	Private EV	1	✗	Power System Voltage Flatten Charging Process Charging Location Dynamic Pricing Fuzzy Control	Min. Charging Cost Min. Power Loss Min. Voltage Flatten Min. Power Loss

[a] Ref. [46] has multiple scenarios with service policy (Scenario 2);
[b] Ref. [53] has multiple scenarios with power management (Scenario 5);
[c] Ref. [56] has multiple scenarios with dispatching and routing (Scenario 4) and power management (Scenario 5).

uncertainty of stochastic variables and then applies them to the optimization model by minimizing the cost of electricity purchased from the power grid. In this model, the swap and solar uncertainties are formulated with probabilistic sequences of stochastic variables. In [48], the authors forecast solar power with the use of real data (e.g., irradiation, temperature, humidity, wind direction, air density, and pressure) and machine learning models (e.g., neural network, XG-Boost, random forecast, and decision tree). After combining the BSS dataflow and the weather forecast, the traffic flow to the BSS and the generation of PV power can be predicted. Then, the objective is to maximize the economic and environmental impacts considering the weather and road traffic conditions and the battery degradation models.

Another challenge of PV-BSSs is how to quantify the self-consumption of PV energy. A system structure and the functions of a PV-based BSS, composed of a PV system, an EV battery system, a grid-connected system, and an energy management system, are proposed in [49]. In this paper, an evaluation index for the self-consumption of PV energy is proposed to evaluate the self-utilization of PV energy representing the percentage of self-consumed PV energy. Then, a charging strategy with a swapping service model and power distribution model is proposed. In a case study with EV taxis, the self-consumption of PV energy is effectively improved with the premise of service availability.

An integrated model with wind and solar power generation was proposed in [50]. The operation mode is an integrated BSS and BCS station with a fast charging and battery swapping facility for EV buses. The demand response, renewable energy, and transformer feeder load are incorporated to minimize the total single-day cost by optimizing the battery charging and discharging capacity. An example of a power supply system (in the Penghu Area) is given with a power grid, a one-wire diagram, and the user end on three main feeders, which is combined with the energy from renewable resources, including four wind turbines (rated power of 2.4 MW) and solar cells (rated power of 1.5). In the case study, the results are adopted as a reference for evaluating the establishment and operating cost of an e-bus system.

In conclusion, a PV-based BSS is a typical operation system that incorporates renewable energy to reduce the cost of electricity purchased from the power grid. If solar and wind energy can be accurately forecast and the construction cost of PV material decreases, the application of renewable energy to BSSs and BCSs can be regarded as a significant approach to reducing station operating costs.

3) Microgrid BSS Schedule: A microgrid is a locally controlled power system with interconnected loads and distributed generation (DG) units that can connect and disconnect from a traditional power grid. Microgrids are flexible and efficient in terms of power generation and renewable energy utilization with the use of grid-connected and island modes [51]. In the BSS and BCS models, stations have a very high demand for electricity and may cause voltage instability in power systems. Thus, many researchers have studied the application of microgrids to BSSs in recent years.

A microgrid day-ahead scheduling problem is proposed as a bilevel optimal scheduling model to coordinate between the microgrid and the BSS [51], where the upper level minimizes the microgrid's net costs and the lower level maximizes the BSS's profit under real-time pricing environments. The proposed microgrid system contains three probabilistic models, the wind turbine, PV, load injection, and an equivalent load model, which are coordinated with the BSS operation schedule.

Another microgrid schedule model is formulated as a bilevel scheduling framework for microgrids and multiple BSS decisions [52]. The upper-level model minimizes the microgrid's total cost, and the lower level minimizes the cost of each BSS. A hybrid probabilistic-possibilistic approach is proposed to address the uncertain features, including the load demand of the microgrid, PV generation, market price, and swapping requests. The effectiveness of the proposed model is evaluated with real microgrid system data and in different scenarios.

4) Power System Schedule: Considering the BSSs' high power demand from the grid and potential influence on voltage stability, the last charging schedule is proposed from the perspective of the power grid. BSSs and BCSs can be regarded as battery aggregators that can transmit power back to the grid to smooth the voltage curve and provide ancillary services, e.g., frequent regulation, load following, and voluntary reserve provisions.

In [53], the objective function is designed to minimize the total charging cost and to reduce the power loss and voltage deviation of the power network, where the charging location is considered with station or bus nodes in a power system. The charging schedule problem is defined as a novel centralized charging strategy considering the optimal charging priority and charging location. The effectiveness of the proposed model is evaluated with an IEEE 30-bus test system, and the results show that the model is viable and that the proposed algorithm outperforms the baseline methods.

To address the uncertainty of power generation, swapping demand, and electricity price, a day-ahead scheduling method is proposed in [54], [55]. In [54], the day-ahead model determines the amount of electricity to buy and sell knowing the battery swapping demand and aims at maximizing the BSS profits, including the revenue obtained from customers, energy purchased from and sold to the grid, cost of the inability to supply demand, and discount to customers. Here, the K-means clustering algorithm is used to fit the load curve to the historical data. In [55], uncertain features, e.g., customer arrivals, electricity price, grid connection limitation, and self-degradation of batteries, are formulated as a day-ahead scheme. The day-ahead plan determines the charging, discharging, and swapping of batteries in stock. The objective is to satisfy customer demand and maximize the BSS's revenue. The key features in the BSS's decision are compared and investigated, including the grid power limitations, battery degradation, and demand uncertainties.

A multiobjective model is proposed in [56] with two cost-based objectives and two technical-based objectives. The cost-based objectives are to minimize EV battery charging and the power loss costs, and the technical-based objectives are to flatten the voltage profile and release the network capacity. The decision variables include the battery swapping locations and the battery group charging priorities. A dynamic pricing procedure is proposed to prevent interruptions in battery charging. Finally, the proposed model is evaluated by an IEEE 33-bus test system, and the results show the proposed models' novelty and functionality.

B. Service Policy

In the opinion of EV drivers, both BSSs and BCSs have a service role, providing swapping and charging services. Here, how long drivers need to wait for swapping/charging and how much drivers need to pay are the two main concerns for building the BSS service policy. Hence, many researchers have proposed service policy BSS models in terms of queuing theory [57]–[59], pricing policy [59]–[61] and service framework establishment [26], [62], [63], as shown in Table II.

