Multi-Stage Day-Ahead Scheduling for Building-Integrated Large-Scale Electrical Vehicle Charging Station

by

Van Quyen NGO

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Ordonnancement de Recharge en Plusieurs Étapes de La Veille Pour La Grande Échelle Station De Véhicules Électriques Intégrée À Bâtiment

Van Quyen NGO

RÉSUMÉ

Afin de répondre à la croissance rapide de la demande de recharge des véhicules électriques (VE) pendant la dernière décennie, les espaces de stationnement des bâtiments ont été transformés en stations de recharge des VE. Cette solution permet de contrôler la demande de recharge des VE ajoutée au micro-réseau du bâtiment d'une manière coopérative pour éviter des effets négatifs sur le bâtiment lui-même ainsi que sur le réseau d'électricité. Dans ce mémoire, nous optimisons un micro-réseau de charge de bâtiment (BCM) équipé d'un système solaire PV et d'un système de stockage d'énergie stationnaire en batterie. Ce modèle proposé a pour but de: 1) minimiser les coûts d'exploitation, 2) contribuer à la stabilité du marché d'énergie en anticipant les demandes de recharge des VEs et de les communiquer avec les fournisseurs la veille de l'opération; et 3) équilibrer la production PV, compte tenu de la limitation du réseau d'électricité, de la limite de capacité du BESS, et des demandes stochastiques des VEs, de la production PV et du prix de l'électricité. Pour résoudre ce problème d'optimisation, nous proposons un algorithme d'ordonnancement de la charge/décharge, qui se compose de trois étapes principales: 1) planifier la recharge une heure avant le jour d'exploitation; 2) résoudre le modèle d'optimisation toutes les 15 minutes en s'adaptant aux erreurs de prévision de la demande des VE; 3) contrôler la recharge des VEs en temps réel. Une modélisation stochastique basée sur la méthode de simulation de Monte Carlo est proposée pour capturer la nature stochastique des comportements des VE. Pour réduire la complexité de calcul résultant d'un grand nombre des VEs, nous appliquons une technique d'agrégation basée sur des clusters pour diviser les flottes de VE en trois groupes en fonction de leur laxité et de leur capacité de décharge, ce qui peut garantir une grande satisfaction aux utilisateurs de VE. Enfin, un algorithme d'ajustement en temps réel est implémenté pour s'adapter au changement de puissance. L'algorithme proposé a été validé à travers de plusieurs expérimentations dans des BCMs de bureau, résidentiels et centres commerciaux en utilisant des données réelles et simulées. Les résultats expérimentaux montrent une réduction de 4,42% du coût moyen d'exploitation tout en maintenant la satisfaction du client à plus de 97% grâce à l'adaptation en temps réel et au nouveau modèle d'agrégation basé sur le regroupement.

Mots-clés: Micro-réseau de bâtiment, BESS, PV solaire, MILP, station de charge EV, V2G.

Multi-Stage Day-Ahead Scheduling for Building-Integrated Large-scale EV Charging Station

Van Quyen NGO

ABSTRACT

Electric vehicle (EV) fleets have grown significantly over the past decade. To meet the increase in EV charging demand, one scenario considered is to convert parking spaces in functional buildings into EV charging stations, so that the large-scale EV charging demand is added to the building microgrid in a cooperatively controlled manner to avoid the negative effect on the building itself as well as on the main grid. In this work, we consider a building charging microgrid (BCM) system equipped with a solar photovoltaic (PV) system and a stationary battery-based energy storage system (BESS), which aims to achieve three objectives: 1) minimize their operating cost, 2) commit to acting as a well-behaved load in the day-ahead electricity market by flattening their power profile and following their day-ahead schedule; and 3) balance PV generation, given the limitation of the main grid, the capacity/power limit of the BESS, and the stochastic behavior of the EV parking pattern, building load, PV generation, and electricity price. The biggest challenges faced by BCM operators are the highly stochastic behavior of the EV parking models, the high computational complexity, and the dynamics of EV load. To address these challenges, we propose a multi-stage charge/discharge scheduling framework, which consists of three main steps: 1) a day-ahead scheduling optimisation is solved one hour in advance of the operating day; 2) an intra-hour rolling horizon optimization is solved every 15 minutes adapting to the forecast errors of EV demand; 3) a real-time heuristic control and adjustment algorithm is based on the laxity and stage of charge (SOC) of the EVs and their real-time flexibility assessment. A stochastic modeling approach for EV fleets adopting the Monte Carlo simulation method assuming known probability distribution of the arrival time, parking duration, initial SOC, battery capacity, and diversity of the charging rate is proposed to capture the stochastic nature of EV behaviors. To reduce the computational complexity related to large-scale EV fleets, a novel cluster-based aggregation technique which divides EV fleets into three clusters based on their laxity and discharge capability is applied to guarantee high satisfaction of EV users. Finally, a real-time adjustment algorithm is applied to track the day-ahead power schedule. The performance of the proposed algorithm is measured through extensive simulations in office, residential and commercial BCMs using both real and simulated data. Our simulation results show a 4.42% reduction of operating cost in average while maintaining customer satisfaction at over 97% thanks to the real-time electric vehicle flexibility assessment and the new cluster-based aggregation model.

Keywords: Building Microgrid, BESS, solar PV, MILP, EV charging station, Vehicle-to-grid, V2G

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BESS	Battery Energy Storage System
DER	Distributed Energy Resource
DSOs	Distribution System Operators
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
MG	Microgrid
BCM	Building Charging Microgrid System
BCMOs	Building Charging Microgrid System operators
MILP	Mixed Integer Linear Programming
MIQP	Mixed Integer Quadratic Programming
MPC	Model Predictive Control
PSO	Particle Swarm Optimization
PV	Photovoltaic
PEVs	Plug-in electric vehicles
PCC	Point of Common Coupling
RES	Renewable Energy Sources
SOC	State of Charge
TOU	Time-of-Use
V2B	Vehicle to Building
V2G	Vehicle to Grid
MCS	Monte Carlo Simulation

INTRODUCTION

Context and Motivation

Worldwide, recently increasing electricity needs from the transportation sector with a tremendous number of new Electric Vehicles (EVs) have been added into the aging power system, especially in big cities. A possible scenario is to equip parking spaces in functional buildings with EV service equipment so that EV fleets can get charged when they are parked. Such scenario results in large-scale EV charging demand added to the building microgrid, which requires a cooperative control to avoid the negative effect on the building itself as well as on the main grid. Without coordination between individual EVs, charging demand surges in specific points in the power system may increase the risks of overload, voltage deviation, frequency fluctuation, and harmonic issues (Deb, Kalita, & Mahanta, 2017). Fortunately, typical cars are parked for most of the time, e.g., the typical UK car is parked 96.5% of the time based on UK national travel survey (Bates & Leibling, 2012). Thus, they potentially provide a wide range of flexibility in energy capacity, power demand, and time for both active and passive demand-side response services if properly coordinated.

However, an individual EV capacity is too small to directly coordinate with the utility. One potential solution is to aggregate a large-scale EV fleet through an aggregator, e.g., building microgrid operators (Deng et al., 2020; Sadeghianpourhamami, Refa, Strobbe, & Develder, 2018). An aggregator plays as a broker in the middle to coordinate the fleets of individual EVs and the utility, while earning their own benefits. At the aggregators point of view, both utility grid and EV's users are their customers. The aggregators can benefit from the arbitrage opportunities of purchasing wholesale electricity from the utility then selling to EVs or even selling back to the utility for providing ancillary services. However, the main goal of the aggregator is to satisfy EV user's requests while meeting resources limits such as power exchange with the utility and stationary energy storage capacity, and consider many uncertainties, such as stochastic EV's arrival/departure time and demand, dynamic electricity prices, building loads variation. In order to reduce the stress on the main grid, and in the same time to provide 'green' energy to EVs, and to gain more benefit, an aggregator may incorporate a renewable energy generation system, i.e., solar photovoltaic (PV), onto the building roof or parking station canopy. However, a renewable generator adds some levels of uncertainty to the system. Therefore, the aggregator should equip a stationary battery-based energy storage system (BESS) to compensate this uncertainty.

