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SINGAPORE

**HOLISTIC MANAGEMENT OF MOBILE
ENERGY STORAGE RESOURCES IN COUPLED
POWER AND TRANSPORTATION SYSTEMS**

LIU XIAOCHUAN

**SCHOOL OF ELECTRICAL & ELECTRONIC
ENGINEERING**

2020

**HOLISTIC MANAGEMENT OF MOBILE
ENERGY STORAGE RESOURCES IN COUPLED
POWER AND TRANSPORTATION SYSTEMS**

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School of Electrical & Electronic Engineering

A thesis submitted to Nanyang Technological University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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20 August, 2020

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Authorship Attribution Statement

This thesis contains material from 3 papers published in the following peer-reviewed journals where I am the first author.

Chapter 3 is published as X. Liu, T. Zhao, S. Yao, P. Wang, C. B. Soh, “Distributed Operation Management of Battery Swapping-Charging Systems”, *IEEE Trans. Smart Grid*, vol.10, no.5, pp. 5320-5333, Nov. 2018.

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The contributions of the co-authors are as follows:

- I prepared the manuscript drafts, designed the case studies and analyzed the algorithms.
- Dr. T. Zhao, S. Yao, Prof. P. Wang, Prof. C. B. Soh revised and proofread the manuscript.

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The contributions of the co-authors are as follows:

- I prepared the manuscript drafts, designed the case studies and analyzed the algorithms.
- Prof. C. B. Soh, Dr. T. Zhao, Prof. P. Wang revised and proofread the manuscript.

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Summary

In the face of future energy and environmental challenges, huge growths in transportation as well as its electrification have been witnessed in recent decades, which has brought a large number of potential mobile energy storage resources. Besides the electric vehicles (EVs) under plug-in charging mode, which have been extensively studied in the literature, newly emerging types of mobile energy storage resources such as the EV batteries under battery leasing and swapping mode, and truck-mounted mobile energy storage systems (MESSs) can also bring potential opportunities to further improve the reliability, flexibility and efficiency of future smart grids. However, as these emerging mobile energy storage resources also bring close couplings and interdependences between power and transportation systems, research gaps still exist in terms of mathematical modeling and management scheme designs, which makes these emerging resources generally underutilized. In order to achieve the coordination between these mobile energy storage resources and power systems, as well as the full utilization of their temporal-spatial mobility while considering certain transportation system characteristics, novel models and management schemes are urgently needed.

To achieve the full utilization of the EV battery mobility under battery leasing and swapping mode while ensuring uninterrupted battery swapping services, and to fill in the gaps in the modeling and management of the coordinated operation between battery charging stations (BCSs) and battery swapping stations (BSSs), this thesis first proposes a novel closed-loop supply chain (CLSC) based battery swapping-charging system (BSCS) model. A novel battery logistics model based on the time-space network (TSN) technique is established to describe and utilize the temporal-spatial mobility of the EV batteries. The charging and discharging of the batteries in the BCSs and the battery logistics are optimally managed

to maximize the revenue of the BSCS while satisfying the battery demand for battery swapping service at each BSS. A heuristic method based on a randomly permuted alternating direction method of multipliers (RP-ADMM) is adopted to solve the optimization problem in a more efficient and distributed way. Simulation results verify the feasibility of the proposed model and the heuristic solution with small optimality losses and less computation time.

To take into account the large-scale deployments of BSCSs in the future, this thesis further extends the single BSCS model to a multi-region battery swapping and charging network (MBSCN) model to achieve efficient and collaborative management of the BSCSs located in different regions with different EV user behavior and local system features. A novel multilayer TSN-based network-wise battery logistics model is proposed to manage both the intra-BSCS and interregional battery logistics more efficiently, which also enables the sharing of the mobile energy storage resources within different BSCSs. A distributionally robust chance-constrained service model is established to address the regional battery demand uncertainties without requiring assumptions on the probability distributions or a large amount of historical data. The battery charging and discharging tasks are optimally allocated to each BSCS and the battery logistics are optimally managed according to the locational energy price and the battery demands. Simulation results are presented to verify that the proposed MBSCN model is more flexible and efficient when interregional battery exchanges are incorporated.

For truck-mounted MESSs, to fully leverage their mobility for enhancing the operational flexibility of coupled distribution and transportation networks (CDTNs) while considering the system uncertainties from variable renewable energy (VRE) sources and the daily traffic demands in transportation networks, this thesis proposes a stochastic management scheme to achieve the coordination among MESSs,

hybrid AC/DC microgrids (MGs) and CDTNs. A novel stochastic multi-layer multi-timescale TSN model that incorporates the hourly traffic user-equilibrium (UE) results obtained from the adopted traffic assignment problem (TAP) model is also proposed to facilitate the modeling and scheduling of different MESSs with various mobility features while considering the uncertainties in the traffic flows in the transportation network and the resulting congestion delays. The scheduling and management of MESSs and CDTNs are formulated as a two-stage stochastic optimization problem, where the uncertainties of traffic demands, VRE outputs and loads are depicted using scenarios. Case studies are performed to verify the effectiveness of the proposed two-stage stochastic management scheme and the UE-TSN model, as well as the effectiveness of MESSs to serve as mobile energy storage resources for MGs with mismatched generation and conversion capabilities.

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List of Abbreviations

ADMM	Alternating Direction Method of Multipliers
APP	Auxiliary Problem Principle
ATC	Analytical Target Cascading
BCS	Battery Charging Station
BSCS	Battery Swapping-Charging System
BSS	Battery Swapping Station
CLSC	Closed-loop Supply Chain
CLSCN	Closed-loop Supply Chain Network
DG	Distributed Generators
DN	Distribution Network
DNO	Distribution Network Operator
ESS	Energy Storage System
EV	Electric Vehicle
G2V	Grid to Vehicle
ICT	Information and Communication Technology
KKT	Karush-Kuhn-Tucker
MBSCN	Multi-region Battery Swapping-Charging Network
MESS	Mobile Energy Storage System
MILP	Mixed-integer Linear Programming
MIQCQP	Mixed-integer Quadratically Constrained Quadratic Programming
OCD	Optimality Condition Decomposition
RP-ADMM	Randomly Permuted Alternating Direction Method of Multipliers

List of Abbreviations

SESS	Stationary Energy Storage System
TSN	Time-space Network
V2G	Vehicle to Grid

Chapter 1

Introduction

This chapter starts with the research backgrounds, detailing the transportation electrification, the emerging mobile energy storage resources and the new challenges brought by them. Then, the motivations and main contributions of this thesis are summarized. This thesis aims to bridge the gap in the modeling and management of the potentially accessible mobile energy storage resources to improve the operational efficiency and flexibility of the corresponding systems while considering the couplings between power and transportation systems. Finally, detailed thesis organization is provided.

1.1 Background

Over the next few decades, the world will face increasing energy challenges [7]. As illustrated in Fig. 1.1, from 1990 to 2019, the global primary energy demand increased by almost 200 qBtu (1.055×10^{18} joules) [2]. Despite the fact that most projections expect slower growth over the next generation, global energy demand still increases significantly in most scenarios by 2040. Amongst all the major economic sectors, the energy consumed by electric power and transportation sectors accounts for the largest proportion of the total global energy consumption. For example, in 2019, the electric power sector and the transportation sector together account for 65.2% of the total energy consumption in the U.S. [8]. Meanwhile, about 1.6 and 1.8 billion metric tons of carbon dioxide emissions were produced by these two sectors, respectively [5]. Decreasing stock of fossil fuel, increasing emissions of greenhouse gases, and more frequent power outages have led to renewed efforts in developing new concepts of electric power and transportation systems using the existing infrastructure.

Figure 1.1: Global primary energy demand [2].

In recent years, researchers have realized that transportation electrification is one of the most effective ways to deal with the energy and environmental issues and achieve the decarbonization of transport. “Transportation electrification” is the term that refers to the use of electricity from external sources of electrical power, including power grids and batteries, for all or part of vehicles, vessels, trains, boats, or other equipment that are mobile sources of air pollution and greenhouse gases, together with the related programs and charging/propulsion infrastructure investments to enable and encourage this use of electricity [9]. Electrifying the transportation sector can bring significant economic and environmental benefits and new opportunities for consumer engagement. Furthermore, the sustainability, efficiency, security, reliability and scalability of the existing power and transportation systems can be greatly improved.

Significant growth in transportation electrification has been witnessed in the recent decades, which has brought a large number of potential mobile energy storage resources, e.g., electric vehicles (EVs) under plug-in charging mode, EV batteries under battery leasing and swapping mode, and truck-mounted mobile energy storage systems (MESSs).

EVs, as an essential part of transportation electrification, have many attractive features. With zero tailpipe emissions in the case of full-electric driving vehicles, EVs can provide a clean alternative to vehicles with internal combustion engines (ICE) by helping to reduce exposure to air pollution resulting from fuel combustion. Meanwhile, EVs can significantly reduce noise, which is especially relevant in urban areas and along major transportation axes. In the past decade, the world has witnessed a rapid deployment of EVs. Until 2019, the global EV stock has reached 7.2 million, while most of the EVs are distributed over China, Europe and the U.S., and it is estimated that EV stock will range between 140 million by 2030 and about 245 million by 2040 [6]. Meanwhile, EV

charging facilities, which are indispensable for EVs usage, are also being widely deployed. By the end of 2019, there are 7.3 million electric vehicle chargers installed worldwide, of which 6.5 million chargers are private light-duty vehicle (LDV) slow or normal chargers and 0.8 million chargers are publicly accessible chargers. The stock of chargers increased by 40% from 5.2 million in 2018 [6]. Besides plug-in charging, to further facilitate the charging process of EVs and alleviate the range anxiety of the potential EV users, which are the main barriers against further EV purchases and deployments, the emerging battery leasing and battery swapping mode are promising and have attracted attentions from many real-world entities [10], [11]. For example, in China, BAIC announced a plan to build 3,000 battery swapping stations (BSSs) nationwide by 2021, the Chinese EV startup NIO also plans to build over 1,000 BSSs, while over 95% of its EV users chose to lease the batteries [12], [13]. Moreover, by introducing battery logistics and a well-designed battery inventory and logistics management scheme into the system operation, the surplus battery packs within certain BCSs or BSSs can be transported and shared with other facilities while ensuring high-quality battery swapping service provisions. This temporal-spatial mobility feature of EV batteries under the battery leasing and swapping mode makes them great potential mobile energy storage resources for both BCSs, BSSs and the associated power systems to achieve higher operational flexibility and efficiency.

Meanwhile, with the development of energy storage and power electronics technologies, as well as the increasing installation of charging/discharging facilities including ultra-fast chargers of which the power rate can reach up to a few megawatts [6], [14], the emerging MESSs can also bring significant benefits to power systems both in response to extreme events [15]–[17] or under normal conditions [18]–[20]. MESSs are generally utility-scale battery energy storage banks mounted on trucks, owned and fully controlled by the utility company [17],

[20]. Compared to normal stationary energy storage systems (SESSs), MESSs have the advantages in terms of mobility and operational flexibility, which makes them also great mobile energy storage resources for power systems.

These mobile energy storage resources and their mobility bring not only opportunities to further improve the economy, reliability, flexibility and efficiency of the future smart grids, but also the close couplings and interdependences between power and transportation systems, i.e., the intrinsic characteristics of transportation systems would have impacts on the routing and scheduling of mobile energy storage resources, which could then affect the interactions between mobile energy storage resources and power systems. Similarly, power-system-side decisions, e.g., electricity price signals and dispatch requests would alter the temporal-spatial behaviors of the mobile energy storage resources, which could then affect transportation systems. There are still many remaining challenges in terms of mathematical modeling and management scheme designing to achieve the coordination between mobile energy storage resources and power systems, and the full utilization of their temporal-spatial mobility while considering certain transportation system characteristics, e.g., network structure, traffic conditions, etc.

1.2 Motivation

The objective of this thesis is to propose a holistic management framework for the potentially accessible and underutilized mobile energy storage resources in coupled power and transportation systems, i.e., EV batteries under battery leasing/swapping mode and MESSs, where they are managed and their mobility are harnessed to achieve improved system operational efficiency, flexibility, and minimized cost, while considering the interactions with both the power and trans-

portation systems, as well as their intrinsic characteristics and constraints.

The potentials of EVs and their batteries to serve as mobile energy storage resources have been increasingly recognized. Extensive literature has endeavored to propose models and management schemes to leverage the mobility and flexibility of EVs under plug-in charging mode [21]–[26]. Still, despite the fast deployment of BSSs, only a few studies have considered utilizing the mobility of EV batteries under battery leasing and swapping mode. Furthermore, due to the large battery demand from EVs, battery inventory shortages may happen during the operation at BSSs, which can result in severe service interruptions. Incorporating centralized battery charging stations (BCSs) to form a battery swapping-charging system (BSCS) is a promising way to deal with this challenge. Since BCSs and BSSs are geographically separated, a logistics system, whose responsibility is to transport batteries among them, is the key to make full use of the mobility of the batteries and achieve the coordinated operation of BCSs and BSSs. In this context, the first part of this thesis aims to bridge the gap in the modeling and management of BCSs, BSSs, intra-BSCS vehicle routing and battery logistics, and to achieve the full utilization of batteries as potential mobile energy storage resources while providing high quality, uninterrupted battery swapping services to the EVs through the coordinated operation among BCSs, BSSs, battery logistics system and the corresponding local power and transportation system.

Moreover, with the continuously increasing number of EVs, further deployments of EV charging facilities, i.e., plug-in charging stations, BCSs and BSSs, can be foreseen in the near future. For example, as also mentioned previously, in China there will be thousands of new BSSs built nationwide in the next few years. This increase in BSCS scale and geographical span could bring great difficulties in battery logistics management as well as battery charging and swapping planning if all these BCSs and BSSs are managed as a single entity, due to the differ-

ences in EV user behaviors, local transportation network structures, and local power network configurations in different geographical regions, which makes the single BSCS model insufficient and inefficient. A practical solution to this challenge is partitioning these stations into smaller groups, where each group acts as a single BSCS to manages its own intra-system battery logistics and provides services to its designated service region, e.g., towns or cities [27]. Moreover, since the EV charging infrastructure usage is highly location-dependent [28], to further leverage the mobility of the EV batteries not only within each BSCS, but also across multiple BSCSs, introducing interregional battery logistics could achieve the sharing of these mobile energy storage resource and collaborations between BSCSs, which could potentially achieve higher efficiency, economy and more operational flexibility for both BSCSs and their local coupled power and transportation systems, i.e., more battery charging tasks are performed at BSCSs where the regional battery demands are low and then transported to the regions with higher EV penetration level. Furthermore, the uncertainties of EV user behaviors should also be addressed to ensure uninterrupted, high-quality battery swapping service provisions [29]. Therefore, the modeling and management of multi-BSCS networks when interregional battery logistics is incorporated and EV uncertainties are considered are still necessary. In this context, the second part of this thesis aims to bridge the gap in the modeling and management of a multi-BSCS network with network-wise (both intra-BSCS and interregional) vehicle routing and battery logistics while considering EV uncertainties, where the mobile energy resources, i.e., the swapped batteries, in different BSCSs are managed holistically and collaboratively to improve the overall system economy, operational efficiency and flexibility.

Besides EVs, with the development of energy storage and power electronics technologies, as well as the increasing installation of charging/discharging fa-

cilities including ultra-fast chargers of which the power rate can reach up to a few megawatts [6], [14], MESSs, as an emerging type of mobile energy resource, are also attracting increasing attentions in recent years. While most of the literatures mainly focus on utilizing MESSs as emergency mobile resources to enhance the power system resilience in response to extreme events such as hurricanes and earthquakes [15]–[17], [30]–[32], only a few publications consider adopting MESSs in normal operations. Meanwhile, in recent years, a hybrid AC/DC microgrid (MG) structure was proposed and has shown its potential in various applications to achieve higher operational efficiency and better integration of variable renewable energy (VRE) sources. However, VRE generation curtailments could still occur due to the mismatch between VRE generation and the power conversion capacity in MGs. Introducing MESSs into the system operation, which has the potential to enhance the power conversion capability of the MGs and serve as flexible energy storage considering their mobility feature, is a promising way to address this issue. Furthermore, MESSs are mainly scheduled to travel within the existing transportation networks to provide services to the facilities in the distribution system at different locations, where other common vehicles such as private cars, EVs, taxis, etc., also travel within the network to fulfil their daily travel demands. Due to the aggregated movements of these vehicles and the selfish behavior of individual travellers in route selection, possible traffic congestions could occur on certain roads with heavy traffic flows during peak hours, which could greatly affect the travel speeds of MESSs and the resulting travel time on these congested roads. Also, the uncertainties in the traffic demands, which could lead to uncertain traffic flow distributions and MESS travel time, should be accounted for. These impacts of traffic flows on the scheduling and operation of MESSs are ignored in most of the aforementioned publications. In this context, the last part of this thesis aims to propose a novel vehicle routing

Figure 1.2: General framework of the proposed schemes.

model that also incorporates the impacts of uncertain traffic flow distributions within the transportation system, which allows a more accurate and efficient vehicle scheduling. Then, this thesis aims to propose a stochastic management scheme that can achieve coordinated operation of MESSs, hybrid AC/DC MGs and coupled distribution and transportation network (CDTNs) under normal conditions while considering the uncertain temporal-spatial distribution of traffic flows, congestions and their impacts on the scheduling of MESSs, as well as the uncertainties in VRE sources and loads.

1.3 Main Contributions

This thesis mainly focuses on filling in the gaps in the modeling and management scheme designs for the newly emerging mobile energy storage resources, i.e., EV

batteries under battery leasing and swapping mode and truck-mounted MESSs, and harnessing their mobility and improve the operational efficiency and flexibility of the corresponding systems, e.g., BSCSs and the local power systems. The generation framework and objectives of the proposed schemes in this thesis are depicted in Fig. 1.2, and the main contributions of this thesis are summarized as follows.

1.3.1 Management of Mobile Energy Storage for Battery Swapping Charging Systems

To achieve the full utilization of the mobility of the EV batteries under battery leasing and swapping mode while ensuring uninterrupted battery swapping services, a novel closed-loop supply chain (CLSC) based battery swapping-charging system (BSCS) model is proposed to fill in the gaps that currently still exist in the literature in terms of the modeling and management of the coordinated operation between BCSs and BSSs with battery logistics. A novel vehicle routing and battery logistics model based on the time-space network (TSN) technique is established to describe and utilize the temporal-spatial mobility of the EV batteries, which has not been seen in any other works. The charging and discharging of batteries and the battery logistics are optimally managed to maximize the revenue of the BSCS while satisfying the battery demand for battery swapping service at each BSS. The optimization problem is formulated as a mixed-integer linear programming (MILP) problem and is solved in a distributed and more efficient way using a novel heuristic method based on randomly permuted alternating direction method of multipliers (RP-ADMM), which also serves as a convergent instance of RP-ADMM against multi-block problems.

1.3.2 Management of Mobile Energy Storage for Multi-region Battery Swapping-Charging Networks

Considering the future expansion in the BSCS scales and geographical spans, this thesis further extends the proposed single BSCS model to a novel closed-loop supply chain network (CLSCN) based multi-region battery swapping-charging network (MBSCN) model to achieve efficient and collaborative management of the BSCSs located in different regions with different EV user behavior and local system features, which has not been studied yet in any of the existing works. To address the differences in the temporal-spatial behavior of the truck fleets in each subsystem considering their varying traveling speeds, sizes, and different regional transportation network structures, a multi-layer TSN based network-wise (both intra-BSCS and interregional) vehicle routing and battery logistics model is proposed. The battery charging/discharging and the battery logistics are optimally scheduled such that collaborative operations among the BSCSs are achieved. Furthermore, to capture the uncertainties of EV arrival and departure at BSSs, which is ignored in most of the BSCS-related works, the network-calculus-based BSS service model is extended to a distributionally robust chance-constrained model, which relaxes the assumptions on the probability distributions of uncertainties.

1.3.3 Stochastic Management of Mobile Energy Storage in Coupled Distribution and Transportation Networks

For the other type of the emerging mobile energy storage resource, i.e., truck-mounted MESSs, as most research works focused on adopting MESSs for service restoration in response to extreme events, e.g., hurricanes, a two-stage stochastic

management scheme is proposed to fill in the gaps in the utilization of MESSs in normal operation while considering the impacts of traffic conditions on the scheduling and operation of MESSs, where the mobility of MESSs is fully leveraged for enhancing the operational flexibility of CDTNs and the system uncertainties from VRE sources and the daily traffic demands in transportation networks are also accounted for. Moreover, the TSN models proposed in Chapter 3 and Chapter 4 are extended to a novel stochastic multi-layer multi-timescale TSN model that incorporates the hourly traffic user-equilibrium (UE) results obtained from the adopted traffic assignment problem (TAP) model is proposed to facilitate the modeling and scheduling of different MESSs with various mobility features while considering the uncertainties in the traffic flows in the transportation network and the resulting congestion delays. The scheduling and management of MESSs and CDTNs are formulated as a two-stage stochastic optimization problem, where the uncertainties of traffic demands, VRE outputs and loads are depicted using scenarios.

1.4 Organization of the Thesis

This thesis consists of six chapters and is organized as follows.

Chapter 1 presents the background, motivation and contribution of the thesis.

Chapter 2 provides a literature review on the related research works, including transportation electrification, mobile energy storage resources, modeling and management of EVs and MESSs, and the couplings between power systems and transportation systems.

Chapter 3 proposes a detailed CLSC-based BSCS model with a TSN-based vehicle routing and battery logistics model to fully utilize the mobility of the batteries

within the BSCS while ensuring high-quality battery swapping service provision. The charging and discharging of batteries and the battery logistics are optimally managed to maximize the revenue of the BSCS while satisfying the battery demand for battery swapping service at each BSS. The optimization problem is formulated as a MILP problem and is solved in a distributed way using a heuristic method based on randomly permuted alternating direction method of multipliers. Simulations and results analysis are also included.

Chapter 4 further extends the single BSCS model in Chapter 3 to a multi-regional one. This chapter proposes a novel CLSCN based MBSCN model to achieve a holistic management of batteries within and across the BSCSs. To address the differences in the temporal-spatial behavior of the truck fleets in each subsystem considering their varying traveling speeds, sizes, and different regional transportation network structures, a multi-layer TSN based network-wise (both intra-BSCS and interregional) vehicle routing and battery logistics model is introduced. The battery charging/discharging and the battery logistics are optimally scheduled such that collaborative operations among the BSCSs are achieved. Furthermore, to capture the uncertainties of EV arrival and departure at BSSs, the network calculus based BSS service model is extended to a distributionally robust chance-constrained model, which requires no assumptions on the probability distributions of uncertainties. The optimization problem is formulated as a MIQCQP problem to minimize the total cost of the MBSCN. Simulations and results are presented to illustrate the efficiency and flexibility of the model and the effectiveness of the proposed scheme for the management of batteries and their mobility within the MBSCN.

Chapter 5 mainly studies the emerging MESSs and also extends the TSN models used in Chapter 3 and Chapter 4 to incorporate the impacts of traffic flows in the transportation system on the scheduling and operation of MESSs, which

brings further couplings between power systems and transportation systems. In this chapter, a stochastic management scheme is proposed to achieve the coordination among MESSs, hybrid AC/DC MGs with high penetration of VRE sources and CDTNs, leveraging the mobility of MESSs for conversion capacity enhancements through energy transporting among the MGs while considering possible traffic congestions. The operation of MESSs, MGs and distribution networks are formulated as a two-stage stochastic optimization problem, where the uncertainties of traffic demands, VRE outputs and loads are depicted using scenarios. In the first-stage, the vehicle scheduling problem of MESSs are modeled and optimized based on a novel proposed multi-layer multi-timescale TSN model that incorporates the hourly traffic UE results obtained from the adopted TAP model to harness the flexibility and mobility of MESSs. In the second-stage, the actual charging/discharging behaviors of MESSs, the output of DGs and power conversions through the BICs are adjusted in accordance with the realized uncertain factors. The proposed model is verified on a test system with Sioux Falls transportation network and a 33-bus distribution system. The results demonstrate the effectiveness of MESSs mobility to serve as potential power conversion enhancements for MGs with mismatched generation and conversion capabilities.

Chapter 6 concludes the research work and recommends prospective areas for further investigation.

Chapter 2

Literature Review

In this chapter, a comprehensive review of the related literature is presented in detail. First, The background of transportation electrification is introduced, including the upcoming energy and environmental challenges, the current EV deployment status and their advantages. Then, with the rising trend of transportation electrification, the emerging mobile energy storage resources are introduced, which include EVs under plug-in charging mode, EV batteries under battery swapping mode and truck-mounted MESSs, and the related state-of-the-art publications are reviewed. Finally, the potential couplings between power systems and transportation systems brought by the mobile energy storage resources are introduced and the related literature are also reviewed.

2.1 Transportation Electrification

2.1.1 Energy and Environmental Challenges

Rapid global economic development brings the world increasing energy and environmental challenges. In the past twenty years, the global primary energy demand has increased by almost 200 qBtu (1.055×10^{18} joules), and is expected to keep increasing over the next few decades [2]. To meet the increasing energy demand, fossil fuels, i.e., coal, petroleum and natural gas are being intensively exploited and utilized on a daily basis, which makes their depletion in the near future foreseeable [33]. Moreover, the burning of fossil fuels contribute greatly to greenhouse gas (GHG) and carbon dioxide emissions, which leads to various consequences including global warming and environmental pollution [34]. As reported by the U.S. Energy Information Administration (EIA) in Fig. 2.1, the carbon dioxide emissions in 2019 mainly came from petroleum, natural gas and coal in the proportions of 46%, 33% and 21%, respectively.

Figure 2.1: U.S. CO₂ emissions by source, 2019 [3].

To prevent global temperatures from further rising over 2 degree Celsius, countries and governments have set goals and made their endeavors to cut their GHG emission. The European Commission committed to curtailing its GHG emissions to 20% below 1990 levels by 2020. It also plans to reduce the GHG emissions from the transportation sector by 20% by 2030 compared to emissions in 2008, and by 60% by 2050 compared to 1990 [35]. Similarly, many states in the U.S. have started pursuing a goal so-called "80 × 50", which aims to achieve 80%

Figure 2.3: U.S. CO₂ emissions by energy sector, 2019 [5].

reduction of GHG emission over 1990 levels [36]. These ambitious goals, along with the depleting stock of fossil fuel, increasing emissions of greenhouse gases, and severer environmental and climate problems have led to renewed efforts in developing new concepts for the electric power and transportation systems.

2.1.2 Rising Trend of Transportation Electrification

Over the past decades, the rising trend of transportation electrification has caught worldwide attention and became a hot topic. “Transportation electrification” is the term that refers to replacing energy sources such as fossil fuel with the electricity from external sources of electrical power, including power system and batteries, for all or part of vehicles, vessels, trains, boats, or other equipment that generates air pollution and GHG, together with the related programs and charging/propulsion infrastructure investments to enable and encourage this use of electricity [9]. Transportation electrification has gradually obtained an increasing recognition as one of the most effective ways to deal with the energy and environmental issues [37].

Transportation electrification has many benefits. For example, as also suggested in many decarbonization studies conducted by utility companies [38], [39], transportation electrification and the deployment of EVs and EV charging facilities can help to achieve the decarbonization of transport. As already discussed earlier, transportation sector accounts for a large proportion of the GHG emissions. With more efficient powertrain systems and the ability of utilizing the electricity generated by renewable energy sources, an electrified transportation system with EVs could achieve reduced GHG emissions [40] and potential global climate change mitigation [41]. Secondly, considering the unstable global political situations, transportation electrification could potentially enhance the security of energy supply through diversifying the energy sources for transportation [37]. Last but not least, tremendous research works have shown the benefits that EVs can bring to the existing power systems as potential energy storages through vehicle-to-grid (V2G) technologies, e.g., load-shifting, frequency regulation, and other ancillary services [42]–[44].

Although great efforts have been put into transportation electrification, the actual progresses of electrification in various transportation modes are at highly different paces. In waterborne transportation sector, the electrification is progressing, but currently only small electric vessels with short range are available [1]. For aeronautics, although there are a growing number of start-ups that are developing demonstrative very small and short-range electric aircraft, the world has to wait for at least few decades to see an actual full-size long-range electric aircraft [37].

Meanwhile, great progress has been made in the electrification of road transportation sector. Various types of EVs, e.g., electric passenger cars, vans and buses are readily available to the public and the global stock as well as the market are growing fast, where they accounted for 2.6% of global car sales and 1% of global car stock in 2019, and marked a 40% year-to-year growth. As depicted in

Figure 2.4: Global EV stock, 2010-2019 [6].

Fig. 2.4, by 2019, the global EV stock had reached 7.2 million, while most of the EVs are distributed over China, Europe and the U.S., and it is estimated that EV stock will range between 140 million by 2030 and about 245 million by 2040 [6].

Compared to the vehicles with internal combustion engines (ICE), EVs have the advantages in terms of energy efficiency and pollutant emissions. For energy efficiency, the U.S. Department of Energy states that EVs can achieve an efficiency around 77% when converting the electrical energy to kinetic energy while conventional ICE vehicles can only achieve 12%-30% conversion efficiencies from the chemical energy stored in gasoline or diesel [45]. Although recently some skeptics are still questioning if EVs are truly more efficient considering that a part of their utilized energy is still from the conventional coal-powered plants, an analysis from Bloomberg points out that EVs are still more efficient in China where coal-fired power plants are more common [46]. Moreover, EVs with regenerative braking could further utilize the kinetic energy when braking to recharge their batteries, which also increases the efficiency of EVs [47].

With zero tailpipe emissions in the case of full-electric driving vehicles, EVs can provide a clean alternative to ICE vehicles by helping to reduce exposure

to air pollution resulting from fuel combustion. Since power plants and battery manufacturing inevitably produce emissions, doubts also appear when comparing EVs and conventional vehicles in terms of environmental impacts. According to [6], the worldwide deployment of EVs saved 0.6 million barrels of oil products on a daily basis in 2019. Moreover, to generate the electric power for the global EV fleet, there were only 51 Mt CO₂-eq produced, which is reduced by almost 50% compared to the emissions when the EVs were replaced with conventional ICE vehicles. Also, with the growing integration of renewable energy sources such as PV and wind power, further reductions in pollutant emissions contributed by EV deployment are foreseeable. As for the emissions from battery manufacturing, although a recent study shows that the carbon dioxide created during battery manufacturing is the same or even higher than ICE engines [48], with the development in battery manufacturing technologies and the recycling of batteries, there is a great potential for further cutting the carbon dioxide emissions.

These advantages together with other benefits such as significantly reduced noise, which is especially relevant in urban areas and along major transportation axes, and better performances in acceleration, make EVs favourable for both the future society and individual users.

2.2 Emerging Mobile Energy Storage Resources

The rising trend of transportation electrification, as well as the growing deployment of electrified facilities over the world's transportation systems, such as EV plug-in charging stations and EV battery charging and swapping stations, bring a huge amount of opportunities and potential applications to the existing power systems. Over the past decade, utilizing the mobility of vehicles including EVs and the emerging truck-mounted energy storage systems, and integrating them

into power system operation as potential mobile energy storage resources have attracted researchers' attentions.

2.2.1 Electric Vehicles as Mobile Energy Storage Resources under Plug-in Charging Mode

As a conventional charging method, plug-in EV charging facilities, which are indispensable for EV usage, are widely distributed over the major countries with high EV penetration levels. Besides the private charging piles located at residential areas owned by EV users, publicly accessible EV charging stations are the most common charging infrastructure around the world. Many charging stations are on-street facilities or located at car parks, equipped with charging piles, some even support fast charging for EVs. By the end of 2019, there were 7.3 million EV chargers installed worldwide, of which 6.5 million chargers are private light-duty vehicle slow or normal chargers and 0.8 million chargers are publicly accessible chargers. The stock of chargers increased by 40% from 5.2 million in 2018 [6].

Table 2.1 provides an overview of the major levels and types of EV chargers used in different regions, including Level 1-3 AC charging and DC fast charging.

- Level 1 AC Charging: Level 1 AC charging usually takes up to 20 hour to fully charge the EV. Therefore it is suitable for overnight charging at home or specific parking locations.
- Level 2 AC Charging: Level 2 AC charging provide slightly higher charging rate compared to Level 1 charging. Still, it is preferred for long-term parking due to the comparatively lower cost than fast charging.
- Level 3 AC Charging: Level 3 AC fast charging, which mainly uses three-phase AC power, provides much higher charging rate compared to Level 1-

Table 2.1: Overview of the EV charger characteristics in key regions [1]

	Conventional plugs	Slow chargers	Fast chargers	
Level	Level 1	Level 2	Level 3	
Current	AC	AC	AC, 3-phase	DC
Power	< 3.7kW	> 3.7 kW and ≤ 22 kW	> 22kW and ≤ 43.5 kW	< 400 kW
China	Type I	GB/T 20234 AC	-	Requires GB/T 20234 DC.
EU	Type C/F/G	IEC 62196-2 Type 2	IEC 62196-2 Type 2	Requires IEC 62196-3.
Japan	Type B	SAE J1772 Type 1	-	All IEC 62196-3 standards.
North America	Type B; SAE J1772 Type 1	SAE J1772 Type 1	SAE J3068	SAE J1772, IEC 62196-3.
Singapore	Type A/B/C/F	IEC 62196-2 Type 2	IEC 62196-2 Type 2	Requires IEC 62196-3.

2 chargers, and can reduce the refueling time to less than 1 hour. These type of chargers are usually installed in publicly accessible charging stations, e.g., commercial areas.

- **DC Fast Charging:** DC fast charging further raises the charging power up to 400 kW, which brings new opportunities for the future deployment of electric heavy-duty vehicles with bulky and high-capacity battery packs. However, particular measures should be taken considering the impacts of fast charging on power systems during load-peaks.

With the development of information and communication technology (ICT) and the maturity of EV supply equipment (EVSE) technology, vehicle-to-grid (V2G) and grid-to-vehicle (G2V) enables the establishment of a bidirectional services

supply relationship between power systems and EVs, where EVs receive energy from power systems while serving as mobile energy storage resources by providing certain services, e.g., load-shifting, frequency regulation and other ancillary services, to power systems. While EVs park at and are connected to various types of charging facilities, their on-board batteries and charging/discharging processes can be integrated into the operation of power systems in the form of both energy and reserves. Extensive research has been conducted to study the coordination between EVs and power systems, where EVs act as potential mobile energy storage resources and offer services to power systems via V2G [43], [49]–[52].