1) Queuing Theory: Considering the long charging time of lithium-ion batteries, the limited number of initial batteries in BSSs, and the limited number of parking piles/spaces in BCSs, the increased EV population will cause a serious queuing

TABLE II
CHARACTERISTICS OF OPERATION MODELS (SCENARIO 2): SERVICE POLICY

Scenario	Ref.	Mode	Decision Maker			EV Category	#. Type Battery	V2G	Focus	Objective
			BSS Operator	EV Driver	Power Grid					
Service Policy	[57]	Integrated BSS & BCS	✓	✓	✗	Private EV	1	✗	Queuing Theory Quality of Service (QoS)	Performance Evaluation
	[58]	Integrated BSS & BCS	✓	✗	✗	Private EV	1	✗	Queuing Theory Charging Policy Ensuring QoS	Min. Charging Cost
	[59]	Multiple BSSs & BCSs	✓	✓	✗	Private EV	1	✓	Queuing Theory Price Rule Game Theory	Max. Utility Max. QoS
	[60]	Single BSS	✓	✗	✗	Private EV	1	✗	Price Strategy Demand Response	Max. Service Capacity Min. Total Cost (Charge Rent Subsidy)
	[61][a]	Multiple BSSs	✗	✓	✓	EV Taxi	1	✗	Real-time Pricing Mode Battery Swap Pricing Two Charging Strategies	Max. Global Benefits
	[62][b]	Integrated BSS & BCS	✓	✗	✗	Private EV	1	✓	BSS Service Framework Two-stage Optimization (Planning & Operation) Initial Num. of Batteries Demand Uncertainty	Min. Investment Cost Min. Operation Cost
	[26]	Multiple BSSs	✓	✓	✗	Private EV	3	✗	BSS Service Framework Battery Heterogeneity Different Types of EVs Reservations for Swap	Min. Waiting Time

[a] Ref. [61] has multiple scenarios with charging schedule (Scenario 1);
[b] Ref. [62] has multiple scenarios with BSS planning (Scenario 3).

problem at both BSSs and BCSs. An example of charging availability is given in Section II-D1. Hence, the most intuitive approach is to define a service model based on queuing theory that manages the players in terms of the defined objective values, e.g., QoS, service capacity, waiting time, and operating costs/profits.

In [58], an optimal charging operation policy is proposed for an integrated BSS and BCS that aims to concurrently minimize the charging cost and ensure QoS. In this work, a mixed queuing network model is defined: the EVs form an open queue, and the batteries circulate in a closed queue. Then, a constrained Markov decision process is formulated, and an optimal policy is derived by the standard Lagrangian method and dynamic programming. The impacts of the numbers of batteries and chargers on the average operating cost are evaluated.

However, how to evaluate BSS and BCS performance is a crucial problem considering the many participants and multiple objectives in the operation system. The authors in [58] also propose an asymptotic performance evaluation model [57], which is based on a novel mixed queuing network model for an integrated BSS and BCS. The key parameters include the number of parking spaces, swapping islands, chargers, and batteries, and the parameters are defined as QoS measures with consideration of the blocking probability. Two types of asymptotic behaviors are evaluated, and the asymptotic lower bound of the blocking probability is derived based on analytical studies.

A BSS queuing model with three queues (EVs, well-charged batteries, and depleted batteries) is proposed in [59], formulated as different curves using network calculus theory. Then, a closed-loop supply chain scheme is proposed to depict the battery-swapping-charging process between BCSs and BSSs. Furthermore, game theory is used to manage depleted batteries and well-charged batteries, where BCSs act as leaders and BSSs act as followers. A case study is illustrated to evaluate the effectiveness of the proposed model with one BSS and three BSSs, where two of the BSSs serve 1,000 electric taxis and one BSS serves 200 electric buses.

2) Pricing Policy: In the BSS operation system, the item with the most significant impact is the service pricing policy. EV drivers prefer to pay less money for swapping/charging if the same service is provided, while a lower service price causes a longer waiting time. Station operators prefer to charge drivers high prices and reduce the payment cost to buy electricity from the power grid. Hence, a proper pricing policy can be used to leverage the queuing load and service profit by balancing the swapping/charging demand and selling electricity back to the grid.

In [59], the proposed game theory for BSS and BCS management schemes determines the optimal prices of depleted batteries and well-charged batteries, as well as the price for supplying depleted batteries. In the defined game, the objective of the leader (BCS) is to maximize its utility, and the objective of the followers (BSSs) is to maximize their utility while guaranteeing the QoS for battery swapping.

Because the peak demand for charging causes an increased cost for deploying a more extensive charging infrastructure, a price-based demand response program is proposed to reduce costs and decrease the peak demand for charging [60]. A multiobjective optimization model is developed that includes a battery demand model, a demand-response-based subsidy cost model, and a charging cost model. Here, the total cost of the battery swapping service includes the charging cost, rental cost, and subsidy cost. The decision variables include the unit price of the charging cost, the unit battery rental price, and the subsidy price based on governmental policies in China.

A battery swap pricing and charging strategy is proposed in [61], addressed to electric taxis in China. Five modules are investigated: power grid load monitoring, generator set dispatch, BSS operation, electric taxi driver response, and evaluation of all stakeholder benefits. To reduce carbon emissions and maximize the global benefit, four real-time battery swap pricing scenarios and two charging strategies for BSSs are developed.

3) Service Framework: In a realistic BSS operation system, the service policy should consider not only online strategies (e.g., pricing policies, queuing) but also the service framework for dealing with BSS planning problems and battery heterogeneity problems.

To address the stochastic visits of EV drivers (demand uncertainty), reference [62] proposes a two-stage optimization model: investment for battery purchases in the planning stage and battery allocation decisions in the operating stage. A modified K-means clustering method is developed to predict the visit distribution. A sensitivity analysis examines the price points, region-specific electricity prices, charging intervals, and EV uptakes.