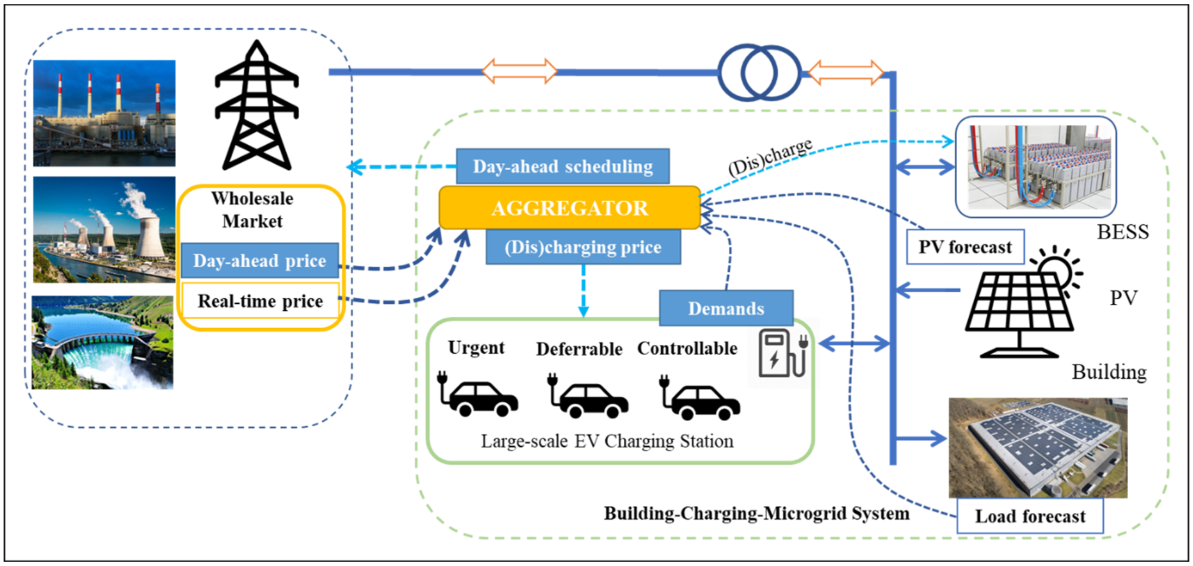

Figure 0.1 Large-scale EV charging station operating in cooperation with PV-building and wholesale energy market

The abovementioned building aggregator is called building charging microgrid (BCM) (Figure 0.1). Although the BCM is equipped with a large-scale EV charging station (EVCS), its capacity generally is not enough to provide ancillary services such as voltage and frequency regulation or regulation reserve to the main grid. Instead, BCM operators (BCMOs), by participating in the day-ahead energy market, aim at minimizing their total operating cost, flattening their power curve at the point of common coupling (PCC), and balancing their own PV power output, while satisfying with the grid constraints, BESS's power/capacity limits, and fulfilling the demand of EV users. To this end, BCMOs face several challenges as follows:

- The uncertainties in the charge/discharge scheduling problem due to the intermittence of EV's behaviors, such as driving pattern, arrival time, departure time, initial energy level, battery capacity, charging rate limit, PV generation, building load, and electricity price.

- The high computational complexity due to the increasing number of EVs in a large-scale charging station.
- The difficulty in evaluating EV flexibility prior to the operating time for providing proper adjustment in real-time.

In the literature, these challenges have been studied extensively. Specifically, to deal with uncertain EV's behaviors, researchers usually tried to capture the stochastic behavior of EVs using a probabilistic distribution function of arrival/departure time, parking duration, and demand (Islam, Mithulananthan, & Hung, 2018; Šepetanc & Pandžić, 2021). The probabilistic model for EV charging demand has been used widely. It relies heavily on the statistical data, which is usually taken from the National Household Travel Survey (NHTS) based on internal combustion engine vehicles in general (Almutairi & Alyami, 2021). The computational complexity resulting from a large-scale EV charging problem has been addressed using decomposition techniques (e.g., (Yi et al., 2020) or aggregating techniques (B. Wang, Zhao, Dehghanian, Tian, & Hong, 2020; Xu, Callaway, Hu, & Song, 2016; H. Zhang, Hu, Song, & Moura, 2016). The evaluation of EV flexibility has been considered in (Deng et al., 2020; H. Zhang, Hu, Xu, & Song, 2017). Regarding the literature, there are still remaining issues which have not been studied thoroughly so far.

- To deal with the uncertain EV's behavior, researchers usually tried to capture the stochastic behavior of EVs using a probabilistic distribution function of arrival/departure time, parking duration, and demand. However, the diversity of EV's battery capacity and the levels of the charging rates are now much higher because there are many new EV's models with different battery configurations joined the EV fleet. This issue has not yet been investigated thoroughly in the literature.
- Although computational efficiency can be improved using the aggregate EV fleet modeling technique (Vandael, Claessens, Ernst, Holvoet, & Deconinck, 2015; B. Wang et al., 2020; H. Zhang et al., 2017), the urgent charging tasks may not be afforded because they have been aggregated into the fleet. This issue has not been fully considered in the literature.

In this thesis, we address these issues in some extents. Firstly, the stochastic characteristics of EV's capacity and charging rate are investigated based on real EV market data. Secondly, an aggregate model of EV fleet is utilized in an efficient way by classifying the whole large-scale EV fleet into “urgent”, “deferrable”, and “controllable” clusters based on their laxity level and V2G capability. This classification technique helps continuously monitor the EVs with “urgent” need to meet users’ satisfaction, while maintaining a small number of EV clusters to reduce significantly computational complexity. A multi-stage day-ahead charge/discharge scheduling algorithm is proposed which consists of three main stages. The first stage is planning charging/discharging power for a day in advance to minimize the operation costs taking into account forecast PV generation, electricity price, building’s load, and the stochastic behaviors of the EV fleets. During the operating day, the second stage is repeated every 15 minutes with a rolling horizon, which recalculates an optimal charging/discharging schedule to the end of the day based on updated forecast data and current measurements. In this stage, the rolling horizon optimization aims to minimize the operation costs while following the day-ahead scheduled in the first stage and fulfilling ‘urgent’ charging tasks for the rest of the day. Only the first set of decisions is then applied for the next interval while discarding all the rest Finally, in the third stage, when the realization of EV fleets is available, real-time EV flexibility is estimated to adjust charging/discharging rates adapting to a realization of PV generation and building’s loads. The real-time adjustment helps the BCMO follow the scheduled day-ahead power exchange as much as possible while satisfying the ‘urgent’ charging tasks under uncertainties.

Problem Statement

In this thesis, we consider a BCM, which operates in the day-ahead electricity market to supply building loads and fulfill charging demands from a large-scale EV fleet. The EV charging demands may have certain level of flexibility which allows BCMOs to manage the charge/discharge schedule for this fleet and the stationary BESS in an optimal way to 1) minimize their operating cost, 2) commit to act as a well-behaved load to the utility, and 3) balance with PV generation. To achieve these goals, the BCMOs have to solve a day-ahead scheduling optimization problem to find an optimal hourly power exchange with the utility for the next operating day based on predicted EV charging demand, PV generation, building load, and electricity prices. The day-ahead exchanged power is then submitted to the DSOs to get the wholesale electricity price. During an operating day, the BCMOs re-solve the charge/discharge scheduling optimization problem at every 15 minutes to obtain a new set of charging/ discharging decision, which adapts to forecast errors and keep track of the day-ahead power schedule.

Such managing/ scheduling procedure is facing certain challenges as follows:

- **P1**. The performance of the charge/discharge scheduling optimization problems depends heavily on the stochastic model of EV behaviors. Moreover, many new EV models have recently been introduced to the market with plenty of choices of battery capacities and charging rates. Their contributions to the stochastic characteristic of the EV fleet need to be considered.
- **P2**. In a large-scale EVCS with many EVs, the traditional aggregating model of EV fleets that helps significantly reduce the computational complexity yet may not guarantee to fulfill the 'urgent' charging demands.
- **P3**. A real-time control algorithm is required to distribute the optimal aggregate charging power rates to individual EVs every 15 minutes. However, variation of PV generation and building's loads requires real-time adjustment in aggregate charging rate before spreading to individuals. This adjustment is subject to the flexibility of EV fleets assessed every time step.