For MGs, when a MG is integrated with RESs such as photovoltaic (PV) and wind power, well-managed interactions with EVs can greatly contribute to the improvement of the supply-demand regulating ability. In [53], a review of the interactions between EVs and renewable energy is presented from the perspective of cost-revenue, energy efficiency and pollution emission. It points out that the integration of EVs can effectively improve the efficiency of a MG and its maximum capacity for renewable energy. For a MG with a high penetration of renewable DGs, [54] propose a stochastic optimization framework to reconfigure the MG to reduce the operation cost, where the EVs serve as moving storages. A optimal operation model based on two-stage robust optimization (RO) is proposed for MGs with solar energy in [55]. In day-ahead decision making stage, the day-ahead marginal electricity sale price is found for the operators to decide the electricity sale price and parking fee for EV customers. In the second stage, an model predictive control (MPC) based real-time operation management scheme is proposed. Based on the real-time EV arrivals and parking behaviors, the total revenue of the MG is maximized. In [56] a day-ahead optimal operation strategy is introduced for a MG with EVs that provide logistics services and multiple EV charging stations. The driving routes, fast-charging time and charg-

ing/discharging schedules are optimally decided to minimize the overall cost and smooth load fluctuations. In [57], an energy management scheme is proposed for a grid-connected MG with thermal units to minimize the expected total operation cost. The energy and storage provided by EVs are considered. The uncertainty of the demand, availability of EVs and the intermittency of the renewable energy is also taken into account. In [58], compared to the aforementioned works, the authors regard EV fleets as a massive support for both active and reactive power demands in the MG. Besides the efficiency, the voltage quality within the MG is also improved by around 43.8%.

For the distribution systems integrated with large-scale EVs, many existing research works have covered a wide variation of topics from valley-filling to the coordinated operation of the distribution networks with multiple charging stations. Reference [26] presents a detailed survey on the utilization of EVs as MESSs in terms of applications, challenges and solutions. In [59], the authors provide an overview on both centralized control architectures and decentralized control architectures for the coordinated charging of large-scale EVs in a distribution network. Centralized control can provide better ancillary services to the power system and ensure higher system efficiency, while decentralized control has good scalability and needs less communication infrastructure. With the growth of PV electricity and EVs, the authors in [60] proposed a bilayer distribution system architecture that consists of a traditional AC layer and a DC layer that interfaces with PV and EVs. Monte Carlo simulations confirm the technical and economic benefits of the architecture. In order to harvest the flexibility of EVs, [61] the EVs arrival model is first established based on queueing theory, the charging demands of different types of EV are forecast using Artificial Neural Networks (ANNs). After obtaining the charging demand of EVs, the distribution network operator (DSO) and the charging stations make operation decisions cooperatively

to reduce their total operation cost. [49] proposes a V2G algorithm to optimally schedule the energy and ancillary services provided by EVs, which could achieve additional operational flexibility as well as load-shifting for distribution systems and cost reduction for EV users. Reference [43] further investigates the technical feasibility of EVs to provide ancillary services for real distribution systems. To utilize the mobility and flexibility of EVs, a V2G mobile energy network model is proposed in [50]. By implementing price control, the power demand balancing in different districts can be achieved by harnessing the mobility of EVs. Reference [62] presents a case study in France to show the effectiveness of using EVs as distributed and mobile energy storage units on cost reduction.

Through EV aggregators and large-scale charging stations, EVs are also capable of achieving energy cooperation with and providing ancillary services to transmission systems. In [63], the conflicts and possible cooperation between transmission system operator (TSO) and DSO is presented. EVs play an important role in providing frequency regulation and voltage support for the transmission system. In [51], a deterministic optimization model for charging and discharging coordination of large-scale EVs is proposed. The EVs at different regions are managed by the associated EV aggregators. Besides participating into the day-ahead wholesale energy market, these aggregators can also provide regulation reserves to the transmission system. Considering the uncertainty of EVs and energy prices, the problem is formulated as a RO problem and the results show that the proposed scheme can eliminate the influence of the uncertainty while satisfying the EVs transportation requirements. In [52], the authors study the opportunities for EVs to provide regulation reserve to the power system. Based on the existing Dutch market, each EV user can earn an extra revenue in the range between 120 Euros to 750 Euros annually. Different from the aforementioned papers, in [64], the EV aggregators are assumed to be price makers in the reserve

market, i.e., the aggregators are able to affect the reserve price in the wholesale market, while providing spinning reserve. In [27], based on Markov chain and dynamic programming, a dynamic scheduling model for EVs to provide ramp reserve to the power system under different time scales is proposed. According to the Monte Carlo simulation results, the reliability and flexibility of the system is improved with EVs.

The methods and models proposed in the aforementioned publications are effective for utilizing EVs under plug-in charging mode as potential mobile energy storage resources to provide energy and ancillary service to the power grids. However, for the newly emerging types of mobile energy storage resources, i.e., EV batteries under battery swapping and leasing mode, and truck-mounted MESSs, these methods are no longer applicable. Although some research has been done to address the potential applications of these newly emerging types of mobile energy storage resources, which will be introduced in the following subsections, detailed models and novel management frameworks are still urgent needs to achieve better coordination among these emerging mobile energy storage resources, power systems and transportation systems, and make full use of their mobility.

2.2.2 Electric Vehicle Batteries as Mobile Energy Storage Resources under Battery Swapping Mode

Besides plug-in charging, to further facilitate the charging process of EVs and alleviate the range anxiety of the potential EV users, which are the main barriers against further EV purchases and deployments, the emerging battery leasing and battery swapping mode [10] is promising and have many attractive features, e.g., much shorter refuelling time (3-5 minutes) [65], lower vehicle cost [10], etc. This emerging business model has attracted attentions from many real-world entities

[10], [11]. For example, in China, BAIC announced a plan to build 3,000 battery swapping stations (BSSs) nationwide by 2021, the Chinese EV startup NIO also plans to build over 1,000 BSSs, while over 95% of its EV users chose to lease the batteries [12], [13]. Under this background, many existing research works that mainly focus on the optimal scheduling of battery charging and coordinated operation between power systems and BSSs have been conducted in the past few years.

In [66], a detailed business and operating model for BSSs is introduced, where batteries are owned by BSSs and leased to EV users. A robust day-ahead optimization framework for the operation of BSSs is then proposed to maximize the BSS profits while considering the uncertainties in energy price and battery demands. Reference [67] proposes a optimal scheduling algorithm for EV batteries that are charged centrally at BSSs while considering charging priority and locational prices to achieve minimized cost, reduced power loss and voltage deviation in the distribution system. The authors in [68] formulate an optimal station assignment problem for the EVs under battery swapping scenarios to minimize their total travel distance and the generation cost for the power system, where each EV is navigated to the optimal BSS location for battery swapping. Reference [69] develops a genetic-algorithm-based optimal scheduling scheme for BSSs to optimally scheduling the battery charging for cost minimization, where the potential damages to the batteries due to high-rate chargers are also accounted for.

However, as all the aforementioned works [66]–[69] mainly manage the batteries as stationary resources, the potential mobility of these batteries under battery swapping mode are actually underutilized. Moreover, with the fast deployment of EVs, battery inventory insufficiency may happen during the operation at BSSs due to the large battery swapping demand, which could result in severe service

interruptions. Also, local battery charging at BSSs could lead to potential safety, spatial and cost issues [70]. Introducing large-scale centralized battery charging stations (BCSs) and battery logistics systems into the operation is promising to address these issues [71]. With a well-designed battery inventory and logistics management scheme, the surplus battery packs within certain BCSs or BSSs can be transported and shared with other facilities. This temporal-spatial mobility feature of EV batteries under battery leasing and swapping mode makes them great potential mobile energy storage resources for BSS's high-quality battery swapping service provision as well as the associated power systems to achieve higher operational flexibility and efficiency.

Recently, the value of the mobility of the batteries under battery leasing and swapping mode with centralized BCSs and battery logistics is increasingly recognized. Reference [71] provides a typical architecture and a performance analysis of a BSCS, which consists of large-scale centralized BCSs, BSSs and battery logistics. Reference [70] proposes a two-stage stochastic optimization framework for the centralized BCS integrated with renewable energy sources to minimize the operational cost while fulfilling the battery demands from multiple BSSs. The authors in [72] study a BCS scheduling problem to optimize the charging process of the charging bays in BCSs, while the fully-charged battery inventory and depleted battery inventory are managed to satisfy the battery demand from the logistics system and BSSs. In [73], with utilized mobility of batteries, the EV battery charging tasks are optimally allocated to different BCSs to reduce the charging cost and air pollutant emissions. It is worth mentioning that the results indicate that the transportation and sharing of batteries among different stations can also achieve reduced expected energy not supplied (EENS) when there are line congestions in the power grid, which further verifies the effectiveness of batteries serving as mobile energy storage resources. Reference [74] introduces a

rolling horizon-based operational planning framework for BCSs, where the mobility of batteries is utilized through the battery gathering and delivering process to achieve cost reduction, smoothed load fluctuations and improved operational flexibility.

These works indicate that under battery leasing and swapping mode, the mobility of EV batteries can be further utilized and serve as great potential mobile energy storage resources and can bring additional flexibility and efficiency to BCSs, BSSs and power systems. Still, it is worth mentioning that all the aforementioned works fail to provide a clear and detailed management scheme for the cooperation between BCSs and BSSs, and the battery logistics among the stations is oversimplified or even ignored, which makes the methods proposed in these works insufficient to fully utilize the EV batteries as mobile energy storage resources in actual power and transportation systems.

2.2.3 Truck-Mounted Mobile Energy Storage Systems

Although the mobility feature of EVs brings them great potential to provide services to power systems, their high uncontrollability and the resulting uncertainties in the available time, location, power and energy reduce the service reliability [75], which are also the main drawbacks of EVs serving as energy storages. Recently, with the increasing installation of charging/discharging facilities including ultra-fast chargers of which the power rate can reach up to a few megawatts [6] due to transportation electrification, and the development of energy storage and power electronics technologies, the emerging MESSs are another promising type of mobile energy storage resource.

MESSs are generally truck-mounted container-type utility-scale energy storage banks integrated with power conversion systems (PCSs), battery management

systems (BMSs) and standard interfaces that allow plug-and-play [20], and are usually owned and fully controlled by the utility company. Although adopting MESSs are more expensive compared to EVs, the full controllability and mobility enable them to provide more reliable and diverse services to power systems. Many demonstration projects have been conducted in recent years. In the U.S., a demonstrative 0.5-MW/2.8-MWh transportable Zinc-Bromine energy storage system was developed by Premium Power and tested by Electric Power Research Institute (EPRI) [76]. A lithium-ion energy storage system developer and manufacturer Altairnano developed 1-MW/250-kWh trailer-mounted Li-ion battery systems that are serving both AES and PJM [76]. Consolidated Edison has started a demonstration project in New York to develop a 1-MW/4-MWh MESS, which is dispatched to travel within its service region to serve loads during the peak season [77].

The significance of the integration of MESSs into power system operation for both extreme events [15], [16], [78] and normal operations [18]–[20], has been increasingly recognized in recent research works. In response to extreme events, a two-stage optimization model is proposed in [15], where the investment cost for MESSs is minimized in the first stage while the installed MESSs are re-routed in the second stage to avoid expected load shedding due to natural disasters. In [16], to facilitate service restoration in post-event stage, a rolling optimization framework is proposed for MESSs scheduling to achieve resource dispatching among different MGs and distribution network reconfiguration, thus enhancing the resilience of distribution systems. Reference [78] proposes a two-stage restoration scheme for distribution systems under seismic disasters. In the first-stage, the damages to distribution branches are estimated in different seismic scenarios, while in the second-stage, MESSs are scheduled to cooperate with the distribution system to achieve coordinated system reconfiguration and

restoration. In [30], a two-stage optimization framework is proposed to incorporate MESSs for the enhancements of distribution system resilience. Before the extreme event, MESSs are pre-scheduled for rapid pre-restoration. After the event, MESSs are dispatched in the distribution system to facilitate system recovery.

Under normal conditions, MESSs have been adopted to increase the operational efficiency of power systems [18]–[20]. For transmission systems, a TSN-based model is proposed in [18] to harness the mobility of MESSs for transmission networks, where MESSs can reduce the grid operation cost by peak load shaving and line congestion relief. A successive work is proposed to reduce operational cost of transmission networks with wind power integration by decreasing wind generation curtailment due to transmission line congestions [19]. However, the models in these works mainly consider railway networks, where the actual network structure and differences between MESSs, e.g., average traveling speed and sizes, are not addressed. Moreover, due to the virtual nodes in the adopted TSN model, additional binary variables are introduced, which results in a higher computational cost. For distribution systems, only a few publications consider adopting MESSs in normal operation. In [20], MESSs are managed to provide load shifting and voltage regulation services to distribution networks, using a transit delay model for MESSs routing. However, this work does not consider the uncertainties of VRE sources, which is crucial for the coordination among MESSs, distribution systems and hybrid AC/DC MGs.

Furthermore, since MESSs are mainly scheduled to travel within the existing transportation networks to provide services to the facilities in the distribution system at different locations, where other common vehicles such as private cars, EVs, taxis, etc., also travel within the network to fulfil their daily travel demands. Possible traffic congestions could occur on certain roads during peak

hours, which could greatly affect the travel speeds of MESSs and the resulting travel time on these congested roads. Also, the uncertainties in the traffic demands, which could lead to uncertain traffic flow distributions and MESS travel time, should be accounted for. These impacts of traffic flows on the scheduling and operation of MESSs are ignored in most of the aforementioned publications.

2.3 Couplings Between Power Systems and Transportation Systems

The aforementioned emerging mobile energy storage resources and their mobility bring not only opportunities to further improve the economy, reliability, flexibility and efficiency of the future smart grids, but also the close couplings and interdependences between power and transportation systems, i.e., the intrinsic characteristics of transportation systems, e.g., network structure, traffic condition, etc., would have impacts on the routing and scheduling of mobile energy storage resources, which could then affect the interactions between mobile energy storage resources and power systems. Similarly, power-system-side decisions, e.g., electricity price signals and dispatch requests would alter the temporal-spatial behaviors of the mobile energy storage resources, which could then affect transportation systems.

To achieve the optimal dispatch and scheduling of mobile energy storage resources, and better utilize their mobility, vehicle routing problem (VRP) model, which was first proposed by Dantzig and Ramser in 1959 [79], are extensively studied and adopted. In [80], the authors proposed a new optimal EV route model based on the traveling salesman problem (TSP), considering battery capacity constraints, charging time constraints and delivery time constraints. Under the time-of-use (TOU) electricity tariff, the results show that the EVs avoid charging

at peak load but at valleys, while the routes are optimally selected. Due to the EV battery capacity, the driving range of EVs is limited. In [81], a navigation system based on power consumption for EVs is proposed to extend driving range of EVs. According to the simulation results, the proposed system can extend 20.67% to 32.29% of the driving range for EVs. Under battery swapping scenarios, a VRP with Time Windows (VRPTW) model is proposed [82]. By properly choosing feasible routes, EVs can achieve longer driving range.

Some recent works adopt TSN techniques [83] for the vehicle routing of mobile energy storage resources and describing their temporal-spatial dynamics. Reference [18] proposes a TSN-based model to harness the mobility of MESSs in railway networks for transmission systems. A successive work is proposed to reduce the operational cost of transmission networks with wind power integration by decreasing wind generation curtailment due to transmission line congestions [19]. Reference [17] proposes a multi-layer TSN model to further facilitate the routing and scheduling of multiple MESSs with different mobility and specifications. These TSN models are effective to some extent, but fail to account for the possible impacts of traffic conditions on the routing and scheduling of mobile energy storage resources.

To further investigate the impacts of mobile energy storage resources routing and operation on transportation systems, the classic traffic assignment problem (TAP) [84] models and user equilibrium (UE) concept [85] in transportation science are borrowed and adopted by the researchers. Reference [21] proposes a modeling and simulation framework to study the interdependencies between distribution systems and transportation systems brought by EV charging facilities, where the EV behaviors are simulated based on dynamic TAP model. The authors in [86] study the traffic congestions caused by the EVs and conventional gasoline vehicles in the transportation network and the impact on the driving behavior of

EVs such as travel time and energy consumption. A successive work is presented in [87] to study the optimal traffic-power flow for cost minimization.

2.4 Summary

This chapter reviews the related literatures. The background of transportation electrification is introduced, including the upcoming energy and environmental challenges, the current EV deployment status and their advantages. Then, with the rising trend of transportation electrification, the emerging mobile energy storage resources are introduced, which include EVs under plug-in charging mode, EV batteries under battery swapping mode and truck-mounted MESSs, and the related state-of-the-art publications are reviewed. Finally, the potential couplings between power systems and transportation systems brought by the mobile energy storage resources are introduced and the related literatures are also reviewed. The management of EV batteries and their mobility under battery swapping mode will be studied in Chapter 3 and Chapter 4, while the management of truck-mounted MESSs in coupled distribution and transportation systems will be elaborated in Chapter 5.

Chapter 3

Management of Mobile Energy Storage for Battery Swapping-Charging Systems

As a type of potential mobile energy storage resource, EV batteries and their mobility under battery leasing and swapping mode are underutilized. To further harness their mobility while ensuring uninterrupted high-quality battery swapping services for EVs, incorporating large-scale centralized BCSs and battery logistics to form a battery swapping-charging system (BSCS) is promising. To achieve the optimal operation of BSCSs, a CLSC based BSCS model is proposed to realize the combined operation of BCSs and BSSs while the quality of battery swapping service at BSSs is ensured with a network calculus based service model. The battery logistics within the BSCS is modeled based on a TSN technique. The charging and the logistics of depleted batteries and well-charged batteries are optimally managed to maximize the revenue of the BSCS. The optimization problem is formulated as a MILP model with various TSN and operation constraints. RP-ADMM is applied as a heuristic to solve the problem in a distributed way. Simulation results verify the feasibility of the proposed model and the heuristic solution with small optimality losses and less computation time.

3.1 Introduction

As an important part of transportation electrification, EVs are now under a rapid deployment [88]. With the development of information and communication technology (ICT), a bidirectional service supply chain between EVs and power systems can be established via charging (grid to vehicle, G2V) and discharging (vehicle to grid, V2G) at EV charging facilities, i.e., power systems fulfill the energy demands of EVs while EVs provide ancillary services in turn [42], [43], [89]. The key role in this service supply chain is the charging facilities.

Plug-in charging stations and BSSs are two major types of charging facilities [65]. Compared with the plug-in charging stations, battery leasing and swapping mode has many attractive features, e.g., shorter service time, lower cost for EV users [10], [65]. However, due to the large battery demand for EVs, battery inventory shortages may happen during the operation at BSSs, which can result in severe service interruptions. Incorporating centralized BCSs and a logistics system to form BSCS is a promising way to deal with this challenge [71].

There are two ways of charging the depleted batteries in a BSCS, i.e., depleted batteries are charged locally at BSSs [66], [90] or charged centrally at BCSs [71]. When depleted batteries are charged locally at BSSs, the main concerns are the quality of battery swapping services [90] and cost minimization [66]. However, this charging method would complicate the BSS structure and bring about spatial and safety issues [70]. For instance, the installation of battery chargers would require extra spaces and bring more complexity to the BSS's electrical system. On the other hand, charging depleted batteries centrally at BCSs doesn't have such problems, and can bring enormous flexibility for grid operators to perform tasks such as load balancing [91] and renewable energy integration [92]. In [72],

the authors studied a BCS scheduling problem to optimally schedule the charging processes of BCSs such that the charging cost is minimized considering battery demand and inventory. Li et al. proposed an optimization framework for a BCS with renewable energy sources to minimize the energy cost [70]. Considering the attractive features shown in [70]–[72], [91], [92], the combined operation of BCSs and BSSs, i.e., batteries are charged centrally at BCSs and swapped at BSSs, is preferred for BSCSs in this chapter.

Since BCSs and BSSs are geographically separated, a logistics system, whose responsibility is to transport batteries among them, is the key component to achieve the combined operation of BCSs and BSSs. Very few researchers have considered the battery logistics within a BSCS, Zhang *et al.* proposed a battery scheduling framework to dispatch batteries between BCSs and BSSs [93], where the authors only considered the optimal routing problem but ignored the operation management of BCSs and BSSs.

The battery flows in a BSCS, i.e., well-charged batteries are transported from BCSs to BSSs and depleted batteries are collected at BSSs and transported to BCSs, can form a closed battery logistics loop. This closed loop logistics can be treated as a closed-loop supply chain (CLSC) [94], where providing well-charged batteries from BCSs to EVs via BSSs is the forward supply chain (FSC) and collecting depleted batteries from EVs to BCSs via BSSs is the reverse supply chain (RSC). To manage the CLSC and achieve optimal operation of BSCSs, detailed mathematical modeling of the logistics system and its temporal-spatial dynamics is necessary.

In this context, this chapter aims to fill the gap in the modeling of the combined operation of BCSs and BSSs and its management. A CLSC based BSCS model is proposed with a time-space network (TSN) based battery logistics model [95],

[96]. The charging and discharging of batteries and the battery logistics are optimally managed to maximize the revenue of the BSCS while satisfying the battery demand for battery swapping service at each BSS. The optimization problem is formulated as a mixed integer linear programming (MILP) problem and is solved in a distributed way. To the best of our knowledge, this work is the first to apply CLSC and TSN to model the battery logistics in BSCSs.

The contributions of this chapter are summarized as follows.

- i) A CLSC-based BSCS model is proposed to bridge the gap in the operation management of BSCS with a battery logistics model formulated based on the TSN technique.
- ii) Operation models of BCSs, BSSs and the logistics system are introduced, and the operation management of BSCSs is formulated as a MILP problem. A heuristic method based on randomly permuted alternating direction method of multipliers (RP-ADMM) is applied to solve the problem in a distributed way.

The rest of this chapter is organized as follows. Section 3.2 presents the CLSC based BSCS model. The TSN based battery logistics model is presented in Section 3.3. The operation models of BSCSs and the optimal operation management problem are formulated in Section 3.4. Distributed solutions based on RP-ADMM are shown in Section 3.5. Case studies and conclusions are given in Section 3.6 and Section 3.7, respectively.

3.2 Closed-loop Supply Chain Based Battery Swapping-Charging System

Figure 3.1: Three CLSC models with trade-ins.

3.2.1 CLSC Models for BSCSs

When managing the BSCS, three CLSCs models can be applied, i.e., Model C, Model R, and Model M, based on the roles played by each player [94]. As shown in Fig. 3.1, in model C, the manufacturer and retailers belong to one integrated firm, who is in charge of production, sales, and trade-ins. In Model R, the manufacturer produces the products, and the retailer is responsible for sales and trade-ins. In Model M, the manufacturer produces products and processes consumer trade-ins, and the retailer is responsible for new product sales. Since in the BSCS, EVs cannot exchange batteries with BCSs directly, Model R type CLSC is applied in this chapter.

3.2.2 Battery Swapping-Charging System

A general framework of the proposed Model R type CLSC based BSCS is illustrated in Fig. 3.2. As mentioned in [71], a BSCS consists of at least one BCS and multiple BSSs. While BSSs are responsible for providing battery swapping services to the EVs within a certain area, BCSs are responsible for charging depleted batteries and providing well-charged batteries to BSSs. Both BCSs

Figure 3.2: CLSC based battery swapping and charging system.

and BSSs are connected to a logistics system, which consists of a transportation network and a number of truck fleets. The trucks are responsible for transporting batteries among the BCSs and the BSSs. In the BSCS, EVs, BSSs and BCSs can be regarded as customers, retailers, and manufacturers, respectively, which composes a generic CLSC [94], [97].

The following assumptions are made throughout this chapter, for the sake of simplicity:

- 1) All the batteries within the BSCS are owned by the BCSs.
- 2) Batteries are of the same type. depleted batteries have the same state of charge (SOC), $\underline{\text{SOC}}$, and well-charged batteries are of the same SOC, $\overline{\text{SOC}}$ after charged and batteries can only be charged at BCSs.
- 3) Each BCS has a charging bay with $N_{\text{CH},\hat{m}}$ bidirectional battery chargers and batteries can be charged or discharged when they are in the charging bay [72]. The total number of well-charged batteries produced by BCSs can fully cover the

battery requirements of BSSs.

4) Each BSS has an initial depleted battery reserve $N_{D,\tilde{m}}^{\text{ini}}$ and an initial well-charged battery reserve $N_{W,\tilde{m}}^{\text{ini}}$ and each BCS has a backup depleted battery reserve in the case of inventory shortage.

5) BCSs can participate in the wholesale market and act as price takers.

6) Trucks are owned by a third-party logistics company and the freight charges [98] for transporting batteries among BCSs and BSSs are omitted.

Note that assumptions 1) and 2) are made since that the BSCS model introduced in this chapter is assumed to adopt a battery swapping and leasing mode [10], where the BSCS owns and manages all the BCSs, BSSs and battery packs, while commercial EV users only own the vehicles and rent the battery packs from the BSCS. Therefore, the BSCS operator could choose to purchase the swappable batteries with universal specifications, which could also help to facilitate the operation and management of the system. Also, since this chapter mainly focuses on the modeling of battery inventory and logistics, for notation and model simplicity, batteries are assumed to have the same SOC. Still, it is noted that the proposed model can be easily extended to consider different types of batteries or different SOC by introducing associated variables.

3.2.3 Network Calculus based Service Model for BSSs

As depicted in Fig. 3.2, the battery swapping/collecting process at each BSS can be modeled as three parts, the queue of EVs waiting to be served, the inventory of well-charged batteries and the inventory of depleted batteries. These three parts capture the coupling nature of the battery swapping/collecting process, which can be used for the analysis of battery swapping service performance at each BSS.

To analyze the performance of the battery swapping service, the queue of EVs is modeled as the arrivals and departures of the demands of battery packs using a discrete cumulative curve method [99], [100], i.e., arrival curves, departure curves and minimum departure curves. Let $\mathcal{T}$ denote the set of time slots, $\mathcal{N}_{\text{BCS}}$, $\mathcal{N}_{\text{BSS}}$ denote the sets of BCSs and BSSs, respectively. Let A^t , D^t , $D_{\min}^t$ denote the arrival curve, departure curve, and the minimum departure curve, respectively, their definitions are given as follows.

Definition 3.2.1 (Arrival Curve). An arrival curve $A_{\tilde{m}}^t, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}}$, is the total EV battery demand that has arrived at the BSS $\tilde{m}$ in time interval $[1, t]$.

Definition 3.2.2 (Departure Curve). A departure curve $D_{\tilde{m}}^t, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}}$, is the total amount of batteries that have been swapped (served) at BSS $\tilde{m}$ in time interval $[1, t]$.

Definition 3.2.3 (Minimum Departure Curve). A minimum departure curve $D_{\min, \tilde{m}}^t, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}}$, defined as the cumulative minimum number of batteries swapped (served) in time interval $[1, t]$ that will satisfy the time requirements of EVs.

For example, there are two EVs, each has three battery packs. EV1 arrives at BSS $\tilde{m}$ at $t - 2$ and wants to leave at t while EV2 arrives at $t - 1$ and leaves at $t + 1$. Then $A_{\tilde{m}}^{t-2} = 3$, $A_{\tilde{m}}^{t-1} = 6$, while $D_{\min, \tilde{m}}^t = 3$ and $D_{\min, \tilde{m}}^{t+1} = 3$. Note that curve $D_{\min, \tilde{m}}^t$ can be regarded as the constraint function such that as long as $D_{\tilde{m}}^t \geq D_{\min, \tilde{m}}^t, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}}$, all the EVs' time requirements of battery swapping service can be well satisfied.

3.3 Battery Logistics Model

To deal with the logistics scheduling problem more efficiently in both time and spatial domains, a detailed TSN model of the battery logistics system, which consists of a vehicle-battery scheduling model and battery inventory models for BCSs and BSSs, is presented in this section.

3.3.1 TSN-based Vehicle-Battery Scheduling Model

In order to model the temporal-spatial dynamics of the trucks in the logistics system and the transportation of batteries among BCSs and BSSs, a time-space network technique is adopted in this work, which has been widely used to model airline and public transportation scheduling problems [95], [96].

To illustrate the proposed TSN-based vehicle-battery scheduling model, a BSCS with one BCS (node 1) and three BSSs (node 2, 3, 4) is considered. The BCS and the BSSs are connected via a transportation network as shown in Fig. 3.3. Each edge is marked with an associated travel time. For example, it takes two time slots for the truck to travel between the BCS and BSS2, whereas only one time slot for any other transit. In order to enable each edge to represent the corresponding status in a single time slot, a virtual node, i.e., node 5 is introduced between the BCS and BSS2, so that travel time of each arc in the network is exactly one time slot [18].

As depicted in Fig. 3.4, the transportation network with travel time is modeled as a TSN, which comprises the BSCS nodes, the virtual node, and the arcs between them that indicate the feasible transit routes. In order to model the temporal-spatial dynamics of the battery logistics system, the trucks' traveling and parking behaviors are described by different types of arcs, i.e., parking arcs and transit

Figure 3.3: Transportation networks. (a) without virtual nodes. (b) with virtual nodes.

Figure 3.4: Time-space network model.

arcs. Transit arcs allow trucks to transport batteries within the BSCS while parking arcs represent that trucks stay at certain nodes for loading and unloading batteries. Note that there are no parking arcs linking node 5 since parking is not allowed at virtual nodes. With this TSN model, the scheduled trip for each truck can be represented by a sequence of arcs, which indicates the departure nodes and destination nodes in a given timetable. Therefore, the scheduling of trucks within the BSCS over the time horizon can be realized.

The mathematical expressions of the TSN-based vehicle scheduling model are

formulated as follows.

$$\sum_{(\hat{n}, \check{n}) \in \mathcal{Z}} \zeta_{\omega, (\hat{n}, \check{n})}^t = 1, \forall \omega \in \Omega, t \in \mathcal{T} \quad (3.1)$$

$$\sum_{(\hat{n}, n) \in \mathcal{Z}_n^-} \zeta_{\omega, (\hat{n}, n)}^t = \sum_{(n, \check{n}) \in \mathcal{Z}_n^+} \zeta_{\omega, (n, \check{n})}^{t+1}, \forall \omega \in \Omega, \hat{n}, \check{n}, n \in \tilde{\mathcal{N}} \cup \mathcal{N}_v, t \in \mathcal{T} \setminus \{T\} \quad (3.2)$$

$$\sum_{(\hat{n}, \check{n}) \in \mathcal{Z}_n^+} \zeta_{\omega, (\hat{n}, \check{n})}^1 = \zeta_{\omega, \hat{n}}^0, \forall \omega \in \Omega, \hat{n}, \check{n} \in \tilde{\mathcal{N}} \cup \mathcal{N}_v \quad (3.3)$$

where $\tilde{\mathcal{N}}$ is defined as $\tilde{\mathcal{N}} = \mathcal{N}_{\text{BCS}} \cup \mathcal{N}_{\text{BSS}}$ for notation simplicity and $\mathcal{N}_v$ is the set of virtual nodes in time-space networks. Ω denotes the set of truck fleets. $\mathcal{Z}$ is the set of arcs in the time-space network, indexed by $(\hat{n}, \check{n})$. $\mathcal{Z}_n^+$ represents the set of arcs starting from node $n \in \tilde{\mathcal{N}} \cup \mathcal{N}_v$ while $\mathcal{Z}_n^-$ is the set of arcs ending at node n . $\zeta_{\omega, (\hat{n}, \check{n})}^t$ is a binary variable, i.e., $\zeta_{\omega, (\hat{n}, \check{n})}^t = 1$ if truck fleet ω is on arc $(\hat{n}, \check{n})$ in time slot t , which indicates that ω is traveling from node $\hat{n}$ to node $\check{n}$, 0 otherwise.

Equation (3.1) ensures that truck ω must be either on a transit arc or a parking arc in each time slot t . Constraint (3.2) refers to the flow conservation for both BSCS nodes and virtual nodes, i.e., truck fleet ω , which ends its trip in time slot t at node n , is certain to keep staying on one of the arcs which start from node n in the next time slot $t + 1$. Similarly, constraint (3.3) declares the initial position of each truck fleet.

Based on the vehicle scheduling model described by (3.1)-(3.3), the battery scheduling model for each truck can be formulated as follows.

$$S_{\text{D}, \omega}^t = - \sum_{h=1}^t \sum_{\hat{m} \in \mathcal{N}_{\text{BCS}}} N_{\text{D}, \text{BCS}, \omega, \hat{m}}^h + \sum_{h=1}^t \sum_{\check{m} \in \mathcal{N}_{\text{BSS}}} N_{\text{D}, \text{BSS}, \omega, \check{m}}^h, \forall \omega \in \Omega, t \in \mathcal{T} \quad (3.4)$$

$$S_{W,\omega}^t = - \sum_{h=1}^t \sum_{\hat{m} \in \mathcal{N}_{\text{BCS}}} N_{W,\text{BCS},\omega,\hat{m}}^h + \sum_{h=1}^t \sum_{\check{m} \in \mathcal{N}_{\text{BSS}}} N_{W,\text{BSS},\omega,\check{m}}^h, \forall \omega \in \Omega, t \in \mathcal{T} \quad (3.5)$$

$$S_{D,\omega}^t + S_{W,\omega}^t \leq C_B, \forall \omega \in \Omega, t \in \mathcal{T} \quad (3.6)$$

$$S_{D,\omega}^t \geq 0, S_{W,\omega}^t \geq 0, \forall \omega \in \Omega, t \in \mathcal{T} \quad (3.7)$$

$$S_{D,\omega}^T = 0, S_{W,\omega}^T = 0, \forall \omega \in \Omega \quad (3.8)$$

$$0 \leq N_{D,\text{BSS},\omega,\check{m}}^t \leq \zeta_{\omega,(\check{m},\check{m})}^t C_B, \forall \check{m} \in \mathcal{N}_{\text{BSS}}, \omega \in \Omega, t \in \mathcal{T} \quad (3.9)$$

$$0 \leq N_{W,\text{BSS},\omega,\check{m}}^t \leq \zeta_{\omega,(\check{m},\check{m})}^t S_{W,\omega}^{t-1}, \forall \check{m} \in \mathcal{N}_{\text{BSS}}, \omega \in \Omega, t \in \mathcal{T} \quad (3.10)$$

$$0 \leq N_{D,\text{BCS},\omega,\hat{m}}^t \leq \zeta_{\omega,(\hat{m},\hat{m})}^t S_{D,\omega}^{t-1}, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, \omega \in \Omega, t \in \mathcal{T} \quad (3.11)$$

$$0 \leq N_{W,\text{BCS},\omega,\hat{m}}^t \leq \zeta_{\omega,(\hat{m},\hat{m})}^t C_B, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, \omega \in \Omega, t \in \mathcal{T} \quad (3.12)$$

where $S_{D,\omega}^t$ and $S_{W,\omega}^t$ are the number of depleted/well-charged batteries carried by truck fleet ω at the end of time slot t . $N_{D,\text{BCS},\omega,\hat{m}}^t$ and $N_{W,\text{BCS},\omega,\hat{m}}^t$ denote the number of depleted/well-charged batteries unloaded/loaded by truck fleet ω at BCS $\hat{m}$ in time slot t , while $N_{D,\text{BCS},\hat{m}}^t$, $N_{W,\text{BCS},\hat{m}}^t$ represent the total number of depleted/well-charged batteries exchanged between BCS $\hat{m}$ and the battery logistics system in time slot t . C_B is the truck capacity.