As discussed in Section II-A7, a practical BSS service framework consists of multiple types of batteries, which results in highly complex scheduling and optimization. A battery heterogeneity-based BSS service framework is proposed in [26], in which EV batteries are divided into subgroups with various associated types of EVs. The proposed battery heterogeneity framework maintains battery heterogeneity and balances the swapping demand with regard to different types of batteries. Furthermore, an EV reservation model is introduced for the BSS service considering the battery type, expected arrival time, and charging duration, which enables anticipation of the demand load and avoidance of potential hotspots for swapping.

C. Construction and Planning

In the BSS construction and planning stage, the localization and placement [24], [64]–[67], station network [68], and BSS configuration [22], [69] are crucial concerns of BSS operators. For this section, the related works can be viewed in Table III.

1) Localization and Placement: Considering the construction investment of BSSs, location has a significant influence on business profits throughout the life cycle. Hence, BSS placement should be fully investigated based on the EV population, land cost, transportation, drivers' traveling patterns, and power grid.

Reference [24] proposes a site selection framework considering three criteria: land occupation cost, driver comfort, and impact on power grid load levels. A fuzzy decision-making trial and evaluation laboratory method is designed to determine the weights of the three criteria. Then, a fuzzy-based method is adopted to rank the candidate locations. A case in Beijing, China, illustrates the effectiveness and robustness of the proposed BSS location decision framework. Another crucial factor for BSS construction is the routing from EVs to stations. Reference [64] introduces a BSS location-routing problem for selecting a BSS location from candidate sites and minimizing the sum of construction and routing costs.

Due to the development of intelligent EVs and data science, a data-driven location selection model for BSSs is proposed in [65]. In this paper, GPS location data and electricity requests are collected for a metropolitan area. Then, a location selection model is proposed with the following three steps: a hidden Markov model for map matching and trajectory extraction, an electricity consumption rate model for demand estimation, and a clustering strategy for location determination. A realistic case study involving 13,700 taxis in the area of Shanghai, China, is presented, and the results outperform those of the state-of-the-art baseline models.

Owing to the high consumption of energy, the limitations of power systems and collaboration among them should also be considered in the BSS construction stage. A framework for the optimal design of an integrated BSS and BCS is proposed in [66] considering the requirement that increased power be provided during the charging period. An efficient method is developed to determine the optimal planning of BSSs and BCSs at the power system distribution level, which includes the locations, sizes, and charging strategies of each BSS. The objective is to optimize the economic profit during each station's life cycle, including the EV investment costs, operational costs, maintenance costs, disposal costs, and benefit of charging and swapping. Focusing on the energy loss reduction and voltage stability factor, an optimal allocation model of DG units and BSSs is proposed in [67]. A zone-based strategy is designed to allocate the DG-BSS in each zone of the distribution grid, and the distribution system is divided into multiple zones to facilitate usage by motorist and increase utility. The feasibility and effectiveness of the proposed model are evaluated by validating the model on IEEE 33-bus and 69-bus networks.

2) Station Network: In the business of battery leasing and EV sharing, an EV operation system can be defined as a network model with multiple BSSs and BCSs. Reference [68] proposes an EV battery service network considering customer satisfaction, including range anxiety and loss anxiety. The objective is defined as the profit from battery leasing and EV sharing minus the construction cost and operating cost of the BSS. A fuzzy system is proposed to model customer demand patterns, the tabu search method is used to search for the location, and the GRASP model is used to determine the number of batteries to be swapped/charged knowing the location strategy. A comprehensive case study is illustrated involving the city cluster of the Yangtze River in China, which consists of 35 cities and 189 million people. The results show that the station network can find a tradeoff between investment and satisfaction level.

3) Configuration: When the BSS locations are obtained, the determination of the configuration is another decision to be optimized; this includes the number of initial batteries [22], [23], [69], number of chargers [22], [69], and charging strategies [22], [69].

TABLE III
CHARACTERISTICS OF OPERATION MODELS (SCENARIO 3): CONSTRUCTION AND PLANNING

Scenario	Ref.	Mode	Decision Maker			EV Category	#. Type Battery	V2G	Focus	Objective
			BSS Operator	EV Driver	Power Grid					
Construct & Planning	[24]	Multiple BSSs	✓	✗	✗	Private EV	1	✗	Site Location Selection Multi-criteria Decision Fuzzy System	Max. Overall Profit
	[64]	Multiple BSSs	✓	✗	✗	EV Taxi	1	✗	Location for BSS Routing of EVs Neighborhood Search	Min. Construction Cost Min. Routing Cost
	[65]	Multiple BSSs	✓	✗	✗	EV Taxi	1	✗	BSS Location Selection Clustering with Data	Min. Avg. Distance
	[66]	Integrated BSS & BCS	✓	✗	✗	EV Bus	1	✗	Location for BSS Capital & Operation Cost Neighborhood Search	Max. Net Present Value of the Project
	[67][a]	Single BSS	✗	✗	✓	Private EV	1	✗	Distributed Generation (DG) Allocation of DG and BSS Large Scale Network	Min. Energy Loss & Max. Voltage Stability
	[68]	Multiple BSSs & BCSs	✓	✗	✗	Private EV	1	✗	Station Network Customer Satisfaction (Range & Loss Anxiety) Fuzzy Consumer Demand	Max. Profit (i. Construction Cost; ii. Operation Cost; iii. Profit by Battery)
	[22][b]	Multiple BSSs	✓	✗	✗	EV Taxi	1	✗	BSS Configuration & Operation Model Three Charging Strategies	Min. Load Difference Min. Emission Max. Financial Benefit
	[69][c]	Single BSS	✓	✗	✗	Private EV	1	✗	BSS Configuration Time-vary Demand & Price Two-stage optimization (Battery Purchasing & Charging Policy)	Min. Battery & Operating Cost Min. Charging Cost

[a] Ref. [67] has multiple scenarios with power management (Scenario 5);
[b] Ref. [22] has multiple scenarios with charging schedule (Scenario 1);
[c] Ref. [69] has multiple scenarios with service policy (Scenario 2).