Research questions

To address the problems stated above, we need to answer the following research questions:

- **Q1.** How to integrate the variable EV's battery capacities and charging rates into the stochastic model of the EV fleets?
- **Q2**. How to afford urgent charging demand while reducing the computational complexity?
- **Q3**. How to evaluate the EV flexibility capacity to adjust the power profile in real-time under uncertain PV output and demands?

Objectives

The goal of this thesis is to improve the operation of a large-scale parking station which is connected to a building-microgrid with support from a solar PV system and stationary BESS. We aim at minimizing the operating cost of the entire microgrid, flattening its power profile at the PCC, and balancing the PV generation, subject to the constraints of the distribution network, BESS power/capacity while ensuring high EV user satisfaction by fulfilling their need before departure. The main objective can be divided into three sub-objectives, as follows:

- **SO1.** To investigate variable characteristic of EV battery capacities and charging rates to calculate power and energy boundaries of the EV fleets based on both real and simulated data.

  This sub-objective aims to answer research question **Q1**. At first, a real EV capacity data set is used to investigate the variable of EV capacities while various EV charging rates are collected from different charging level I, II, and fast charging. Then, the variable characteristics of EV capacities and charging rates in combination with arrival/departure time, parking duration, and initial stage of charge behaviors are used to simulate the power and energy boundaries of the EV fleets.
- **SO2.** To develop a cluster-based aggregating algorithm for large-scale EV fleets with low complexity and meeting the requirements of EV users.

  The aggregate EV fleet model greatly reduces the complexity by using only aggregate power and demand variables of the entire EV fleet. However, this aggregation results in unaffordable demand of “urgent” EVs. To address **Q2**, a clustering technique based on the ‘urgent’ level and V2G capacity is proposed.
- **SO3.** To propose a heuristic to assess the EV flexibility for adjusting EV charging in real-time to compensate the mismatching with the day-ahead schedule caused by the uncertainty of PV generation and building load.

  EV flexibility should be evaluated in real-time. Traditional optimization methods with high complexity cannot meet this constraint. A heuristic algorithm is therefore required to address **Q3**.

Contributions

The main contributions of this thesis are as follows:

- Unlike prior works in which the authors assume few types of EVs with specific charging rate and battery capacity, our proposed aggregate model takes the stochastic of the battery capacity and charging rate into consideration adapting to the various emerging EV models in the market. We use the Monte Carlo Simulation method to generate multiple EV's charging tasks based on statistical data and probability distribution function of arrival/departure time, parking duration, initial stage of charge, battery capacity and charging rate.
- We develop an aggregate model for large-scale charging station. Compared with the aggregate model proposed in (Vandael et al., 2013) and (H. Zhang et al., 2017), our proposed clustering method for modeling a large-scale EVs charging load takes into account 'urgent' demand by avoiding circulation charge/discharge effects of the aggregate EVs fleet.
- We propose a low-complexity multi-stage charge/discharge scheduling algorithm to integrate EVCS into buildings with PV-system and stationary BESS. Our EV-size-independent optimization algorithm computes repeatedly the optimal charging/discharging decision for each individual EV in a high time resolution (15 minutes instead of 1 hour).
- We carry out extensive simulations based on both real and simulated dataset to validate the proposed algorithm.

Thesis outline

This thesis is organized as follows.

Introduction

Context and motivation of our work are presented in this section. Then, we define a problem statement, and research questions for guiding our research toward the main objective which is constructed through three subobjectives.

Chapter 1: Literature review

In this chapter, we will review the studies in the literature which are related to our work. We will analyze the similarities and differences between our work and those studies.

Chapter 2: Methodology

A research methodology is presented in this chapter to answer the research questions.

At first, variable characteristic of EV battery capacities and charging rates are investigated. The Monte Carlo Simulation method is adopted to generate the uncertainty set of EV's parking behavior based on probability distribution function of arrival/departure time, parking duration, initial stage of charge, battery capacity and charging rate.

Second, the cluster-based aggregate EV model is introduced, which classify a large-scale EV fleet into three specific clusters to reduce the computational complexity while ensuring a high satisfaction for EV users.

Third, a multi-stage day-ahead charge/discharge scheduling optimization problem is formulated, which consists of three main steps in different time scales. The first step is day-ahead scheduling which is processed at least one hour in advance of the operating day. During the operating day, a rolling horizon optimal charging/discharging problem will update the charging/discharging schedule following the day-ahead plan while adapting with the realization of EV parking behavior. Finally. a real-time adjustment technique is represented along with real-time EV flexibility assessment to compensate the uncertainty of PV generation and loads.

Chapter 3: Numerical Simulation and Results

In this chapter, the numerical simulations based on real and simulated data consider three different types of BCM i.e., office, commercial, and residential buildings. Proposed algorithm is compared to a baseline algorithm in three criteria: user satisfaction index, EV flexibility, and cost efficiency. The simulation results prove the effectiveness of the proposed algorithm.

Conclusion

This section presents our conclusions and future works.

CHAPTER 1

LITERATURE REVIEW

1.1 Literature Review

In this chapter, we are going to review previous works in the literature related to our study. Firstly, an aggregating EV model is widely used in the literature to reduce complexity caused by increasing the number of EVs in the large-scale EV charging stations (Vandael et al., 2013; H. Zhang et al., 2017). Besides, the stochastic parking behavior as an individual or an aggregate EV has been investigated in many different aspects in the literature (Islam et al., 2018; Sun, Neumann, & Harrison, 2020; P. Zhang, Qian, Zhou, Stewart, & Hepburn, 2012). Finally, a day-ahead charge/discharge scheduling problem from the aggregator point of view to minimize operation cost or maximize revenue has attracted many studies in the literature (R. Wang, Wang, & Xiao, 2016; D. Wu, Zeng, Lu, & Boulet, 2017; Y. Zhang & Cai, 2018).

1.1.1 Aggregating EV model

The widespread adoption of EVs presents both challenges and opportunities to the management of generation and transmission in the power grid. On one hand, adding a massive load demand from EV charging in particular areas could jeopardy the stability and efficiency in the operation of the power grid. This raises concerns about the potential impact to the operating cost, voltage stability, and the frequency excursion (Deb et al., 2017; Eftekharnejad, Vittal, Heydt, Keel, & Loehr, 2013; Yilmaz & Krein, 2013). Thus, uncontrolled EV charging may result in inefficient power network operation or even security issues (Tang, Bi, & Zhang, 2016). On the other hand, EVs exhibit the potential of flexibility in storage capacity and time to offer a demand-side response service to the utility. Moreover, with Vehicle to Grid (V2G) capability, EVs can potentially act as mobile storage systems to improve the power performance, such as flattening demand curve, fast frequency control, voltage regulation, and facilitating renewable energy integration. Therefore, a proper control and management system is required, in particular through an aggregator in a high EV concentration area such as an office, commercial or residential building parking station (Rafique, Hossain, Nizami, Irshad, & Mukhopadhyay, 2021; Wan, Li, He, & Prokhorov, 2018; D. Wu et al., 2017; Yi et al., 2020).

Aggregating EV model is one of the most widely used approaches for exploiting the synthesized value of EVs (You, Hu, & Ziras, 2016). An aggregate EV fleet can behave similarly to a deferrable or controllable load, a mobile storage system, or a virtual power plant to provide demand response, arbitrate energy, or ancillary services to the main grid. Aggregating (dis)charge scheduling approach can be neither fully centralized nor decentralized (Vandael et al., 2013). In which, a collective (dis)charging plan for a fleet of EVs is effectively calculated centrally, while the aggregate (dis)charging power will be spread to each EV locally using a heuristic real-time control algorithm. Therefore, the aggregating approach is much less computationally intensive and independent of the number of EVs in the fleet. However, in (Vandael et al., 2013), EVs are grouped regardless of their stage of charge and their charging time flexibility so that the 'urgent' charging tasks may not be fulfilled. The real-time heuristic control only bases on EV's laxity may lead to a reduction of the EV's flexibility. For example, an EV with a low stage of charge (SOC) but supposed to be parked for a long time (high laxity) may provide a minor contribution to up-regulation service, while another with high SOC but short parking duration (low laxity) will be fully charged too soon then loss ability for down-regulation service. Whereas, in (H. Zhang et al., 2017), the aggregate model of the uncontrollable and controllable EVs are separately formulated to consider the urgent charging tasks; however, the whole EV fleet is treated as a single aggregated storage system in the optimization problem. To solve this problem, a heuristic real-time control based on both EV's laxity and SOC is proposed to fairly spread the aggregate charging power rate to individual EVs. Yet, the achieved optimal aggregate power rate assign to the EV fleet at a particular time step could be less than the need of the uncontrollable groups to satisfy their requirement before their departure time.