Equations (3.4) and (3.5) determine the stock of depleted batteries and well-charged batteries carried by truck ω at the end of time slot t . Constraint (3.6) limits the total battery stock of each truck within its capacity. Constraint (3.7) indicates that the stock of depleted batteries and well-charged batteries at each truck should always be nonnegative while constraint (3.8) means that at time T , all the batteries on each truck should be unloaded. Constraints (3.9) and (3.10) establish the feasible sets of the number of depleted batteries and well-charged batteries exchanged between truck ω and BSS $\check{m}$ in time slot t . Similarly, constraints (3.11) and (3.12) describe the feasible sets of the number of batteries exchanged between truck ω and BCS $\hat{m}$ in time slot t .

Remark 3.3.1. As described in constraints (3.9)-(3.12), the loading and unloading of batteries can only be performed when a truck parks at a BCS or a BSS. For example, when $\zeta_{\hat{m},\hat{m}}^t = 1$, truck fleet ω can exchange batteries with BCS $\hat{m}$. Otherwise, there is no battery exchange when $\zeta_{\hat{m},\hat{m}}^t = 0$.

3.3.2 Battery Inventory Models in CLSC

Based on the proposed network calculus based service model and the vehicle-battery scheduling model presented in Section 3.2.3 and Section 3.3.1, respectively, the battery inventory models for BCSs and BSSs can be formulated as follows.

3.3.2.1 Battery inventory model for BCSs

The dynamic battery inventory model for BCS $\hat{m} \in \mathcal{N}_{\text{BCS}}$ is expressed as follows.

$$N_{\text{D,BCS},\hat{m}}^t = \sum_{\omega} N_{\text{D,BCS},\omega,\hat{m}}^t, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, \omega \in \Omega, t \in \mathcal{T} \quad (3.13)$$

$$N_{\text{W,BCS},\hat{m}}^t = \sum_{\omega} N_{\text{W,BCS},\omega,\hat{m}}^t, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, \omega \in \Omega, t \in \mathcal{T} \quad (3.14)$$

$$S_{\text{bay},\hat{m}}^t = \sum_{h=1}^t N_{\text{bay},\hat{m}}^h - \sum_{h=1}^{t-1} N_{\text{Wout},\hat{m}}^h, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \quad (3.15)$$

$$S_{\text{D,BCS},\hat{m}}^t = \sum_{h=1}^t (N_{\text{BP},\hat{m}}^h + N_{\text{D,BCS},\hat{m}}^h - N_{\text{bay},\hat{m}}^h), \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \quad (3.16)$$

$$S_{\text{W,BCS},\hat{m}}^t = \sum_{h=1}^t (N_{\text{Wout},\hat{m}}^h - N_{\text{W,BCS},\hat{m}}^h), \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \quad (3.17)$$

$$\sum_{h=1}^t N_{\text{Wout},\hat{m}}^h \leq \sum_{h=1}^{t-(T_c-1)} N_{\text{bay},\hat{m}}^h, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \quad (3.18)$$

$$S_{\text{W,BCS},\hat{m}}^t \geq 0, S_{\text{D,BCS},\hat{m}}^t \geq 0, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \quad (3.19)$$

$$S_{\text{bay},\hat{m}}^t \leq N_{\text{CH},\hat{m}}, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \quad (3.20)$$

where $N_{\text{bay},\hat{m}}^t$ is the number of depleted batteries loaded into the charging bay. $N_{\text{Wout},\hat{m}}^h$ indicates the number of well-charged batteries produced by BCS $\hat{m}$. $S_{\text{D},\text{BCS},\hat{m}}^t, S_{\text{W},\text{BCS},\hat{m}}^t$ represent the current depleted/well-charged battery inventory at BCS $\hat{m}$ in time slot t , $S_{\text{bay},\hat{m}}^t$ is the number of batteries in the charging bay and $N_{\text{CH},\hat{m}}$ represents the number of bi-directional battery chargers at BCS $\hat{m}$.

Equations (3.13) and (3.14) are the total number of depleted batteries and well-charged batteries that BCS $\hat{m}$ received from and delivered to the logistic system in time slot t . They also serve as the coupled constraints that link BCSs and the logistics system. Equation (3.15) defines the number of batteries in the charging bay. Equations (3.16) and (3.17) model the depleted battery and well-charged battery inventory at BCS $\hat{m}$ at the end of time slot t , where $N_{\text{BP},\hat{m}}^t$ is the backup depleted batteries employed by BCS $\hat{m}$ in time slot t . Constraint (3.18) guarantees that the batteries stay in the charging bay for at least T_c time slots, where $T_c = \lceil E_B/(\eta_c \bar{P}_c \Delta t) \rceil$ is the minimum charging time required for a battery to be fully charged. Constraint (3.19) indicates that the battery inventory should be nonnegative and constraint (3.20) ensures that the number of the batteries in the charging bay does not exceed the number of the chargers in BCS $\hat{m}$.

3.3.2.2 Battery inventory model for BSSs

For BSS $\check{m} \in \mathcal{N}_{\text{BSS}}$, the dynamic battery inventory model can be depicted as follows.

$$N_{\text{D},\text{BSS},\check{m}}^t = \sum_{\omega} N_{\text{D},\text{BSS},\omega,\check{m}}^t, \forall \check{m} \in \mathcal{N}_{\text{BSS}}, \omega \in \Omega, t \in \mathcal{T} \quad (3.21)$$

$$N_{\text{W},\text{BSS},\check{m}}^t = \sum_{\omega} N_{\text{W},\text{BSS},\omega,\check{m}}^t, \forall \check{m} \in \mathcal{N}_{\text{BSS}}, \omega \in \Omega, t \in \mathcal{T} \quad (3.22)$$

$$S_{\text{D},\text{BSS},\check{m}}^t = N_{\text{D},\check{m}}^{\text{ini}} + D_{\check{m}}^t - \sum_{h=1}^t N_{\text{D},\text{BSS},\check{m}}^h, \forall \check{m} \in \mathcal{N}_{\text{BSS}}, t \in \mathcal{T} \quad (3.23)$$

$$S_{\text{W,BSS},\tilde{m}}^t = N_{\text{W},\tilde{m}}^{\text{ini}} - D_{\tilde{m}}^t + \sum_{h=1}^t N_{\text{W,BSS},\tilde{m}}^h, \forall \tilde{m} \in \mathcal{N}_{\text{BSS}}, t \in \mathcal{T} \quad (3.24)$$

$$S_{\text{W,BSS},\tilde{m}}^t \geq 0, S_{\text{D,BSS},\tilde{m}}^t \geq 0, \forall \tilde{m} \in \mathcal{N}_{\text{BSS}}, t \in \mathcal{T} \quad (3.25)$$

$$|S_{\text{D,BSS},\tilde{m}}^T - N_{\text{D},\tilde{m}}^{\text{ini}}| \leq \epsilon_{\text{b}}, \forall \tilde{m} \in \mathcal{N}_{\text{BSS}} \quad (3.26)$$

$$|S_{\text{W,BSS},\tilde{m}}^T - N_{\text{W},\tilde{m}}^{\text{ini}}| \leq \epsilon_{\text{b}}, \forall \tilde{m} \in \mathcal{N}_{\text{BSS}} \quad (3.27)$$

where $N_{\text{D,BSS},\omega,\tilde{m}}^t$ and $N_{\text{W,BSS},\omega,\tilde{m}}^t$ denote the number of depleted/well-charged batteries loaded/unloaded by truck fleet ω at BSS $\tilde{m}$ in time slot t , while $N_{\text{D,BSS},\tilde{m}}^t$, $N_{\text{W,BSS},\tilde{m}}^t$ represent the total number of depleted/well-charged batteries exchanged between BSS $\tilde{m}$ and the battery logistics system in time slot t . $S_{\text{D,BSS},\tilde{m}}^t$, $S_{\text{W,BSS},\tilde{m}}^t$ represent the current depleted/well-charged battery inventory at BSS $\tilde{m}$ in time slot t .

Alongside the inventory model for BCSs, equations (3.21) and (3.22) ensure that the depleted batteries supplied and well-charged batteries required by BSS $\tilde{m}$ in time slot t are fully collected/delivered by the logistics system, respectively, which couples the decisions of BSSs and the logistics system. Equations (3.23) and (3.24) calculate the depleted battery and well-charged battery inventory at BSS $\tilde{m}$ at the end of time slot t . Since in this chapter only battery swapping service is considered, $D_{\tilde{m}}^t$ represents both the number of well-charged batteries served to and depleted batteries obtained from the EVs. Constraint (3.25) guarantees that the inventory is nonnegative, which in turn enhances (3.9). Constraints (3.26) and (3.27) ensure that by the end of the operation horizon, the battery inventory at each BSS will return to its initial inventory state with an acceptable deviation ϵ_{b} , which enables the sustainable operation of the BSCS.

Remark 3.3.2. In this chapter, it is assumed that the unloading of depleted batteries at BCSs, the unloading of well-charged batteries at BSSs and the loading of depleted batteries into charging bays are finished at the beginning of time slot

t , while the loading of well-charged batteries at BCSs, the loading of depleted batteries at BSSs and the unloading of produced well-charged batteries from charging bays are carried out at the end of time slot t . This avoids the confusion about the number of depleted batteries and well-charged batteries available in time slot t . For example, depleted batteries produced at BSS $\tilde{m}$ in time slot t can be loaded and transported when a truck parks there during time slot t .

3.4 Optimal Operation Management of BSCSs

With the battery logistics system, the flexibility and the economy of the BSCS can be improved through the combined operation of BCSs and BSSs. To achieve the optimal operation of BSCSs, the mathematical formulations of the operation models for BCSs, BSSs and the logistics system are provided in this section with detailed objective functions and constraints.

3.4.1 Operation Model for BCSs

BCSs act as price takers in the wholesale market. After obtaining the price signals from the wholesale market, the operator of BCS $\hat{m}$ will make optimal operation plan to maximize its revenue $C_{\text{BCS},\hat{m}}$, considering providing ancillary services to the power system while fulfilling the operational constraints. The objective function is shown as follows.

$$\begin{aligned} \max C_{\text{BCS},\hat{m}} = & \sum_{t=1}^T \left[-\lambda_{\text{DA}}^t (P_{\text{C},\hat{m}}^t - P_{\text{DC},\hat{m}}^t) \Delta t \right. \\ & + \lambda_{\text{S}}^t R_{\text{S},\hat{m}}^t \Delta t + (\lambda_{\text{rd}}^t r_{\text{d},\hat{m}}^t + \lambda_{\text{ru}}^t r_{\text{u},\hat{m}}^t) \Delta t \\ & \left. - C_{\text{d}} (P_{\text{DC},\hat{m}}^t + P_{\text{C},\hat{m}}^t) \Delta t - C_{\text{BP}} N_{\text{BP},m}^t \right] \end{aligned} \quad (3.28)$$

where λ_{DA}^t , λ_{S}^t , λ_{ru}^t , λ_{rd}^t are the day-ahead energy price, spinning reserve price, regulation-up price and regulation-down price, while C_{d} and C_{BP} denotes the battery charging cost and backup battery cost. $P_{\text{C},\hat{m}}^t$, $P_{\text{DC},\hat{m}}^t$ are the aggregated charging/discharging power at BCS $\hat{m}$ in time slot t . $R_{\text{S},\hat{m}}^t$, $r_{\text{u},\hat{m}}^t$, $r_{\text{d},\hat{m}}^t$ represent the spinning reserve and up/down regulation reserve provided by BCS $\hat{m}$ in time slot t , respectively. $N_{\text{BP},\hat{m}}^t$ is the number of backup depleted batteries employed by BCS $\hat{m}$.

The first term on the right-hand side of (3.28) stands for the battery charging cost induced in time slot t . The second term and the third term represent the revenue obtained by providing spinning reserve and regulation reserves to the power systems in time slot t . The fourth term calculates the simplified battery charging (degradation) cost induced by repeated charging and discharging in time slot t , where C_{d} is the economic cost coefficient for batteries [101], while the last term is the cost of backup depleted batteries.

Detailed operation constraints for BCS $\hat{m}$ are formulated as follows.

3.4.1.1 Energy Constraints

$$\sum_{h=1}^t \left(P_{\text{C},\hat{m}}^h \eta_{\text{c}} - \frac{P_{\text{DC},\hat{m}}^h}{\eta_{\text{dc}}} \right) \Delta t \geq \sum_{h=1}^t N_{\text{Wout},\hat{m}}^h E_{\text{B}}, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \setminus \{T\} \quad (3.29)$$

$$\sum_{h=1}^T \left(P_{\text{C},\hat{m}}^h \eta_{\text{c}} - \frac{P_{\text{DC},\hat{m}}^h}{\eta_{\text{dc}}} \right) \Delta t = \sum_{h=1}^T N_{\text{Wout},\hat{m}}^h E_{\text{B}} \quad (3.30)$$

$$\sum_{h=1}^t \left(P_{\text{C},\hat{m}}^h \eta_{\text{c}} - \frac{P_{\text{DC},\hat{m}}^h}{\eta_{\text{dc}}} \right) \Delta t - \alpha_{\text{S}} R_{\text{S},\hat{m}}^t - \alpha_{\text{R}} r_{\text{u},\hat{m}}^t \geq \sum_{h=1}^t N_{\text{W},\text{BCS},\hat{m}}^h E_{\text{B}}, \quad \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \quad (3.31)$$

$$\sum_{h=1}^t \left(P_{C,\hat{m}}^h \eta_c - \frac{P_{DC,\hat{m}}^h}{\eta_{dc}} \right) \Delta t + \alpha_R r_{d,\hat{m}}^t \leq \sum_{h=1}^t (N_{BP,\hat{m}}^h + N_{D,BCS,\hat{m}}^h) E_B, \quad \forall \hat{m} \in \mathcal{N}_{BCS}, t \in \mathcal{T} \quad (3.32)$$

where E_B denotes the energy required for each battery to reach $\overline{\text{SOC}}$ to $\underline{\text{SOC}}$. η_c and η_{dc} represent the charging, discharging efficiency, respectively.

Constraint (3.29) ensures that the total energy consumed by BCS $\hat{m}$ at each time slot should at least fulfill the well-charged batteries requirements. Equation (3.30) indicates that by the end of each operation horizon, all the energy is used for producing well-charged batteries. Constraint (3.31) guarantees the energy for fulfilling the well-charged battery requirements in each time slot t , considering the energy loss due to providing spinning and upward regulation reserve. In (3.32), the maximum energy consumed by BCS $\hat{m}$ in time slot t cannot exceed the total energy capacity of all the depleted batteries available, considering the energy surplus of providing down regulation reserve. α_S and α_R are the minimum duration that the spinning reserve and regulation reserves should be maintained [102].

3.4.1.2 Power Constraints

$$P_{C,\hat{m}}^t \geq \left\{ \sum_{h=t+1}^{\min(t+T_c-1, T)} \bar{P}_C N_{Wout,\hat{m}}^h + \frac{[E_B - (T_c - 1) \bar{P}_C \eta_c \Delta t]}{\Delta t} N_{Wout,\hat{m}}^t \right\} \quad (3.33)$$

$$P_{C,\hat{m}}^t - P_{DC,\hat{m}}^t + r_{d,\hat{m}}^t \leq \bar{P}_C S_{bay,\hat{m}}^t, \forall \hat{m} \in \mathcal{N}_{BCS}, t \in \mathcal{T} \quad (3.34)$$

$$P_{DC,\hat{m}}^t - P_{C,\hat{m}}^t + R_{S,\hat{m}}^t + r_{u,\hat{m}}^t \leq \bar{P}_{DC} S_{bay,\hat{m}}^t, \forall \hat{m} \in \mathcal{N}_{BCS}, t \in \mathcal{T} \quad (3.35)$$

$$P_{C,\hat{m}}^t \leq \beta_{\hat{m}}^t \bar{P}_C N_{CH,\hat{m}}, \forall \hat{m} \in \mathcal{N}_{BCS}, t \in \mathcal{T} \quad (3.36)$$

$$P_{DC,\hat{m}}^t \leq (-\beta_{\hat{m}}^t) \bar{P}_{DC} N_{CH,\hat{m}}, \forall \hat{m} \in \mathcal{N}_{BCS}, t \in \mathcal{T} \quad (3.37)$$

$$P_{C,\hat{m}}^t, P_{DC,\hat{m}}^t, R_{S,\hat{m}}^t, r_{u,\hat{m}}^t, r_{d,\hat{m}}^t \geq 0, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}, t \in \mathcal{T} \quad (3.38)$$

where $\overline{P}_C, \overline{P}_{DC}$ denote the maximum charging/discharging rate of each bidirectional battery charger. $\beta_{\hat{m}}^t$ is a binary variable, $\beta_{\hat{m}}^t = 1$ if BCS $\hat{m}$ is charging the batteries, 0 otherwise.

Constraint (3.33) ensures that the charging power at each time slot should at least fulfill the production of well-charged batteries according to the operation plan of BCS $\hat{m}$. It is assumed that the batteries are charged at maximum charging rate for $(T_c - 1)$ time slots before the required output time. The maximum charging and discharging power constraints are shown in (3.34) and (3.35), respectively. Joint constraints (3.36) and (3.37) indicate that each BCS can only operate in either charging or discharging mode in each time slot. All the decision variables are nonnegative as shown in (3.38).

3.4.1.3 Inventory Constraints

The battery inventory of each BCS should conform to the BCS inventory model (3.13)-(3.20) introduced in Section 3.3.2.1.

3.4.2 Operation Model for BSSs

For BSS $\tilde{m}$, the objective is to maximize its revenue $C_{\text{BSS},\tilde{m}}$ by optimally demanding well-charged batteries, supplying depleted batteries and providing battery swapping services. The objective function is formulated as follows.

$$\max C_{\text{BSS},\tilde{m}} = \lambda_p D_{\tilde{m}}^t \quad (3.39)$$

where λ_p denotes the payoff of each battery swapping service.

Since the freight rates are omitted in this chapter, only the payoff from providing battery swapping services to the EVs is considered as the revenue (3.39) of BSS $\check{m}$.

For each BSS, in order to guarantee the quality of battery swapping services and the feasibility of its operation plan, the following constraints should be considered.

3.4.2.1 Service Constraint

For BSS $\check{m}$, the service constraint is shown as follows.

$$A_{\check{m}}^t \geq D_{\check{m}}^t \geq D_{\min, \check{m}}^t, \forall t \in \mathcal{T}, \check{m} \in \mathcal{N}_{\text{BSS}} \quad (3.40)$$

As also introduced in Section 3.2.3, constraint (3.40) guarantees the quality of battery swapping services considering the time preferences of EVs.

3.4.2.2 Inventory Constraints

The battery inventory of each BSS should conform to the BSS inventory model (3.21)-(3.27) introduced in Section 3.3.2.2.

Remark 3.4.1. To further ensure the feasibility of the BSCS model, the initial battery reserves $N_{\text{D}, \check{m}}^{\text{ini}}$ and $N_{\text{W}, \check{m}}^{\text{ini}}$ should be determined such that the battery swapping service requirements can be fulfilled during the first several time slots, considering the charging time of batteries at BCSs, the loading/unloading time and the traveling time of truck fleets, i.e., constraints (3.23)-(3.27). In this chapter, the values of $N_{\text{D}, \check{m}}^{\text{ini}}$ and $N_{\text{W}, \check{m}}^{\text{ini}}$ are decided such that

$$N_{\text{W}, \check{m}}^{\text{ini}} \geq A_{\check{m}}^{T_{\text{near}} + T_{\text{c}} + \epsilon_{\text{r}}}, \forall t \in \mathcal{T}, \check{m} \in \mathcal{N}_{\text{BSS}} \quad (3.41)$$

$$N_{\text{D}, \check{m}}^{\text{ini}} \geq D_{\min, \check{m}}^T - D_{\min, \check{m}}^{T - T_{\text{near}} - \epsilon_{\text{r}}}, \forall t \in \mathcal{T}, \check{m} \in \mathcal{N}_{\text{BSS}} \quad (3.42)$$

where T_{near} denotes the time slots needed for a truck fleet to travel from the nearest BCS to BSS $\tilde{n}$, and ϵ_r represents the degree of conservatism considering the possible delays in the arrival time of truck fleets.

Also it is worth mentioning that the choice of the number of BSSs to BCSs for each specific BSCS is another important issue that needs to be discussed. These numbers should be determined mainly based on the factors including total daily battery demand in the service area, the maximum allowable size of each BCS, the number of battery chargers in each BCS, the maximum charging/discharging rate of each battery charger, etc. For simplicity, if the space issue is ignored, the daily maximum battery productivity of a BCS can be estimated as follows

$$N_{\text{Wout},\tilde{n}}^{\text{daily}} = T \cdot N_{\text{CH},\tilde{n}} \cdot \left\lfloor \frac{\eta_{\text{C}} \bar{P}_{\text{C}} \Delta t}{E_{\text{B}}} \right\rfloor \quad (3.43)$$

Therefore, to ensure a high-quality battery swapping service provision, the following inequality should be satisfied when determining the number of BCSs and BSSs,

$$\sum_{\tilde{n} \in \mathcal{N}_{\text{BCS}}} N_{\text{Wout},\tilde{n}}^{\text{daily}} + \sum_{\tilde{n} \in \mathcal{N}_{\text{BSS}}} N_{\text{W},\tilde{n}}^{\text{ini}} \geq \sum_{\tilde{n} \in \mathcal{N}_{\text{BSS}}} A_{\tilde{n}}^T \quad (3.44)$$

Moreover, when deciding the number of BSSs and their geographical locations, the actual EV battery demands and their distribution in the whole system should be considered. This planning issue is also crucial to ensure the system performance and is worth being addressed in future studies.

3.4.3 Operation Model for the Logistics System

For the logistics system, the objective is to optimally schedule the trucks and batteries considering the battery demands of BSSs and BCSs while maximizing

its revenue C_{LS} . The objective function is given as follows.

$$\begin{aligned} \max C_{LS} = \sum_{t=1}^T \left[-C_{\text{tran}} \sum_{\omega \in \Omega} \sum_{(\hat{n}, \tilde{n}) \in \mathcal{Z}} \zeta_{\omega, (\hat{n}, \tilde{n})}^t \right. \\ \left. - \lambda_{\text{lb}} \sum_{\hat{m} \in \mathcal{N}_{\text{BCS}}} (N_{\text{D}, \text{BCS}, \hat{m}}^t + N_{\text{W}, \text{BCS}, \hat{m}}^t) \right. \\ \left. - \lambda_{\text{lb}} \sum_{\tilde{m} \in \mathcal{N}_{\text{BSS}}} (N_{\text{D}, \text{BSS}, \tilde{m}}^t + N_{\text{W}, \text{BSS}, \tilde{m}}^t) \right] \end{aligned} \quad (3.45)$$

where C_{tran} is the unit transportation cost and λ_{lb} denotes the labor cost for loading/unloading batteries.

The first term on the right-hand side of (3.45) refers to the transportation cost. The second term and the third term represent the labor cost for loading and unloading batteries.

Based on the vehicle-battery scheduling model proposed in Section 3.3.1, to satisfy the battery demands of BSSs and BCSs, the following constraints must be met. i) *Logistics constraints*: (3.1)-(3.12); ii) *Coupled battery demand constraints*: (3.13), (3.14), (3.21) and (3.22).

3.4.4 Optimal Operation Management of BSCSs

By integrating the operation models introduced in the previous sections, the optimal operation management of BSCSs can be formulated as a MILP problem as follows, which can be solved in a centralized way using existing commercial solvers.

$$\begin{aligned} \max \quad & \sum_{\hat{m} \in \mathcal{N}_{\text{BCS}}} C_{\text{BCS}, \hat{m}} + \sum_{\tilde{m} \in \mathcal{N}_{\text{BSS}}} C_{\text{BSS}, \tilde{m}} + C_{\text{LS}} \\ \text{s.t.} \quad & (3.1) - (3.27), (3.29) - (3.38), (3.40). \end{aligned} \quad (3.46)$$

3.5 Distributed Solutions

Although problem (3.46) can be solved in a centralized way, distributed solutions are preferred in this chapter. The main reasons are provided as follows.

Firstly, solving this model in a centralized way requires the global information from all the BCSs, BSSs and the logistics system, including the battery inventory information of BCSs and BSSs and the cost/revenue functions. In real-world applications, BCSs and BSSs can be invested and operated by different economic entities, where inventory information and cost/revenue functions are often regarded as their private information [103]. Sharing private information with a central unit may lead to certain privacy concerns, which may discourage these entities from investing.

Secondly, as the number of nodes, time slots and trucks increase, the computation time of centralized algorithms also grows significantly due to the large amount of integer and binary variables. Compared to centralized algorithms, distributed algorithms have the potential to achieve shorter runtime [104], as will be shown in the numerical results presented in Section 3.6.

In this section, a brief literature review of the existing distributed algorithms is provided. Then a novel extension of ADMM called RP-ADMM is applied to achieve the distributed operation management of BSCSs.

3.5.1 Existing Algorithms

In [105], the authors presented a thorough survey of the existing distributed optimization and control algorithms. According to the authors, current distributed algorithms can be mainly categorized into two types. The first type of algorithms is

based on augmented Lagrangian decomposition, including Dual Decomposition, ADMM, Analytical Target Cascading (ATC) and the Auxiliary Problem Principle (APP). The second type of algorithms is based on decentralized solution of the Karush-Kuhn-Tucker (KKT) necessary conditions for local optimality, including Optimality Condition Decomposition (OCD) and Consensus + Innovation.

In this chapter, the algorithms based on KKT conditions are not applicable due to the existence of integer and binary variables. For the algorithms based on augmented Lagrangian decomposition, alternating direction method of multipliers (ADMM) is preferred since there has been some attempts on using it to solve MILP problems [104], [106].

3.5.2 RP-ADMM

ADMM is a widely used distributed algorithm in applied statistics and machine learning [107]. Consider an n -block convex minimization problem with linear constraints and an objective function which is the sum of the functions without coupled variables shown as follows.

$$\begin{aligned} \min \quad & \sum_{i=1}^n f_i(x_i) \\ \text{s.t.} \quad & \sum_{i=1}^n H_i x_i = b \\ & x_i \in \mathcal{X}_i, \forall i = 1, \dots, n \end{aligned} \tag{3.47}$$

where $\mathcal{X}_i$ and $f_i(x_i)$, $\forall i = 1, 2, \dots, n$, are closed convex sets and closed convex functions, respectively. For problems with $n = 2$, ADMM is proved to have good decomposability and superior convergence properties. However, when n is larger than 2, the direct extension of ADMM is not necessarily convergent [108].

Recently, a randomly permuted ADMM (RP-ADMM) was proposed with proved

expected convergence on solving this kind of multi-block problems [109], [110].

Specifically, the RP-ADMM first picks a permutation σ of $\{1, 2, \dots, n\}$ uniformly at random and then iterates as follows:

$$\begin{cases} x_{\sigma(1)}^{k+1} = \operatorname{argmin}_{x_{\sigma(1)}} \mathcal{L} \left(x_{\sigma(1)}, x_{\sigma(2)}^k, \dots, x_{\sigma(n)}^k; \mu^k \right) \\ x_{\sigma(2)}^{k+1} = \operatorname{argmin}_{x_{\sigma(2)}} \mathcal{L} \left(x_{\sigma(1)}^{k+1}, x_{\sigma(2)}, x_{\sigma(3)}^{k+1}, \dots, x_{\sigma(n)}^k; \mu^k \right) \\ \vdots \\ x_{\sigma(n)}^{k+1} = \operatorname{argmin}_{x_{\sigma(n)}} \mathcal{L} \left(x_{\sigma(1)}^{k+1}, x_{\sigma(2)}^{k+1}, x_{\sigma(3)}^{k+1}, \dots, x_{\sigma(n-1)}^{k+1}, x_{\sigma(n)}; \mu^k \right) \end{cases} \quad (3.48)$$

$$\mu^{k+1} = \mu^k - \rho \left(\sum_{i=1}^n H_i x_i^{k+1} - b \right) \quad (3.49)$$

where ρ is the step size and σ_i represents the i th entry of the permutation. For example, when $n = 3$ and $\sigma = (312)$, then $\sigma(1) = 3$, $\sigma(2) = 1$ and $\sigma(3) = 2$, respectively. $\mathcal{L}$ is the augmented Lagrangian function of problem (3.47).

The following theorem states the expected convergence of RP-ADMM, which can also be found in [109] and [110].

Theorem 3.5.1. *Assume that $f_i(x_i), \forall i = 1, 2, \dots, n$ are linear functions and the following condition holds*

$$\begin{bmatrix} H_1^T H_1 & 0 & \cdots & 0 \\ 0 & H_2^T H_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & H_n^T H_n \end{bmatrix} \succ 0$$

Suppose that RP-ADMM is employed to solve problem (3.47), then the expected iterative sequence converges to some KKT point of (3.47).

3.5.3 Distributed Solutions

To apply the RP-ADMM, problem (3.46) should first be reformulated into the standard form as (3.47). Three constraint sets with only local variables are defined as follows.

$$\Phi_1 = \left\{ \begin{array}{l} P_{C,\hat{m}}^t, P_{DC,\hat{m}}^t, R_{S,\hat{m}}^t, r_{u,\hat{m}}^t, r_{d,\hat{m}}^t, \\ N_{Wout,\hat{m}}^t, N_{BP,\hat{m}}^t, S_{D,BCS,\hat{m}}^t, S_{W,BCS,\hat{m}}^t, \\ \forall \hat{m} \in \mathcal{N}_{BCS}, t \in \mathcal{T} \end{array} \middle| (3.15)-(3.20), (3.29)-(3.38) \right\} \quad (3.50)$$

$$\Phi_2 = \left\{ \begin{array}{l} N_{D,BSS,\check{m}}^t, N_{W,BSS,\check{m}}^t, D_{\check{m}}^t, \\ S_{D,BSS,\check{m}}^t, S_{W,BSS,\check{m}}^t \forall \check{m} \in \mathcal{N}_{BSS}, t \in \mathcal{T} \end{array} \middle| (3.23)-(3.27), (3.40) \right\} \quad (3.51)$$

$$\Phi_3 = \left\{ \begin{array}{l} \xi_{\omega,(\hat{n},\check{n})}^t, N_{D,BCS,\omega,\hat{m}}^t, N_{W,BCS,\omega,\hat{m}}^t, \\ N_{D,BSS,\omega,\check{m}}^t, N_{W,BSS,\omega,\check{m}}^t, S_{D,\omega}^t, S_{W,\omega}^t, \\ \forall (\hat{n},\check{n}) \in \mathcal{Z}, \omega \in \Omega, t \in \mathcal{T} \end{array} \middle| (3.1)-(3.12) \right\} \quad (3.52)$$

For simplicity, three vectors $\mathbf{x}_1 \in \Phi_1$, $\mathbf{x}_2 \in \Phi_2$ and $\mathbf{x}_3 \in \Phi_3$ formed by the local variables of BCSs, BSSs, and LS are introduced, whereby the remaining coupled battery demand constraints (3.13), (3.14), (3.21) and (3.22) can be rewritten into the following matrix form.

$$H_1 \mathbf{x}_1 + H_2 \mathbf{x}_2 + H_3 \mathbf{x}_3 = 0 \quad (3.53)$$

Then problem (3.46) can be reformulated as follows.

$$\begin{aligned} \min \quad & \left(\sum_{\hat{m} \in \mathcal{N}_{BCS}} C_{BCS,\hat{m}} + \sum_{\check{m} \in \mathcal{N}_{BSS}} C_{BSS,\check{m}} + C_{LS} \right) \\ \text{s.t.} \quad & H_1 \mathbf{x}_1 + H_2 \mathbf{x}_2 + H_3 \mathbf{x}_3 = 0, \\ & \mathbf{x}_i \in \Phi_i, \forall i = 1, 2, 3. \end{aligned} \quad (3.54)$$

Algorithm 1: RP-ADMM

```

1 Initialization:  $\mathbf{x}_i^0 \in \Phi_i, i = 1, 2, \dots, n; \mu^0 \in \mathbb{R}^{M \times 1};$ 
2 for iteration round  $k$  ( $k = 1, 2, 3, \dots$ ) do
3   Primal update:
4   Pick a permutation  $\sigma$  of  $\{1, 2, \dots, n\}$  uniformly at random;
5   for  $i = 1, 2, \dots, n$  do
6     Compute  $\mathbf{x}_{\sigma(i)}^{k+1}$  according to (3.48);
7   end
8   Dual update:
9   Update the dual variable by (3.49);
10  if the termination criterion is met then
11    Terminate.
12  end
13 end

```

where the maximization problem is converted into a minimization problem and the original BSCS is separated into three subsystems consisting of BCSs, BSSs and the logistics system.

Detailed steps of the RP-ADMM to solve the reformulated problem (3.54) are given in Algorithm 1, where in this chapter $M = |\Phi_1| + |\Phi_2| + |\Phi_3|$, $n = 3$ and the augmented Lagrangian is formulated as follows.

$$\begin{aligned}
\mathcal{L}(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3; \mu) = & \sum_{\hat{m} \in \mathcal{N}_{\text{BCS}}} C_{\text{BCS}, \hat{m}} + \sum_{\hat{m} \in \mathcal{N}_{\text{BSS}}} C_{\text{BSS}, \hat{m}} + C_{\text{LS}} \\
& - \mu^T \sum_{i=1}^n H_i \mathbf{x}_i + \frac{\rho}{2} \left\| \sum_{i=1}^n H_i \mathbf{x}_i \right\|_2^2
\end{aligned} \tag{3.55}$$

Remark 3.5.1. In this chapter, the BSCS has been separated into three subsystems. By decomposing the system into more subsystems, the RP-ADMM has the potential to converge faster. For example, the logistics system can be further decomposed into $|\Omega|$ subsystems by simply dividing C_{LC} , the associated variables and constraints into $|\Omega|$ parts.

3.5.4 Convergence Discussion

As mentioned in Section 3.5.2, the expected convergence of RP-ADMM under convexity assumptions has been analytically proved in [109], [110]. In the proposed BSCS model, due to the existence of the integer and binary variables, problem (3.46) is highly non-convex, which makes the convergence results no longer applicable. Therefore, currently there is no convergence guarantee for RP-ADMM when it is used to solve non-convex problems.

However, many practical evidences suggest that ADMM can be an effective method to approximately solve some nonconvex problems [104], [106], [111], [112]. In this sense, the adopted RP-ADMM can be regarded as a distributed heuristic method and has the potential to obtain suboptimal solutions of problem (44) with small optimality loss, good feasibility and less computation time, compared to the centralized solutions.

3.6 Case Studies

In this section, two case studies are performed to verify the effectiveness of the proposed CLSC-based BSCS and the RP-ADMM based distributed operation management scheme. In case 1, the BSCS acts as a price taker in the wholesale market. In case 2, the BSCS is integrated into a real transportation network and a transmission network, where it is managed by one system operator. In all the cases, the operation horizon is considered to have $T = 48$ time slots, the length of each time slot Δt is 0.5 h. The optimization model is implemented using MATLAB 2016a and solved by Gurobi [113], on a computer with an Intel Core i7 3.4 GHz CPU and 128 GB RAM.

Figure 3.5: Arrival curves and minimum departure curves of BSSs.