A BSS configuration and operation model with three charging strategies is proposed in [22]. With the use of dynamic and historical data, the model determines the configuration of chargers, swappers, and reserved batteries. In addition, the annual battery rental fees are considered to satisfy the battery swapping demand. The BSS profit model is evaluated and compared with other models considering battery technology, policy, and BSS planning, and it is concluded that the battery cost and battery swapping price are key factors determining the BSS's net income in its life cycle period.

Reference [69] proposes a battery purchasing and charging strategy for BSSs with three decision models: a long-term decision on the number of charging bays, a medium-term decision on the number of batteries, and short-term decisions on when and how many batteries to recharge. To address the time-varying swapping demand and electricity price, a periodic fluid model is proposed to determine an optimal battery purchasing and charging policy to trade off the battery investment cost and operating cost. A two-stage optimization model is designed to determine the optimal amount of battery fluid and the optimal charging rule.

D. Dispatching and Routing

If the locations and sizes of BSSs are deployed in a region, when an EV requests a swap, the BSS operator assigns a target station at which the driver can swap his/her battery, defined as a BSS dispatching problem in the literature [63], [70]–[74]. If the road and traffic information are known, the routing paths from the EVs' current location to the assigned BSSs can also be optimized, as in [75]–[78], [81]. Considering the influence of power on the grid and the management of swapped batteries, some works study models that charge batteries in a centralized charging station and deliver fully charged batteries to distributed BSSs [79], [80], [82]. The related works on the topic of BSS dispatching and routing problems are illustrated in Table IV.

1) Dispatching: The basic operation system of the EV dispatching problem selects an optimal BSS from candidate BSSs with several objectives, e.g., maximizing the operation revenue [70], [72]–[74], minimizing the waiting/traveling/delay time [63], [71], [74], and minimizing the traveling distance [72], [73].

A self-adaptive dispatching strategy is proposed to enhance the responsiveness and reconfiguration of BSS systems [70], which could meet the dynamic swapping demand from EV drivers and balance the varied demands. The proposed self-adaptive dispatching strategy includes the EV scheduling and battery scheduling stages, which determine the optimal BSS for swapping and battery control (charging, discharging, sleeping, and swapping) for each BSS.

With the development of mobile edge computing and vehicle-to-vehicle communication, intelligent BSS management is proposed in [71] to determine where to swap the battery in a distributed system. The objective is to minimize the average waiting time for each EV at a BSS. Based on

TABLE IV

CHARACTERISTICS OF OPERATION MODELS (SCENARIO 4): DISPATCHING AND ROUTING

Scenario	Ref.	Mode	Decision Maker			EV Category	#. Type Battery	V2G	Focus	Objective
			BSS Operator	EV Driver	Power Grid					
Dispatch & Routing	[70]	Multiple BSSs	✓	✗	✗	Private EV	1	✓	Dispatching Strategy Two-Stage Framework Shared Battery Stations	Max. Operation Revenue
	[71]	Multiple BSSs	✓	✗	✗	Private EV	1	✗	BSS Dispatching Mobile Edge Computing Predict Service Availability	Min. Waiting Time (Average)
	[72] [73]	Multiple BSSs	✗	✗	✓	Private EV	1	✗	Assign a BSS to EVs Power Grid Requirement Centralized Solution [72] Distributed Solutions [73]	Min. Weighted Obj: i. EVs Travel Distance ii. Electric. Gen. Cost
	[74][a]	Multiple BSSs & BCSs	✓	✓	✗	Private EV	3	✗	Find Optimal BCS/BSS EV Network with Multiple Charging Options	Min. Total Travel Time & Recharging Cost
	[63][a]	Multiple BSSs & BCSs	✓	✓	✗	EV Taxi	1	✗	Assign Taxis to BSS/BCS Hybrid Charging Management Framework	Min. Trip Delay
	[75]	Multiple BSSs	✗	✓	✗	EV Taxi	1	✗	Dynamic Taxi Routing Look-ahead Policy	Min. Length of Path
	[76]	Multiple BSSs	✓	✓	✗	EV Taxi	1	✗	Taxi Routing Demand Profile & Power Consumption	Min. Time Cost Driving
	[77]	Multiple BSSs	✗	✓	✗	EV Taxi	1	✗	Vehicle Routing Dial-a-Ride Problem	Min. Routing Costs & BSS Costs
	[78]	Multiple BSSs	✓	✗	✓	EV Trucks	2	✗	Vehicle Routing Delivery Strategy Two-echelon Structure	Min. Total Cost: EV Shipping; Load & Unload; Swapping
	[79][a]	Multiple BSSs	✓	✗	✓	Private EV	1	✗	Deliver Battery to BSSs Battery Degradation Schedule Charging	Min. Charging Cost
	[80]	Multiple BSSs & BCSs	✓	✗	✗	Private EV	1	✗	Deliver Battery to BSSs	Min. Length of Path
	[81]	Integrated BSS & BCS	✓	✗	✗	EV Truck	5	✗	Vehicle Routing Deliver Goods Joint Optimization	Min. Operation Cost & Max. Environmental Benefits
	[82]	Multiple BSSs & BCSs	✓	✗	✓	Private EV	1	✗	Deliver Battery to BSSs Supply Chain Scheme	Max. Revenue

[a] Ref. [63], [74], [79] have multiple scenarios with charging schedule (Scenario 1).

the BSS status and EV reservation information, BSS service availability is predicted.

Two scheduling models for EV battery swapping have been proposed with centralized [72] and distributed [73] approaches. The dispatching problem is defined as assigning an optimal BSS for each EV based on its current location and SOC. The objective is to minimize the weighted sum of the EV traveling distance and electricity cost. In the centralized solution [72], second-order cone programming relaxation of the optimal power flow and generalized Benders decomposition is proposed when global information is available. In decentralized solutions [73], two solutions are proposed based on the alternating direction method of multipliers and dual decomposition, which handle separate BSS entities with distributed grids, stations, and EVs.