From a modeling perspective, a single aggregate model for a large-scale EV fleet is introduced in (Vandael et al., 2013), and separated models for uncontrollable and controllable EV fleets are presented in (H. Zhang et al., 2017). Unfortunately, both models failed to avoid unexpected vehicle-to-vehicle (V2V) circulating (dis)charging in nature among the aggregate fleet when V2G feature is enable. Unlike these studies, we divide the whole EV charging station into several clusters based on their 'urgent' level and V2G ability to ensure the satisfaction of all charging requests.

1.1.2 EV parking behavior

A key challenge in managing the EV charging process is the intermittent nature of EV parking behavior including arrival time, parking duration, initial SOC, demand, battery capacity, and charging rate limits. Managing and planning EV's charging station to achieve certain operating goals under the stochastic EV's behavior have been studied intensively in the past two decades, with a focus on the stochastic modeling techniques and stochastic solution methods. One of the most popular methods is the probability distribution presentation of stochastic variables. The EV's parking behavior is highly stochastic in nature but can follow a certain probability distribution function (Xu et al., 2016). According to (P.Zhang et al, 2012), stochastic behavior of the initial EV battery SOC is evaluated as a probability density function (PDF) related to travel distances. (Zheng et al., 2008) assumes that the arrival time of the EVs in the residential and office parking areas can be represented as a Poisson process while SOC follows a Gaussian distribution. Similarly, (Islam et al., 2018) also considers the SOC distribution of the aggregate EV fleet be either Lognormal or Gaussian, and then chooses the Gaussian distribution to represent the combined SOC distribution for simplicity. In practice, the initial EV's SOC distribution is truncated normal distribution since it is usually limited, e.g., from 10% to 90%, to void fast degradation of the battery life (Kostopoulos, Spyropoulos, & Kaldellis, 2020). However, the diversity of the battery capacity on the EVs was not considered adequately in most previous works. A recent work that considers the difference of the EV's characteristics is presented in (Šepetanc & Pandžić, 2021). The authors proposed a cluster-based modeling method for an EV depot charging station to minimize electricity costs while taking into account battery degradation and nonlinear charging/discharging efficiency and speeds (Šepetanc & Pandžić, 2021). This method requires discretized SOC levels to cluster EVs in different groups based on their SOC level. Even though the computational complexity is independent of the number of EVs, it increases exponentially according to the number of the clusters and is only applicable if the EV fleets have identical battery capacity. Similarly, authors in (Islam et.al., 2018) also require the identical battery capacity of the EVs in the same group and assume that the travel distance made by EVs are the same before arriving at the parking station to forecast the aggregate EV fleet's SOC. In our work, the diversity of EV's battery capacities will be taken into account in a probabilistic model of the aggregate EV clusters.

Although the research on the probability distribution of the EV's behavior parameters has been carried out for about two decades, data available from the real charging tasks is still limited. To replicate the stochastic behavior of the EV fleet from limited data set, the well-known Monte Carlo simulation (MCS) method is widely used. In (Bai & Qiao, 2015), an MCS method is used to generate a random data set based on the stochastic mobility behavior of the EVs in the aggregator provided from the actual survey to perform a robust optimal bidirectional dispatch of the large-scale EV charging station. In (Zhou et al., 2018), based on the actual traffic data, the probability distribution model of the EV's traveling and parking behavior is established, then MCS is adopted to simulate a largescale EVs traveling and charging tasks to improve the load prediction accuracy. An MCS based method is proposed in (Ni & Lo, 2020), to model daily charging load in the EV charging station taken into account multiple random factors i.e., charging modes, battery capacities, charging duration, initial SOC, and arrival time of the EVs. In their paper, two levels of charging power i.e., slow and fast, are assumed to be randomly chosen by the EV's users and modeled using a Bernoulli distribution. In (Kim et al., 2020), a probabilistic method is proposed to assess the steady-state security of power systems, reflecting the uncertainty of EVs demand and wind power generation applying MCS. The empirical EVs charging demand and wind power output data are modeled as a probability distribution, and then MCS is performed, integrating the power system operation to represent the steady-state security as a probability index. Recent work in (Sun.W et al., 2020), takes into account the comprehensive and realistic knowledge of the multiple sources of uncertainty to increase the chances of the feasibility of the charging schedule despite parameter deviation and makes the results robust up to a certain level. In their paper, MCS is utilized to generate multiple scenarios of the EV's charging task which is felt into the model as a predicted data. By comparison, the probability model of complete stochastic parameters, in our work, is considered to generate the probabilistic model of the aggregate EV fleets instead of the individual EV's charging task.

1.1.3 Day-ahead charge/discharge scheduling

A large-scale EV charging station aggregator usually aims at minimizing system operating costs and maximize their profits. The aggregator takes advantages of the indirect demand control methods proposed by the grid operators i.e., time-of-use and day-ahead market price policies, by wisely scheduling the EV charging demand based on the predicted data then iteratively adjusts this schedule in a real-time manner to compensate the mismatches caused by predicting errors at the minimum cost. An EVCS integrated into a building that equipped a solar PV system and stationary ESS, is investigated in (D.Wu et al., 2017). In this article, the authors propose a two-stage stochastic optimization method that schedules a day-ahead market based on forecast data in the first stage, then, recourses are made based on the results of scheduled day-ahead from the first stage. The deviation of the realization charging demand from the scheduled point will cost extra fees. When the day-ahead power market is larger than the actual used power, the aggregator needs to cancel the overscheduled energy and pays certain cancelation fee. If the scheduled power is insufficient, the extra energy used in actual operation will be provided in time-of-use price policy that is usually higher than the wholesale day-ahead market price. The EV's stochastic behavior is handled using forecasts based on their probability distribution function. However, to reduce computational complexity caused by a huge number of scenarios, the authors use one-hour time resolution. Consequently, if an EV arrives in the middle of two consecutive time samples, a maximal delay of about an hour may be observed before EV charging starts. This delay is not convenient for EV's user who may need to leave urgently. Likewise, a two-stage EV charging scheduling algorithm based on the day-ahead market, with support from renewable energy sources, is presented in (R. Wang et al., 2016), to reduce energy cost and flatten the peak load. A charging rate compression algorithm is developed in this work to significantly reduce the computational complexity aiming at solving the problem in real-time to quickly respond to the EVs. A similar study is found in (Jin, Tang, & Ghosh, 2013), with support from the stationary BESS to compensate for the mismatch between the prediction and realization of EV charging in real-time. The large-scale charging problem is also not considered in this work.

In addition, in (Y. Zhang & Cai, 2018), a charging station in a workplace parking lot, powered by a solar PV power system and connected to the main grid without stationary BESS, is considered. In their work, a model predictive control is embedded in a dynamic charging scheduling scheme to deal with real-time information of EV charging requirements based on a dynamic charging schedule. By analyzing the relationship among the EV charging requirements, the charging load, and the harvested solar energy, the authors derive several necessary conditions for obtaining an optimal decision, such that the primal optimization problem can be simplified. The distribution of EV's arrival/departure times is assumed to be approximated to a normal distribution.

Regarding the aforementioned studies, our work considers a configuration of EVCS interconnected to a building microgrid with a PV system and ESS operating in day-ahead planning and real-time adjusting manner. However, we focus on a large-scale EVCS in a shorter time resolution (5 to 15 minutes). Based on a predicted model of the aggregate EV fleet, we exploit the EV's flexibility to keep track of the day-ahead market plan for minimizing the operating cost, flattening the load profile, and self-balancing PV generation, while ensuring the satisfaction of EV's users and the limitation of the power exchange with the utility.