3.6.1 Case 1

3.6.1.1 Case Description

In the first case study, a BSCS with one BCS and three BSSs is considered, all of them are connected to a logistics system with $|\Omega| = 4$ truck fleets and a transportation network as depicted in Fig. 3.3. BSS 1 and BSS 2 exclusively provide battery swapping services to electric taxis while BSS 3 is for electric buses. There are 1500 electric taxis with two battery packs and 200 electric buses with four battery packs in this case. The battery demands of each kind of EV are taken from [114]. Since taxis can have at least 5 hours of leisure every day [115] and according to the scheduling plan of buses [116], it is assumed that EVs require the battery swapping service to be finished within one or two hours, each with a probability of 0.5. The arrival curves and the minimum departure curves at each BSS are shown in Fig. 3.5.

Figure 3.6: Energy price, spinning reserve price and regulation reserve prices.

Day-ahead energy price λ_{DA} , spinning reserve price λ_s and regulation reserve prices λ_{ru} , λ_{rd} on Dec-15 2017 are obtained from EMC of Singapore [117] and are depicted in Fig. 3.6. The step length for RP-ADMM $\rho = 0.1$ and $\epsilon_r = 3$. According to Fig. 3.5, $N_{D,\tilde{m}}^{ini}$ and $N_{W,\tilde{m}}^{ini}$ are both set to be 200. Other simulation parameters are given in Table 3.1

3.6.1.2 Simulation Results

The operation plan of the BCS is shown in Fig. 3.7. It can be seen that at the beginning of the operation horizon, 302 backup batteries are employed by the BCS to ensure that the total number of batteries within the BSCS can satisfy its operation requirement considering each BSS's initial battery stock and EVs' battery demand. Batteries are mainly charged when the electricity price is relatively low, e.g., (0:00-8:00) and (12:00-20:00). However, due to the battery demand of BSSs and the charging power limits, a few batteries have to be charged when the

Table 3.1: Simulation Parameters

Truck fleet #	1	2	3	4
Initial position (node #)	1	1	1	1
Battery energy requirement E_B (kWh)	40			
Maximum charging/discharging power $\bar{P}_C, \bar{P}_{DC}$ (kW)	42/42			
Charging/discharging efficiency η_c, η_{dc}	0.95/0.9			
Battery swapping service payoff λ_p (\$)	1			
Battery charging cost C_d (\$/kWh)	0.02			
Backup battery cost C_{BP} (\$/pack)	5			
Transportation cost C_{tran} (\$/transit)	20			
Labor cost C_{lb} (\$/pack)	0.1			
Truck battery capacity C_B	300			
Number of bidirectional chargers at each BCS $N_{CH,\hat{m}}$	200			

price is relatively high, i.e., (20:00-22:00). Note that the first well-charged battery production is observed at 1:00, since Δt is set to be 0.5h and it takes at least two time slots for each battery to be fully charged. At the end of the operation horizon, the total number of batteries at the BCS is 292, i.e., 92 depleted batteries are in the inventory and 200 depleted batteries stay in the charging bay to provide reserves. This number is very close to the number of backup batteries employed at the beginning, which ensures the sustainable and economic operation of the BSCS. It is worth mentioning that, although it is not shown in the figure, the number of the batteries in the charging bay is always kept 200 to provide reserves for revenue maximization.

The aggregated charging/discharging and ancillary service provision plan is depicted in Fig. 3.8. It can be observed that in general the charging/discharging

Figure 3.7: Operation plan of the BCS.

Figure 3.8: BCS aggregated charging/discharging and ancillary service provision plan.

behavior of the BCS is in accordance with the battery-related operation plan depicted in Fig. 3.7. Besides the energy for battery charging, the batteries are

Figure 3.9: Operation plan of BSS2. (a) Service curves. (b) Battery inventory.

mainly scheduled to provide regulation up reserve capacity, which is because that in charging mode, a battery can stop charging and transition to discharging mode within an ignorable amount of time to provide up reserves. The maximum up reserve that the battery can provide in this case is $P_{C,\hat{m}}^t + \overline{P}_{DC}$, which is larger than its maximum power rating. It is worth mentioning that in this case studies, detailed regulation/reserve activations are not considered for simplicity.

As an example to illustrate the operation at each BSS, the operation plan of BSS2 is depicted in Fig. 3.9. It can be observed that the departure curve of BSS2 is located between its arrival curve and minimum departure curve, which

Figure 3.10: Vehicle-battery scheduling results for the logistics system.

indicates that the quality of battery swapping service at BSS2 is guaranteed. Furthermore, BSS2 also provide certain operational flexibility for the BCS to reduce the charging cost and for the logistics system to reduce the transportation cost. For example, in Fig. 3.9 (a), the battery swapping service at BSS2 during (3:30-4:00) and (5:30-6:30) is postponed. Similar phenomena can be observed at other BSSs. Further detailed observations about these trade-offs between the revenue maximization for the whole system and the service quality in BSSs can be obtained in Fig. 3.10. Fig. 3.9 (b) shows the battery inventory of BSS2. It can be seen that both the well-charging battery inventory and the depleted battery inventory return to their initial states with acceptable deviations of about 10 battery packs.

Fig. 3.10 shows the vehicle-battery schedules for the four truck fleets and their spatiotemporal dynamics, which verifies the effectiveness of the proposed TSN based battery scheduling model. It can be seen that at the beginning of the day, truck fleet #1-#3 first travel to the three BSSs to collect all the available depleted batteries and transport them back to the BCS, which reduces the number of backup batteries needed, while truck fleet #4 stays at the BCS to fulfill the battery requirements of BSS2. Furthermore, as also mentioned before, the postponements in the battery swapping service at each BSS can be explained according to this figure. Firstly, the maximum charging capacity limited by the number of chargers in the charging bay at the BCS and the delays in the battery logistics system can be parts of the reasons. As can be observed in Fig. 3.7, the battery charging during (0:00-8:00) is performed at the maximum charge rate, because the energy price is relatively low. However, since the number of well-charged batteries at 2:00 is 227, which cannot fully satisfy the battery swapping requirements at BSS2 in the next few hours, truck fleet #4, as depicted in Fig. 3.10, waits until 2:30 for the BCS to charge more batteries in order to transport enough batteries to BSS2 in a single trip to reduce transportation cost. It finishes loading 240 well-charged batteries at 3:00 and can only arrive at BSS2 at 4:00 due to the travel time, thus causing the postponement in the battery swapping service during (3:30-4:00). Another reason is the number of truck fleets. Since the only available truck fleet #1 at the BCS is transporting batteries to BSS1 during (5:00-6:00), the battery swapping service has to be postponed until fleet #3 is available. Although truck fleet #2 seems to be available, considering the travel time of 2 time slots between BSS2 and the BCS and the loading/unloading time, truck fleet #2 cannot transport well-charged batteries to BSS2 on time.

Fig. 3.11 shows the performance comparisons between RP-ADMM and the original ADMM. In Fig. 3.11 (a), it can be seen that RP-ADMM converges to

a feasible solution after 160 iterations while the output of ADMM keeps fluctuating. Similar results can be observed in Fig. 3.11 (b), the primal residual of RP-ADMM becomes very small after 160 iterations while the primal residual of ADMM is around 47.35 and does not converge, which indicates that the original ADMM cannot find a feasible solution to the problem. RP-ADMM takes 723s to converge, while the computation time of the centralized algorithm is 2661s. The total revenue under the distributed operation management scheme is \$49426.9 while the revenue obtained by the centralized solution is \$50687.8. The optimality gap is about 2.5%.

3.6.1.3 Sensitivity Analysis

Fig. 3.12 shows the impacts of the number of truck fleets and the total battery demand in the BSCS on the objective values. Note that when the model is infeasible, the objective value is regarded as zero. It can be seen that when there is only one truck fleet in the system, the system is always infeasible. As the number of truck fleets increases, the objective value also grows larger. However, when there are enough truck fleets in the system, the objective value, i.e., revenue, no longer increases. This is because that the battery transportation capability in the system has saturated, additional truck fleets cannot further improve the scheduling plan. It can also be observed that the objective value rises with the total battery demand due to the battery swapping service revenue. But when the demand exceeds the total battery production capacity of BCSs within one operation horizon, the model is infeasible.

Table 3.2 depicts the relationship between the maximum charging/discharging power and the obtained total revenue of the BSCS. When the maximum charging rate is too low, the BCS is unable to produce enough well-charged batteries to

Figure 3.11: Performance comparisons between RP-ADMM and ADMM. (a) Objective value. (b) Primal residual.

fulfill the battery demands of BSSs, thus causing the model infeasible. The total revenue grows with the charging rate due to the additional flexibility brought to the operation plans of BCSs.

Table 3.2: Impacts of Maximum Charging/Discharging Power

$\bar{P}_C, \bar{P}_{DC}$ (kW)	25	45	65	85	105
Objective Value (\$)	Infeasible	51657	56544	61927	66644

To elaborate on the impacts of the number of virtual nodes on the computational

Figure 3.12: Impacts of the number of truck fleets and the total battery demand in the BSCS on the objective values.

complexity of the model, a sensitivity analysis has been performed. Several virtual nodes have been added between the BCS and BSS2 to see the computation time for the centralized solver Gurobi to obtain a result with the same optimal gap. The results are shown in the following Table 3.3. It can be observed that along with the increasement of the number of the virtual nodes between the BCS and BSS2, the computation time doesn't increase so much. The reason for this result is that when the distance between the BCS and BSS2 become too long, this route will no longer be considered and all the trucks will choose alternative routes such as BCS-BSS1-BSS2 to minimize the transportation cost. However, if virtual nodes are added on multiple arcs, for example, one virtual node is added between BCS and BSS3 and another is added between BSS2 and BSS3, the computation time is increased to 3453s.

Table 3.3: Impacts of the Number of Additional Virtual Nodes on the Computation Time

Additional virtual node #	1	2	3	4	5	6	7
Computation time (s)	2673	2696	2658	2718	2686	2677	2701

Table 3.4: Impacts of Battery Charging Cost C_d

C_d (\$/kWh)	0.02	0.04	0.06	0.08	0.1
Objective Value (\$)	50687.8	45082.2	39422.6	33689.4	27984.8

Another sensitivity analysis is performed to further study the impacts of battery charging cost C_d on the total revenue of the BSCS and the results are presented in Table 3.4. It can be observed that the objective value decreases almost linearly as the battery charging cost increases. Still, the increasing battery charging cost does not affect much the overall operation plans for BCSs, BSSs and the battery logistics. This is because that the system is still profitable by following these plans. However, when C_d reaches 0.2 \$/kWh, the system can no longer obtain positive revenue by providing energy and ancillary services to the grid due to high battery charging costs. Therefore, the BSCS would choose to provide only the battery swapping services to the EVs instead.

3.6.1.4 Robust Operation Under EV Uncertainty

In real situations, buses are usually punctual according to their predetermined timetables. However, due to the stochastic characteristics of the taxi drivers, uncertainties are brought to the arrival curves and departure curves at each BSS

[118]. To further study the robustness of our model and the RP-ADMM based heuristic method, a robust optimization approach proposed in [119] is applied to deal with the uncertainties in these curves.

Let $a_{\tilde{m},t}$ denote the number of the EVs that arrive at BSS $\tilde{m}$ in time slot t where $a_{\tilde{m},t}$ takes values in $[\bar{a}_{\tilde{m},t} - \hat{a}_{\tilde{m},t}, \bar{a}_{\tilde{m},t} + \hat{a}_{\tilde{m},t}]$. The scaled deviation of $a_{\tilde{m},t}$ is defined as $z_{\tilde{m},t} = (a_{\tilde{m},t} - \hat{a}_{\tilde{m},t})/\hat{a}_{\tilde{m},t}$, which takes values in $[-1,1]$. Budget constraints of uncertainty are introduced as follows to rule out large deviations in the cumulative curves:

$$\sum_{h=1}^t |z_{\tilde{m},h}| \leq \Gamma_t, \forall \tilde{m} \in \mathcal{N}_{\text{BSS}}, t \in \mathcal{T} \quad (3.56)$$

where Γ_t is assumed to increase with t since the uncertainty increases with the number of time slots considered.

Based on these definitions, instead of constraint (3.40), the service constraint under EV behavior uncertainties for BSS $\tilde{m}$ can be formulated as follows.

$$D_{\tilde{m}}^t \leq A_{\tilde{m}}^t - q_{\tilde{m},t}\Gamma_t - \sum_{h=1}^t r_{\tilde{m},h}, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}} \quad (3.57)$$

$$D_{\tilde{m}}^t \geq D_{\min,\tilde{m}}^t + q_{\tilde{m},t}\Gamma_t + \sum_{h=1}^t r_{\tilde{m},h}, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}} \quad (3.58)$$

$$q_{\tilde{m},t} + r_{\tilde{m},t} \geq \hat{a}_{\tilde{m},t}, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}} \quad (3.59)$$

$$q_{\tilde{m},t} \geq 0, r_{\tilde{m},t} \geq 0, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}} \quad (3.60)$$

Constraints (3.57) and (3.58) ensure that the battery swapping service requirements at BSS $\tilde{m}$ can be satisfied with very high probability [120]. Constraint (3.59) models the worst case of deviation at each time slot t , where $q_{\tilde{m},t}$ and $r_{\tilde{m},t}$ are the variables that quantify the conservativeness and the bounds of the

uncertain variables. Constraint (3.60) indicates that $q_{\tilde{m},t}$ and $r_{\tilde{m},t}$ are nonnegative.

The results show that when $\Gamma_1 = 0.6$ and increases by 0.05 with t , and assume that $\hat{a}_{\tilde{m},t} = 5$. The RP-ADMM algorithm finds a feasible solution after 140 iterations, with a computation time of 1029s, while the centralized algorithm takes 3132s to solve it. The total revenue obtained using the algorithm is \$48100.5, while the revenue obtained by the centralized solution is \$49118.2. The optimality gap is 2.1%. Compared to the normal operation model, \$1569.6 is lost due to the conservativeness at BSSs.

3.6.2 Case2

3.6.2.1 Case Description

In the second case study, instead of a wholesale market, the proposed BSCS model can also participate in the operation of power systems to provide more flexibility in the commitment scheduling for thermal generators, i.e., spinning reserve, regulation reserves and power injections. As depicted in Fig. 3.13, a BSCS with two BCS, seven BSSs and a logistics system with $|\Omega| = 7$ truck fleets is implemented based on the real data of the transportation network of Singapore. To study the flexible operation of BCSs in power system scheduling, the two BCSs are connected to a modified IEEE 6-bus test system, considering the geographic characteristic of Singapore. BCS1 and BCS2 are connected to bus 2 and bus 3, respectively. The unit commitment model [102] is adopted to manage the BCSs and power systems. The detailed BCS operation model is shown as follows.

In the operation model with a power system, instead of the price signals from a wholesale market, BCSs now directly follow the control signals from the system

Figure 3.13: A BSCS within the transportation network of Singapore.

operator. The combined operation model for the power system and BCSs is formulated as:

$$\begin{aligned} \max C_{\text{PS-BCS}} = & - \sum_{t=1}^T \left\{ \sum_{g \in \mathcal{G}} [C_g(P_g^t) + c_{g,\text{NL}}u_g^t + c_{g,\text{SU}}v_g^t] \right. \\ & \left. + \sum_{m \in \mathcal{N}_{\text{BCS}}} [C_d(P_{\text{DC},\hat{m}}^t + P_{\text{C},\hat{m}}^t) \Delta t + C_{\text{BP}}N_{\text{BP},\hat{m}}^t] \right\} \quad (3.61) \end{aligned}$$

where $\mathcal{G}$ is the set of generators. $C_g(\cdot)$ and P_g^t denote the cost function and power output for generator g in time slot t . $c_{g,\text{NL}}$ and $c_{g,\text{SU}}$ are the no-load cost and startup cost for generator g , respectively. $u_{g,t}$ is the binary unit commitment variable for generator g , $u_{g,t} = 1$ if online, 0 otherwise, while $v_{g,t}$ is the startup variable, 1 for startup, 0 otherwise.

Problem (3.61) is subject to the energy constraints (3.29)-(3.32), the power constraints (3.33)-(3.38), the inventory constraints (3.13)-(3.20) and an additional coupling constraint between BCSs and the power system given as follows.

$$\begin{aligned} \sum_{g \in \mathcal{G}} P_g^t + \sum_{k \in \delta_{(l)}^+} P_k^t - \sum_{k \in \delta_{(l)}^-} P_k^t \\ + \sum_{\tilde{m} \in \mathcal{N}_l} (P_{\text{DC}, \tilde{m}}^t - P_{\text{C}, \tilde{m}}^t) = d_{l,t}, \forall t \in \mathcal{T}, l \in \mathcal{N}_{\text{bus}} \end{aligned} \quad (3.62)$$

where δ_l^+ and δ_l^- denote the sets of transmission lines with "to" and "from" bus l . P_k^t is the active power flow on transmission line k in time slot t , and $d_{l,t}$ is the active power demand at bus l in time slot t .

Constraint (3.62) guarantees the power balance at each bus in the power systems. Further operation constraints for the power system and generators, such as power flow constraints, line-flow limit constraints, minimum up and down time requirements, capacity limits, and ramp rate constraints, are referred to [102]. Other parameter settings are the same as in Table 3.1, and all the scenarios were solved in a distributed way.

Four scenarios are conducted in this case, as follows:

- (1) Scenario I: BSSs provide battery swapping service according to the arrival curve, i.e., $A_{\tilde{m}}^t = D_{\tilde{m}}^t, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}}$;
- (2) Scenario II: BSSs provide battery swapping service according to Eq. (3.40), i.e., $A_{\tilde{m}}^t \geq D_{\tilde{m}}^t \geq D_{\min, \tilde{m}}^t, \forall t \in \mathcal{T}, \tilde{m} \in \mathcal{N}_{\text{BSS}}$;
- (3) Scenario III: Uncertainties of arrival and departure curves are considered, where $\Gamma_1 = 0.6$ and increases by 0.05 with t , and $\hat{a}_{\tilde{m}, t} = 5$, as introduced in Section 3.6.1.4;
- (4) Scenario IV: The power flow on transmission line 2-3 is limited to 50 MW, while the other parameters are the same as scenario III.

Figure 3.14: Comparison of scheduling under scenario III and scenario IV. (a) Real power flow on transmission line 2-3. (b) Operation plan of BCS 2. (c) Unit commitment status for generator 2 (0 offline, 1 online).

3.6.2.2 Simulation Results

The total revenues under each scenario are \$62338.34, \$65298.85, \$63549.06 and \$62876.37, respectively. The comparison between scenario I and scenario II shows that, the revenue increases by 4.75% due to the operational flexibility

provided by the BSSs. The results of scenario II and scenario III show that the total revenue reduces by 2.95% due to the EV uncertainties. As depicted in Fig. 3.14 (a), the power flow on transmission line 2-3 is higher than 50 MW during (18:00-19:30) under scenario III. As an example to illustrate the impacts of the power flow limitation, the operation plan of BCS 2 is shown in Fig. 3.14 (b). When the power flow on transmission line 2-3 is limited to 50 MW, BCS 2 is not discharging under scenario IV to achieve the load shifting at bus 2 and bus 3. In addition, as illustrated in Fig. 3.14 (c), generator 2, which is integrated into bus 2, is online during 22:00-24:00 to meet the energy requirements of BSCSs under scenario IV, while the revenue decreases by 1.44% due to the flow limitation.

The above results reveal the potential applications of the proposed BSCSs model to provide additional operational flexibility for power systems.

3.7 Summary

In this chapter, to fill the gap in the combined operation of BCSs and BSSs, a CLSC based BSCS model is proposed. A network calculus based service model for BSSs and a TSN-based battery logistics model are introduced. Based on these models, the charging and discharging of batteries and the battery logistics are optimally scheduled to maximize the revenue of the BSCS while guaranteeing the quality of battery swapping service provided to EVs at each BSS. The operation management problem is formulated as a MILP problem, which is solved in a distributed way by decomposing the BSCS into small subsystems and applying RP-ADMM. Simulation results show that the proposed CLSC-TSN based BSCS model is practical and the RP-ADMM can obtain heuristic solutions with small optimality losses, good feasibilities and less computation time, thus achieving the distributed management of BSSs, BCSs and the battery logistic while ensuring

the quality of battery swapping service at BSSs.

Chapter 4

Management of Mobile Energy Storage for Multi-region Battery Swapping–Charging Networks

As already discussed in Chapter 3, BSCS is efficient for battery swapping service provision to commercial EVs in a certain region, harnessing the EV battery mobility. When multiple BSCSs are considered to serve a larger geographical span, achieving the efficient and collaborative management of the BSCSs located in different regions with various EV user behavior and system features is essential to further utilize battery mobility. This chapter proposed a closed-loop supply chain network based multi-region battery swapping-charging network model (MBSCN) and a battery logistics model based on a multi-layer time-space network technique. A distributionally robust chance-constrained service model is proposed to address the EV uncertainties without requiring assumptions on the probability distributions or a large number of historical data. The battery charging and discharging tasks are optimally allocated to each BSCS according to the locational energy price and the battery demands while the battery logistics are optimally managed to ensure high-quality battery swapping service provision considering regional battery demand uncertainties. The optimization problem is formulated as a mixed-integer quadratically-constrained programming model and is verified

by two case studies. The results indicate that the MBSCN model is more flexible and efficient when interregional battery exchanges are incorporated.

4.1 Introduction

In the previous chapter, to fill in the gaps in the modeling of the coordinated operation of BCSs and BSSs and its management, a CLSC based BSCS model is proposed with a battery logistics model formulated based on the TSN technique. However, with a continuously increasing number of EVs, further deployments of electric vehicle supply equipment (EVSE) can be foreseen. For example, in China, BAIC announced a plan to build 3,000 BSSs nationwide by 2021, the Chinese EV startup NIO also plans to build over 1,000 BSSs for some of its EVs [12]. This increase in BSCS scale and geographical span could bring great difficulties in battery logistics management as well as battery charging and swapping planning if all these BCSs and BSSs are managed as a single entity, due to the differences in EV user behaviors, local transportation network structures and local power network configurations in different geographical regions, which makes the single BSCS model introduced in Chapter 3 insufficient and impractical.

A practical solution to this challenge is partitioning these stations into smaller groups, where each group acts as a single BSCS to manages its own intra-system battery logistics and provides services to its designated service region, e.g., towns or cities [27]. Moreover, since the EV charging infrastructure usage is highly location-dependent [28], resource sharing and collaborations between BSCSs could potentially achieve higher efficiency, economy and more operational flexibility for both BSCSs and the local distribution networks (DNs) through inter-regional battery exchange, i.e., more battery charging tasks are performed at BSCSs where the regional battery demands are low and then transported to the regions with higher EV penetration level. Very few works have considered a multi-BSCSs model and its operation. In [93], the authors propose a k-means clustering algo-

rithm to pre-partition the BCSs and BSSs for easier battery dispatch among them, where the detailed mathematical models and the potential collaborations between each BSCS are ignored. Furthermore, none of the aforementioned papers consider the uncertainties of EV user behaviors, which should also be addressed to ensure uninterrupted, high-quality battery swapping service provisions [29]. To the best of the authors' knowledge, this chapter is the first to study the modeling and management of a multi-BSCS network when interregional battery logistics is incorporated, considering EV uncertainties.

This chapter aims to bridge the gap in the modeling and management of a multi-BSCS network with interregional battery logistics. A novel closed-loop supply chain network (CLSCN) based multi-region battery swapping-charging network (MBSCN) model is proposed. To address the differences in the temporal-spatial behavior of the truck fleets in each subsystem considering their varying traveling speeds, sizes, and different regional transportation network structures, a multi-layer TSN [96], [121] based network-wise (both intra-BSCS and interregional) battery logistics model is introduced. The battery charging/discharging and the battery logistics are optimally scheduled such that collaborative operations among the BSCSs are achieved. Furthermore, to capture the uncertainties of EV arrival and departure at BSSs, the network calculus based BSS service model is extended to a distributionally robust chance-constrained model, which requires no assumptions on the probability distributions of uncertainties. The optimization problem is formulated as a mixed-integer quadratically-constrained quadratic programming (MIQCQP) problem to minimize the total cost of the MBSCN. The contributions of this chapter are summarized as follows.

- i) A CLSCN-based MBSCN model is proposed and a network-wise battery logistics model is introduced based on a multi-layer TSN technique;

ii) A distributionally robust chance-constrained BSS service model is proposed to address the EV and battery demand uncertainties. The effectiveness and reliability of the MBSCN model are verified through two case studies.

The remainder of this chapter is organized as follows. Section 4.2 introduces the CLSCN based MBSCN model. In Section 4.3, a multi-layer TSN based network-wise battery logistics model is introduced. In Section 4.4, the operation model of the MBSCS and the distributionally robust chance-constrained BSS model are formulated. Case studies are given in Section 4.5 and conclusions are drawn in Section 4.6.

4.2 System Model

As illustrated in both Fig. 4.1 and Fig. 4.2, in a single BSCS model, multiple BCSs and BSSs are deployed within its designated service region. The depleted batteries collected from EVs are transported to BCSs for recharging and then the well-charged batteries are distributed to each BSS for battery swapping services. At the power system level, BCSs are connected to the buses in the local distribution network for electricity supply. At the transportation system level, BCSs and BSSs are interconnected through an urban transportation network and an intra-BSCS logistics system is responsible for battery exchanges among the stations. By abstracting the battery swapping, collection, transportation and recharging processes into product flows, a CLSC model can be applied to better describe the battery flows within each BSCS [122], where BCSs, BSSs and EVs can be considered as manufacturers, retailers, and customers, respectively.

As also mentioned in Section 4.1, when a larger geographical span with numerous BCSs and BSSs is considered, partitioning them into multiple smaller

Figure 4.1: Illustrative CLSCN model with two CLSCs based on the Singapore transportation network.

BSCSs is beneficial. To achieve potential collaborations and resource sharing among BSCSs, an interregional battery logistics system is introduced to for cross-regional battery exchanges among BSCSs. BSCSs together with the interregional battery logistics thus form an MBSCN. To better describe the combined intra-BSCS and interregional battery logistics, the single CLSC model is extended to a CLSCN model by interconnecting different CLSCs with interregional product flow [123].

The general framework of the proposed MBSCN model is illustrated in Fig. 4.2. The interregional battery logistics system interconnects all the BSCSs through

Figure 4.2: CLSCN-based MBSCN.

an interregional/intercity highway network. The MBSCN operator collects and aggregates the each station's battery inventory and demand information and allocates battery charging/discharging tasks to the BSCSs considering their local energy prices and charger availability, while each BSCS manage its intra-BSCS battery logistics accordingly to guarantee battery inventory at each station for high-quality service provision.

For simplicity, in this chapter, similar assumptions are made as those in Chapter 3:

- 1) All the batteries are owned by the MBSCN and have universal specifications;
- 2) Depleted and well-charged batteries have the same state of charge (SOC), i.e., $\underline{\text{SOC}}$ and $\overline{\text{SOC}}$, respectively;

- 3) The charging bay at BCS $\hat{m}$ in BSCS θ has $N_{CH,\hat{m}}^\theta$ bidirectional battery chargers and only the batteries loaded into charging bay can perform charging or discharging [72];
- 4) Proper battery management system is incorporated into each BCS operation such that no battery overcharging (over/under voltage) will occur;
- 5) In the day-ahead energy market, DNOs are price takers;
- 6) Fault conditions in transportation and distribution systems are not considered.

Note that assumptions 1) and 2) are made since that the MBSCN in this chapter is assumed to adopt a battery swapping and leasing mode [10], where the MBSCN owns and manages all the BCSs, BSSs and battery packs, while commercial EV users only own the vehicles and rent the battery packs from the MBSCN. Therefore, the MBSCN operator could choose to purchase the swappable batteries with universal specifications, which could also help to facilitate the operation and management of the system. Also, since this chapter mainly focuses on the modeling of battery inventory and logistics, for notation and model simplicity, batteries are assumed to have the same SOC. Still, it is noted that the proposed model can be further extended to consider different types of batteries or different SOC, which will be discussed in Remark 4.4.1.

4.3 Battery Logistics Model

To achieve more efficient management of battery logistics in time-space domains, a battery logistics model based on TSN techniques was proposed in [122]. However, the original single-layer TSN model, where all the subsystem network structures and the possible temporal-spatial dynamics of every truck fleets are presented in the same layer, would be inefficient when dealing with the existence of

multiple transportation network structures and different truck speeds. To handle this challenge, a multi-layer TSN based battery logistics model is presented in this section.

4.3.1 Transportation Network Model

With a slight abuse of notation for simplicity, $\mathcal{K} = \mathcal{N}_{\text{BSCS}} \cup \{\text{IL}\}$ is defined as a set that includes all the subsystems in the MBSCN, i.e., $k \in \mathcal{K}$ can either represent a BSCS or the interregional logistics system, and the associated family of sets $\{\Omega_k\}_{k \in \mathcal{K}}$ includes both Ω_{IL} and $\Omega_\theta, \forall \theta \in \mathcal{N}_{\text{BSCS}}$. The transportation network of k is modeled as a weighted graph $\mathcal{G}_{\text{TN}}^k = (\mathcal{V}_{\text{TN}}^k, \mathcal{E}_{\text{TN}}^k)$, where the vertex set $\mathcal{V}_{\text{TN}}^k$ models the intersections and crossroads while the edge set $\mathcal{E}_{\text{TN}}^k$ denotes the paths connecting each intersections. Let $\tilde{\mathcal{N}}^k$ denote the set of the possible originating/destination stations in k , i.e., if k is a BSCS, $\tilde{\mathcal{N}}^k = \mathcal{N}_{\text{BCS}}^k \cup \mathcal{N}_{\text{BSS}}^k$, otherwise $\tilde{\mathcal{N}}^k = \tilde{\mathcal{N}}^{\text{IL}} = \bigcup_{\theta \in \mathcal{N}_{\text{BSCS}}} \mathcal{N}_{\text{BCS}}^\theta$. Define a mapping $\mathcal{F}_{\text{TN}}^k : \tilde{\mathcal{N}}^k \rightarrow \mathcal{V}_{\text{TN}}^k$ maps each station to the corresponding geographical location in the transportation network.

4.3.2 Construction of a Multi-layer TSN Model

As illustrated in Fig. 4.3, the proposed multi-layer TSN model for the MBSCN consists of $|\mathcal{K}|$ stacks of layers, each stack has $|\Omega_k|$ layers and is associated with a subsystem k of the MBSCN, while each layer in stack k is associated with a truck fleet $\omega \in \Omega_k$ to model its possible temporal-spatial behavior.

For the construction of one layer ω in stack k , assume that when traveling between two stations $\hat{m}, \check{m} \in \tilde{\mathcal{N}}^k$, truck fleet $\omega \in \Omega_k$ will always choose the path with shortest distance in the transportation network between $\mathcal{F}_{\text{TN}}^k(\hat{m}), \mathcal{F}_{\text{TN}}^k(\check{m})$. Let

Figure 4.3: Multi-layer time space network model.

$l_{\hat{m}\tilde{m}}^k$ denote the length of this shortest path, which can be easily obtained by using many existing methods such as Dijkstra's algorithm [124], and each path is associated with a travel time $\tau_{\hat{m}\tilde{m},\omega}^k = \lceil l_{\hat{m}\tilde{m}}^k / v_{\omega}^k \Delta t \rceil, \forall \hat{m}, \tilde{m} \in \tilde{\mathcal{N}}^k$, indicating the number of time intervals required for truck fleet ω to travel between $\hat{m}$ and $\tilde{m}$, where $\lceil \cdot \rceil$ is the ceiling function.

To further illustrate the proposed multi-layer TSN model, consider a simple BSCS θ_1 with one BCS (denoted by $\hat{m}$), three BSSs (denoted by $\tilde{m}_1, \tilde{m}_2, \tilde{m}_3$). A truck fleet $\omega \in \Omega_{\theta_1}$ is traveling within $\mathcal{G}_{\text{TN}}^k$. Let $l_{\hat{m}\tilde{m}_2}^{\theta_1} = l_{\hat{m}_1\tilde{m}_3}^{\theta_1} = 80$ km,

while $l_{\hat{m}\check{m}_1}^{\theta_1}, l_{\hat{m}\check{m}_3}^{\theta_1}, l_{\check{m}_1\check{m}_2}^{\theta_1}, l_{\check{m}_2\check{m}_3}^{\theta_1}$ are all 40 km and $v_{\omega}^{\theta_1} = 40$ km/h. It is clear that $\tau_{\check{m}\check{m}_2, \omega}^k = \tau_{\check{m}_1\check{m}_3, \omega}^k = 2$, while all the other paths only take one interval.

The constructed layer ω in stack θ_1 that models the time-space dynamics of this truck fleet ω is shown in Fig. 4.3, which comprises as follows.

- 1) *Station time-space nodes* $\mathcal{N}_{S, \omega}^k = \{(m, \hat{t}) | m \in \tilde{\mathcal{N}}^k, \hat{t} \in \hat{\mathcal{T}}\}$: represent the stations at specific time points, indexed by $n, \hat{n}, \check{n}$, e.g., the 2-tuple $(\hat{m}, \hat{0})$ represent the BCS at time point $\hat{0}$.
- 2) *Transit arcs* $\mathcal{A}_{T, \omega}^k$: a transit arc shows a feasible origin-destination pair of $\mathcal{N}_{S, \omega}^k$, e.g., arc $((\check{m}_2, \hat{0}), (\hat{m}, \hat{2}))$ indicates that the truck leaves BSS $\check{m}_2$ at $\hat{0}$ and arrives at BCS $\hat{m}$ at $\hat{2}$.
- 3) *Parking arcs* $\mathcal{A}_{P, \omega}^k$: a parking arc connects two time-space nodes of the same station in a single time interval, which indicates that the truck fleet stays at the same station in a certain time interval, e.g., $((\check{m}_3, \hat{0}), (\check{m}_3, \hat{1}))$ claims that the truck stays at BSS $\check{m}_3$ during time interval 1.

Following the same procedures, all the other layers in the multi-layer TSN model can be formed, which enables the efficient management of the truck fleets in the MBSCN where different average truck speeds and different transportation network structures can exist. For example, when another BSCS θ_2 with one BCS, two BSSs and a truck $\varpi \in \Omega_{\theta_2}$ with $v_{\varpi}^{\theta_2} = 20$ km/h is considered, the structure of ϖ -th layer in stack θ_2 would be completely different from layer ω in stack θ_1 , as depicted in Fig. 4.3.

Remark 4.3.1. When the single-layer TSN technique is used to model the possible temporal-spatial behaviors of the aforementioned truck fleet ω in BSCS θ_1 and ϖ in θ_2 , the total number of arcs and the associated arc-wise binary variables is 1180, since both the transportation network structure of θ_1 and θ_2 need be presented in a single TSN layer. Meanwhile, when the multi-layer TSN model

is used, the total number of arcs/binary variables is only 590, reduced by 50%. Note that this difference in modeling efficiency would be much larger when more subsystems and truck fleets are considered, which also shows the efficiency of the proposed multi-layer TSN model.