Different from the multiple BSSs in the operation system, two related works develop an integrated mode with multiple BSSs and BCSs, where the decision is not only the optimal BSS but also the optimal charging/swapping method for gaining energy. In [74], a smart charging strategy is proposed to find an optimal charging station along the path with minimized travel time and charging cost. Multiple options, including AC level 2 charging, DC fast charging, and battery swapping facilities, are deployed at the integrated charging stations. The authors in [26] also investigate another holistic management framework for a public electric taxi system with multiple BSSs and BCSs [63]. The decision guides the taxis to an appropriate station given time-varying requirements and uncertain demand. The objective is to reduce the trip delay of all electric taxis. The effectiveness of the proposed framework is evaluated under a realistic taxi system in Helsinki city, where the drivers' trip duration is minimized and the charging performance is satisfied at the electric taxi, charging, and swapping stations.

2) Routing: In the BSS routing problem, the aim is to find the optimal BSS at which to swap a battery when the current traveling path is determined. For example, in the electric taxi scenario, the vehicle owner prefers to swap the battery during the pickup tour rather than the drop-off period considering the customer waiting time. Hence, the EV BSS routing problem is usually applied to commercial vehicle swapping, e.g., electric taxis [75]–[77] and electric trucks [78].

In the electric taxi scenario, the aim is to find the optimal BSS at which to swap batteries without wasting precious time during operation. Reference [80] proposes a dynamic routing model with a look-ahead policy that assigns an optimal taxi fleet to customers with elastic demand. The aim is to maximize social benefit, including the limited battery capacity, detours to BSSs, integration of customer delay, and system cost. Reference [76] proposes an upgraded urban electric taxi system to determine the optimal BSS scheme, which determines whether to assign electric taxis to a BSS. With the use of mobile sensor networks, historical routes, demand profiles, power consumption, and driving time between positions in the road network, the real-time algorithm schedules some occupied taxis to BSSs earlier than expected, which avoids swapping congestion at the BSSs. To address customers with special needs, a dial-a-ride problem is proposed in [45] to assign taxi routes and schedules to customers. Four types of resources are defined for EVs: an accompanying person, the seat of a person with a disability, a stretcher, and a wheelchair. The objective is to minimize the total routing costs and BSS costs.

A two-echelon capacitated EV routing problem with BSSs (2E-EVRP-BSS) is presented in [78] to determine the delivery strategy, where the two echelons indicate different load capacities, battery driving ranges, power consumption rates, and battery swapping costs. In the first echelon, the freight is transported from a depot to the transfer stations (satellites) by large EVs. In the second echelon, small EVs deliver goods from satellites to customers. Hence, there are two types of EVs and two types of batteries for swapping. The goal is to minimize the total EV travel costs, swapping costs, and handling costs at the satellites.

3) Deliver Battery to BSSs: In most BSS operation systems, the swapping and charging processes are executed at the same station. However, to manage the depleted battery (DB) charging process, some studies consider swapping the battery at a BSS, delivering swapped batteries to a BCS, and delivering the battery to the BSS when it is fully recharged [79]–[82].

Reference [79] proposes scheduling the charging processes of the chargers in BCSs to minimize the charging cost and satisfy fully charged batter (FB) demand, where the charging rate of each charger is determined. The proposed system consists of four parts: a power system, a centralized BCS, distributed BSSs, and a transportation system. However, the DB and FB delivery strategies in transportation systems are not studied in this research. A dynamic optimization model is proposed to maximize social welfare to balance customer demand and operator costs [80]. The proposed model helps the planning process considering inventory, routing, and dynamic pricing, where the joint inventory and delivery system is demonstrated with BCS supply nodes and BSS demand nodes.

From the perspective of the power grid, two studies are investigated in terms of the power-generation schedule [81] and distributed operation management [82]. In [81], an EV battery swapping-charging system is designed to schedule batteries that are centrally charged and then dispatched via delivery truck to BSSs. The objective is to minimize the traveling cost by optimizing the route planned for the trucks, which would meet the battery demand of all BSSs within the given time window. A closed-loop supply-chain-based battery swapping charging system is proposed in [82] to optimize the charging and logistics of DBs and FBs. In the proposed network calculus-based service model, three steps in the battery swapping/collecting processes are defined: the queue of EVs waiting to be served, the inventory of DBs, and the inventory of FBs.

E. Power Management

Due to the large-scale energy consumption of BSSs, a series of studies have been conducted not only to reduce the BSSs' influence on the grid but also to enhance the intelligence and collaboration of the power grid and the BSSs. Three approaches are summarized in Table V to review the power management studies on BSS operation systems: microgrids [28], [83]–[85], load forecasting [29], [86], and energy management [30], [31], [87], [88].

1) Microgrid: In Section III-A3, the recent microgrid BSS works were reviewed with a focus on the BSS charging schedule. Here, the microgrid and the BSS are studied with regard to energy management and the power system.

Real-time energy management for a smart-community microgrid with a BSS was proposed in [84]; it uses RESs to supply charging and residential loads. The variability in supply, demand, and energy prices is investigated without forecasting methods. The simulation results show that the proposed system could improve the economics and utilization of renewable energy. In [83], an optimal scheduling model is proposed for microgrid resources and the BSS, where the microgrid consists of PV and wind DG units. The optimal power flow from the microgrid to the BSS is determined considering the network constraints, power loss, and reactive power dispatch. The objective is to minimize the operating cost of the microgrid, including the cost of active and reactive power provision.

Two shadow-price-based coordination methods are proposed in [28] to coordinate the scheduling of microgrids and BSSs, with a focus on the price and power trading requests between the two entities. In addition, a coordination mechanism is defined as an AC power flow model to optimize the operation of the microgrid and a mixed-integer linear programming model to optimize BSS operation. The proposed model is evaluated with a standard IEEE 33-bus system and a BSS model for serving private EVs and electric buses.

The microgrid plays an important role in the power grid system, managing distributed renewable energy power generators and improving customers' perception of the reliability of electrical energy. Recently, nanogrids have been introduced as a smaller type of microgrid that serves a smaller region and is equipped with a smaller power capacity.

A nanogrid-based BSS energy management system is proposed to determine the optimal sizing and operation of networked nanogrids [85] to enhance energy supply reliability, resilience, and economics. Three management methods are presented in this model. First, the system can determine the optimal size and scheduling of nanogrids, and the BSS can help to smooth the voltage variation from the RES. Second, the energy generated from the RES can be stored in the BSS if the electricity demand is in peak hours. Third, with the use of a networked nanogrid structure, BSS resources can be shared by delivering batteries within a transportation network.