1.2 Summary

This chapter presents the related works addressing the research questions presented in this thesis. Most of the previous studies used lumped sums to present the power and energy boundaries for the entire EV fleets to reduce the computational complexity. Yet the stochastic behaviors of the EV fleet have not been studied thoroughly. In particular, the diversity of EV charging rates has not been taken into account. The capacity of the battery installed in the EVs is becoming more stochastic since many new EV models introduced to the market have not been investigated so far. The main related work is summarized in Table 1.1 below.

Table 1.1 Summary of previous work

Research issue	**Articles**	**Methodology**	**Limitations**
- Aggregate EV model - 'Urgent' charging satisfaction	Vandael et al., 2013	- Single aggregating model - Three-steep control approach - Dynamic programing approach	'Urgent' charging tasks are not considered Dividing charging power based on 'laxity' only could reduce the EV flexibility
	H. Zhang et al., 2017	- Uncontrollable and controllable EVs are separately modeled - MIQP modeling approach	The whole EV fleet is treated as a single aggregated storage system may lead to 'Urgent' charging tasks unsatisfied
- EV Parking behavior - Variable characteristic of EV capacities and charging rates	Islam et al., 2018	- Probability modeling approach - Aggregating SOC updating	Require the identical battery capacity of the EVs in the same group and assume that the travel distance made by EVs are the same
	Sun, Neumann, & Harrison, 2020	- MCS - Robust optimal charge/discharge planning	Diversity of EV capacity is neglected
	Šepetanc & Pandžić, 2021	- Cluster-based methods based on discrete SOC levels.	Computational complexity depends on the number of the clusters Considering identical EV battery capacity
	Bai & Qiao, 2015	- MCS	Diversity of EV capacity is neglected
- Day-ahead planning - Real-time EV flexibility assessment	R. Wang, Wang, & Xiao, 2016	- Two-stage EV charging scheduling algorithm based on the day-ahead market - Charging rate compression algorithm	EV flexibility is not assessed
	D. Wu, Zeng, Lu, & Boulet, 2017	- Two-stage stochastic optimization method	high time-resolution (1 hour) lead to high EV waiting time large-scale is not considered
	Y. Zhang & Cai, 2018	- Model predictive control - Dynamic programing considering individual charring tasks	EV flexibility is not assessed

CHAPTER 2

METHODOLOGY

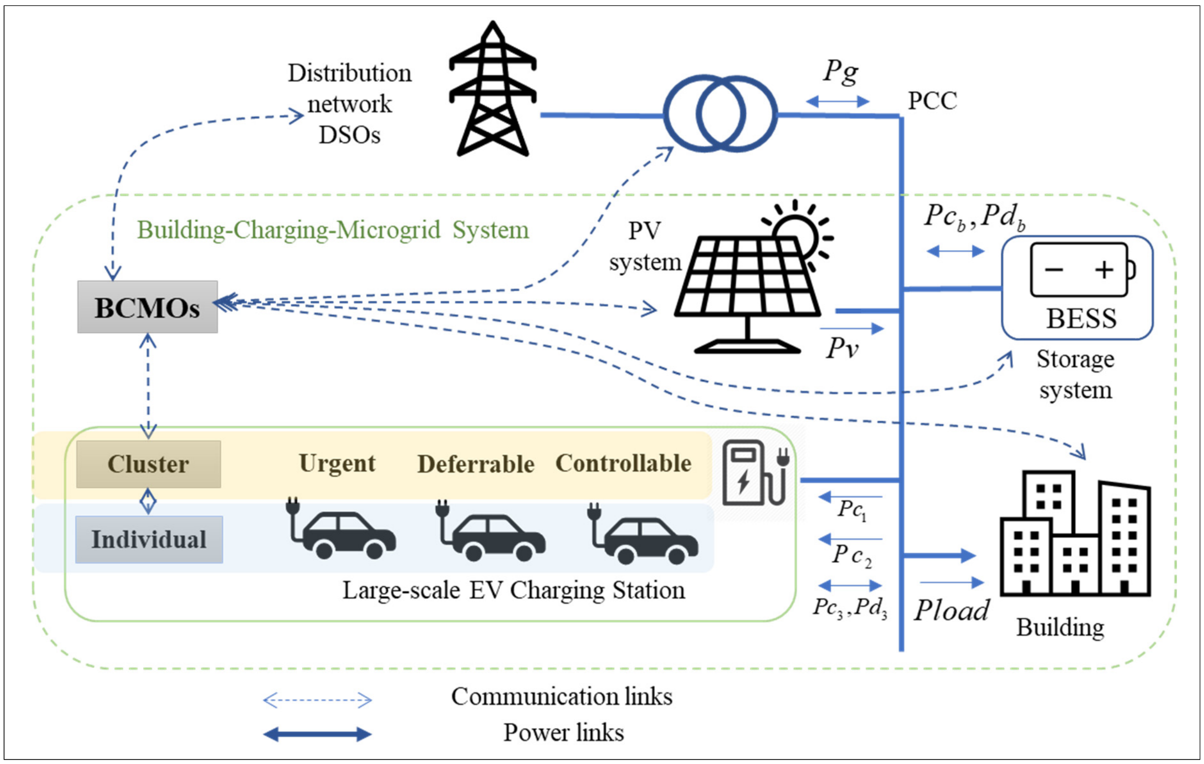

Figure 2.1 Microgrid configuration with power direction and sign convention in the system study

This chapter presents our proposed methodologies to address the research questions. At first, we describe a BCM configuration in which a parking station with a large number of connected EVs is considered (Figure 2.1). To handle the uncertainty in the EV availability, PV output, and building load, the Monte Carlo simulation method (M1) is utilized based on the assumption of knowledge about the statistical distribution of the stochastic variables to estimate a series of possible scenarios. Then a cluster-based aggregating technique (M2) is presented to group the EVs in three clusters based on their 'laxity' and V2G ability. We proposed a multi-stage charge/discharge scheduling optimization problem (M3) which consist of day-ahead planning, rolling horizon optimization, and real-time heuristic control. In which, the day-ahead planning and rolling horizon optimization problems are formulated in low-complexity MIQP models to find the aggregated charging/discharging power rate for those clusters of EVs based on the day-ahead market framework. Next, to assign the charging/discharging rate to each EV in the clusters, the Least Laxity First (LLF)-SOC algorithm is applied. Finally, the availability of V2G capacity and flexibility offered from the aggregated EVs will be investigated to compensate for the mismatch between the day-ahead schedule and real-time realization caused by the stochastic variables.

2.1 Assumptions and limitations of the study

We consider the BCM system in Figure 2.1 under the following assumptions and limitations:

- The solar PV power generation is volatile in nature and strongly relies on weather conditions, solar irradiation, and cloud cover condition. That could be predicted based on the weather forecast but expected to have a wide range of uncertainty.
- To maintain the reliable operation of the grid, constrained power exchange with the main grid is a feasible solution. With constrained grid connection, the distribution operator specifies the power limit so that at any point in time, the utility only provides a specific maximum exchanged power at PCC.
- The high capital cost for implementing BESS is remaining the main concern for BCMOs. Choosing an optimal BESS size for a specific application is not a trivial task, however, we will not consider this challenge in our study.
- In this study, three typical buildings, i.e., residential, office and commercial are investigated. This tendency leads to specific EV parking and charging patterns that can be predictable by simply collecting the basic data from users. Each EV arrival to the parking station is assumed to be connected to the charging pot. Its charging ID (the number is generated by the BCMOs to keep track of every single charging task), arrival time, initial SOC, battery capacity is collected through the communication line between EVs and charging pot. Users are requested to enter their preferred departure time and expected energy level before departure. We assume that an EV, when parked, will leave the parking

station no sooner than their predefined departure time.

- In order to generalize the stochastic of the EV behavior including arrival time, parking duration, initial SOC, and battery capacity of each EV are considered to be independent and identical distributed (iid).
- We assume that the market share of all EV models is equal to be able to model the EV battery capacity.
- In this study, we approximate the degradation cost to be proportional to the amount of charging/discharging energy in the battery, as be used in (Zhang et.al., 2017).
- BCMOs can access and control the entire building, BESS as well as every charging ports. They can decide how much energy will be purchased from the main grid and participate in the electricity market as a price-taker.