4.3.3 Multi-layer TSN-based Battery Logistics Model

With the proposed multi-layer TSN model, the vehicle routing results and the associated temporal-spatial dynamics of the truck fleets in different subsystems of the MBSCN can be depicted by a sequence of arcs in each layer and arc-wise binary variables $\zeta_{\hat{n}\tilde{n}}^\omega$.

To facilitate the description of the truck behavior using arcs and time-space nodes, as also depicted in Fig. 4.3, a cut in each time interval t is introduced, which divides $\mathcal{N}_{S,\omega}^k$ into two disjoint subsets $(\mathcal{N}_{L,\omega}^{t,k}, \mathcal{N}_{R,\omega}^{t,k})$, where $\mathcal{N}_{L,\omega}^{t,k}$ represents the set of all time-space nodes on the left-hand side of the cut while $\mathcal{N}_{R,\omega}^{t,k}$ denotes those nodes on the right-hand side. The corresponding cut-set denoted by $\Phi_\omega^{t,k} = \{(\hat{n}, \tilde{n}) \in \mathcal{A}_{T,\omega}^k \cup \mathcal{A}_{P,\omega}^k | \hat{n} \in \mathcal{N}_{L,\omega}^{t,k}, \tilde{n} \in \mathcal{N}_{R,\omega}^{t,k}\}$, is defined as the set of all the arcs that cross the time interval t .

Based on the multi-layer TSN model, the truck fleet scheduling model can be formulated as follows:

$$\sum_{(\hat{n}, \tilde{n}) \in \Phi_\omega^{t,k}} \zeta_{\hat{n}\tilde{n}}^\omega = 1, \forall k \in \mathcal{K}, \omega \in \Omega_k, t \quad (4.1)$$

$$\sum_{(\hat{n}, \tilde{n}) \in \mathcal{A}_{n,\omega}^k} \zeta_{\hat{n}\tilde{n}}^\omega = \sum_{(\hat{n}, \tilde{n}) \in \mathcal{A}_{n,\omega}^k} \zeta_{\hat{n}\tilde{n}}^\omega, \forall k \in \mathcal{K}, \omega \in \Omega_k, n \in \mathcal{N}_{S,\omega}^k \quad (4.2)$$

$$\sum_{(\hat{n}, \tilde{n}) \in \mathcal{A}_{n,\omega}^k} \zeta_{\hat{n}\tilde{n}}^\omega = \zeta_{\text{init}}^\omega, \forall k \in \mathcal{K}, \omega \in \Omega_k, n \in \mathcal{N}_{S,\omega}^k \quad (4.3)$$

Equation (4.1) constrains that truck ω can only stay on one of the arcs in each time

interval t , where $\zeta_{\hat{n}\check{n}}^\omega \in \{0, 1\}, \forall (\hat{n}, \check{n}) \in \mathcal{A}_{T,\omega}^k \cup \mathcal{A}_{P,\omega}^k, k \in \mathcal{K}, \omega \in \Omega_k$. Equations (4.2)-(4.3) serve as the flow conservation constraints, i.e., for each truck ω , if it ends the trip at time-space node n , it will stay on one of the arcs that start from node n for the subsequent trip, while $\zeta_{\text{init}}^\omega$ indicate the initial position of truck ω . $\hat{\mathcal{A}}_{n,\omega}^k$ and $\check{\mathcal{A}}_{n,\omega}^k$ are the sets of arcs start from and end at time-space node n .

According to the vehicle scheduling model in (4.1)-(4.3), the numbers of batteries loaded on each truck fleet in the MBSCN are constrained as follows:

$$S_{D,\omega}^{t,\theta} = - \sum_{h=1}^t \sum_{\hat{m} \in \mathcal{N}_{\text{BCS}}^\theta} N_{D,\text{BCS},\omega,\hat{m}}^{h,\theta} + \sum_{h=1}^t \sum_{\check{m} \in \mathcal{N}_{\text{BSS}}^\theta} N_{D,\text{BSS},\omega,\check{m}}^{h,\theta} \quad \forall \omega \in \Omega_\theta, \theta, t \quad (4.4)$$

$$S_{W,\omega}^{t,\theta} = - \sum_{h=1}^t \sum_{\hat{m} \in \mathcal{N}_{\text{BCS}}^\theta} N_{W,\text{BCS},\omega,\hat{m}}^{h,\theta} + \sum_{h=1}^t \sum_{\check{m} \in \mathcal{N}_{\text{BSS}}^\theta} N_{W,\text{BSS},\omega,\check{m}}^{h,\theta} \quad \forall \omega \in \Omega_\theta, \theta, t \quad (4.5)$$

$$S_{D,\omega}^{t,\text{IL}} = \sum_{h=1}^t \sum_{m \in \tilde{\mathcal{N}}^{\text{IL}}} N_{D,\omega,m}^{h,\text{IL}}, \quad \forall \omega \in \Omega_{\text{IL}}, t \quad (4.6)$$

$$S_{W,\omega}^{t,\text{IL}} = \sum_{h=1}^t \sum_{m \in \tilde{\mathcal{N}}^{\text{IL}}} N_{W,\omega,m}^{h,\text{IL}}, \quad \forall \omega \in \Omega_{\text{IL}}, t \quad (4.7)$$

$$S_{D,\omega}^{t,k} + S_{W,\omega}^{t,k} \leq C_{B,\omega}, \quad \forall k \in \mathcal{K}, \omega \in \Omega_k, t \quad (4.8)$$

$$S_{W,\omega}^{t,k} \geq 0, S_{D,\omega}^{t,k} \geq 0, \quad \forall k \in \mathcal{K}, \omega \in \Omega_k, t \quad (4.9)$$

$$S_{W,\omega}^{T,k} = 0, S_{D,\omega}^{T,k} = 0, \quad \forall k \in \mathcal{K}, \omega \in \Omega_k, t \quad (4.10)$$

Equations (4.4)-(4.7) describe the depleted and well-charged battery loading status of truck fleet ω at the end of time interval t (time point $\hat{t}$) in both intra-BSCS and interregional battery logistics system. Constraint (4.8) ensures that the batteries loaded on each truck fleet should be within its capacity. Constraint (4.9) is the non-negativity constraint while constraint (4.10) claims that every

truck fleet should be unloaded at the end of the scheduling horizon.

Similarly, the battery exchange model for each truck can be expressed as follow:

$$\begin{aligned} 0 \leq N_{\text{D,BSS},\omega,\tilde{m}}^{t,\theta} &\leq \zeta_{\hat{n}\tilde{n}}^\omega C_{\text{B},\omega}, \forall (\hat{n}, \tilde{n}) \in \mathcal{A}_{\text{P},\omega,\tilde{m}}^{\theta,t}, \\ \tilde{m} &\in \mathcal{N}_{\text{BSS}}^\theta, \omega \in \Omega_\theta, \theta, t \end{aligned} \quad (4.11)$$

$$\begin{aligned} 0 \leq N_{\text{W,BSS},\omega,\tilde{m}}^{t,\theta} &\leq \zeta_{\hat{n}\tilde{n}}^\omega S_{\text{W},\omega}^{t-1,\theta}, \forall (\hat{n}, \tilde{n}) \in \mathcal{A}_{\text{P},\omega,\tilde{m}}^{\theta,t}, \\ \tilde{m} &\in \mathcal{N}_{\text{BSS}}^\theta, \omega \in \Omega_\theta, \theta, t \end{aligned} \quad (4.12)$$

$$\begin{aligned} 0 \leq N_{\text{D,BCS},\omega,\hat{m}}^{t,\theta} &\leq \zeta_{\hat{n}\tilde{n}}^\omega S_{\text{D},\omega}^{t-1,\theta}, \forall (\hat{n}, \tilde{n}) \in \mathcal{A}_{\text{P},\omega,\hat{m}}^{\theta,t}, \\ \hat{m} &\in \mathcal{N}_{\text{BCS}}^\theta, \omega \in \Omega_\theta, \theta, t \end{aligned} \quad (4.13)$$

$$\begin{aligned} 0 \leq N_{\text{W,BCS},\omega,\hat{m}}^{t,\theta} &\leq \zeta_{\hat{n}\tilde{n}}^\omega C_{\text{B},\omega}, \forall (\hat{n}, \tilde{n}) \in \mathcal{A}_{\text{P},\omega,\hat{m}}^{\theta,t}, \\ \hat{m} &\in \mathcal{N}_{\text{BCS}}^\theta, \omega \in \Omega_\theta, \theta, t \end{aligned} \quad (4.14)$$

$$\begin{aligned} -\zeta_{\hat{n}\tilde{n}}^\omega C_{\text{B},\omega} &\leq N_{\text{D},\omega,m}^{t,\text{IL}} \leq \zeta_{\hat{n}\tilde{n}}^\omega S_{\text{D},\omega}^{t-1,\text{IL}}, \forall (\hat{n}, \tilde{n}) \in \mathcal{A}_{\text{P},\omega,m}^{\text{IL},t}, \\ m &\in \tilde{\mathcal{N}}^{\text{IL}}, \omega \in \Omega_{\text{IL}}, t \end{aligned} \quad (4.15)$$

$$\begin{aligned} -\zeta_{\hat{n}\tilde{n}}^\omega C_{\text{B},\omega} &\leq N_{\text{W},\omega,m}^{t,\text{IL}} \leq \zeta_{\hat{n}\tilde{n}}^\omega S_{\text{W},\omega}^{t-1,\text{IL}}, \forall (\hat{n}, \tilde{n}) \in \mathcal{A}_{\text{P},\omega,m}^{\text{IL},t}, \\ m &\in \tilde{\mathcal{N}}^{\text{IL}}, \omega \in \Omega_{\text{IL}}, \hat{t}, t \end{aligned} \quad (4.16)$$

where $\mathcal{A}_{\text{P},\omega,m}^{k,t}$ denotes the set of parking arcs of station m in time interval t on layer ω .

Constraints (4.11)-(4.14) determine the feasible regions of the depleted/well-charged battery exchanges among truck fleets, BSSs and BCSs in each intra-BSCS battery logistics system, considering each truck fleet's loading status and temporal-spatial dynamics. Similarly, (4.15) and (4.16) are the battery exchange constraints between the trucks in the interregional logistics system and BCSs during time interval t . Note that all these constraints also indicate that the loading and unloading of batteries at a certain station can only be performed when a truck is on a parking arc, i.e., when $\zeta_{\hat{n}\tilde{n}}^\omega = 1, \forall (\hat{n}, \tilde{n}) \in \mathcal{A}_{\text{P},\omega,m}^{k,t}, m \in \tilde{\mathcal{N}}^k$.

Note that all the variables in (4.4)-(4.16) are integer variables, i.e., $S_{D,\omega}^{t,k}, S_{W,\omega}^{t,k}, N_{D,BCS,\omega,\hat{m}}^{t,\theta}, N_{W,BCS,\omega,\hat{m}}^{t,\theta}, N_{D,BSS,\omega,\hat{m}}^{t,\theta}, N_{W,BSS,\omega,\hat{m}}^{t,\theta}, N_{D,\omega,m}^{t,IL}, N_{W,\omega,m}^{t,IL} \in \mathbb{Z}$. The upper bounds for these variables are the payload capacities of the corresponding truck fleets $C_{B,\omega}$. The lower bounds for $N_{D,\omega,m}^{t,IL}$ and $N_{W,\omega,m}^{t,IL}$ are $-C_{B,\omega}$ considering that the truck fleets in the interregional battery logistics system can perform both loading and unloading of well-charged batteries and depleted batteries at each BCS, while the lower bounds for other variables are 0.

Remark 4.3.2. The intra-BSCS logistics only distribute well-charged batteries from BCSs to BSSs and transport depleted batteries collected at BSSs back to BCSs for recharging. On the other hand, the interregional battery logistics allows both well-charged batteries and depleted batteries to be transported between BCSs in different BSCSs.

4.4 Optimal Operation Management of MBSCN

By introducing interregional battery logistics into MBSCN operations, the operational flexibility and efficiency of each BSCS, as well as the local DN, can be improved through their collaborative operation. In this section, the operation models for DNOs, logistics systems, BCSs and BSSs are provided.

4.4.1 Distribution System Model

The corresponding DN of BSCS θ is modeled as a graph $\mathcal{G}_D^\theta = (\mathcal{V}_D^\theta, \mathcal{E}_D^\theta)$ and let mapping $\mathcal{F}_D^\theta : \tilde{\mathcal{N}}^\theta \rightarrow \mathcal{V}_D^\theta$ indicate the bus that each station is connected to. In each DN, it is assumed that each bus serves one traditional load with fixed demand and some of the buses are connected to distributed generators (DGs).

For each DNO, the AC optimal power flow problem is formulated as follows to

minimize the cost C_{DNO}^θ :

$$\min C_{\text{DNO}}^\theta = \sum_{t \in \mathcal{T}} \left\{ \sum_{i \in \mathcal{V}_D^\theta} \left[a_i^\theta \left(P_{G,i}^{t,\theta} \right)^2 + b_i^\theta P_{G,i}^{t,\theta} \right] + \lambda_{\text{DA}}^{t,\theta} P_0^{t,\theta} \right\} \quad (4.17)$$

where a_i^θ, b_i^θ are the generation cost coefficients for DGs at bus i and $P_0^{t,\theta}$ is the power injection at the substation bus. The first term in (4.17) calculates the generation cost for DGs in the DN and the second term is the cost for purchasing electricity from the main grid.

The active power balance constraints for each bus i considering power injections from BCSs are formulated as follows:

$$\begin{aligned} P_{G,i}^{t,\theta} - \sum_{\forall \hat{m}, \mathcal{F}_D^\theta(\hat{m})=i} \left(P_{C,\hat{m}}^{t,\theta} - P_{\text{DC},\hat{m}}^{t,\theta} \right) - P_{L,i}^{t,\theta} \\ = \sum_{(i,j) \in \mathcal{E}_D^\theta} P_{ij}^{t,\theta} - \sum_{(u,i) \in \mathcal{E}_D^\theta} \left(P_{ui}^{t,\theta} - r_{ui}^\theta I_{ui}^{t,\theta} \right), \forall i, t, \end{aligned} \quad (4.18)$$

$$Q_{G,i}^{t,\theta} - Q_{L,i}^{t,\theta} = \sum_{(i,j) \in \mathcal{E}_D^\theta} Q_{ij}^{t,\theta} - \sum_{(u,i) \in \mathcal{E}_D^\theta} \left(Q_{ui}^{t,\theta} - x_{ui}^\theta I_{ui}^{t,\theta} \right), \forall i, t, \quad (4.19)$$

where $P_{G,i}^{t,\theta}, Q_{G,i}^{t,\theta}, P_{ij}^{t,\theta}, Q_{ij}^{t,\theta}, I_{ij}^{t,\theta}, P_{C,\hat{m}}^{t,\theta}, P_{\text{DC},\hat{m}}^{t,\theta} \in \mathbb{R}$ and their upper, lower bounds are referred to [125] and [122], respectively. Other constraints including apparent power equation, the network operation constraints for generation capacity, voltage limitation and line transmission capacity are referred to the DistFlow model with conic relaxation [125].

4.4.2 Operation Model for MBSCN

Based on the distribution network model and the MBSCN framework proposed in Section 4.2, the operation management model for MBSCN can be formulated

as a MIQCQP for cost minimization given as follows.

$$\min \sum_{k \in \mathcal{K}} C_{\text{LS}}^k + \sum_{\theta \in \mathcal{N}_{\text{BSCS}}} \left(\sum_{\hat{m} \in \mathcal{N}_{\text{BCS}}^\theta} C_{\text{BCS}, \hat{m}}^\theta + \sum_{\tilde{m} \in \mathcal{N}_{\text{BSS}}^\theta} C_{\text{BSS}, \tilde{m}}^\theta + C_{\text{DNO}}^\theta \right) \quad (4.20)$$

where $C_{\text{BCS}, \hat{m}}^\theta$ and $C_{\text{BSS}, \tilde{m}}^\theta$ are the cost of BCS $\hat{m}$ and BSS $\tilde{m}$ in BSCS θ , while C_{LS}^k is the cost of the logistics system in k . The detailed formulations are given as follows:

$$\begin{aligned} C_{\text{BCS}, \hat{m}}^\theta = \sum_{t \in \mathcal{T}} & \left[\lambda_{\text{DA}}^{t, \theta} \left(P_{\text{C}, \hat{m}}^{t, \theta} - P_{\text{DC}, \hat{m}}^{t, \theta} \right) \Delta t - \lambda_{\text{S}}^{t, \theta} R_{\text{S}, \hat{m}}^t \Delta t \right. \\ & - \left(\lambda_{\text{rd}}^{t, \theta} r_{\text{d}, \hat{m}}^{t, \theta} + \lambda_{\text{ru}}^{t, \theta} r_{\text{u}, \hat{m}}^{t, \theta} \right) \Delta t + C_{\text{BP}} N_{\text{BP}, \hat{m}}^{t, \theta} \\ & \left. + C_{\text{d}} \left(P_{\text{DC}, \hat{m}}^{t, \theta} + P_{\text{C}, \hat{m}}^{t, \theta} \right) \Delta t \right] \end{aligned} \quad (4.21)$$

$$C_{\text{BSS}, \tilde{m}}^\theta = \sum_{t \in \mathcal{T}} C_{\text{delay}} \left(\bar{A}_{\tilde{m}}^{t, \theta} - D_{\tilde{m}}^{t, \theta} \right) \quad (4.22)$$

$$C_{\text{LS}}^k = C_{\text{tran}}^k \sum_{\omega \in \Omega_k} \sum_{(\hat{n}, \tilde{n}) \in \mathcal{A}_{\text{T}, \omega}^k} \zeta_{\hat{n} \tilde{n}}^\omega \Delta t \quad (4.23)$$

where $\bar{A}_{\tilde{m}}^{t, \theta} = \frac{1}{\mathfrak{S}} \sum_{s=1}^{\mathfrak{S}} \tilde{A}_{\tilde{m}, s}^{t, \theta}$ is the calculated mean value given $\mathfrak{S}$ historical EV arrival data.

The first term of (4.21) calculates the battery charging cost in time interval t , while the second and third terms are the payoff for spinning and regulation reserve services provided to the DN. The fourth term stands for the cost of backup depleted batteries. The last term is the cost due to repeatedly charging and discharging the battery, where C_{d} is the simplified economic cost coefficient that accounts for the battery degradation cost [101]. For BSSs, a penalty is induced for every delayed battery pack swapping in each time interval, as shown in (4.22). Equation (4.23) calculates the total transportation cost for the logistics system in k .

Problem (4.20) is subjected to the following constraints:

4.4.2.1 BCS inventory constraints

$$S_{\text{bay},\hat{m}}^{t,\theta} = \sum_{h=1}^t N_{\text{bay},\hat{m}}^{h,\theta} - \sum_{h=1}^{t-1} N_{\text{Wout},\hat{m}}^{h,\theta}, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}^\theta, \theta, t \quad (4.24)$$

$$S_{\text{D,BCS},\hat{m}}^{t,\theta} = \sum_{h=1}^t \left(N_{\text{BP},\hat{m}}^{h,\theta} + \sum_{\omega \in \Omega_\theta} N_{\text{D,BCS},\omega,\hat{m}}^{h,\theta} - N_{\text{bay},\hat{m}}^{h,\theta} + \sum_{\omega \in \Omega_{\text{IL}}} N_{\text{D},\omega,\hat{m}}^{h,\text{IL}} \right), \forall \hat{m} \in \mathcal{N}_{\text{BCS}}^\theta, \theta, t \quad (4.25)$$

$$S_{\text{W,BCS},\hat{m}}^{t,\theta} = \sum_{h=1}^t \left(N_{\text{Wout},\hat{m}}^{h,\theta} - \sum_{\omega \in \Omega_\theta} N_{\text{W,BCS},\omega,\hat{m}}^{h,\theta} + \sum_{\omega \in \Omega_{\text{IL}}} N_{\text{W},\omega,\hat{m}}^{h,\text{IL}} \right), \forall \hat{m} \in \mathcal{N}_{\text{BCS}}^\theta, \theta, t \quad (4.26)$$

$$\sum_{t=1}^T \sum_{\omega \in \Omega_{\text{IL}}} \left(N_{\text{W},\omega,\hat{m}}^{t,\text{IL}} + N_{\text{D},\omega,\hat{m}}^{t,\text{IL}} \right) = 0, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}^\theta, \theta \quad (4.27)$$

$$\sum_{h=1}^t N_{\text{Wout},\hat{m}}^{h,\theta} \leq \sum_{h=1}^{t-(T_c-1)} N_{\text{bay},\hat{m}}^{h,\theta}, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}^\theta, \theta, t \quad (4.28)$$

$$S_{\text{W,BCS},\hat{m}}^{t,\theta} \geq 0, S_{\text{D,BCS},\hat{m}}^{t,\theta} \geq 0, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}^\theta, \theta, t \quad (4.29)$$

$$0 \leq S_{\text{bay},\hat{m}}^{t,\theta} \leq N_{\text{CH},\hat{m}}^\theta, \forall \hat{m} \in \mathcal{N}_{\text{BCS}}^\theta, \theta, t \quad (4.30)$$

where all the variables in (4.24)-(4.30) are integer variables. The upper bounds of $S_{\text{bay},\hat{m}}^{t,\theta}$, $N_{\text{bay},\hat{m}}^{t,\theta}$ and $N_{\text{Wout},\hat{m}}^{t,\theta}$ are $N_{\text{CH},\hat{m}}^\theta$ and their lower bounds are 0.

Equation (4.24) determines charging bay loading status in time interval t . Equations (4.25) and (4.26) calculate the inventory of depleted/well-charged battery of BCS $\hat{m}$ at time point $\hat{t}$, considering battery exchanges with the interregional logistics system. Constraint (4.27) indicates that the net battery exchange between the BSCSs should be zero at the end of each scheduling horizon. As constrained by (4.28), the batteries should be kept in the charging bay for more than $T_c = \lceil E_B/(\eta_C \bar{P}_C \Delta t) \rceil$ time intervals to be fully charged, where E_B is the battery

energy demand, η_C and $\bar{P}_C$ are the charging efficiency and maximum charging power allowed for each battery charger. Constraint (4.29) is the non-negativity constraint and constraint (4.30) limits the maximum number of batteries in each charging bay.

4.4.2.2 Distributionally robust chance-constrained BSS service constraints

To address EV behavior and battery demand uncertainties, the actual arrival and minimum departure curves of batteries, which depicts EV user battery service requirements, are introduced and denoted by random variables $\tilde{A}_{\tilde{m}}^{t,\theta}$ and $\tilde{D}_{\min,\tilde{m}}^{t,\theta}$, respectively. More detailed definitions of these curves are referred to Chapter 3. Then the linear inequality that ensures the BSS service provision is

$$\tilde{D}_{\min,\tilde{m}}^{t,\theta} \leq D_{\tilde{m}}^{t,\theta} \leq \tilde{A}_{\tilde{m}}^{t,\theta}, \forall \tilde{m} \in \mathcal{N}_{\text{BSS}}^\theta, \theta, t \quad (4.31)$$

where $\tilde{D}_{\min,\tilde{m}}^{t,\theta} \leq D_{\tilde{m}}^{t,\theta}$ guarantees the battery swapping service quality considering the EV user preferences.

For notation simplicity, (4.31) is rewritten into a more general matrix form $W(\boldsymbol{\xi})\mathbf{x} \geq y(\boldsymbol{\xi})$, where $W(\boldsymbol{\xi})$ and $y(\boldsymbol{\xi})$ are the matrix and vector containing the coefficients in the inequality (4.31). $\boldsymbol{\xi}$ is incorporated to indicate that the coefficients are affected by the uncertainties. Note that in this chapter, all the vectors are column vectors if not specified.

To address EV uncertainties while ensuring a proper degree of conservatism, chance constraints are usually introduced [126], which require certain assumptions on probability distributions. However, probability information is not always perfectly known due to insufficient historical data. To deal with this issue, a distributionally robust chance-constrained BSS service model is formulated as

follows, where no assumptions on probability distributions are needed.

$$\inf_{f(\boldsymbol{\xi}) \in \Xi} \mathbb{P}(W_\gamma(\boldsymbol{\xi})\mathbf{x} \geq y_\gamma(\boldsymbol{\xi})) \geq 1 - \epsilon_\gamma, \forall \gamma = 1, \dots, \Gamma \quad (4.32)$$

where W_γ, y_γ represent the γ th row of matrix W and γ th entry of vector y . All Γ chance constraints in (4.32) should be satisfied with a probability of $1 - \epsilon_\gamma$. Ξ is the ambiguity set describing possible probability mass functions of $\boldsymbol{\xi}$, i.e., $f(\boldsymbol{\xi})$ obtained from the available data, given by:

$$\Xi = \left\{ f(\boldsymbol{\xi}) : \begin{aligned} &\sum f(\boldsymbol{\xi}) = 1 \\ &\mathbb{E}[\boldsymbol{\xi}] - \mu_0 = 0 \\ &\mathbb{E}[(\boldsymbol{\xi} - \mu_0)(\boldsymbol{\xi} - \mu_0)^\top] = \Theta_0 \end{aligned} \right\}$$

where $\mu_0 = \frac{1}{\mathfrak{S}} \sum_{s=1}^{\mathfrak{S}} \boldsymbol{\xi}_s$ and $\Theta_0 = \frac{1}{\mathfrak{S}} \sum_{s=1}^{\mathfrak{S}} (\boldsymbol{\xi}_s - \mu_0)(\boldsymbol{\xi}_s - \mu_0)^\top$ are the calculated mean and covariance matrix, respectively, given $\mathfrak{S}$ data samples.

Without loss of generality, W_γ and y_γ can be defined as affine functions of $\boldsymbol{\xi}$ [127], i.e.,

$$W_\gamma = W_{\gamma 0} + \sum_{j=1}^J W_{\gamma j} \boldsymbol{\xi}^j, y_\gamma = y_{\gamma 0} + \sum_{j=1}^J y_{\gamma j} \boldsymbol{\xi}^j$$

where $\boldsymbol{\xi}^j$ denotes the j th entry of vector $\boldsymbol{\xi}$ and J is its dimension. $W_{\gamma 0}, y_{\gamma 0}$ are the deterministic parts and $W_{\gamma j}, y_{\gamma j}$ are the affine coefficients of $\boldsymbol{\xi}^j$. Then (4.32) can be reformulated as follows:

$$\sup_{f(\boldsymbol{\xi}) \in \Xi} \mathbb{P}((W_\gamma^x)^\top \boldsymbol{\xi} \leq y_\gamma^x) \leq \epsilon_\gamma, \forall \gamma = 1, \dots, \Gamma \quad (4.33)$$

where $W_\gamma^x = \langle y_{\gamma 1} - W_{\gamma 1}\mathbf{x}, \dots, y_{\gamma J} - W_{\gamma J}\mathbf{x} \rangle$, $y_\gamma^x = y_{\gamma 0} - y_{\gamma 0}$ and $\langle \cdot \rangle$ denotes the stacked column vector. Specifically, in this chapter $W_{\gamma 1}\mathbf{x} = W_{\gamma 2}\mathbf{x} = \dots = W_{\gamma J}\mathbf{x} = 0$, since the coefficient of $D_m^{t,\theta}$ is not related to $\boldsymbol{\xi}$, according to (4.31). Therefore W_γ^x can be further simplified as $\langle y_{\gamma 1}, \dots, y_{\gamma J} \rangle$.

Following a variant of the Chebyshev inequality, the distributionally robust chance constraints (4.32) are equivalent to

$$\sqrt{(W_\gamma^x)^\top \Theta_0 (W_\gamma^x)} \leq \sqrt{\frac{\epsilon_\gamma}{1 - \epsilon_\gamma}} (y_\gamma^x - (\mu_0)^\top W_\gamma^x), \forall \gamma = 1, \dots, \Gamma \quad (4.34)$$

The derivation is referred to [127]. With constraint (4.34), the MBSCN model can be solved efficiently with guaranteed battery swapping service quality and less required historical data .

4.4.2.3 Other operational constraints

1) *Other BSCS operation constraints*: the energy constraints (3.29)-(3.32), power constraints (3.33)-(3.38) for BCSs and the inventory constraints (3.21)-(3.27) for BSSs are referred to Chapter 3 with the same notations and omitted in this chapter due to space limitation.

2) *Battery logistics constraints*: See (4.1)-(4.16);

3) *Distribution system operation constraints*: (4.18), (4.19) and other constraints referred to [125].

Remark 4.4.1. The feasibility of the operation model for MBSCN is mainly related to several factors. One is the productivity of well-charged battery, including the number of chargers in each BCS $N_{CH, \hat{m}}^\theta$ and its allowed maximum charging rate $\bar{P}_C$. Another one is the capability of battery transportation, i.e., the number of truck fleets in each subsystem $|\Omega_k|$ and the truck maximum payload capacity $C_{B, \omega}$. With insufficient battery productivity, BCSs are unable to complete battery charging in time to fulfil the well-charged battery demands from EVs, while the lack of transportation capability can also cause battery inventory insufficiency at BSSs. Also, it is noted that the MBSCN model can be further extended to consider different types of batteries or batteries with different SOC by introduc-

ing additional variables. For example, $S_{\text{W,BCS},\hat{m}}^{t,\theta,\alpha}$ and $N_{\text{W,BCS},\omega,\hat{m}}^{t,\theta,\alpha}$ can be defined for managing the inventory and logistics of type α well-charged batteries while $\text{SOC}^{\alpha,\text{high}}$, $E_{\text{B}}^{\alpha,\text{high}}$ can be defined to describe the SOC and the energy demand of type α depleted batteries with relatively high remaining SOC, etc.

4.5 Case Studies

In this section, case studies are conducted to validate the proposed MBSCN model with interregional battery logistics. A scheduling horizon with $T = 24$ time intervals is considered for both cases and the length of each interval is $\Delta t = 1$ h. The simulations are implemented using Python 3.6 and solved using an off-the-shelf solver Cplex 12.8.0 [128].

4.5.1 Test Systems

For the simulations, an MBSCN test system with three BSCSs $\mathcal{N}_{\text{BSCS}} = \{\theta_1, \theta_2, \theta_3\}$ in different regions, three corresponding 33-bus distribution systems, and an interregional battery logistics system with $|\Omega_{\text{IL}}| = 3$ truck fleets, i.e., fleet #1, #2 and #3, is considered. Initially, the three truck fleets park at the BCS of θ_1, θ_2 and θ_3 , respectively. All the BSCSs are interconnected with a interregional highway network with higher speed limits and $l_{\theta_1\theta_2}^{\text{IL}} = l_{\theta_1\theta_3}^{\text{IL}} = l_{\theta_2\theta_3}^{\text{IL}} = 120\text{km}$.

For the BSCSs, a test system based on the Sioux Falls transportation network with tripled edge lengths [129] is considered, as shown in Fig. 4.4. Each BSCS has one BCS, three BSSs and an intra-BSCS logistics system with $|\Omega_{\theta}| = 4$ truck fleets, where BSS1 and BSS3 mainly serve electric taxis and BSS2 is for electric buses. Fig. 4.5 shows the corresponding 33-bus distribution system. The BCS, located at node #5 in the transportation network, is connected to bus #2 in the distribution

Figure 4.4: BSCS within the Sioux Falls transportation network.

Figure 4.5: A modified 33-bus distribution test system.

system. A total number of 2400, 1600, 1200 electric taxis and 100, 80, 80 electric buses with four battery packs travel within the three BSCSs, respectively. Monte Carlo simulation is performed to generate $\mathfrak{S} = 1000$ samples of hourly battery arrival and departure each BSCS following a normal distribution, where the mean value is the typical battery demand data obtained from [114], [122] with modified parameters and the standard deviation is 5% of the hourly arrival and departure. Only a part of the samples, e.g., 5 samples or 20 samples, is randomly selected to construct Ξ to simulate the situation when only limited historical data are available. Fig. 4.6 provides some of the obtained typical arrival and minimum departure curves and the uncertain intervals (prediction error) based on the generated data samples. More detailed definitions of these curves are referred to Chapter 3. The hourly nodal energy and reserve prices for θ_1, θ_2

Figure 4.6: Typical battery demand data for BSS1 in each BSCS.

and θ_3 on are obtained from NYISO [130] based on the zonal data of N.Y.C, HUD VL and North Zone on Jul-17 2018, respectively, and $a_i^\theta = \$0.025/\text{kWh}^2$, $b_i^\theta = \$0.5/\text{kWh}$. Other simulation parameters are provided in Table 4.1, which mainly follows Chapter 3.

Two cases are considered as follows, to study the effectiveness of the proposed MBSCN model with interregional battery logistics. Note that both cases follow the assumptions made in Section 4.2.

Case 1): There are no interregional battery exchanges and all the BSCSs work independently for service provision (adopted by many demonstration projects

Table 4.1: Simulation Parameters

Subsystem #	θ_1	θ_2	θ_3	IR
$ \Omega_k $	4			3
$N_{\text{CH},\tilde{m}}^\theta$	200	200	300	-
$E_{\text{B}}(\text{kWh})$	40			-
$\overline{P}_{\text{C}}, \overline{P}_{\text{DC}}(\text{kW})$	42/42			-
$\eta_{\text{c}}, \eta_{\text{dc}}$	0.95/0.9			-
$C_{\text{delay}}(\$/\text{pack})$	2			-
$C_{\text{d}}(\$/\text{kWh})$	0.02			-
$C_{\text{BP}}(\$/\text{pack})$	5			-
$C_{\text{tran}}^k(\$/\text{h})$	20			40
$v_{\omega}^k(\text{km/h})$	40			80
$C_{\text{B},\omega}^k(\text{pack})$	300			

[71], [131]);

Case 2): Three BSCSs form a MBSCN via the interregional battery logistics and work collaboratively.

4.5.2 Simulation Results

Fig 4.7 shows the cost and reliability results of the BSCSs in Case 1 and the MBSCN model in Case 2, when given different numbers of available historical data samples under different reliability requirements. Note that the reliability in each case is calculated as the percentage of constraint (4.31) violations in all the BSS service constraints in the generated 1000 samples. It can be seen that the reliability results achieved using the distributionally robust chance-constrained BSS service model are considerably high in both cases, i.e., most of the EV bat-

Figure 4.7: Cost and Reliability Results of Case 1 and Case 2.

tery swapping demands can be well-fulfilled. Also, in both cases, the reliability is always higher when more data samples are available, while the operational costs also become higher with more data samples under the same $1 - \epsilon$. This is because, with fewer data samples, the estimation error of battery demands is larger, which results in unwanted relaxations in constraint (4.31) as well as less reliability. Meanwhile, with the same number of data samples, it can be seen that in each case, larger $1 - \epsilon$ yields more reliable results, which increases the operational cost in return. Note that under all the settings, the MBSCN model in Case 2 results in the lowest cost. For example, given 20 samples and $1 - \epsilon = 95\%$, the total cost in Case 1 is \$ 11964.98, while the cost of the MBSCN in Case 2 is \$10184.56, reduced by 14.9%.