TABLE V
CHARACTERISTICS OF OPERATION MODELS (SCENARIO 5): POWER MANAGEMENT

Scenario	Ref.	Mode	Decision Maker: BSS Operator	Decision Maker: EV Driver	Decision Maker: Power Grid	EV Category	#. Type Battery	V2G	Focus	Objective
Power Manage	[84][a]	Single BSS	✓	✗	✓	Private EV	1	✓	Microgrid Renewable Energy Smart Community Queuing Theory	Min. Overall Cost
	[83]	Single BSS	✓	✗	✓	Private EV	1	✓	Microgrid Renewable Energy	Min. Microgrid's Operation Cost
	[28][a]	Single BSS	✓	✗	✓	Private EV EV Bus	1	✗	Microgrid Shadow Price Co-ordination Methods Distributed Generators	Min. Microgrid's Cost: i. Fuel cost of DGs; ii. Power Trading Cost; iii. Sell Power to BSS
	[85]	Single BSS	✓	✗	✓	EV Bus	1	✗	Nanogrids with BSS Deliver Batteries Nanogrid for Recharging	Min. Investment Cost
	[29]	Single BSS	✓	✗	✓	EV Bus	1	✗	Load Demand Forecasting	Max. Accuracy of Forecasting
	[86]	Multiple BSSs	✓	✗	✓	Private EV	1	✗	Cluster Model Forecast Day-ahead Energy Reserve Capacity Markets Bi-Level Structure	Max. Overall Profit (Upper Level) Min. Generation & Reserve Capacity Cost (Lower Level)
	[87][a]	Integrated BSS & BCS	✓	✗	✓	EV Bus	4	✓	Forecast Energy Price Day Ahead, Real-time & Ancillary Services Game Theory	Max. Operation Profit
	[30]	Single BSS	✓	✗	✓	Private EV	1	✓	Fast Frequency Regulation Deep Learning Q Network Demand Uncertainty	Max. BSS Revenue
	[31]	Single BSS	✓	✗	✓	Private EV	1	✓	Fast Frequency Regulation Policy Gradient Reinforcement Learning Power Uncertainty	Max. BSS Revenue Max. Long-term Return on Investment
	[88]	Multiple BSSs	✓	✗	✓	Private EV	1	✓	Power System Planning Distributed Solution Collaborative Methods Blockchain Consensus	Min. Generation Cost Min. Load Variance

[a] Ref. [28], [84], [87] have multiple scenarios with service policy (Scenario 2).

2) Load/Price Forecasting: In a BSS operation system, the arbitrary arrival pattern of EV drivers causes an uncertain battery charging pattern, resulting in the BSS power load demand following a random distribution. To reduce the influence of random demands, the charging load characteristics can be estimated based on method-driven (computational intelligent algorithms) and data-driven (historical data) approaches. Additionally, the variation in electricity price is a crucial factor in the BSS operation system, and it can also be predicted if the model and data are well determined.

In [29], a stochastic model is defined with four variables: hourly swapping demands from EV drivers, charging start time, travel distance from the position of the EV to the BSS, and charging duration. Then, an estimation model is defined to forecast the energy consumption of the BSS, and a generic nonparametric method with a backpropagation neural network is proposed to estimate the uncertainty in the charging load demand. In the simulation studies, the predicted BSS charging load and interval fit the real distribution over 24 hours.

After obtaining the day-ahead energy and reservation capacity data, a discrete cluster model is defined to optimize the operation model of aggregated BSSs [86]. A bilevel structure is proposed: the upper level determines the charging/discharging schedules and reservation capacity of the BSSs, and the lower level clears the market and provides marginal prices for each BSS and reserve capacity price. The proposed framework is evaluated with six BSSs in the IEEE RTS-24 system, with 32 generators and 9 wind farms.

In [87], an artificial neural network with a nonlinear autoregressive exogenous (NARX) method is used to forecast the energy price for the next 24 hours, and historical day-ahead and real-time data are used to train the proposed network. Thereafter, an optimal energy management system for BSSs is proposed to address day-ahead, real-time and ancillary services. An incentive-based V2V game-theoretic model is proposed to maximize the BSS's profit. Finally, the proposed system is evaluated with a fleet of 100 EVs with four different types of batteries, and the results validate the proposed methods.

3) Energy Management: To address the potential influence of BSSs on the power grid, some new approaches have been studied in recent years, e.g., fast frequent regulation service [30], [31], reinforcement learning [31], deep learning [30] and the blockchain consensus mechanism [88].

Two studies on BSS-based frequency regulation services are conducted in [30], [31] with the use of reinforcement learning and Q-learning algorithms. In [31], an economic risk assessment model is investigated in terms of infrastructure investment for V2G service, battery aging cost, and uncertainties with regard to charging costs. The value at risk is defined by combining the daily revenue and the long-term return on investment (ROI), which is a metric for comparing BSSs with and without proposed regulation models. The ROI model is formulated as a policy-gradient-based reinforcement learning algorithm. Another work of these authors uses the stochastic dynamic problem and deep Q-learning method for automatic optimal control of a BSS-based fast frequent regulation service [30]. The proposed scheduling strategy maintains each battery's fixed regulation capacity within each hour. The objective is to maximize each BSS's revenue, and the results are verified on real-world data.

Concerning data security during the distributed scheduling in BSS operation systems, a collaborative optimization model with a blockchain consensus mechanism is proposed in [88]. The transmission network level, distribution network level, and BSS level are structured in a power system, and the objective is to minimize the generation cost and daily load variance at each level. The blockchain consensus mechanism is used to verify the accuracy of the transaction data, and the production data of all entities are encoded by a hash function before storage.