The following sections present in detail the set of methods and algorithms used to achieve the operation goals of the proposed BCM system.

Before modeling the system and formulating the problem, we introduce all symbols which are used in this thesis. Specifically, Table 2.1 shows the symbols of an individual EV, while in Table 2.2 and 2.3, variables and parameters used to form the problems are illustrated.

Table 2.1 Individual EV's characteristic

Symbols	Description
N	Number of EV in the parking lots
Nv	Number of vacancies at EVCS
$i^{th} \in \mathbf{I} := \{1,2,3,...,N\}$	EV index (EV i^{th})
ta_i, td_i	Arrival and expected departure time [hour]
dm_i	Desired energy demand entered by EV users [kWh]
$sa_i, sd_i, s_i^{\max}$	Stage of charge at arrival, departure and maximum SOC $\in [0,1]$
$pc_i^{\max}, pd_i^{\max}$	Maximum charging and discharging power [kW]
$e_i^{\max}, e_i^{\min}$	Maximum energy charged/discharged [kWh]
c_i	Battery capacity of EV i^{th} [kWh]
Cb	Capacity of BESS [kWh]
lx_i	Laxity of EV i^{th} [hour]
Δt	Time step duration [hour]
dp_i	Parking duration of EV i^{th} [hour]
$\eta c_i, \eta d_i$	Charging/discharging efficiencies of EVs i^{th}
$\mu_{ta}, \mu_{dp}, \mu_{so}$	Means of stochastic arrival, departure time, initial SOC
$\sigma_{ta}, \sigma_{dp}, \sigma_{so}$	Standard deviation of stochastic arrival, departure time, initial SOC
μ_{cap}, σ_{cap}	Probability distribution parameters of EV battery capacity

Table 2.2 Variables

Variables	Description
	Decision Variables
$Pc_b(t), Pd_b(t)$	Charging and discharging power of BESS at time t, [kW]
$Pc_1(t)$	Charging power of the 'urgent' EV group at time t, [kW]
$Pc_2(t)$	Charging power of the 'deferrable' EV group at time t, [kW]
$Pc_3(t), Pd_3(t)$	Charging/discharging power of the 'controllable' EV group at time t, [kW]
	Binary Variables
$\delta b(t)$	Indicator for charging status of BESS at time t
$\delta g(t)$	Indicator for buying energy from the grid at time t
$\delta(t)$	Indicator for charging status of 'controllable" EV group at time t
	Dependent variables
$Pb(t), Ps(t)$	Buying/selling power from/to the utility at time t, [kW]
$P_{DA}(t)$	Day-ahead power exchange with the utility at time t, [kW]
$E_b(t)$	Energy level of BESS at time t, [kWh]
$E_1(t)$	Energy charged to 'urgent' EV groups at time t [kWh]
$E_2(t)$	Energy charged to 'deferrable' EV groups at time t [kWh]
$E_3(t)$	Energy charged/discharged to/from 'controllable' EV groups at time t [kWh]

Table 2.3 Input data

Symbols	Description
	Parameters and coefficients
$Pb_{\max}, Ps_{\max}$	Maximum buying/selling power allowed by the utility [kW]
$Pc_{\max}, Pd_{\max}$	Maximum charging/discharging power of BESS [kW]
$E_{\min}, E_{\max}$	Minimum/maximum energy levels of BESS, [kWh]
Cb	Energy capacity of BESS, [kWh]
c_{V2G}	Unit cost of V2G support, [$/kWh]
c_{bat}	Operation and maintenance cost for energy exchanged in BESS, [$/kWh]
$\eta c, \eta d$	Charging/discharging efficiencies of BESS
λ_1, λ_2	Coefficients $\left[\frac{\$}{kW^2}\right]$
$j^{th} \in J := \{1,2,3\}$	Cluster index
	Forecasts
$Pu_j(t), Pl_j(t)$	Power boundaries of EV groups at time t, group $j \in J$, [Wh]
$Eu_j(t), El_j(t)$	Energy boundaries of EV groups at time t, group $j \in J$, [kWh]
$Pv(t)$	Production from PV system at time t, [kW]
$Pload(t)$	Demand of the building at time t, [kW]
$c_b(t), c_s(t)$	Selling/buying energy price at time t, [$/kWh]

2.3 System model

2.3.1 Individual EV model

We consider a fleet of N electric vehicles which are already parked and potentially arrival at the parking station in the next 24 hours. An EV $i^{th} \in \mathbf{I} := \{1, 2, 3, ..., N\}$ is connected or has expected arrival at time ta_i [hour]. Its initial stage of charge, sa_i and battery capacity, c_i are reported to the BCMOs. The users enter a desired departure time, td_i and a preferred demand, dm_i (or the stage of charge at the departure, sd_i). If an infeasible demand i.e., a short parking time with a high expected demand which is over the capability of the battery, electronic components, and charger limits, is chosen by users, charger's controller will automatically return a feasible one with a notice to the EV user. The user, then, can prolong their estimated parking duration to get their desired energy level. Otherwise, they will be aware of a lower level of energy available in the event that they want to keep the desired leaving time. From the EV user's perspective, they expect to charge their vehicle as quick as possible at reasonable cost to avoid unexpected energy shortage for the next trip causing by their uncertain parking behavior e.g., in the event that they decide to leave sooner than their desired departure time. However, in order to focus on the other aspect of the EV uncertainty, on the above assumptions, we assume that an EV, when parked, will leave the parking station no sooner than their predefined departure time. The user can decide to take part into demand side response activity by enabling the vehicle to grid (V2G) feature, by doing so, the energy from EV battery can be discharged during their parking time to support the microgrid and utility grid, in return, the users can benefit from pay-back money for contributed energy. Then each arrival EV is considered as a charging task which can be characterized by an 8-tuple $\left(i, ta_i, td_i, sa_i, sd_i, c_i, pc_i^{\max}, pd_i^{\max}\right)$ in comparison with 5-tuple model proposed in (Jin et al., 2014). In which, $pc_i^{\max}, pd_i^{\max}$ are maximum charging and discharging power rates, respectively. They are limited by the minimum charging/discharging rate of the EV battery itself, power electronic elements, and charger capability. These values are specific for each charging task (a pair of EV and charging port).

Similar to the works in (Vandael et al., 2013) and (H. Zhang et al., 2016), the EV charging characteristics can be estimated using flexible lower and upper boundaries, that define the feasible regions of the charging rate and energy demand over the scheduling horizon, and are denoted by pu_i, pl_i, eu_i, el_i respectively. The upper bound, $pu_i(t)$ represents the maximum charging power, $pc_i^{\max}$ and the lower bound $pl_i(t)$ corresponds the maximum discharging power $pd_i^{\max}$ of the EV i^{th} at time t. These values are calculated in equation (2.1) and (2.2), respectively.

$$pu_i(t) = \begin{cases} 0 & t > td_i \text{ or } t \le ta_i \\ pc_i^{\max}.\eta c_i & ta_i < t \le td_i \end{cases} \tag{2.1}$$

$$pl_i(t) = \begin{cases} 0 & t > td_i \text{ or } t \le ta_i \\ -pd_i^{\max} / \eta d_i & ta_i < t \le td_i \end{cases} \tag{2.2}$$

The energy demands of each EV is changing overtime depending on how much energy is charged at every time step. The upper bound eu_i defines the fastest path to charge up the battery to its maximum capacity, while lower bound el_i defines the highest delay in charging the EV i^{th}. The lower and upper boundaries define an area, in which the demand of EV i^{th} at each interval can be feasible everywhere.

$$eu_i(t) = \begin{cases} 0 & ,t \le ta_i \\ \min\left(e_i^{\max}, eu_i(t-1) + pc_i.\eta c_i.\Delta t\right) & ,ta_i < t \le td_i \\ e_i^{\max} & ,t > td_i \end{cases} \tag{2.3}$$

In which, Δt is the time step, while $e_i^{\max} = c_i.\left(s_i^{\max} - sa_i\right)$ denotes the maximum energy that could be charged into the EV i. $s_i^{\max} \in [0,1]$ is the maximum stage of charge (SOC) which is designed for EV i. As recommended, the maximum SOC is set to be 0.95. $e_i^{req} = c_i.\left(sd_i - sa_i\right)$ is the energy acquired by the EV i before its departure.

$$el_i(t)=\begin{cases}0 & ,t\le ta_i\\ \max\begin{pmatrix}e_i^{\min},\\ el_i(t-1)-pd_i/\eta d_i.\Delta t,\\ e_i^{req}+pc_i.\eta c_i.(t-td_i).\Delta t\end{pmatrix} & ,ta_i<t\le td_i\\ e_i^{req} & ,t>td_i\end{cases} \tag{2.4}$$

In which, $e_i^{\min}=(s_i^{\min}-so_i).c_i$ denotes the maximum amount of energy can be discharged from EV battery.