Fig. 4.8 shows the vehicle-battery scheduling results for the interregional bat-

Figure 4.8: Interregional battery logistics scheduling results in Case 2 given

$$\mathfrak{S} = 20 \text{ and } 1 - \epsilon = 95\%.$$

tery logistics system in Case 2 and the temporal-spatial dynamics of the truck fleets, where the sequence of movements and associated loading/unloading behaviors are optimized considering the transportation costs, local energy prices and battery availability. The bars and the left Y-axis show the number of well-charged/depleted batteries that are currently carried by each truck fleet in each hour, while the lines with circle markers and the right Y-axis indicate the movements of each truck fleet, i.e., the circle markers represent the truck fleet locations at the corresponding time points. For instance, truck fleet #3 initially parks at the BCS in BSCS θ_3 during (0:00-1:00), at the same time 300 well-charged batteries produced are loaded onto the fleet. Then it takes two intervals for the fleet to travel to θ_1 , where all the well-charged batteries are unloaded during (3:00-4:00) to supply θ_1 's battery demand and instead, 124 depleted batteries are loaded onto

the truck. Next, it starts another trip at 4:00 for battery transportation and reaches the BCS in θ_3 at 6:00. It parks at θ_3 during (6:00-10:00), where it first unloads all the 124 depleted batteries to θ_3 in (7:00-8:00) to replenish the depleted battery inventory, then 300 well-charged batteries are loaded onto it in the same hour. Again, it leaves θ_3 at 10:00 and arrives at θ_1 at 12:00 to unload the carried 300 well-charged batteries there in (12:00-13:00). Truck fleet #3 stays at θ_1 during (12:00-19:00) to wait until θ_1 has surplus depleted battery inventory, where 117 depleted batteries are loaded into it during (18:00-19:00). After traveling to θ_2 and unloading the carried 300 depleted batteries there in (21:00-22:00), it leaves θ_2 at 22:00 and arrives at its initial location θ_3 at 24:00.

The operation plans of the BCSs in the two cases are shown in Fig. 4.9, where the bars and the left Y-axis show the number of well-charged batteries produced by the BCS in each BSCS during each hour, while the dashed lines and the right Y-axis indicate the locational energy price in each BSCS. It can be seen that in Case 1 when the BSCS works individually, the battery charging at each BCS is highly dependent on its battery inventory and its own charging capability. For example, due to the limited battery charging capacity, the BCS in θ_1 has to perform battery charging during most of the day even the energy price is relatively high, e.g., (1:00-3:00), (11:00-13:00) and (17:00-18:00), to satisfy the battery requirements from BSSs. On the other hand, in Case 2 when interregional battery exchanges are introduced, more operational flexibility is brought to BCSs, i.e., some of the charging tasks can be allocated to the BCSs in other regions with relatively low energy price and battery demands. For instance, in θ_1 , the charging tasks that appeared in Case 1 are scheduled to θ_3 instead, the produced well-charged batteries are then transported to θ_1 via the interregional battery logistics.

Besides battery demands, battery inventory also affects the charging schedules. Note that in Case 1, the battery charging is mainly conducted during (14:00-

Figure 4.9: Operation plan of the BCS in each BSCS in Case 1 and Case 2 given

$$\mathfrak{S} = 20 \text{ and } 1 - \epsilon = 95\%.$$

22:00) in θ_3 , while in Case 2, the battery charging is shifted to lower price periods, e.g., (0:00-2:00) and (4:00-11:00). This observation mainly has two reasons. Firstly, in Case 1, the main way for the BCS to replenish its depleted battery inventory is to wait for the intra-BSCS logistics system to collect swapped batteries from BSSs, which results in depleted battery insufficiency during the off-peak hours, e.g., (6:00-11:00). However, in Case 2, the surplus depleted batteries in other regions can be transported to θ_3 for centralized battery charging. For example, as can be seen in Fig. 4.8, truck fleet #1 unloaded 100 and 200 depleted batteries to BSCS θ_3 during (8:00-9:00) and (10:00-11:00), respectively, fleet #2 unloaded 163 depleted batteries at θ_3 in (8:00-9:00) while fleet #3 also transported 126 depleted batteries to θ_3 in (7:00-8:00). This type of battery inventory sharing improves the efficiency of the whole system significantly. Secondly,

with interregional battery logistics, BSCSs are more flexible to employ backup depleted batteries. In case 1, without interregional battery exchanges, the number of backup depleted batteries utilized by each BSCS mainly depends on its own total daily battery demand. For example, although it is not shown in Fig. 4.9, θ_3 in Case 1 only employs 436 backup depleted batteries at the beginning of the day for charging considering the total number of batteries required within it, which also causes the battery inventory insufficiency during the hours with low energy prices, i.e., (6:00-11:00). Also, it is not beneficial for θ_3 to employ more backup depleted batteries during the operation only to schedule battery charging tasks to these off-peak hours, due to the resulting surplus battery inventory and the maintenance cost for additional backup batteries. On the other hand, BSCSs can employ backup batteries more flexibly with interregional battery exchanges, since the surplus batteries can be shared and transported to other BSCSs. For example, in Case 2, θ_3 employs 969 backup depleted batteries for battery charging during (0:00-8:00) before the depleted batteries are collected and transported to θ_3 in both intra-BSCS and interregional battery logistics systems. Then some of the produced well-charged batteries are transported to θ_1 and θ_2 to achieve battery inventory sharing. Moreover, in Case 2, discharging behavior is observed at θ_1 during (2:00-3:00), (12:00-13:00) and (16:00-18:00), while no discharging exists in Case 1, which demonstrates that the MBSCN model has the potential to serve as a mobile energy storage system [19], achieving energy sharing among different regions/DNs.

Fig. 4.10 depicts the power flow results on the distribution line (1,2) in BSCS θ_1 . It can be seen that compared to Case 1, the active power on the branch in Case 2 is usually lower, i.e., (13:00-14:00) and (18:00-22:00), which indicates that some of the local loads in DN θ_1 is shifted to other areas with lower locational energy price. These observations also suggest that the MBSCN model has the

Figure 4.10: Active power on the distribution line (1,2) in BSCS θ_1 .

Table 4.2: Model Feasibility with Different Settings

	Parameter settings					
	$ \Omega_{\theta_1} $			$N_{CH, \tilde{m}}^{\theta_1}$		
	4	3	2	140	120	100
Case 1	F	F	Inf	F	F	Inf
Case 2	F	F	F	F	F	F

potential to relieve system congestion, which is an important factor of locational pricing [132]. Table 4.2 compares the model feasibility in the two cases with different parameter settings. It can be seen that the MBSCN model is robust and less sensitive to the parameters, which verifies that the MBSCN model is more effective, efficient and flexible.

To demonstrate the effectiveness of the proposed distributionally robust chance-constrained BSS service model, simulations are also performed in Case 2 where the BSS service model is reformulated using a widely-used scenario-based approximation approach [133], [134], i.e., constraint (4.34) is replaced with

$$\tilde{D}_{\min, \tilde{m}}^{t, \theta, s} \leq D_{\tilde{m}}^{t, \theta} \leq \tilde{A}_{\tilde{m}}^{t, \theta, s}, \forall s \in \mathcal{S}, \tilde{m} \in \mathcal{N}_{BSS}^{\theta}, \theta, t \quad (4.35)$$

Table 4.3: Comparison of the Results Achieved with Other Approaches

Approach	Available Sample #	Reliability(%)	CPU Time(s)
DRCC	20	99.99	883.29
	20	97.76	894.64
Scenario	100	99.02	1030.75
Based	200	99.69	1120.34
	300	99.91	1192.72

where $\mathcal{S}$ is the set of samples that are randomly picked from the generated 1000 samples in Section 4.5.1. These samples are used to represent the possible realizations of the uncertainties, while $\tilde{A}_{\tilde{m}}^{t,\theta,s}$ and $\tilde{D}_{\min,\tilde{m}}^{t,\theta,s}$ are the realized arrival and minimum departure of battery demands in sample s . A comparison of the results achieved by the two approaches in terms of reliability and CPU time is given in Table 4.3. It can be seen that with the same number of available data samples, the reliability results achieved by the scenario-based approach is much worse compared with the proposed model (denoted by DRCC). It needs more than 300 samples for the scenario-based approach to achieve similar results as the proposed model. However, these large amount of data samples are not always available for certain systems. Moreover, the model size and the CPU time needed for solving the problem also increase when more samples are required.

To further test the robustness of the proposed model, more simulations are performed under different levels of uncertainty in EV behavior and battery demands. For each simulation, 1000 new samples of hourly battery demands are generated following a normal distribution with the same mean values as described in Section 4.5.1 and different standard deviations, while other simulation parameters remain the same as in Section 4.5.1. Table 4.4 shows the cost and reliability results of the proposed model in Case 2 given $\mathfrak{S} = 20$ samples available and 1 –

Table 4.4: Results in Case 2 under Different Levels of Uncertainty

Standard Deviation(%)	Cost(\$)	Reliability(%)
5	10184.6	99.99
10	10633.8	99.96
15	11314.3	99.78
20	11924.5	99.42
25	12636.6	98.68
30	14025.1	97.18
35	15377.6	93.19

$\epsilon = 95\%$. It can be observed that the reliability becomes lower as the standard deviation increases. Even when the standard deviation reaches 30% of the hourly battery demand arrival/departure, the proposed distributionally robust chance-constrained BSS service model can still achieve a satisfactory reliability result, i.e., 97.18%, which is higher than the desired $1 - \epsilon = 95\%$. When the standard deviation reaches 35%, the proposed approach starts to degrade significantly, i.e., only 93.19% of the total BSS service constraints (4.31) in the generated 1000 samples can be satisfied. Still, the results verify that the proposed model can achieve satisfactory performances under moderate uncertainty levels. Another observation is that the operational cost increases with higher uncertainty level, this is because a higher uncertainty level leads to a smaller feasible region of problem (4.20) due to constraint (4.34), which also shows a trade-off between the quality of battery swapping service at each BSS and the total system cost.

The case studies verify that the proposed MBSCN model is more efficient, flexible and economically beneficial for the test system in this chapter. However, it is noted that the results could vary depending on the actual parameters in each specific system. The MBSCN model could witness similar results as when the

BSCSs work independently under certain conditions. For example, when all the BSCSs have high EV battery demands, neither of them has surplus charging resources to perform charging task scheduling between different regions. Moreover, during the days when the BSCSs have similar locational energy prices, the MBSCN model could also be less beneficial. Still, as also discussed in Section 4.1, with further deployments of BSSs in different geographical regions, introducing interregional battery logistics between BSCSs could be more promising in the future. Also, it is worth mentioning that although fault conditions are not considered in this chapter, the MBSCN model can be further extended to consider fault conditions in both distribution systems and transportation systems in future works. For example, the binary variables which represent the line outage status can be introduced in the distribution system model [19], and the multi-layer TSN model can be updated according to road conditions [17].

4.6 Summary

This chapter proposes a CLSCN based MBSCN model to achieve collaborative operations and service provisions of BSCSs in different regions. The two-level network-wise battery logistics is modeled based on a multi-layer time-space network technique. A distributionally robust chance-constrained BSS service model is proposed to address the EV uncertainties without requiring assumptions on the probability distributions and large number of historical data. The charging and discharging of the batteries, together with both the intra-BSCS and interregional battery logistics are optimally managed for cost minimization. Case studies are conducted to validate the effectiveness of the model and the reliability of the BSS service model, where the results show that the MBSCN model is more efficient, flexible, and can bring potential congestion solutions to distribution systems.

Chapter 5

Stochastic Management of Mobile Energy Storage in Coupled Distribution and Transportation Networks

As an emerging type of mobile energy storage resource, the mobility and flexibility of MESSs make them a promising solution to enhancing the operational flexibility of coupled distribution and transportation networks (CDTNs), as well as the conversion capacities of hybrid AC/DC microgrids (MGs). To achieve the coordination among MESSs, hybrid AC/DC microgrids and CDTNs, while considering the system uncertainties from variable renewable energy (VRE) sources and the daily traffic demands of common vehicles in transportation networks, a two-stage stochastic management scheme is proposed to minimize the expected system operational cost. In the first-stage, the vehicle scheduling problem of MESSs is modeled and optimized based on the proposed user-equilibrium-based multi-layer multi-timescale time-space network model to fully utilize the mobility of MESSs under traffic uncertainties, i.e., MESSs are scheduled to travel within CDTNs for energy transfer or local energy scheduling. In the second-stage, the actual charging/discharging behaviors of MESSs, outputs of VRE sources and the power conversions at each MG are adjusted in accordance with uncertainty realizations. The proposed model is verified on a test system with Sioux Falls transportation network and a 33-

bus distribution system. The results demonstrate the effectiveness of MESSs mobility to serve as potential power conversion enhancements for MGs with mismatched generation and conversion capabilities.

5.1 Introduction

The existing distribution systems are witnessing an increasing integration of power electronics based variable renewable energy (VRE) sources such as photovoltaic (PV) cells and wind turbines (WTs), which contribute greatly to enhancing the efficiency and resilience of power systems [135], [136]. With high penetration of VRE, variability and uncertainty features of VRE source are crucial to be considered. Energy storage systems (ESSs) have been widely adopted to deal with these issues in many published works [137]–[139]. Besides, ESSs can also provide certain ancillary services to the corresponding distribution system, e.g., voltage regulation and congestion relief [140]. For better integration and management of VRE sources and ESSs, a hybrid AC/DC microgrid (MG) structure was proposed and has shown its potential in various applications to achieve increased efficiency, reduced capital expenditure and harmonizing AC and DC sub-grids by reducing unnecessary conversion stages [141].

Due to the uncertain and undispachable nature of VRE sources, proper configuration and sizing of each component in the hybrid AC/DC MG, including ESSs and bi-directional interlinking converters (BICs) [142], is essential to minimize unwanted load shedding and VRE generation curtailment ascribed to insufficient conversion and storage capacities while ensuring economical and operationally flexible operation of the MG [143]. Many studies have been conducted to study this issue [144]–[147]. In [144], a two-stage iterative approach based on a genetic algorithm is proposed to optimally decide the capacities of PV, WTs, and ESSs with consideration of contingencies while minimizing the installation, operation and load shedding cost. A model for the optimal configuration of hybrid AC/DC MGs is proposed in [145], where the size of distributed generators, distributed energy resources (DERs) and converters, as well as the point of connection of

each DER to a feeder and the type of each feeder are determined. In [146], the capacity of the interlinking converters in a hybrid AC/DC MG is optimized considering the power exchange requirements between AC and DC sub-grids. In [147], a model for planning isolated MGs is proposed to minimize the total planning cost while the type of the MG and the size of generators, capacitors, storage units and interlinking converters are optimally configured. To ensure sufficient BIC capacity and reliability, connecting multiple BICs in parallel is usually adopted since single BIC has limited capacity due to the limitations of the semiconductor devices [148]. However, the increased number of parallel BICs could bring other issues. For example, more possible circulating currents among the BICs could happen, which will result in three-phase asymmetry or even damage the BICs [149]. Also, increased control complexity and costs would be introduced into the MG operation to manage the BICs. Moreover, BICs with large capacities could be very costly [150], and their O&M costs are not negligible. Due to these concerns, curtailments of VRE generation could still occur during low load, high VRE generation periods, or after the installation of new VRE sources, when MGs are more willing to have fewer BICs, leading to insufficient power conversion capacities. Introducing MESSs into the system operation, which has the potential to enhance power conversion capability of the MGs and serve as flexible energy storage considering their mobility feature, is a promising way to solve these challenges.

MESSs are generally utility-scale energy storage banks mounted on trucks with internal combustion engines, owned and fully controlled by the utility company [20]. The significance of the integration of MESSs into power system operation for both extreme events [15], [16] and normal operations [18]–[20], has been increasingly recognized in recent researches. In response to extreme events, a two-stage optimization model is proposed in [15], where the investment cost for

MESSs is minimized in the first stage while the installed MESSs are re-routed in the second stage to avoid expected load shedding due to natural disasters. In [16], to facilitate service restoration in post-event stage, a rolling optimization framework is proposed for MESSs scheduling to achieve resource dispatching among different MGs and distribution network reconfiguration, thus enhancing the resilience of distribution systems.

Under normal conditions, MESSs have been adopted to increase the operational efficiency of power systems [18]–[20]. For transmission systems, a time-space network (TSN) based model is proposed in [18] to harness the mobility of MESSs for transmission networks, where MESSs can reduce the grid operation cost by peak load shaving and line congestion relief. A successive work is proposed to reduce operational cost of transmission networks with wind power integration by decreasing wind generation curtailment due to transmission line congestions [19]. The models in these works mainly consider railway networks, where the actual network structure and differences between MESSs, e.g., average traveling speed and sizes, are not addressed. Moreover, due to the virtual nodes in the adopted TSN model, additional binary variables are introduced, which results in a higher computational cost.

For distribution systems, only a few publications consider adopting MESSs in normal operation. In [20], MESSs are managed to provide load shifting and voltage regulation services to distribution networks, using a transit delay model for MESSs routing. However, this work does not consider the uncertainties of VRE sources, which is crucial for the coordination among MESSs, distribution systems and hybrid AC/DC MGs.

Furthermore, MESSs are mainly scheduled to travel within the existing transportation networks to provide services to the facilities at different locations in the

distribution system, where other common vehicles such as private cars, electric vehicles (EVs), taxis, etc., also travel within the network to fulfil their daily travel demands. Due to the aggregated movements of these vehicles and the selfish behavior of individual traveller in route selection, possible traffic congestions could occur on certain roads with heavy traffic flows during peak hours, which could greatly affect the travel speeds of MESSs and the resulting travel time on these congested roads [87]. Also, the uncertainties in the traffic demands, which could lead to uncertain traffic flow distributions and MESS travel time, should be accounted for. These impacts of traffic flows on the scheduling and operation of MESSs are ignored in most of the aforementioned publications. In [20], the congestion delays are obtained according to the hourly traffic volume within one day and are assumed to be the same on each road. However, this method ignores the uncertainties of traffic demands and is unable to obtain the traffic flows and congestions on different roads in each hour, which highly depends on the structure of the transportation network. Therefore, a stochastic management scheme that can achieve coordinated operation of MESSs, hybrid AC/DC MGs and coupled distribution and transportation network (CDTNs) under normal conditions while considering the uncertain temporal-spatial distribution of traffic flows, congestions and their impacts on the scheduling of MESSs, as well as the uncertainties in VRE sources and loads, is still missing and necessary.

In this context, this chapter aims to bridge the gap in the coordination among MESSs, hybrid AC/DC MGs with high penetration of VRE sources, distribution and transportation networks, leveraging the mobility of MESSs for energy service provision while considering possible traffic congestions. The operation of MESSs, MGs and distribution networks are formulated as a two-stage stochastic optimization problem, where the uncertainties of traffic demands, VRE outputs and loads are depicted using scenarios. In the first-stage, the vehicle scheduling

Table 5.1: Comparison of Related Studies

	MG Type	Routing Model	Congestion Model	Traffic Uncertainty
[20]	-	Transit Delay	Fixed Delay	-
[15]	AC MG	Transit Delay	-	-
[16]	AC MG	Multi-layer TSN	-	-
[18]	-	TSN	-	-
[19]	-	TSN	-	-
Proposed Model	Hybrid AC/DC MG	UE-based TSN	TAP	✓

problem of MESSs are modeled and optimized based on a proposed multi-layer multi-timescale TSN model that incorporates the hourly traffic user-equilibrium (UE) results obtained from the adopted traffic assignment problem (TAP) model to harness the flexibility and mobility of MESSs. In the second-stage, the actual charging/discharging behaviors of MESSs, the output of diesel generators (DGs) and power conversions through BICs are adjusted in accordance with the realized uncertain factors, which is formulated as an optimal power flow problem. A comparison between the proposed scheme and the previous studies is given in Table 5.1. The contribution of this chapter can be summarized as follows:

1) A novel stochastic UE-based multi-layer multi-timescale TSN model, which will be referred to as UE-TSN in the following context, is proposed to facilitate the modeling and scheduling of different MESSs with various mobility features while considering uncertainties in the traffic demands of the common vehicles in

the transportation network and the resulting congestion delays.

2) Based on the UE-TSN model, a stochastic management scheme is proposed to coordinate the scheduling and operation of MESSs, hybrid AC/DC MGs and CDTNs while considering the uncertainties of VRE sources as well as the uncertainties in both distribution and transportation networks. The mobility of MESSs is fully utilized to achieve energy transfer among the hybrid AC/DC MGs and serve as potential power conversion enhancements for the MGs with mismatches between VRE generation and power conversion capacity to reduce VRE curtailments, thus improving the system operational efficiency.

The remainder of this chapter is organized as follows. The UE-based multi-layer multi-timescale TSN model and the UE-TSN-based stochastic scheduling of MESSs are introduced in Section 5.2. Section 5.3 presents the stochastic management scheme for CDTNs with MESSs and MGs. Case studies and conclusions are given in Section 5.4 and 5.5, respectively.

5.2 Stochastic Modeling of Mobile Energy Storage Systems

In this section, the basic structure of a coupled distribution and transportation network (CDTN) is first introduced and an hourly scenario-based TAP model is presented to study the distribution of traffic flows and congestions at the UE with uncertain traffic demands. Based on the obtained UE traffic flow results, a UE-TSN model and a UE-TSN-based MESS scheduling model are proposed to achieve more accurate and efficient MESS scheduling and routing among the MGs while considering the impacts of uncertain traffic flow distributions and the resulting congestion effects.

5.2.1 System Structure

A general framework of a CDTN is illustrated in Fig. 5.1, which comprises two sub-systems, a distribution network, modeled as a graph $\mathcal{G}_{\text{DN}} := (\mathcal{V}_{\text{DN}}, \mathcal{E}_{\text{DN}})$ and a transportation network, denoted by $\mathcal{G}_{\text{TN}} := (\mathcal{V}_{\text{TN}}, \mathcal{E}_{\text{TN}})$. $\mathcal{V}_{\text{DN}}, \mathcal{E}_{\text{DN}}$ are the sets of buses and distribution lines in the distribution network while $\mathcal{V}_{\text{TN}}, \mathcal{E}_{\text{TN}}$ denote the sets of intersections and roads in the transportation network, respectively. These two networks are coupled together by a set of hybrid AC/DC MGs $\mathcal{M}$ and the MESS charging/discharging behaviors at each MG. The MGs and a set of depots $\mathcal{D}$ for MESSs are located in the transportation network. For notation simplicity, let mapping $\mathcal{F}_{\text{TN}} : \mathcal{M} \cup \mathcal{D} \rightarrow \mathcal{V}_{\text{TN}}$ maps each MG and depot to its corresponding geographical location in the transportation network. In this chapter, it is assumed that a hybrid AC/DC MG consists of a DC sub-grid, an AC sub-grid and the BICs that links the two sub-grids. A DC sub-grid includes DC WTs, PV panels, stationary ESSs (SESSs), DC loads and bi-directional MESS charging facilities, while an AC sub-grid consists of DGs, AC WT generators, AC loads and a point of common coupling switch along with a transformer connected to the distribution network [151].

5.2.2 Transportation System Model

As also mentioned in Section 5.1, the impacts of traffic flows and the resulting congestions on the scheduling and operation of MESSs need to be considered. TAP models and the UE solution concept, which have been widely used in the transportation research field to estimate the distribution of traffic flows and the associated congested travel time in a transportation network [84], [152], could be utilized to study these impacts of common vehicle behaviors on MESSs. More-

Figure 5.1: Coupled distribution and transportation network with MESSs.

over, the uncertainties in their traffic demands, which could lead to uncertainties in the traffic flow distributions and MESS travel time, should also be accounted for. In this section, an hourly TAP model with a scenario-based formulation is adopted and introduced.

Every vehicle that travels within the transportation network leaves its origin node $u \in \mathcal{V}_{\text{TN}}$ and wants to reach its destination $w \in \mathcal{V}_{\text{TN}}$. The uncertain aggregated traffic demand between such an origin-destination (O-D) pair ($u-w$) during hour t is described using scenarios, and denoted by $d_{uw}^{t,s}$, where the superscript s represents scenario s . Let $\mathcal{K}_{uw}$ denote the set of routes that connect u, w , and $\mathcal{O}$ be the set of all feasible O-D pairs. Due to congestion effects, the travel time for common vehicles on road (link) $\alpha \in \mathcal{E}_{\text{TN}}$ in hour t , denoted by $\tau_{\alpha}^{t,s}(f_{\alpha}^{t,s})$, is related to the hourly traffic flow on α , denoted by $f_{\alpha}^{t,s}$. This relationship is usually depicted using volume delay functions [153]. In this chapter, the most widely used Bureau of Public Roads (BPR) function is adopted, which is given

as follows [154].

$$\tau_{\mathfrak{a}}^{t,s}(f_{\mathfrak{a}}^{t,s}) = \tau_{\mathfrak{a}}^0 \left[1 + 0.15 \left(\frac{f_{\mathfrak{a}}^{t,s}}{\bar{f}_{\mathfrak{a}}} \right)^4 \right], \forall s, t, \mathfrak{a} \in \mathcal{E}_{\text{TN}} \quad (5.1)$$

where $\tau_{\mathfrak{a}}^0$ is the free-flow travel time on link $\mathfrak{a}$ without any congestions and $\bar{f}_{\mathfrak{a}}$ is the link capacity.

Let $\delta_{uw,k,\mathfrak{a}}$ denote link-route indicator variable, i.e., $\delta_{uw,k,\mathfrak{a}} = 1$ if route $k \in \mathcal{K}_{uw}$ uses link $\mathfrak{a}$, and $\mathfrak{h}_{uw,k}^{t,s}$ be the total traffic flow on route k . Assume that all vehicle users are selfish and want to minimize their own travel time. To determine the traffic flow distribution, the famous Wardrop first principle is proposed to describe the stable condition considering the congestion effects and the selfish decision-making of individual travellers, which states that the travel time on all routes actually used are equal, and are less than those which would be experienced by a single vehicle on any unused route [85]. The traffic flow distribution that satisfies this principle is usually referred to as a UE. To find the desired equilibrium, a TAP can be formulated as follows.

$$\begin{aligned} \min \quad & \sum_{\mathfrak{a} \in \mathcal{E}_{\text{TN}}} \int_0^{f_{\mathfrak{a}}^{t,s}} \tau_{\mathfrak{a}}^{t,s}(\theta) d\theta \\ \text{s.t.} \quad & \sum_{k \in \mathcal{K}_{uw}} \mathfrak{h}_{uw,k}^{t,s} = d_{uw}^{t,s}, \forall (u-w), s, t, \\ & \sum_{(u-w) \in \mathcal{O}} \sum_{k \in \mathcal{K}_{uw}} \delta_{uw,k,\mathfrak{a}} \mathfrak{h}_{uw,k}^{t,s} = f_{\mathfrak{a}}^{t,s}, \forall s, t, \mathfrak{a} \in \mathcal{E}_{\text{TN}}, \\ & \mathfrak{h}_{uw,k}^{t,s} > 0, \forall (u-w), k, s, t. \end{aligned} \quad (5.2)$$

Since the adopted BPR function (5.1) is strictly increasing and the transportation network is strongly connected, it can be proved that problem (5.2) is convex and its first-order optimality conditions are equivalent to the Wardrop UE conditions, i.e., the optimal solution of problem (5.2) determines the traffic flow pattern at the UE in hour t . The proof and more details are referred to [84]. Note that convex

TAP (5.2) can be readily solved using nonlinear programming solvers. In this chapter, the bi-conjugate Frank-Wolfe algorithm is adopted [155].

It is worth mentioning that compared to the large amount of common vehicles on each road, the scheduling and travelling of one or several MESSs will have negligible impacts on the distribution of the traffic flow, therefore they are omitted in the formulated problem (5.2). Also, a static TAP model is considered in this chapter, while the traffic UE pattern during the whole scheduling horizon can be obtained by solving TAP (5.2) for $|\mathcal{T}|$ times sequentially, given the predicted hourly traffic demands $d_{uw}^{t,s}, \forall (u-w) \in \mathcal{O}$. Although this approach cannot yield very precise traffic flow distribution, it is still a practical way to integrate the impacts of traffic flows and congestion effects into MESS scheduling, considering its merits including low computational cost, its ability to solve large-scale problems and to converge to precise equilibriums [156], and that the exact distribution of traffic flow at a specific time point is not so crucial for the scheduling of MESSs with discrete time intervals. To obtain a more detailed and precise traffic flow pattern, dynamic traffic assignment models [156] or machine learning models [157] can be adopted in future research.

5.2.3 Construction of UE-based Multi-layer Multi-timescale Time-space Networks

TSN models have been utilized by many researchers to deal with vehicle scheduling problems involving both space decision and discrete time intervals [16], [18], [19], [122]. However, the impacts of traffic flow distribution, traffic congestion effects, and traffic demand uncertainties on the scheduling of MESSs are ignored when constructing these TSN models. Moreover, the different mobility features and scheduling timescale requirements of various types of MESSs with different

sizes should also be considered. In this section, a stochastic UE-based multi-layer multi-timescale TSN model is proposed and constructed for MESS scheduling, after solving the TAP (5.2) for each scenario s and obtaining the hourly UE traffic flow on each link, denoted by $f_a^{t,s*}$, as well as the corresponding congested travel time $\tau_a^{t,s*}$. For each scenario $s \in \mathcal{S}$, the proposed model consists of $|\Omega|$ layers, so there are $|\mathcal{S}| \times |\Omega|$ layers in total. Each single layer is associated with one MESS $\omega \in \Omega$ to describe its specific possible temporal-spatial behavior in s .

Let $\mathcal{T}$ denote the set of hours in the general scheduling horizon of the whole CDTN. For a single MESS ω (and its associated ω -th layer of the TSN), its individual scheduling time horizon at transportation system level is described using a set of time slots $\mathcal{T}_\omega$, indexed by t_ω . Every slot is of the same length and let Γ_{t_ω} denote the set of hours in time slot t_ω , i.e., $|\mathcal{T}_\omega| = |\mathcal{T}|/|\Gamma_{t_\omega}|$. Each time slot t_ω has two endpoints and let $\widehat{\mathcal{T}}_\omega$ denote the set of these time points, indexed by $\widehat{t}_\omega$. In each scenario $s \in \mathcal{S}$, a matrix $\mathfrak{M}_\omega^{t_\omega,s}$ with elements $\mathfrak{t}_{a,\omega}^{t_\omega,s}$ is defined to describe the average travel time (hours) on each link $a \in \mathcal{E}_{\text{TN}}$ if MESS ω wants to use link a in time slot t_ω , given the obtained hourly traffic UE pattern and the associated congested time. Moreover, since some of the trips between MGs could take more than one time slot to complete, to take into account the possible changes in the hourly link traffic flow during the trip, $\mathfrak{t}_{a,\omega}^{t_\omega,s}$ is calculated as follows, i.e., if the travel time on link a in time slots t_ω is longer than the length of a single time slot, its travel time is estimated by taking the average of the congested travel times during the hours in t_ω and the next time slot $t_\omega + 1$.

$$\mathfrak{t}_{a,\omega}^{t_\omega,s} = \begin{cases} \sum_{t \in \Gamma_{t_\omega}} \frac{\tau_{a,\omega}^{t,s}}{|\Gamma_{t_\omega}|}, & \text{if } \sum_{t \in \Gamma_{t_\omega}} \frac{\tau_{a,\omega}^{t,s}}{|\Gamma_{t_\omega}|} \leq |\Gamma_{t_\omega}|, \\ \sum_{t \in \Gamma_{t_\omega} \cup \Gamma_{t_\omega+1}} \frac{\tau_{a,\omega}^{t,s}}{2|\Gamma_{t_\omega}|}, & \text{otherwise,} \end{cases} \quad \forall \omega, t_\omega, s, a, \quad (5.3)$$

where a subscript ω is added in $\tau_{a,\omega}^{t,s}$ to address the differences in the MESSs'

travel time on link a . Since the free-flow travel time of MESSs on each link is related to their average speeds V_{avg}^ω , i.e., $\tau_{a,\omega}^{t,s} = \tau_a^{t,s*} V_{\text{avg}}^C / V_{\text{avg}}^\omega$, where V_{avg}^C is the average speed of common vehicles. Note that only two time slots are considered for travel time estimation, which is because this chapter mainly consider urban transportation networks and the total travel time between two MGs are within a few hours.

Assume that when MESS ω is scheduled to start a trip between a pair of MGs or depots $m_1, m_2 \in \mathcal{M} \cup \mathcal{D}$ in time slot t_ω , it will always choose the route with the shortest total travel time in the transportation network between $\mathcal{F}_{\text{TN}}(m_1), \mathcal{F}_{\text{TN}}(m_2)$ in t_ω , and let $k_{m_1 m_2}^{t_\omega, s}$ denote such a route. With graph $\mathcal{G}_{\text{TN}}$ and the travel time matrix $\mathfrak{W}_{\omega}^{t_\omega, s}, k_{m_1 m_2}^{t_\omega, s}$ can be easily obtained by using many existing methods such as Dijkstra's algorithm [124]. The number of time slots needed for MESS ω to travel on $k_{m_1 m_2}^{t_\omega, s}$ is given as follows.

$$\mathfrak{T}_{m_1 m_2, \omega}^{t_\omega, s} = \left\lceil \sum_{a \in k_{m_1 m_2}^{t_\omega, s}} \frac{t_{a,\omega}^{t_\omega, s}}{|\Gamma_{t_\omega}|} \right\rceil, \forall m_1, m_2 \in \mathcal{M} \cup \mathcal{D}, \omega, t_\omega, s \quad (5.4)$$

where $\lceil \cdot \rceil$ is the ceiling function. Note that in this chapter, the timescale of each layer is chosen as $|\Gamma_{t_\omega}| = \min\{\lceil \sum_{a \in k_{m_1 m_2}^{t_\omega, s}} \tau_{a,\omega}^0 \rceil | m_1, m_2 \in \mathcal{M} \cup \mathcal{D}\}$, a smaller timescale can also be adopted for more flexible scheduling.

To illustrate the construction of ω -th layer in the proposed UE-TSN model, consider a simple CDTN with $|\mathcal{D}| = 1$ depot and $|\mathcal{M}| = 4$ MGs. MESS $\omega \in \Omega$ with $V_{\text{avg}}^\omega = 40\text{km/h}$ is travelling within the transportation network $\mathcal{G}_{\text{TN}}$. Also, it is assumed that the obtained UE results in scenario s indicate that the minimum time distance between two MGs within the day is 46 minutes, therefore, the scheduling timescale for ω -th layer is set to be 1 hour, i.e., $|\Gamma_{t_\omega}| = 1$.

The constructed layer ω that models the time-space dynamics of MESS ω in this scenario is shown in Fig. 5.2, which comprises two types of time-space nodes

Figure 5.2: UE-based multi-layer multi-timescale time-space network model in scenario s .

defined as follows.

- 1) *MG time-space nodes* $\mathcal{N}_\omega^s = \{(m, \hat{t}_\omega) \mid m \in \mathcal{M}, \hat{t}_\omega \in \widehat{\mathcal{T}}_\omega\}$: represent the MGs at specific time points.
- 2) *Depot nodes* $\tilde{\mathcal{N}}_\omega^s = \{(d, \hat{0}_\omega), (d, \hat{T}_\omega) \mid d \in \mathcal{D}\}$: indicate the initial and end depot position of MESS ω . Let $\mathcal{N}_{\text{TS}}^{\omega,s} = \mathcal{N}_\omega^s \cup \tilde{\mathcal{N}}_\omega^s$ denote all the time-space nodes on layer ω in scenario s .