In conclusion, five typical BSS decision scenarios are reviewed in this section, and these are compared in terms of the operation modes, decision makers, EV categories, number of battery types, V2G models, focuses, and optimization objectives. These decision scenarios are discussed and summarized as follows:

- Most of the decision scenarios are studied in independent models, which should be correlated in future works. For example, in the construction and planning stage, the determined BSS locations and number of stock batteries are preconditions of the charging schedule scenario, while, in return, the charging schedule could be used to optimize the charging process to minimize the stock batteries.
- The four operation modes should be extended to five decision scenarios. In charging schedule scenarios, most of the operation modes are single BSSs, but there are few works on determining the charging schedule for multiple BSS. In the dispatch and routing scenario, the decision models are mainly for commercial EVs and should be extended to private EVs and multiple BSSs and BCSs.
- The majority of recent studies handle only one type of battery. However, with the development of EV technology, the current BSS operation models should be extended for multiple types of EVs and batteries. In this case, the operation modes and decision scenarios should be revised to address complicated optimization problems.

To solve the above problems in BSS operation scenarios, extensive research directions are presented in Section IV.

IV. Research Directions

The worldwide promotion of EV technology has accelerated the urgent demand for BSSs in recent years, which creates some challenging research topics and new directions. Although some works on EV BSS operation models have been conducted, there are still some gaps in this research area. Based on the reviewed papers, several research directions are highlighted in terms of different operation models and decision scenarios.

A. Extended BSS Models

Most of the existing works build the BSS model as a typical optimization problem under the different scenarios discussed in Section III. Although some studies have investigated building specific mathematical models for swapping stations, including battery heterogeneity [26], [46], [74], [78], [81], [87], V2G [30], [31], [45], [50]–[52], [54], [59], [62], [70], [83], [84], [87], [88], and multiobjective [22], [28], [31], [50]–[53], [56], [59], [60], [62], [64], [67], [69], [72], [74], [78], [81], [86], [88] models, there are still large research gaps in BSS model formulation.

1) Swapping Demand Pattern: The swapping demand pattern from EV drivers is the principal factor in the BSS operation model. First, different categories of EVs have different demand patterns, e.g., private EVs, taxis, buses, and trucks, the swapping frequency of which varies from 1 to 5 days per swap. Second, the swapping demand during a day also varies with the traffic flow, weather conditions, and distribution of BSSs. Third, with the growth in the EV population, the swapping demand could be forecast by learning-based models with historical data. In summary, EV drivers' swapping demand pattern should be modeled in future research.

2) Battery Specifications: A realistic BSS decision model should also rely on the development of EV battery technology considering the battery capacity, acquisition cost, and battery heterogeneity. First, the capacity of lithium-ion batteries has reached 50, 75, and 100 kWh in recent years. Thus, previous works studying lower capacity may not be appropriate for current situations. Second, with the increasing number of EVs, the material price and manufacturing cost of batteries have been reduced, and construction and planning studies should use the updated battery acquisition cost for optimization. Third, because the battery pack is one of the most expensive components in an EV, the BSS should optimize the charging and swapping process to reduce the battery's charging damage and extend the state of health of the battery in the future. Last, serving multiple types of EVs and batteries is the most complicated problem in building BSS decision models. With diverse battery types, the complexity of model formulation and optimization is much higher than that of single-type cases. Hence, operation models considering battery heterogeneity require further study.

3) BSS Specifications: In previous literature, the swapping operation time and number of swapping spots in BSSs were not fully investigated. For a commercial BSS [20], the swapping process usually takes approximately five minutes, including driving into the swapping spot, unloading the used battery, loading the recharged battery and checking the system. Hence, the swapping operation time cannot be ignored if the swapping demand is high. Increasing the number of swapping spots in a BSS is considered a possible approach to avoid

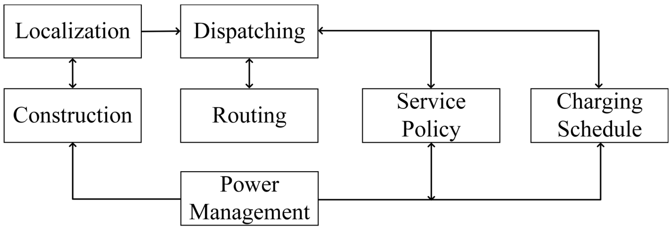

Fig. 5. Scenario Correlation.

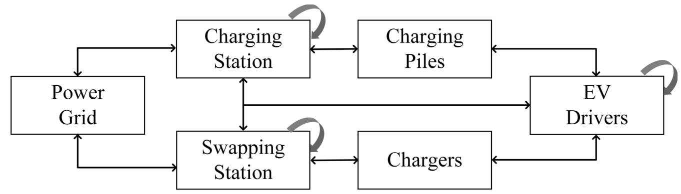

Fig. 6. Decision Participants.

making drivers wait for the swapping operation. In this case, more than one EV can swap batteries in parallel, which can effectively reduce the queuing time. To the best of the author's knowledge, no researcher has studied the determination of BSS swapping spots.

4) Strict Constraints: In real-world applications, the decision should be subject to a series of constraints, considering the specification of EVs, batteries, chargers, and power grids. Some constraints are defined as linear and nonlinear models, while some constraints cannot be formulated as standard mathematical models. In EV charging and swapping studies, the EV charging process follows a constant-current/constant-voltage strategy, which affects the estimation of the charging time and SOC. However, the charging process is defined as a piecewise and nonlinear function and cannot be solved by some linear programming methods. Hence, to solve real-world problems, strict constraints are crucial in decision models, and a more flexible framework should be estimated to determine the optimal solution in future research.

5) Power Grid: Considering the large electric storage in batteries, EVs are expected to be an important energy storage unit in the power system. Collaborating with the power grid and renewable energy (PV power and wind power), the BSS can obtain an optimal schedule to minimize the cost of buying electricity from the grid and minimize the power variation when the power load is high. Additionally, with the use of V2G and V2V technology, EV batteries act as a supply unit in an intelligent power system. The EV and BSS models can extend the research directions of microgrids, nanogrids and smart grids in the future.

B. Multiple Scenarios

Fifteen references in the literature have been formulated as multiple scenario problems; these are indicated in the footnotes of Tables I to V. References [63], [74], [79] have multiple scenarios with charging schedules and dispatching & routing, and references [28], [84], [87] have multiple scenarios with service policy and power management, which are the two most popular cases with multiple scenarios in this research area. In addition, reference [56] presents three scenarios: charging schedule, dispatching & routing and power management. In the future, the correlations among the scenarios should be clarified beforehand, and then multiple scenarios can be defined for intelligent BSS models.