2.3.2 Cluster-based aggregate EV model (M1)

In this study, we proposed a cluster-based aggregate model of a large-scale EVCS that takes into consideration the urgent charging demand to model three separated aggregate EV fleets instead of a single group as proposed in the literature. The proposed cluster-based aggregate model not only realizes the urgent needs among EVs to fulfill as much as possible, but also allows more precise evaluation of the EV fleet's capacity flexibility which may help improving the demand-side response service offer to the utility and real-time power adjustment. The cluster division is based on the laxity and the ability to provide V2G service of the charging tasks.

A laxity lx_i is commonly used for indicating the time-flexibility of an EV charging task i^{th} (Chen, Kurniawan, Nakahira, Chen, & Low, 2021; Nakahira, Chen, Chen, & Low, 2017; Subramanian, Garcia, Callaway, Poolla, & Varaiya, 2013). It is defined as the difference between the parking time and the minimum time required to charge the EV battery to its desired energy level.

$$\begin{aligned} lx_i &= dp_i - dm_i / pc_i^{\max} \\ &= (td_i - ta_i) - \frac{(sd_i - sa_i).c_i}{pc_i^{\max}}, i\in I \end{aligned} \tag{2.5}$$

In which, $dp_i=(td_i-ta_i)$ is the parking duration of EV i^{th}

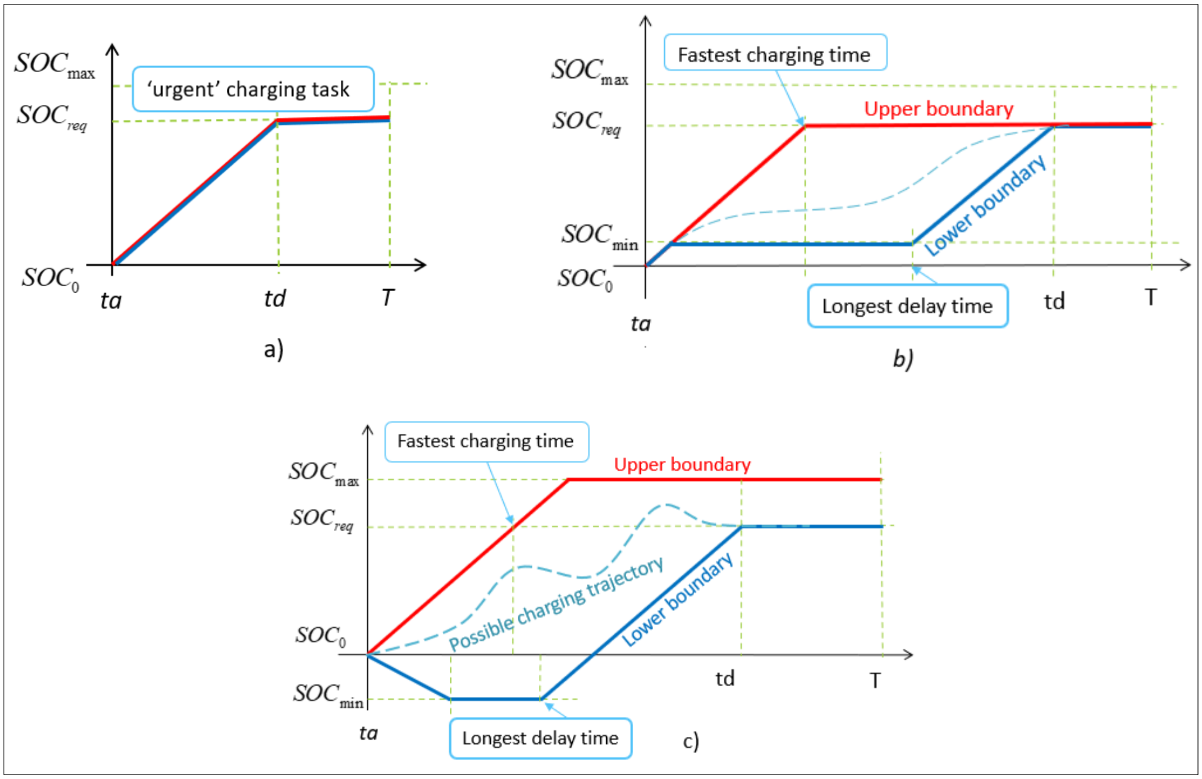

Figure 2.2 Single EV's upper and lower energy demand (in term of SOC) illustration for EV in a) urgent, b) deferrable, and c) controllable fleets

If $lx_i < 0$, the EV's demand entered by the user is infeasible, that means there is not enough time to charge the EV battery to the desired energy level. However, the system described in subsection 2.2.1 ensures that the infeasible requested demand is adjusted upon arrival. $lx_i = 0$ means that the EV i^{th} battery needs to be charged right away at its maximum charging rate in order to fulfill user's need. The bigger lx_i, the more time-flexible the charging task is.

Unlike (H. Zhang et al., 2017), we calculate individual laxity index in order to classify the EV fleet into designed clusters before separately modeling the aggregate EV fleets. By doing so, the unexpected circulating charging/discharging phenomena between EVs in the same cluster will not affect the urgent need of the EVs. Here, inspired by the work in (Šepetanc & Pandžić, 2021; H. Zhang et al., 2017), we define three specific EV clusters based on their laxity index as follows.

Urgent charging model (Cluster No.1)

'Urgent' EV cluster includes the EVs which have a low level of time-flexibility with laxity $lx_i \le lx_{\min}$ and need to be charged right after being plugged into the charging port, in order to achieve their desired energy level before departure. In which, $lx_{\min}$ is a predefined laxity threshold. An EV with a laxity index being equal to zero must continue to charge throughout its parking duration. It is considered as an uncontrollable load in (H. Zhang et al., 2017). However, to deal with the uncertain departure behavior, EV battery should be fully charged several intervals, e.g., 30 minutes, before its departure time. Therefore, EV i^{th} with laxity index being lower or equal to $lx_{\min} = 30/\Delta t$, with Δt being a time step duration in minutes, should be charged without delay at its maximum charging rate up to the desired SOC sd_i. Therefore, its upper charging power is calculated as equation (2.1), and upper energy demand follows equation (2.3). While they are not be able to discharge energy, their lower charging rate is equal to zeros by replacing $pl_i(t) = 0$ into (2.2).

Deferrable charging model (Cluster No.2)

'Deferrable' EV cluster is composed of the EVs which have longer parking time with laxity higher than the minimum threshold, i.e., $lx_i > lx_{\min}$ but do not allow to discharge ($pd_i^{\max} = 0$) energy back to the grid and/or building. They can only be charged or idled but their charging time is more flexible. Because of $pd_i^{\max} = 0$, the lower bound of charging power $pl_i(t) = 0$, and the lower bound of energy demand can be calculated based on equation (2.4). Consequently, in this fleet, EVs can not be charge higher than their request energy demand, e_i^{req} since it is unable to discharge later. Their upper energy boundary can be calculated using equation (2.3) with $e_i^{\max} = e_i^{req}$.