These time-space nodes are interconnected by two types of arcs to illustrate the MESS's temporal-spatial behaviors, i.e., transit arcs and parking arcs, defined as follows.

- 1) *Transit arcs* $\mathcal{A}_T^{\omega,s}$: a transit arc shows a feasible pair of the nodes in $\mathcal{N}_{\text{TS}}^{\omega,s}$ in scenario s , considering the congested travel time between the corresponding

MGs. For example, arc $((m_4, \hat{2}_\omega), (m_3, \hat{4}_\omega))$ shows that the MESS leaves MG m_4 at time point $\hat{2}_\omega$ and arrives at MG m_3 at time point $\hat{4}_\omega$, which indicates that in scenario s , if MESS ω is scheduled to start a trip between m_3 and m_4 in time slot 3_ω , the congested travel time is two time slot, i.e., $\mathfrak{T}_{m_3m_4,\omega}^{2_\omega,s} = 2$.

2) *Parking arcs* $\mathcal{A}_p^{\omega,s}$: a parking arc connects two time-space nodes of the same MG in a time slot, which indicates that the MESS stays at the MG in the certain time slot, e.g., $((m_4, \hat{1}_\omega), (m_4, \hat{2}_\omega))$ claims that the MESS stays at m_4 during time slot 2_ω . Note that only the transit arcs $\mathcal{A}_T^{\omega,s}$ are scenario-dependent due to different UE patterns and congestion delays, while the time-space nodes and parking arcs on each layer are the same in all the scenario. Still, a superscript s is added to all the notations for consistency.

Remark 5.2.1. As already mentioned in Section 5.2.3, the hourly distribution of traffic flows within the transportation network in different scenarios will affect the travel time matrix $\mathfrak{W}_\omega^{t_\omega,s}$ and the feasible temporal-spatial behaviors of the MESSs. In the proposed UE-TSN model, these impacts are captured and depicted using the scenario-dependent transit time-space arcs $\mathcal{A}_T^{\omega,s}$ with varying lengths. For example, as shown in Fig. 5.2, a feasible transit arc $((m_4, \hat{1}_\omega), (m_3, \hat{2}_\omega))$ indicates that if MESS ω is scheduled to start a trip from m_4 to m_3 at $\hat{1}_\omega$ (in time slot 2_ω), the travel time is one time slot. However, if MESS ω leaves m_4 for m_3 in time slot 3_ω , the travel time is increased to two time slots, due to the high traffic demands and the resulting congestions during the peak hours in time time slot 3_ω . This delay in time is represented by a delayed transit arc $((m_4, \hat{2}_\omega), (m_3, \hat{4}_\omega))$ when constructing the UE-TSN. Congestions on other routes between the MGs can also be depicted using similar delayed arcs (red curves) in Fig. 5.2. If the TSN models that ignore the possible traffic congestion delays are adopted [17], [19], [122], the scheduling results could be inaccurate and suboptimal. For example, the plan for MESS ω to leave MG m_4 at $\hat{2}_\omega$ and

reach m_3 at $\widehat{3}_\omega$ for charging/discharging during time slot 4_ω will fail due to the congestions. Also, it is worth mentioning that in the UE-TSN model, according to (5.3) and (5.4), some arcs starting in certain time slots could be very long when there are heavy congestions between the two MGs, indicating that if the MESS is scheduled to start a trip between the two MGs in these time slots, it can take three or more time slots for it to arrive its destination. In this case, these arcs may not accurately describe the temporal-spatial behavior of the MESS since the actual congestions could be mitigated in the third or a later time slot. However, the proposed UE-TSN can still help identifying the possible spatial and temporal distribution of congestions, thus the MESSs are more likely to be optimally scheduled to avoid these congestions by parking at MGs or choosing another destination with less congested travel time.

Remark 5.2.2. As discussed in [17], a multi-layer TSN model can achieve much fewer numbers of binary variables and constraints compared to the models with additional virtual nodes [19], [122], leading to a lower computational complexity. However, this model requires a unified timescale on each layer of the TSN. When there are MESSs with various types and sizes [76], [158] in the CDTN, different temporal preferences due to their mobility limitations, which are described using $\min\{\lceil \sum_{a \in k_{m_1 m_2}^{t_\omega, s}} \tau_{a, \omega}^{t, s} \rceil | m_1, m_2 \in \mathcal{M}, t, s\}$ in this chapter, could exist. For example, a bulky MESS that needs multiple hours to travel between two MGs may prefer a longer time span between two scheduled trips, while smaller MESSs could be more flexible to travel frequently. With the extended multi-timescale feature, the UE-TSN model has the potential to further reduce the problem size by considering the possible various temporal preferences of MESSs. Take the four-MG case in Fig. 5.2 for instance, and it is assumed that one of the MESS $\omega \in \Omega$ is very bulky and it needs at least two hours to travel between any two of the MGs so that ω may prefer a two-hour timescale. In each scenario, the multi-

timescale UE-TSN model reduces the number of binary variables by 48.39% on this layer with a scheduling timescale of two hours, compared to the single-timescale model with a unified one-hour timescale on every layer considering other flexible MESSs. Still, it is worth mentioning that if all MESSs have unified specifications or temporal preferences, the proposed multi-timescale model will have the same performance as the single-timescale model.

5.2.4 UE-TSN-Based MESS Scheduling Model

With the proposed multi-layer multi-timescale UE-TSN model, the scheduling of MESSs in the CDTN can be represented by a sequence of the time-space arcs in each layer which starts from an initial depot node and ends at an end depot node. The formulation is based on arc-wise binary variables $\zeta_{\hat{n}\check{n}}^{\omega,s}$, which are 1 if MESS ω is on arc $(\hat{n}, \check{n}) \in \mathcal{A}_P^{\omega,s} \cup \mathcal{A}_T^{\omega,s}$ in scenario s .

To further facilitate the description of the vehicle behavior using arcs and time-space nodes, as also depicted in Fig. 5.2, a cut in each time slot t_ω is introduced, which divides $\mathcal{N}_{TS}^{\omega,s}$ into two disjoint subsets $(\mathcal{N}_{L,\omega}^{t_\omega,s}, \mathcal{N}_{R,\omega}^{t_\omega,s})$ where $\mathcal{N}_{L,\omega}^{t_\omega,s}$ represents the set of all time-space nodes on the left-hand side of the cut while $\mathcal{N}_{R,\omega}^{t_\omega,s}$ denotes those on the right-hand side. The corresponding cut-set denoted by $\Phi_\omega^{t_\omega,s} = \{(\hat{n}, \check{n}) \in \mathcal{A}_T^{\omega,s} \cup \mathcal{A}_P^{\omega,s} | \hat{n} \in \mathcal{N}_{L,\omega}^{t_\omega,s}, \check{n} \in \mathcal{N}_{R,\omega}^{t_\omega,s}\}$, is introduced to describe all the feasible arcs that intersect time slot t_ω in scenario s .

With the previous definitions, the multi-layer multi-timescale UE-TSN based MESS scheduling model can be formulated as follows.

$$\sum_{(\hat{n}, \check{n}) \in \Phi_\omega^{t_\omega,s}} \zeta_{\hat{n}\check{n}}^{\omega,s} = 1, \forall \omega, t_\omega, s \quad (5.5)$$

$$\sum_{(\hat{n}, \check{n}) \in \mathcal{A}_n^{\omega,s}} \zeta_{\hat{n}\check{n}}^{\omega,s} = \sum_{(\hat{n}, \check{n}) \in \mathcal{A}_n^{\omega,s}} \zeta_{\hat{n}\check{n}}^{\omega,s}, \forall n \in \mathcal{N}_\omega^s, \omega, s \quad (5.6)$$

$$\sum_{(\hat{n}, \check{n}) \in \mathcal{A}_n^{\omega, s}} \zeta_{\hat{n}\check{n}}^{\omega, s} = \zeta_{\text{init}}^{\omega, s}, \forall n \in \tilde{\mathcal{N}}_{\omega}^s, \omega, s \quad (5.7)$$

Equation (5.5) indicates that MESS ω can only be on one arc at each time slot. Constraint (5.6)-(5.7) refers to the flow conservation, i.e., any MESS ω ends its trip at time-space node n must stay on one of the arcs that start from node n , while $\zeta_{\text{init}}^{\omega}$ indicates the initial location of MESS ω . $\mathcal{A}_n^{\omega, s}$, $\mathcal{A}_n^{\omega, s}$ are the sets of arcs that start from and end at time-space node n in scenario s .

When staying on a parking arc, i.e., $\zeta_{\hat{n}\check{n}}^{\omega, s} = 1, \forall (\hat{n}, \check{n}) \in \mathcal{A}_p^{\omega, s}$, MESS ω can provide energy services to the corresponding MG, as well as the distribution system. The relationship between its power/energy behavior and its temporal-spatial dynamics is constrained as follows.

$$0 \leq P_{\text{ME},c,m}^{\omega, t, s} \leq \zeta_{\hat{n}\check{n}}^{\omega, s} \bar{P}_{\text{ME},c}^{\omega}, \forall t \in \Gamma_{t_{\omega}}, (\hat{n}, \check{n}) \in \mathcal{A}_{p,m}^{\omega, t_{\omega}, s}, \omega, m, s \quad (5.8)$$

$$0 \leq P_{\text{ME},d,m}^{\omega, t, s} \leq \zeta_{\hat{n}\check{n}}^{\omega, s} \bar{P}_{\text{ME},d}^{\omega}, \forall t \in \Gamma_{t_{\omega}}, (\hat{n}, \check{n}) \in \mathcal{A}_{p,m}^{\omega, t_{\omega}, s}, \omega, m, s \quad (5.9)$$

$$0 \leq R_{\text{ME},m}^{\omega, t, s} \leq \zeta_{\hat{n}\check{n}}^{\omega, s} \max(\bar{P}_{\text{ME},d}^{\omega}, \bar{P}_{\text{ME},c}^{\omega}), \quad \forall t \in \Gamma_{t_{\omega}}, (\hat{n}, \check{n}) \in \mathcal{A}_{p,m}^{\omega, t_{\omega}, s}, \omega, m, s \quad (5.10)$$

$$0 \leq \sum_{m \in \mathcal{M}} P_{\text{ME},c,m}^{\omega, t, s} \leq I_{\text{ME},c}^{\omega, t, s} \bar{P}_{\text{ME},c}^{\omega}, \forall \omega, t, s \quad (5.11)$$

$$0 \leq \sum_{m \in \mathcal{M}} P_{\text{ME},d,m}^{\omega, t, s} \leq I_{\text{ME},d}^{\omega, t, s} \bar{P}_{\text{ME},d}^{\omega}, \forall \omega, t, s \quad (5.12)$$

$$I_{\text{ME},d}^{\omega, t, s} + I_{\text{ME},c}^{\omega, t, s} \leq \zeta_{\hat{n}\check{n}}^{\omega, s}, \forall t \in \Gamma_{t_{\omega}}, (\hat{n}, \check{n}) \in \mathcal{A}_{p,m}^{\omega, t_{\omega}, s}, \omega, s \quad (5.13)$$

$$E_{\text{ME}}^{\omega, t, s} = E_{\text{ME}}^{\omega, t-1, s} + \eta_{\text{ME},c}^{\omega} \sum_{m \in \mathcal{M}} P_{\text{ME},c,m}^{\omega, t, s} - \sum_{m \in \mathcal{M}} P_{\text{ME},d,m}^{\omega, t, s} / \eta_{\text{ME},d}^{\omega}, \forall \omega, t, s \quad (5.14)$$

$$E_{\text{ME},\text{cap}}^{\omega} E_{\text{ME}}^{\omega} \leq E_{\text{ME}}^{\omega, t, s} \leq E_{\text{ME},\text{cap}}^{\omega} \bar{E}_{\text{ME}}^{\omega}, \forall \omega, t, s \quad (5.15)$$

Constraints (5.8)-(5.10) determine the feasible charging, discharging power and output flexibility of MESS ω at MG m during hour t in time slot t_{ω} , respectively,

where $\mathcal{A}_{p,m}^{\omega,t_\omega,s}$ denotes the parking arcs of MG m in time slot t_ω in scenario s . Constraints (5.11)-(5.12) indicate that MESS ω can either perform charging or discharging at hour t , which is also constrained by its temporal-spatial behaviors in (5.13). Equation (5.14) illustrates the remaining battery energy while (5.15) ensures the state-of-charge (SOC) of MESS ω is within the desired range.

5.3 Stochastic Management of Coupled Distribution Transportation Networks

With the UE-TSN model, MESSs can be dispatched more accurately and efficiently among the MGs for energy service provision. In this section, a scenario-based stochastic management scheme for CDTNs is proposed and the detailed mathematical formulations are provided to further incorporate MESSs into the system operation and achieve coordinated scheduling of MESSs and CDTNs, while considering the uncertainties of VRE sources, load, and traffic demands, where MESSs could also serve as potential conversion capacity enhancements through transporting energy among the MGs.

5.3.1 Problem Formulation

The proposed stochastic management scheme for CDTNs utilizes a two-stage stochastic programming framework, where the decision variables are divided into two groups:

1) First-stage decisions (here-and-now) are assumed to be made a day ahead before the realization of uncertainties, which consist of the variables for the day-ahead scheduling and energy-reserve procurements of all the MESSs, SESSs and DGs in each hour $t \in \mathcal{T}$, i.e., $\zeta_{nn}^{\omega,s}$, $P_{ME,c(d),m}^{\omega,t,s}$, $R_{ME,m}^{\omega,t,s}$, $I_{ME,c(d)}^{\omega,t,s}$, $P_{SE,c(d),m}^{t,s}$, $R_{SE,m}^{t,s}$,

$I_{SE,c(d)}^{t,s}$ and $P_0^{t,s}$. To ensure that the first-stage variables are scenario-independent, nonanticipativity constraints are introduced and formulated in Section 5.3.5.

2) Second-stage decisions, including the actual outputs of VRE sources, MESSs, SESSs, MGs and DGs in each hour $t \in \mathcal{T}$, are made accordingly given the first-stage decisions, when the uncertainties unfold. The second-stage decision variables are $p_{ME,c(d),m}^{\omega,t,s}$, $p_{SE,c(d),m}^{\omega,t,s}$, $p_{DG,m}^{t,s}$, $q_{DG,m}^{t,s}$, $p_{MG,m}^{t,s}$, $q_{MG,m}^{t,s}$, $p_{PV,m}^{t,s}$, $p_{W,m}^{t,s}$, $e_{DoD,ME}^{\omega,s}$ and $e_{DoD,SE,m}^s$. For notation simplicity, let $\mathbf{x}_s$ and $\mathbf{y}_s$ denote the vectors of the first-stage and second-stage variables in scenario s , respectively.

The objective of the stochastic management model is to seek a first-stage decision that minimize the total operation cost formulated as follows.

$$\min_{\mathbf{x} \in \mathbf{X}} g(\mathbf{x}) + \mathbb{E}[\mathcal{Q}(\mathbf{x}, \boldsymbol{\xi})] \quad (5.16)$$

where $g(\mathbf{x})$ is the first stage cost, $\mathbb{E}[\mathcal{Q}(\mathbf{x}, \boldsymbol{\xi})]$ is the expected second-stage cost and $\boldsymbol{\xi}$ denotes the vector that contains all the uncertain parameters, i.e., d_{uw}^t , $p_{L,j}^t$, $q_{L,j}^t$, $p_{L,AC,m}^t$, $q_{L,AC,m}^t$, $p_{L,DC,m}^t$, $\tilde{p}_{PV,m}^t$ and $\tilde{p}_{W,m}^t$.

As also mentioned in Section 5.2.2, the uncertainties of traffic demands in the transportation network and the uncertainties of VRE sources and loads in the distribution network are captured by generating a finite number of scenarios that describe the possible realizations of these uncertainties. The aforementioned random vector $\boldsymbol{\xi}$ and uncertain parameters in each scenario s are denoted with superscript s . Meanwhile, scenario reduction algorithms, e.g., fast forward selection and simultaneous backward reduction [159], can be adopted to address computational issues.

With the obtained scenarios, (5.16) can be rewritten as

$$\min_{\mathbf{x}_s \in \mathbf{X}_s, \forall s \in \mathcal{S}} \sum_{s \in \mathcal{S}} \pi_s [g(\mathbf{x}_s) + \mathcal{Q}(\mathbf{x}_s, \boldsymbol{\xi}_s)] \quad (5.17)$$

where $F(\mathbf{x}_s)$ and $\mathcal{Q}(\mathbf{x}_s, \boldsymbol{\xi}_s)$ are given as follows.

$$g(\mathbf{x}_s) = \sum_{t \in \mathcal{T}} \left[\lambda_{\text{DA}}^t P_0^{t,s} + \sum_{\omega \in \Omega} \sum_{(\hat{n}, \tilde{n}) \in \mathcal{A}_T^{\omega,s}} C_T^\omega l_{\hat{n}\tilde{n}}^{\omega,s} \zeta_{\hat{n}\tilde{n}}^{\omega,s} |\Gamma_{t_\omega}| \right] \quad (5.18)$$

$$\begin{aligned} \mathcal{Q}(\mathbf{x}_s, \boldsymbol{\xi}_s) = \min_{\mathbf{y}_s \in \mathbf{Y}_s(\boldsymbol{\xi}_s)} \sum_{t \in \mathcal{T}} \sum_{m \in \mathcal{M}} & \left[c_{\text{DG},m} p_{\text{DG}}^{t,s} + c_{\text{W},m} p_{\text{W},m}^{t,s} \right. \\ & + c_{\text{PV},m} p_{\text{PV},m}^{t,s} + c_{\text{SE},m} (p_{\text{SE,d},m}^{t,s} + p_{\text{SE,c},m}^{t,s}) \\ & + \sum_{\omega \in \Omega} c_{\text{ME},\omega} (p_{\text{ME,d},m}^{\omega,t,s} + p_{\text{ME,c},m}^{\omega,t,s}) \\ & \left. - B_{\text{SE},m} e_{\text{DoD,SE},m}^s - \sum_{\omega \in \Omega} B_{\text{ME},\omega} e_{\text{DoD,ME}}^{\omega,s} \right] \\ \text{s.t.} \quad & \mathbf{D}\mathbf{y}_s \leq \mathbf{h} - \mathbf{T}\mathbf{x}_s \end{aligned} \quad (5.19)$$

The first term in (5.18) represents the cost of day-ahead electricity procurement from the main grid [160] and the second term denotes the transportation cost of MESSs, where $l_{\hat{n}\tilde{n}}^{\omega,s}$ is the length (number of time slots) of arc $(\hat{n}, \tilde{n}) \in \mathcal{A}_T^{\omega,s}$. Note that the transportation cost is calculated based on travel time, considering the impacts of traffic congestions on fuel consumptions [161]. In (5.19), the first three terms are the generation costs of DGs, WTs and PV, respectively, the fourth and fifth terms calculate the battery operation and maintenance (O&M) costs of SESSs and MESSs, respectively, while the last two terms stand for the battery degradation cost considering the daily depth of discharge, i.e., higher daily depth of discharge would lead to a higher battery degradation cost. More details about the modeling of battery degradation cost can be referred to [162]. The feasible sets and the associated constraints for the first-stage and second-stage variables, i.e., $\mathbf{X}_s$ and $\mathbf{Y}_s(\boldsymbol{\xi}_s)$, the coupling constraints between the two stages, $\mathbf{D}\mathbf{y}_s \leq \mathbf{h} - \mathbf{T}\mathbf{x}_s$, and the nonanticipativity constraints are formulated in the following sections.

5.3.2 First-stage Constraints

5.3.2.1 Constraints for MESSs

As introduced in Section 5.2.3, each MESS $\omega \in \Omega$ must follow the MESS scheduling model (5.5)-(5.7), as well as the power/energy constraints (5.8)-(5.15).

5.3.2.2 Constraints for SESSs

The SESS within each MG m should also follow similar constraints in (5.8)-(5.15), by setting binary variable $\zeta_{\hat{n}\tilde{n}}^{\omega,s}$ to 1, while (5.14) is replaced with the following constraint.

$$E_{SE,m}^{t,s} = E_{SE,m}^{t-1,s} + \eta_{SE,c} P_{SE,c,m}^{t,s} - P_{SE,d,m}^{t,s} / \eta_{SE,d}, \forall m, s, t \quad (5.20)$$

5.3.3 Second-stage Constraints

In the second-stage, the output of VRE sources, DGs, SESSs and MESSs are adjusted to meet the following operational constraints after the unfolding of uncertainties.

5.3.3.1 Constraints for distribution network

In this chapter, a linearized Distflow model, which has been widely used in the literature [17], [163], is used for power flow analysis, and the detailed formulations

are given as follows.

$$p_{G,j}^{t,s} + \sum_{m \in \mathcal{M}_j} p_{MG,m}^{t,s} - p_{L,j}^{t,s} = \sum_{k \in \mathcal{N}_{DN}} p_{jk}^{t,s} - \sum_{i \in \mathcal{N}_{DN}} p_{ij}^{t,s}, \forall j, t, s \quad (5.21)$$

$$q_{G,j}^{t,s} + \sum_{m \in \mathcal{M}_j} q_{MG,m}^{t,s} - q_{L,j}^{t,s} = \sum_{k \in \mathcal{N}_{DN}} q_{jk}^{t,s} - \sum_{i \in \mathcal{N}_{DN}} q_{ij}^{t,s}, \forall j, t, s \quad (5.22)$$

$$v_j^{t,s} - v_i^{t,s} = \frac{r_{ij}p_{ij}^{t,s} + x_{ij}q_{ij}^{t,s}}{v_0}, \forall (i, j), t, s \quad (5.23)$$

$$-\bar{S}_{ij} \leq p_{ij}^{t,s} \leq \bar{S}_{ij}, \forall (i, j), t, s \quad (5.24)$$

$$-\bar{S}_{ij} \leq q_{ij}^{t,s} \leq \bar{S}_{ij}, \forall (i, j), t, s \quad (5.25)$$

$$-\sqrt{2}\bar{S}_{ij} \leq p_{ij}^{t,s} + q_{ij}^{t,s} \leq \sqrt{2}\bar{S}_{ij}, \forall (i, j), t, s \quad (5.26)$$

$$-\sqrt{2}\bar{S}_{ij} \leq p_{ij}^{t,s} - q_{ij}^{t,s} \leq \sqrt{2}\bar{S}_{ij}, \forall (i, j), t, s \quad (5.27)$$

$$\underline{v}_i \leq v_i^{t,s} \leq \bar{v}_i, \forall i, t, s \quad (5.28)$$

The active/reactive power balance equations at bus j under scenario s are shown in (5.21) and (5.22), note that $p_{G,j}^{t,s} = P_0^t$ if j is the substation bus. Constraint (5.23) indicate the forward voltage drop, where $v_0 = 1$. Equations (5.24)-(5.27) provide a linearized approximation regarding branch capacity. Constraint (5.28) is the voltage limit on each bus.

To further address the impacts of daily EV flows and their temporal-spatial distribution on the load profile of the distribution network, it is envisioned that some of the links in the transportation network of the CDTN are installed with wireless power transfer (WPT) equipment and are able to provide battery charging services to the EVs moving on them [164]. Assuming that EVs share the same proportion of traffic on each link, the load profile $p_{L,j}^{t,s}$ on each bus j can be extended as follows [87], according to the traffic UE results.

$$p_{L,j}^{t,s} = p_{N,j}^{t,s} + \eta_{EV} \sum_{a \in \mathcal{E}_{TN}^j} f_a^{t,s}, \forall j, t, s \quad (5.29)$$

where $p_{N,j}^{t,s}$ is the traditional load, $\mathcal{E}_{TN}^j$ denotes the set of electrified links in the transportation network served by bus j , η_{EV} is the parameter that models the relationship between EV load and traffic flow, and $\eta_{EV} \sum_{a \in \mathcal{E}_{TN}^j} f_a^{t,s}$ calculates the total EV charging load at bus j in hour t in scenario s . It is worth mentioning that although not considered in this chapter, optimally influencing the EV behaviors and route choices by introducing different congestion tolls or charging prices on these electrified links [87], which would in turn affects the scheduling and operation of MESSs as well as the distribution system, could be addressed in the future works.

5.3.3.2 Constraints for hybrid AC/DC microgrids

For each MG $m \in \mathcal{M}$, the power constraints are shown as follows:

$$p_{MG,m}^{t,s} + p_{A2D,m}^{t,s} = p_{DG,m}^{t,s} + \eta_{D2A,m} p_{D2A,m}^{t,s} - p_{L,AC,m}^{t,s}, \forall m, s, t \quad (5.30)$$

$$q_{DG,m}^{t,s} - q_{L,AC,m}^{t,s} = q_{MG,m}^{t,s}, \forall m, s, t \quad (5.31)$$

$$\begin{aligned} p_{SE,d,m}^{t,s} - p_{SE,c,m}^{t,s} + \eta_{A2D,m} p_{A2D,m}^{t,s} - p_{D2A,m}^{t,s} + p_{W,m}^{t,s} + p_{PV,m}^{t,s} \\ = p_{L,DC,m}^{t,s} + \sum_{\omega \in \Omega} (p_{ME,c,m}^{\omega,t,s} - p_{ME,d,m}^{\omega,t,s}), \forall m, \omega, s, t \end{aligned} \quad (5.32)$$

$$0 \leq p_{PV,m}^{t,s} \leq \tilde{p}_{PV,m}^{t,s}, \forall m, s, t \quad (5.33)$$

$$0 \leq p_{W,m}^{t,s} \leq \tilde{p}_{W,m}^{t,s}, \forall m, s, t \quad (5.34)$$

$$\underline{P}_{DG,m} \leq p_{DG,m}^{t,s} \leq \overline{P}_{DG,m}, \forall m, s, t \quad (5.35)$$

$$-\overline{Q}_{DG,m} \leq q_{DG,m}^{t,s} \leq \overline{Q}_{DG,m}, \forall m, s, t \quad (5.36)$$

$$-\text{RD}_m \leq p_{DG,m}^{t,s} - p_{DG,m}^{t-1,s} \leq \text{RU}_m, \forall m, s, t \quad (5.37)$$

$$-\overline{P}_{PCC,m} \leq p_{MG,m}^{t,s} \leq \overline{P}_{PCC,m}, \forall m, s, t \quad (5.38)$$

$$-\overline{Q}_{PCC,m} \leq q_{MG,m}^{t,s} \leq \overline{Q}_{PCC,m}, \forall m, s, t \quad (5.39)$$

$$0 \leq p_{D2A,m}^{t,s} \leq \overline{P}_{BIC,m}, \forall m, s, t \quad (5.40)$$

$$0 \leq p_{A2D,m}^{t,s} \leq \bar{P}_{BIC,m}, \forall m, s, t \quad (5.41)$$

$$p_{D2A,m}^{t,s} p_{A2D,m}^{t,s} = 0, \forall m, s, t \quad (5.42)$$

Constraints (5.30) and (5.31) are the active and reactive power balance equations on the AC bus of MG m , respectively, while (5.32) depicts the power balance on the DC bus of MG m . Constraints (5.33)-(5.34) indicate the actual utilized PV/wind power range. The active, reactive power capacities and the hourly ramp rate of DG in MG m are given in (5.35)-(5.37). Constraints (5.38)-(5.39) limits the power exchanges between MG m and distribution network through the PCC. Constraint (5.40)-(5.41) illustrate the BIC conversion capacity, while (5.42) ensures that power conversion on BIC is unidirectional.

5.3.3.3 Constraints for MESSs and SESSs

The energy status of MESSs in real-time operation formulated as follows.

$$\begin{aligned} e_{ME}^{\omega,t,s} &= e_{ME}^{\omega,t-1,s} + \sum_{m \in \mathcal{M}} \eta_{ME,c}^{\omega} p_{ME,c,m}^{\omega,t,s} \\ &\quad - \sum_{m \in \mathcal{M}} p_{ME,d,m}^{\omega,t,s} / \eta_{ME,d}^{\omega}, \forall \omega, s, t \end{aligned} \quad (5.43)$$

$$e_{SE,m}^{t,s} = e_{SE,m}^{t-1,s} + \eta_{ME,c} p_{SE,c,m}^{t,s} - p_{SE,d,m}^{t,s} / \eta_{SE,d}, \forall m, s, t \quad (5.44)$$

$$e_{DoD,ME}^{\omega,s} \leq e_{ME}^{\omega,t,s}, \forall \omega, s, t \quad (5.45)$$

$$e_{DoD,SE,m}^s \leq e_{SE,m}^{t,s}, \forall m, s, t \quad (5.46)$$

$$E_{ME,cap}^{\omega} \underline{E}_{ME}^{\omega} \leq e_{DoD,ME}^{\omega,s} \leq E_{ME,cap}^{\omega} \bar{E}_{ME}^{\omega}, \forall t \in \mathcal{T} \setminus \{T\}, \omega, s \quad (5.47)$$

$$E_{SE,cap}^m \underline{E}_{SE,m} \leq e_{DoD,SE,m}^s \leq E_{SE,cap}^m \bar{E}_{SE,m}, \forall m, s \quad (5.48)$$

$$E_{ME,cap}^{\omega} \underline{E}_{ME}^{\omega} \leq e_{ME}^{\omega,t,s} \leq E_{ME,cap}^{\omega} \bar{E}_{ME}^{\omega}, \forall \omega, s, t \quad (5.49)$$

$$p_{ME,c,m}^{\omega,t,s} p_{ME,d,m}^{\omega,t,s} = 0, \forall \omega, s, t \quad (5.50)$$

where constraints (5.43) and (5.44) describe the actual SOC of MESS ω and SESS m in scenario s , respectively. Constraints (5.45) and (5.46) indicate that the SOC of MESSs and SESSs during the operation should be higher than a desired lowest SOC to reduce the daily depth of discharge considering battery degradation [162], which is also mentioned in (5.19). Constraints (5.47)-(5.48) limit the range of the daily lowest SOC choices. Constraint (5.49) shows the MESS's SOC range, while constraint (5.50) ensures that MESSs can either perform charging or discharging in each hour. Note that for SESS, constraints (5.49)-(5.50) can be directly applied by using SESS variables.

5.3.4 Coupling constraints between the first-stage and second-stage variables

The coupling constraints between the first-stage and second-stage variables, i.e., $\mathbf{Dy}_s \leq \mathbf{h} - \mathbf{Tx}_s$ are shown as follows.

$$p_{\text{ME,d},m}^{\omega,t,s} - p_{\text{ME,c},m}^{\omega,t,s} \leq R_{\text{ME}}^{t,\omega} + P_{\text{ME,d},m}^{t,\omega} - P_{\text{ME,c},m}^{t,\omega}, \forall \omega, m, s, t \quad (5.51)$$

$$p_{\text{ME,c},m}^{\omega,t,s} - p_{\text{ME,d},m}^{\omega,t,s} \leq R_{\text{ME}}^{t,\omega} + P_{\text{ME,c},m}^{t,\omega} - P_{\text{ME,d},m}^{t,\omega}, \forall \omega, m, s, t \quad (5.52)$$

$$p_{\text{SE,d},m}^{t,s} - p_{\text{SE,c},m}^{t,s} \leq R_{\text{SE},m}^t + P_{\text{SE,d},m}^t - P_{\text{SE,c},m}^t, \forall m, s, t \quad (5.53)$$

$$p_{\text{SE,c},m}^{t,s} - p_{\text{SE,d},m}^{t,s} \leq R_{\text{SE},m}^t + P_{\text{SE,c},m}^t - P_{\text{SE,d},m}^t, \forall m, s, t \quad (5.54)$$

where constraints (5.51)-(5.54) limit the charging/discharging power range of each MESS and SESS, respectively.

Note that the bilinear constraints (5.42) and (5.50) can be omitted given that λ_{DA}^t , $c_{\text{DG},m}$, $c_{\text{SE},m}$, $c_{\text{ME},\omega}$, $c_{\text{W},m}$ and $c_{\text{PV},m}$ are positive. The proof is a direct extension of the result in [165] and is omitted here.

5.3.5 Nonanticipativity constraints

Since that the first-stage decision variables are made day-ahead thus are not allowed to depend on the realizations of the uncertain data, the nonanticipativity constraints are formulated as follows to ensure that the first-stage variables are scenario-independent and equal to each other in every scenario [166].

$$\zeta_{\hat{n}\check{n}}^{\omega,s} = \sum_{s \in \mathcal{S}} \pi_s \zeta_{\hat{n}\check{n}}^{\omega,s}, \forall (\hat{n}, \check{n}) \in \mathcal{A}_T^{\omega,s} \cup \mathcal{A}_P^{\omega,s}, \omega, s \quad (5.55)$$

$$P_{ME,c,m}^{\omega,t,s} = \sum_{s \in \mathcal{S}} \pi_s P_{ME,c,m}^{\omega,t,s}, \forall \omega, m, t, s \quad (5.56)$$

Similar nonanticipativity constraints for $P_{ME,d,m}^{\omega,t,s}$, $R_{ME,m}^{\omega,t,s}$, $I_{ME,c,(d)}^{\omega,t,s}$, $E_{ME}^{\omega,t,s}$, $P_{SE,c(d),m}^{t,s}$, $R_{SE,m}^{t,s}$, $I_{SE,c(d)}^{t,s}$ and $P_0^{t,s}$ can also be formulated as (5.56) and are not listed here to conserve space.

Note that $\bigcup_{s \in \mathcal{S}} \mathbf{X}_s \neq \emptyset$ since the parking arcs $\mathcal{A}_P^{\omega,s}$ are scenario-independent and are the same in each scenario. Therefore, introducing the nonanticipativity constraints will not lead to infeasibility.

The overall framework of the proposed stochastic management scheme of CDTNs is illustrated in Algorithm 1.

5.4 Case Study

In this section, case studies are performed to verify the effectiveness of the proposed two-stage stochastic management scheme for CDTNs with high penetration of VRE and MESSs serving as potential power conversion/transmission enhancements for hybrid AC/DC MGs with limited conversion capacities. The model is implemented using Python 3.6 and solved using an off-the-shelf solver Cplex 12.8.0. [128].