1) Scenario Correlation: Most of the existing BSS operation studies concentrate on simple and isolated scenarios, which have been discussed in Section III. However, in practice, operations are usually determined by multiple scenarios, and the correlation relationships among the seven scenarios are shown in Fig. 5. For example, the charging schedule in a BSS affects the availability of fully recharged batteries, which is a precondition for the dispatching and routing decision. Hence, the correlation among the scenarios should be investigated in future works.

2) Integrated Scenarios Models: In Fig. 5, seven scenarios are presented along with their correlations. Separate scenarios were studied in the previous section. The integrated scenario models aim to involve multiple scenarios in an integrated model to represent a realistic BSS operation system. The directions of the lines indicate the decision sequences among the scenarios. For example, the localization of BSSs determines the dispatching process, while the dispatching and charging schedules are affected interactionally. Concerning the proposed scenario correlations, integrated models should be established with multiple scenarios in the future.

C. Collaborative Decision

In Tables I to V, the decision makers correspond to the purposes of the operation models: BSS operator, EV driver and power grid. Among the references, works that consider multiple decision makers include the following. In the charging schedule scenario, six of the works [48]–[50], [52], [53] have both the BSS operator and the power grid as decision makers. In the service policy scenario, references [26], [57], [59] are determined by the BSS operator and the EV driver, while reference [61] is determined by the EV driver and the power grid. In the dispatching and routing scenario, references [63], [74], [76] have multiple decision makers: the BSS operator and EV driver, and another aspect of this scenario is determined by the BSS operator and the power grid [78], [79], [82]. It should be noted that all the references in Table V have multiple decision makers with BSS operators and power grids, which are the main concerns of power systems with BSS operations. Different from the other scenarios, the decisions of the construction and planning scenarios are made by only one participant in Table III.

1) Decision Participants: As shown in Fig. 6, there are multiple participants in the BSS decision models. Because most recent studies consider a single participant's objective (denoted by the self-looped arrow in Fig. 6), the existing BSS models cannot achieve collaborative decision results. To establish a realistic model and achieve a global decision, the BSS operation model needs to consider the effects of multiple participants. For example, in a single BSS charging schedule scenario (Section III-A), the power grid, swapping station, and EV drivers can be considered together to improve voltage stability, reduce operating costs and maximize the QoS, respectively.

2) Collaboration Model: To maximize the participant contributions, the collaboration model should be established by choosing collaborative participants, confirming participants' relationships, building solution variables, and determining decision results. First, the participants should be chosen based on different decision objectives; the six candidate participants are given in Fig. 6. Second, the relationship between the participants should be confirmed based on the decision flow, as illustrated by the directed lines in Fig. 6. Third, the solution variables should be built by combining the subsolutions from all participants, and the decision structure should be further investigated. Finally, after building the decision models, intelligent algorithms should be studied to solve the optimization problem.

D. Flexible Decision Structure

Some decision structures and service frameworks have been formulated in previous studies to solve the multiobjective problem [26], [62], [62], [69], [69], [70], [78]. However, the proposed structures are usually defined as bilevel programming [26], [62], [69], [78] or two-stage optimization [62], [69], [70]. To build realistic BSS decision models and determine collaborative decisions, a flexible decision structure needs to be established in the future with the following three aspects: multiobjective models, hierarchical structures, and optimization algorithms. To the best of our knowledge, a flexible decision structure has not been proposed in previous BSS and BCS optimization models.

1) Multiobjective Models: Multiobjective models have been used in BSS decision scenarios in past studies. With the use of multiobjective models, two or more optimization objectives can be satisfied. However, these objectives are defined by the scenarios and participants (see Sections IV-B and IV-C); hence, hidden attributes and correlations cannot be used to obtain the globally optimal decision.

2) Hierarchical Structure: Based on the decision scenarios in the BSS operation modes, the current problems are commonly defined as optimization models with one or multiple objective values. As discussed in this paper, decision processes will be crucial in future BSS decision models. Hence, a hierarchical structure is needed to build decision models with multiple scenarios and to solve optimization problems with multiple participants. To solve multiobjective problems, multilevel decision models have been proposed in previous works [51], [52], [62], [70], [86], which are a type of hierarchical structure in the decision process. In future studies, the hierarchical structure should be applied to both the model construction and solution optimization procedures.

3) Optimization Algorithms: Because BSS operation scenarios are defined as complicated optimization models, comprehensive optimization algorithms should be studied considering the number of solutions, multiscenario integration, and interparticipant decision collaboration. First, because of the increasing EV and BSS/BCS population, the decision variables grow concurrently. Thus, more efficient algorithms are needed to solve the NP-hard problem. Second, to handle multiple scenarios, an algorithm structure is also needed for decision models with different priorities. Third, when collaboration occurs between different participants, a collaboration algorithm should be proposed to guide the participants to obtain the global best solutions. Hence, optimization algorithms still need further development.

V. Conclusion

In this paper, a comprehensive survey of BSS models for EVs was presented in terms of the operation modes and decision scenarios. In particular, the state-of-the-art development of swapping was introduced, including its current business operation status worldwide and the advantage of BSS modes, and some key challenges were summarized. The operation of BSSs was first classified into four modes with different combinations of BSSs and BCSs (a single BSS, multiple BSSs, an integrated BSS and BCS, and multiple BSSs and BCSs). Under each mode, the flowcharts of the EV, battery, and charging status were discussed, as well as the specific operational problems in each mode. Research works on the BSS operation system were reviewed considering the aspects of the charging schedule, service policy, construction and planning, dispatching and routing, and power system. For each aspect, the BSS mode, decision makers, EV category, number of battery types, V2G technology, focus, and objective were summarized and compared in tables. To the best of our knowledge, this is the first paper to summarize the operation mode and decision scenarios of BSSs considering realistic operating procedures and optimization directions, shedding light on EV BSSs and BCSs. Finally, several research directions for the future development of BSS models and the decision methodology were outlined.

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