Algorithm 2: Stochastic management of CDTNs

- 1 **Input** the distribution network $\mathcal{G}_{\text{DN}} = (\mathcal{V}_{\text{DN}}, \mathcal{E}_{\text{DN}})$, the transportation network $\mathcal{G}_{\text{TN}} = (\mathcal{V}_{\text{TN}}, \mathcal{E}_{\text{TN}})$, MGs $\mathcal{M}$, depots $\mathcal{D}$ and MESSs Ω ;
- 2 Obtain scenario set $\mathcal{S}$ through scenario generation and reduction;
- 3 **for** $t \in \mathcal{T}$ **do**
- 4 **for** each scenario $s \in \mathcal{S}$ **do**
- 5 Obtain UE traffic flow $f_a^{t,s*}$ and the congested travel time $\tau_a^{t,s*}$ on each link $a \in \mathcal{E}_{\text{TN}}$ by solving the TAP (5.2);
- 6 **for** each MESS $\omega \in \Omega$ **do**
- 7 Calculate the congested travel time matrix $\mathfrak{W}_{\omega}^{t\omega,s}$ and the total travel time $\mathfrak{T}_{m_1 m_2, \omega}^{t\omega,s}, \forall m_1, m_2 \in \mathcal{M} \cup \mathcal{D}$ between all the pairs of MGs or depots;
- 8 Construct the ω^{th} layer of UE-TSN for scenario s ;
- 9 **end**
- 10 **end**
- 11 **end**
- 12 Solve the following optimization problem using CPLEX:

$$\begin{aligned}
 & \min \sum_{s \in \mathcal{S}} \pi_s [g(\mathbf{x}_s) + \mathcal{Q}(\mathbf{x}_s, \boldsymbol{\xi}_s)] \\
 & \text{s.t.} ((5.7)) - ((5.15)), ((5.20)) - ((5.56))
 \end{aligned} \tag{5.57}$$

- 13 **return** optimal first-stage solution $\mathbf{x}^*$.
-

5.4.1 Test System

Figure 5.3: CDTN test system based on the Sioux Falls transportation network.

Figure 5.4: Distribution system: a modified 33-bus test system.

For the simulations, a CDTN test system is proposed, which comprises a modified Sioux Falls transportation network that has electrified roads with WPT facilities, as shown in Fig.5.3, and a 33-bus distribution system [167], as illustrated in Fig.5.4. The transportation network parameters and the predicted daily O-D trip demands are obtained from [129], where the length of each road is tripled and the daily trip demands are scaled up 10 times, while the proportion of the trip demands in each hour is extracted from [168] and is shown in Fig. 5.5(a). The average speed of common vehicles is $V_{avg}^C = 60$ km/h. The traffic forecasting error is assumed to follow a normal distribution, where the mean value is the hourly predicted traffic demand and the standard deviation is set to be 10% of the predicted demand. There are one depot and four hybrid AC/DC MGs in the CDTN. The depot is located at #10 in the transportation network, while the MGs are located at nodes #2, #3, #19, #24 in the transportation network and bus #2, #4, #10, #30 in the distribution network, respectively. Moreover, these buses also serve the electrified roads connected to the corresponding MG, while the charging rate of unit traffic flow is $\eta = 0.01$ kW.

It is assumed that all the MGs are installed with a 500kW PV array, while MG #3 and #4 are installed with a 1MW DC WT. The normalized predicted PV profile, wholesale energy price from SDG&E [169] and predicted wind profile [19] are shown in Fig. 5.5(b). The local loads at each MG are of different types, i.e.,

Figure 5.5: Day-ahead data. (a) Hourly traffic demand. (b) Energy price and predicted PV/wind profile.

residential (R), commercial (C) and industrial (I). The predicted load profiles follow the load curves in [17]. The forecasting errors of PV/wind power and MG loads are represented using a normal distribution, where the mean value is the hourly predicted profile and the standard deviation is set to be 5% of the predicted profile. Monte Carlo simulation is used to generate 1000 random scenarios, which are then reduced to 10 scenarios using fast forward selection algorithm [159]. The unit transportation cost is \$20/h. The unit battery O&M

Table 5.2: Simulation Parameters

	MG #	1	2	3	4
	Load type	R	C	R	I
MGs	AC/DC peak load (MW)	0.5/0.5			
	$\bar{P}_{DG,m}, \underline{P}_{DG,m}$ (MW)	1/0.1			
	$\bar{Q}_{DG,m}$ (MVar)	0.8			
	RU_m, RD_m (MW/h)	0.3			
	$\bar{P}_{SE,c,m}, \bar{P}_{SE,d,m}$ (MW)	0.3	0.3	0.6	0.6
	$E_{SE, \text{cap}, m}$ (MWh)	1	1	2	2
	$\eta_{SE,c}, \eta_{SE,d}$	0.95/0.95			
	$\bar{P}_{BIC,m}$ (MW)	0.5			
	$\bar{P}_{PCC,m}$ (MW)	1			
	$\bar{Q}_{PCC,m}$ (MVar)	1			
	$\eta_{A2D,m}, \eta_{D2A,m}$	0.95			
	MESS #	1	2	3	4
MESSs	$\bar{P}_{ME,c}^\omega, \bar{P}_{ME,d}^\omega$ (MW)	0.3	0.3	0.6	0.6
	$E_{ME, \text{cap}}^\omega$ (MWh)	1	1	2	2
	$\eta_{ME,c}, \eta_{ME,d}$	0.95/0.95			
	V_{avg}^ω (km/h)	40	40	20	20

costs and the battery degradation costs for both MESSs and SESSs are 0.03 cents/kWh, following [170], while for both MESSs and SESSs are \$0.2/kWh. The generation costs of DG, PV and WT are \$0.25/kWh, \$0.0376/kWh and \$0.0366/kWh [171], and the initial, maximum and minimum SOC of SESSs and MESSs are set to be 50%, 90% and 10%, respectively. Other simulation parameters are given in Table 5.2.

Two case studies are performed to show the effectiveness of MESS mobility

for power/energy service provision and potential power conversion capacity enhancement, as well as the performance of the proposed UE-TSN model against uncertainties due to traffic congestions.

Case 1) There are only SESSs;

Case 2) SESSs are replaced with MESSs.

After solving problem (5.57) for the two cases, another 50 random scenarios are generated to test the performance of the day-ahead scheduling results under the possible realizations of the uncertainties other than the considered 1000 scenarios by re-solving the second-stage problem (5.19) for each test scenario while keeping $\mathbf{x}_s$ fixed at the obtained first-stage solutions, i.e., $\mathbf{x}_s = \mathbf{x}^*$. To avoid infeasible second-stage problems, slack variables representing involuntary load curtailments are added to the power balance constraints (5.21), (5.30), (5.32) and penalized with a large cost of \$9000/MWh [102] in the objective function (5.19).

It is worth mentioning that when implementing the day-ahead MESS routing plans in each test scenario, the actual MESS locations at each hour are adjusted according to the realization of traffic demands and traffic flows. For example, if a MESS is scheduled to travel from MG #2 to MG #4 during (14:00-15:00) in the first-stage results, while there are congestions between the two MGs in the test scenario. Then the MESS routing results in this test scenario are adjusted such that the MESS leaves MG #2 at 14:00 and reaches MG #4 at 16:00 due to the congestion delay. Moreover, all the scheduling plans for this MESS after 16:00 are also delayed.

5.4.2 Simulation Results

Table 5.3 compares the numerical results of the two cases in terms of operation cost and VRE curtailment.

Case 1) There are only SESSs: This case assumes that there are only SESSs installed at each MG. The overall average cost obtained with the 50 test samples is \$15251.02 and the total average VRE curtailment is 6.37 MWh. Without mobility, MGs can only store the surplus VRE generation at their local SESSs for future local use during peak load periods when the energy price is high. It can be observed that a considerable amount of VRE generation is curtailed due to the imbalance between the local generation and load demand, as well as the insufficient conversion capacities of BICs, which further restrict the power transmission from the VRE sources to other potential users through the distribution network.

Case 2) SESSs are replaced by MESSs with the same size: With the proposed stochastic management scheme for CDTNs, this case co-optimizes the routing, charging and discharging of MESSs considering uncertain traffic conditions, the generation dispatching of MGs and day-ahead energy procurement for the distribution network. The overall average cost and the average VRE curtailment are \$14448.41 and 3.34 MWh, respectively, which are reduced by 5.3% and 47.6% compared to Case 1. The main reason for this cost reduction is the additional power conversion-transmission capacity achieved by the MESSs through their traveling within the transportation network and charging/discharging at different MGs, which leads to a significant decrease in the curtailment of VRE generation as well as the power imported from the transmission system as reflected in the reduced first-stage cost. Another observation is that the second-stage cost achieved in Case 2 is higher than Case 1, this is due to the increases in VRE utilization, MESS charging/discharging behavior, and battery degradation, which will also

Table 5.3: Simulation Results

		First-stage	Second-stage		VRE	
		Cost (\$)	Cost (\$)		Curtailment (MWh)	
Case 1	8066.11	avg	7184.91	avg	6.37	
		max	8174.85	max	7.51	
		min	6821.75	min	5.24	
Case 2	7208.37	avg	7240.04	avg	3.34	
		max	8546.05	max	4.19	
		min	6989.36	min	2.77	

be discussed later. These results in the test scenarios indicate the effectiveness of the proposed stochastic management scheme for CDTNs with high penetration of VRE sources in reducing operational costs and VRE curtailments.

5.4.2.1 Effectiveness of MESS Mobility

Fig. 5.6 provides the charging and discharging schedules with respect to the MESS routing results in a randomly picked realization of the uncertainties s_1 in the 50 test scenarios, where location d denotes the depot while m_1 - m_4 represent MG #1-#4, respectively. The dashed lines with pentagrams and the right Y-axis represent MESSs' movements and their locations at specific time points according to the day-ahead (first-stage) routing results, while the red and blues bars together with the left Y-axis show the real-time charging and discharging active power of MESSs in each hour, respectively, after the realization of uncertainties.

Unlike SESSs, the mobility of MESSs is fully utilized to achieve energy transfer between the MGs with/without surplus VRE generation. For instance, MESS #1 initially travels from depot to MG #3 during (0:00-1:00) and stays there during

Figure 5.6: Scheduling results of MESSs in test scenario s_1 .

(1:00-3:00) to store the surplus wind generation. Then it leaves MG #3 at 3:00, which is because the MESSs with less mobility, i.e., MESS #3 and #4, arrive at MG #3 at 2:00 and are able to help storing the surplus VRE generation at MG #3 from then on. MESS #1 then travels for one time slot to reach MG #4 and stays there to further charge its battery during (4:00-5:00) considering it's SOC limit. Next, it moves to MG #2 to discharge and help support the peak loads at MG #2 during (6:00-11:00), which achieves energy transfer between the two MGs without requiring extra AC/DC conversion stages. Then, it moves back to MG #3 to perform local energy service. Finally, it returns to the depot after replenishing the energy to the initial level. Note that none of the MESSs travel between (16:00-20:00) and most of them perform discharging during (16:00-19:00), which are

due to the heavy traffic flows and congestions in the transportation network as well as the resulting EV charging load. Also, the energy transfer is mainly from MG #3, #4 to MG #1 and #2, the reason for this phenomenon is that the VRE energy cannot be fully consumed by the local loads at MGs or transmitted to the distribution network due to the capacity limitations of BICs. It can be seen that MESS #3 and #4 with larger sizes, lower speed and longer (2-hour) scheduling time-scale have fewer movements compared to MESS #1 and #2, this is because when the proposed model optimizes the MESSs' schedules, their differences in mobility and time-scale preference are also accounted for. Another observation is that MESSs can also serve as SESSs. For example, MESS #1 stays at MG #3 during (13:00-23:00), where it stores the surplus local VRE generation when the MG load is low and discharges during the hours with high load and high energy price, i.e., (17:00-21:00). It is worth mentioning that the travel time for MESS #2 from MG #2 to MG #4 is two hours in (8:00-10:00), which is longer compared to the time in (6:00-7:00) due to the heavy traffic during (8:00-10:00), as also shown in Fig. 5.5(a). However, this trip with congestion delay is actually in accordance with the obtained first-stage solution, i.e., the potential congestion delays are already considered by the proposed scheme and MESS #2 is intentionally scheduled to travel during the peak hours, since it's more beneficial to the whole system.

Fig. 5.7 shows the SOC of the MESSs during the operation in the test scenario. It can be observed that the daily depth of discharge of MESS #1 and #2 is much higher than that of MESS #3 and #4. This observation mainly has two reasons. First of all, the loads during hours (8:00-13:00) at MG #2 and the peak loads at MG #1, #3, #4 and in the distribution network during (16:00-21:00) can be satisfactorily supported by the local generation and MESSs. Secondly, due to the higher mobility of MESS #1, #2 with smaller size and higher average speed, they

Figure 5.7: SOC of MESSs in test scenario s_1 .

are more flexible and able to perform more charging and discharging at different MGs. Therefore, MESS #1 and #2 choose to bear higher daily depth of discharge to achieve more energy transfer among the MGs while MESS #3 and #4 keep their SOC above 50% to reduce battery degradation.

Fig. 5.8 depicts the real-time operation of hybrid AC/DC MGs #3 with high penetration of VRE sources and MESSs, where p_L denotes the total local loads. It is noted that in most of the hours, the BIC is operating with its full capacity to convert the VRE generation into AC power, while the unconverted DC energy is used to supply the local DC load or charged into the MESSs. However, VRE generation curtailments are still observed even though MESSs are introduced into the system operation to store the surplus energy due to the capacity and mobility limitations of MESSs. The curtailments at the first and last hour are due to the traveling of the MESSs between the depot and the MG, while the curtailments during (8:00-13:00) are mainly because the energy stored in MESS #3 can already fully support the loads in the system (see Fig. 5.6, Fig. 5.7), which has been discussed before. Therefore it is no longer beneficial for MESS #3 to store more surplus energy, which will in turn introduce extra generation cost. Nevertheless, the curtailments are significantly reduced compared to Case 1, when there are only SESSs in each MG.

Figure 5.8: Second-stage results of MG #3 in test scenario s_1 .

$$p_L = p_{L,AC} + p_{L,DC}.$$

All these results verify the effectiveness of the proposed UE-TSN-based stochastic management scheme in utilizing the MESS mobility and coordinating the operation of MESSs, hybrid AC/DC MGs and distribution network, while considering various traffic conditions.

5.4.2.2 Effectiveness of the UE-TSN Model

To elaborate on the effectiveness of the UE-TSN model in dealing with uncertain traffic demands and the resulting congestion delays, different TSN models are studied and tested in Case 2 with the 50 test scenarios, including the TSN model without considering traffic congestions (denoted by N-TSN), the TSN model with fixed delays on each road (F-TSN) [20] according to the hourly traffic pattern in Fig. 5.5(a) and the proposed UE-TSN model.

The comparison of the results obtained with these models in terms of the objective value and MESS scheduling accuracy, i.e., the number of MESSs' successful

Table 5.4: Comparison of TSN Models

	N-TSN	F-TSN	UE-TSN
Objective Value (\$)	14576.85	14502.34	14448.41
MESS Scheduling Accuracy (%)	94.25	83.33	100

arrivals at their destinations according to the day-ahead scheduling plan, is given in Table 5.4. It can be seen that the proposed UE-TSN model achieves 100% scheduling accuracy and the lowest cost compared to the other models, which indicates that the model can address the distribution of traffic congestions and their uncertainties. N-TSN model achieves the highest cost and the scheduling accuracy is 94.25%. Since no traffic congestions are considered, MESSs are also scheduled to travel during (16:00-18:00), i.e., the peak hours in the transportation network, where most of the inaccurate vehicle schedules are observed. F-TSN obtains the worst scheduling accuracy, where the inaccurate schedules are mainly between MG #1, #2 and MG #2, #4 during (7:00-9:00). This is because although the TSN model with fixed congestion delays can, to some extent, capture the congestion distribution with regard to time, it fails to describe the congestions on different roads within each hour and their uncertain nature. The congestions mainly exist on the roads in the central area, e.g., (9,10), (10,15), (10,11) during (7:00-9:00) while the congestions between MG #1, #2 and MG #2, #4 are not so heavy. F-TSN model overestimates the congestion delays so the MESSs arrive at their destination earlier than the schedule. Still, these early arrivals result in less suboptimality, compared to the delayed arrivals in N-TSN.

It is worth mentioning that although in this case study, the inaccurate MESS schedules only lead to insignificant increases in the objective values, severer results could occur if MESSs are scheduled for emergencies [15], [17].

Figure 5.9: Impact of total BIC capacity on the overall cost.

5.4.2.3 Sensitivity Analysis

As also mentioned in Section 5.1, connecting multiple BICs in parallel is usually adopted to improve the capacity, so the total BIC capacity in an MG depends on the number of BICs and their individual capacities. Fig. 5.9 shows the relationship between the overall expected cost and the total BIC capacity in each MG. Note that when there are no ESSs and the BIC capacity is smaller than 500 kW at each MG, the cost increases dramatically due to heavy load curtailments, since the DC loads at each MG cannot be fully served during peak hours. Also, when the BIC capacity is larger than 700 kW, the mobility of MESSs can no longer bring economic benefits to the system operation. This is because when MGs have enough power conversion capacities, they can achieve optimal utilization of local generation from VRE sources with SESSs. It is more beneficial for MESSs to stay at each MG and serve as SESSs for local energy scheduling due to their transportation costs. Still, it is observed that with MESSs, the whole system can achieve similar objective values while smaller BIC capacities are required.

Fig. 5.10 depicts the impacts of the number of MESSs that have the same specifications as MESS #1 shown in Table 5.2. It is observed that the overall ex-

Figure 5.10: Impact of number of MESSs on the overall cost and VRE curtailment.

pected cost and the VRE curtailment decrease as the number of MESSs increases. However, the benefits brought by each additional MESSs also become smaller as the number of MESSs increases. When there are more than 11 MESSs in the whole system, the cost and VRE curtailment no longer decrease. This is because the energy transfer capability and operational flexibility introduced by the MESSs in the system are saturated, additional MESSs cannot further improve the scheduling plan. Note that the VRE curtailment is not zeros, which is mainly due to the curtailments during the hours that MESSs travel from/to the depot, as also indicated in Fig. 5.8.

5.4.3 Cost-Benefit Analysis

Following [102], a cost-benefit analysis is performed to study the economic feasibility of utilizing MESSs in daily operations. Besides the numerical results presented previously (denoted by D0), simulations are performed in Case 1 and Case 2 on additional four typical days D1-D4 in a year, where D1, D4 are the days in spring and winter with weak winds, while D2, D3 are the days in summer and autumn with strong winds, respectively. The seasonal price and predicted

Table 5.5: Summary of Expected Cost Savings (\$)

	D0	D1	D2	D3	D4	Yearly Sum
SESS	859.9	1241.4	956.2	1447.4	1082.5	407880.6
MESS	1662.6	1445.1	2314.4	3107.1	1243.2	713385.2

PV, load profile are based on [172]–[174], respectively, while the typical daily wind data are obtained from one of the wind farms in the Eastern U.S. [175]. For simplicity, the predicted travel demands are assumed to be the same in the four days, while other simulation parameters also remain the same as in Section 5.4.1.

The summary of the expected cost savings achieved by the SESSs/MESSs in D0-D5 compared to the system with no ESSs is shown in Table 5.5, where the yearly sum is calculated based on the expected daily savings in D0-D5.

For the battery life, it is assumed that the depth of discharge in each discharging cycle has little impact on the lifetime. Since the SOC of each SESS/MESS at the end of the operating horizon returns to the initial value, the number of daily discharging cycles for MESS ω can be calculated as follows, while the number of daily discharging cycles for SESSs can be obtained similarly.

$$DCY_{ME}^{\omega} = \sum_{s \in S} \pi_s \frac{\sum_{t \in T} \sum_{m \in \mathcal{M}} p_{ME,d,m}^{t,s} / \eta_{ME,d}^{\omega}}{E_{ME,cap}^{\omega} (\bar{E}_{ME}^{\omega} - \underline{E}_{ME}^{\omega})}, \forall \omega \quad (5.58)$$

The results are given in Table 5.6. Note that since there are multiple MESSs/SESSs, the largest number of discharging cycles among all the MESSs/SESSs is depicted here for each day and used to calculate the battery lifetime of the whole system.

Assume that both MESSs and SESSs are using lithium-ion batteries with a cycle life of 5475 cycles [102]. Therefore, the shortest expected lifetime of SESSs/MESSs is $LT_{SE} = 5475/408.8 = 13.4$ years and $LT_{ME} = 5475/472.1 = 11.6$ years, respectively. Considering that MESSs have stricter technical requirements than

Table 5.6: Expected Discharging Cycles

	D0	D1	D2	D3	D4	Yearly Sum
SESS	1.15	1.09	1.04	1.03	1.29	408.8
MESS	1.76	0.96	1.49	1.63	0.79	472.1

SESSs due to their mobility, which makes MESSs more costly, the battery capital cost, power conversion system cost, balance of plant cost, and construction and commissioning cost for MESSs are set to be \$323/kWh, \$470/kW, \$120/kW and \$110/kWh, respectively, while these costs for SESSs are \$223/kWh, \$230/kW, \$80/kW and \$92/kWh, respectively, according to [170]. The truck and container cost for one MESS is assumed to be \$60,000. So the total capital costs for the SESSs in Case 1 CC_{SE} and MESSs in Case 2 CC_{ME} are \$2,448,000 and \$3,900,000, respectively. The fixed yearly O&M cost for one MESS is assumed to be $OM_{ME} = \$30,000$ per year including the ESS and the truck, while the cost for a SESS is $OM_{SE} = \$18,000$ per year.

Assume that the yearly cost savings achieved by MESSs CS_{ME} and SESSs CS_{SE} remain the same in each year and the discount factor is 6% per year, Based on the obtained lifetime and yearly cost savings, the net present values of the cost savings for SESSs and MESSs during their lifetime, i.e., NPV_{SE} and NPV_{ME} , can be calculated as follows.

$$NPV_{ME(SE)} = \sum_{t \in LT_{ME(SE)}} \frac{CS_{ME(SE)} - OM_{ME(SE)}}{(1 + 0.06)^t} - CC_{ME(SE)} \quad (5.59)$$

where the obtained NPV_{ME} and NPV_{SE} are \$547,097 and \$270,200.

It is worth mentioning that although SESSs are replaced by MESSs in the case studies to better demonstrate the effectiveness of the MESS mobility, this chapter does not claim by any means that MESSs can fully replace SESSs in real-world applications, considering that SESSs can respond within seconds to contribute to

the improvements of power system stability [137], while it takes hours for MESSs to travel. Another observation is that MESSs are less efficient and beneficial during the days with low VRE generation, e.g., D1 and D4, which also reduce the value of MESSs. A practical way to address these issues is introducing both SESSs and MESSs into the system, where SESSs perform local energy scheduling and help improving the stability of the distribution system, while MESSs are mainly scheduled for energy transferring between the MGs during the days with surplus VRE generation. When there are two 0.3-MW/1-MWh MESSs and two 0.6-MW/2-MWh SESSs in the test system, the net present value of the cost savings is \$928,900.

These cost-benefit results indicate that MESSs are more beneficial to the test system than SESSs in this case study. However, these numerical results only apply to this specific test system that includes hybrid AC/DC MGs with high penetration of VRE sources and insufficient energy conversion capacities. For the systems with less VRE penetration or enough BIC capacities, MESSs are likely to have similar or even worse performances compared to SESSs, due to their higher capital and O&M costs. Therefore, economic feasibility analyses are still necessary for specific systems.

For the potential real-world applications, MESSs and the proposed scheme could be especially applicable for the systems with rich and high penetration of VRE sources and certain demands for the integration of MESSs. For example, the areas located on the east coast of the U.S. are rich in wind power but also have to bear a higher risk of natural disasters such as hurricanes. These cities and the system operators would be more interested in integrating MESSs into the system operation in preparation for the natural disasters since they can bring significant benefits in response to the extreme events [15], [16]. Meanwhile, when there are no forecasted upcoming extreme events, e.g., hurricanes, and the MESSs are not

in use, with the proposed framework, the CDTN operator could still make full use of these idle MESSs to further enhance the conversion capabilities of MGs and reduce possible VRE curtailments under normal conditions.

5.5 Summary

This chapter proposes a two-stage stochastic management scheme to minimize the total system cost by coordinating the operation of MESSs, hybrid AC/DC MGs with high VRE penetration and CDTNs while considering the uncertainties in both transportation and distribution networks. A more accurate day-ahead vehicle scheduling of MESSs is achieved by using the proposed UE-based multi-layer multi-timescale TSN model, which is constructed according to the results of an hourly scenario-based TAP model from the transportation research filed and incorporates the impacts of the uncertain daily traffic and the resulting congestions within the transportation network on the scheduling and operation of MESSs. The real-time charging/discharging behaviors of MESSs, the actual utilized VRE generation, the output of DGs and power conversions through the BICs in each MGs are adjusted in accordance with the realized uncertain factors. Two cases are studied to verify the effectiveness of MESSs and their mobility to serve as potential power conversion enhancements for MGs and the results indicate that MESSs can achieve reduced costs and VRE curtailments in the 50 test scenarios. The comparison of different TSN models demonstrates that the proposed UE-TSN model could achieve a higher MESS scheduling accuracy under traffic uncertainties. A cost-benefit analysis of MESSs is also provided to show that MESSs are cost-effective for the test system.

Chapter 6

Conclusions and Future Works

The summary and overall conclusion of this thesis are presented in this chapter. The thesis begins with the reviews on the related research works including transportation electrification, the emerging types of mobile energy storage resources and the couplings between power systems and transportation systems brought by these mobile resources. Then the operating models and management schemes for the EV batteries under battery leasing and swapping mode, and the MESSs in CDTNs are proposed. Simulations are performed and the results are carefully analysed, which highlight the effectiveness of the proposed models, management schemes and the mobility of mobile energy storage resources for system operational efficiency and flexibility improvements. Also, future works are presented as well.

6.1 Conclusions

This thesis developed a novel holistic management framework for the emerging mobile energy storage resources to improve system operational efficiency and flexibility. The main results are summarized as follows.

In Chapter 1, the background of developing the novel holistic management framework for the emerging potential mobile energy storage resources has been introduced. The motivation and main contributions of this research work are presented as well.

Chapter 2 reviewed the related literature. The background of transportation electrification has been introduced, including the upcoming energy and environmental challenges, the current EV deployment status and their advantages. Then, with the rising trend of transportation electrification, the emerging mobile energy storage resources have been introduced, which include EVs under plug-in charging mode, EV batteries under battery swapping mode and truck-mounted MESSs, and the related state-of-the-art publications are reviewed. Finally, the potential couplings between power systems and transportation systems brought by the mobile energy storage resources have been introduced and the related literature have also been reviewed.

In Chapter 3, to utilize the mobility of EV batteries under battery leasing and swapping mode, a CLSC based BSCS model is proposed. A network calculus based service model for BSSs and a TSN-based battery logistics model are introduced. Based on these models, the charging and discharging of batteries and the battery logistics are optimally scheduled to maximize the revenue of the BSCS while guaranteeing the quality of battery swapping service provided to EVs at each BSS. The operation management problem is formulated as a

MILP problem, which is solved in a distributed way by decomposing the BSCS into small subsystems and applying RP-ADMM. It should be noted that the single BSCS model proposed in this chapter is more suitable for small-scale systems with less than 10 stations. For large-scale systems which may consist of hundreds of BCSs/BSSs, the model may no longer be applicable due to the differences in EV user behaviors, local transportation network structures and local power network configurations in different geographical regions. Also, the management problem may take days to be solved, which makes the model computationally intractable due to the virtual nodes introduced by the TSN model. Still, as the simulation results indicated, when dealing with small-scale systems, the proposed CLSC-TSN based BSCS model is practical and the RP-ADMM can obtain heuristic solutions with small optimality losses, good feasibilities and less computation time, thus achieving the distributed management of BSSs, BCSs and the battery logistic while ensuring the quality of battery swapping service at BSSs. Moreover, the proposed model bridges the gap in the combined operation of BCSs, BSSs and the battery logistics system and can serve as a reference for the future BSCS-related works.

Chapter 4 extends the single BSCS model introduced in Chapter 3 to a CLSCN based MBSCN model, which can achieve further collaborative operations, service provisions of BSCSs in different regions and the mobile energy resource sharing among them, when compared to the single BSCS model. The two-level network-wise battery logistics is modeled based on a multi-layer TSN technique, which is also far more efficient than the single-layer TSN model. For example, when considering a MBSCN with two BSCSs, the total number of arc/binary variables introduced using the multi-layer TSN model is reduced by 50% compared to the single TSN model. The proposed distributionally robust chance-constrained BSS service model can address the EV uncertainties without requir-

ing assumptions on the probability distributions and large number of historical data. Case studies validate the effectiveness of the model and the reliability of the BSS service model, where the results show that with battery mobility, is more efficient, flexible when dealing with multiple BSCSs, and can bring potential congestion solutions to distribution systems. However, it is worth mentioning that the results could vary depending on the actual parameters in each specific system. The MBSCN model could witness similar results as when the BSCSs work independently under certain conditions. For example, when all the BSCSs have high EV battery demands, neither of them has surplus charging resources to perform charging task scheduling between different regions. Moreover, during the days when the BSCSs have similar locational energy prices, the MBSCN model could also be less beneficial.

Chapter 5 presents a two-stage stochastic management scheme to minimize the total system cost by coordinating the operation of MESSs, hybrid AC/DC MGs with high VRE penetration and CDTNs while considering the uncertainties in both transportation and distribution networks. The proposed UE-based multi-layer multi-timescale TSN model can achieve a more accurate day-ahead vehicle scheduling of MESSs. Although the UE-TSN model sometimes may fail to accurately describe the temporal-spatial behavior of the MESS when there are heavy congestions between the MGs, since the actual congestions could be mitigated in a later time slot, it can still help to identify the possible spatial and temporal distribution of these congestions and contribute to the scheduling and operation of MESSs while considering the impacts of the uncertain daily traffic and the resulting congestions within the transportation network. Two cases are studied to verify the effectiveness of MESSs and their mobility to serve as potential power conversion enhancements for MGs and the results indicate that MESSs can achieve reduced costs and VRE curtailments in the 50 test scenarios. The

comparison of different TSN models demonstrates that the proposed UE-TSN model could achieve a higher MESS scheduling accuracy under traffic uncertainties. A cost-benefit analysis of MESSs is also provided to show that MESSs are cost-effective for the test system. It is worth mentioning that the proposed scheme is more suitable for the systems with rich and high penetration of VRE sources and certain demands for the integration of MESSs. For example, the areas located on the east coast of the U.S. are rich in wind power but also have to bear a higher risk of natural disasters such as hurricanes. These cities and the system operators would be more interested in integrating MESSs into the system operation in preparation for the natural disasters since they can bring significant benefits in response to the extreme events. Meanwhile, when there are no foreseeable upcoming extreme events, e.g., hurricanes, and the MESSs are not in use, with the proposed framework, the CDTN operator could still make full use of these idle MESSs to further enhance the conversion capabilities of MGs and reduce possible VRE curtailments under normal conditions. For the systems with smaller installed VRE generation capacities or surplus conversion capabilities, adopting MESSs in normal operations could be less or even not beneficial.

6.2 Recommendations for Further Research

This thesis developed a novel holistic management framework for the emerging mobile energy storage resources to improve system operational efficiency and flexibility. Considering the assumptions and limitations of the models proposed in this thesis, further investigation can be conducted in the following potential areas.

6.2.1 Optimal Bidding Strategy for BCSs

In this thesis, BCSs are assumed to act as price takers, i.e., the optimization process depends on static pricing signals or price scenarios. However, in real-world applications, their biddings could lead to a different market clearing price, which will then affect their actual costs/revenues. Therefore, a market clearing model can be further included to consider the market influence of BCSs. A possible solution is to adopt a two-stage optimization framework, where the management decision-making process for BSCSs and the market clearing are conducted iteratively. The iterations terminate when a predetermined tolerance is reached.

6.2.2 Incorporating More Accurate TAP Models

In Chapter 5 of this thesis, a static hourly TAP model is adopted considering its merits including low computational cost, its ability to solve large-scale problems and to converge to precise equilibriums, while the traffic UE pattern during the whole scheduling horizon is obtained by solving this TAP model sequentially. However, this approach can only obtain a very rough traffic flow distribution in each hour and is unable to yield precise traffic flows along each road with a time resolution in minutes. The roughly estimated traffic flow distribution could still lead to inaccurate MESS routing and scheduling plans.

Dynamic traffic assignment (DTA) model [156] is another powerful tool to study and estimate traffic conditions with the ability to obtain more precise hourly traffic flow distributions and the resulting congestions. Further extending the proposed UE-TSN to incorporate DTA models is promising. Moreover, the emerging machine learning models [157] can also be adopted in the future researches.

6.2.3 Impacts on Transportation Systems

In this thesis, the couplings between power systems and transportation systems considered by the proposed models and schemes are mainly represented by the impacts of transportation systems on the scheduling and management of mobile energy storage resources, which will then affect power system operation. In Chapter 3 and Chapter 4, battery logistics, i.e., the logistics truck fleets and batteries, is mainly managed considering different local transportation network structures. In Chapter 5, besides the transportation network structure, MESSs are routed and scheduled in further consideration of the traffic flows of conventional vehicles and the resulting congestion effects. In the future works, the impacts of the routing and scheduling of mobile energy storage resources on transportation systems can be studied and included. For example, the mobility of batteries introduced by battery logistics brings timely changes to the battery inventory status in each BSSs and BCSs, which could lead to the changes of EV arrivals and battery demands at these stations, as well as different EV traffic flow distributions. This could in turn affect the routing and scheduling of logistics truck fleets. Moreover, with the envisioned deployments of electrified roads with wireless charging abilities that allows EVs to be charged while traveling on these roads, the power system operator could influence EVs' temporal-spatial behaviours in the transportation system by setting different tolls on these roads, which would in turn bring impacts on MESSs' routing and scheduling, and ultimately affect power system operation. These interactions and couplings among mobile energy storage resources, power systems and transportation systems are intriguing for future researches.

List of Publications

Journal Publications

- [1]. **X. Liu**, T. Zhao, S. Yao, P. Wang, C. B. Soh, "Distributed Operation Management of Battery Swapping-Charging Systems", *IEEE Trans. Smart Grid*, vol.10, no.5, pp. 5320-5333, Nov. 2018.
- [2]. **X. Liu**, C. B. Soh, S. Yao, H. Zhang, T. Zhao, "Operation Management of Multi-Region Battery Swapping-Charging Networks for Electrified Public Transportation Systems", *IEEE Trans. Transportation Electrification*, vol.6, no.3, pp. 1013-1025, Jun. 2020.
- [3]. **X. Liu**, C. B. Soh, T. Zhao, P. Wang, "Stochastic Scheduling of Mobile Energy Storage in Coupled Distribution and Transportation Networks for Conversion Capacity Enhancement", *IEEE Trans. Smart Grid*, vol.12, no.1, pp.117-130, Jan. 2021.
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- [5]. H. Zhang, P. Wang, S. Yao, **X. Liu**, T. Zhao, "Resilience Assessment of Interdependent Energy Systems under Hurricanes", *IEEE Transactions on Power Systems*, Early Access, 2019.
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submitted to IEEE Transactions on Power Systems.

- [7]. S. Yao, P. Wang, T. Zhao, **X. Liu**, H. Zhang, J. Gu, "Resilient Service Restoration in Internet Data Centers Considering Mobile Energy Storage Fleets: A Deep Reinforcement Learning Approach", to be submitted.

Conference Proceedings

- [1]. **X. Liu**, T. Zhao, P. Wang and C. B. Soh, "Quality of Service Oriented Impact Analysis on Power Systems Considering EV Dynamics", *2018 IEEE Power and Energy Society General Meeting*, 2018.
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