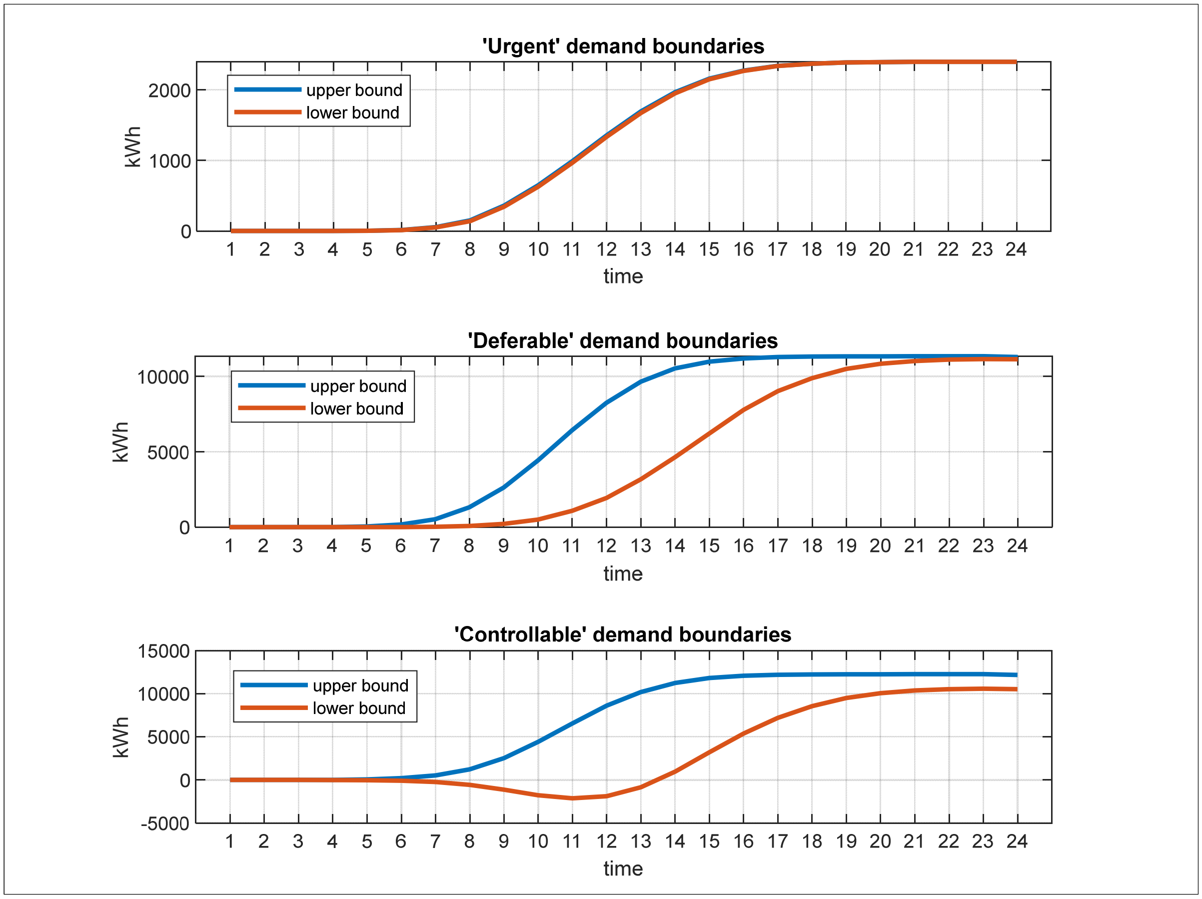

Figure 2.3 Cumulative charging demand boundaries in three EV clusters with sample of 1000 EVs in the office parking CS, predicted over 24-hour

Fully controllable charging model (Cluster No.3)

'Controllable' EV cluster contains the rest of EV fleet, which have long parking time, i.e., $lx_i > lx_{\min}$, with V2G feature is enable. The EVs in this cluster can be fully controllable by charging/discharging or idling during their parking period. Their power and energy demand boundaries are calculated using equations 2.1-2.4 and illustrated in Figure 2.2c.

The lumped summation of the energy and power boundaries of all EVs in the same cluster will present their aggregate energy and power boundaries, which are denoted by a capital letters and can be calculated as follows:

$$\begin{aligned}
Pu_j(t) &= \sum_{i \in cluster \mathbf{j}} pu_i(t) \quad ,\forall t, j \in J \\
Pl_j(t) &= \sum_{i \in cluster \mathbf{j}} pl_i(t) \quad ,\forall t, j \in J \\
Eu_j(t) &= \sum_{i \in cluster \mathbf{j}} eu_i(t) \quad ,\forall t, j \in J \\
El_j(t) &= \sum_{i \in cluster \mathbf{j}} el_i(t) \quad ,\forall t, j \in J
\end{aligned} \tag{2.6}$$

Figure 2.3 provides a sample of energy demand boundaries for each EV fleet over 24-hour. It shows the smooth and continuous boundaries instead of discontinuous individual EV boundaries as in Figure 2.2.

2.3.3 Stochastic EVs behavior model (M2)

The behavior of EV fleet is represented through stochastic variables, which is difficult to predicted accurately. It strongly depends on the behavior of the EV's users, travel distances, road's condition including weather situation, parking behavior, driving culture, and so on. Instead of dealing with the individual charging task in a large population of EVs at a parking station, the proposed cluster-based aggregate modeling method significantly reduces the problem size to only three clusters which are characterized by the smooth and relatively steady power and energy boundaries. Because there is insufficient existing data recorded for the aggregate EV fleet, we use the well-known Monte Carlo Simulation method to predict the aggregate EV characteristics based on the statistical knowledge of the arrival time, parking duration, initial SOC, and battery capacity of the EV fleet in residential, office, and commercial building parking station (Ni & Lo, 2020; Soares, Lopes, & Almeida, 2010).

In order to generalize the stochastic of the EV behavior including arrival time, parking duration, initial SOC, and battery capacity of each EV are considered to be independent and identical distributed (iid). Finding suitable probability distributions for these variables is a challenge and should be driven by the real data. However, representing these variables as normal or lognormal distributions is a common use among literature. For example, in (Arias et al., 2017) , the lognormal distribution is adopted to represent EV-related random variables (arrival time, departure time, and initial state of charge). Likewise, arrival and departure time are represented by means of Gaussian distributions in (Gao et al., 2019, Zhou. Y et al., 2018). The duration of the parking period $dp_i = td_i - ta_i$ is stochastic in nature since it relies on many uncertain parameters such as driving and parking behavior like personal or business use of EVs, the characteristic of parking station e.g., residential, office or commercial area. Generally, EVs' parking duration in a residential (night-time parking) and office (day-time parking) building is much longer than needed to fully charge their battery. This potentially provides the BCMOs the chance to effectively manage the cooperation among their microgrids. In this study, we represent the EV's arrival time and parking duration as normal distribution functions (pdf) with means, μ_{ta}, μ_{dp} and standard deviation, σ_{ta}, σ_{dp}, respectively, that can express as follows:

$$f\left(ta, \mu_{ta}, \sigma_{ta}\right) = \frac{1}{\sigma_{ta}\sqrt{2\pi}} e^{-(ta-\mu_{ta})/2\sigma_{ta}^2}, 0 < ta < 24 \tag{2.7}$$

$$f\left(dp, \mu_{dp}, \sigma_{dp}\right) = \frac{1}{\sigma_{dp}\sqrt{2\pi}} e^{-(dp-\mu_{dp})/2\sigma_{dp}^2}, 0 < dp < 24 \tag{2.8}$$

The EV's initial SOC can be considered to follow a truncated normal distribution with the upper and lower bounds of 0.95 and 0.2, respectively, as designed by many EV's manufactures to avoid fast degradation of the battery (Islam et al., 2018) . That is defined as follows:

$$f(sa) = \begin{cases} 0 & , sa < 0.2 \\ \dfrac{1}{\sigma_{sa}\sqrt{2\pi}} e^{-(sa-\mu_{sa})/2\sigma_{sa}^2} & , 0.2 \le sa \le 0.95 \\ 0 & , sa > 0.95 \end{cases} \tag{2.9}$$

Likewise, charging rates depend on the capability of the battery characteristics, electronic devices like build-in charger, and charging port. We collect a set of possible discrete charging power rates from the real-life data (SAE, 2017; Yong, Ramachandaramurthy, Tan, &

Mithulananthan, 2015), then it is randomly assigned to each charging task in the generated population. Besides, EV battery capacities vary in a wide range from 4.4 kWh in a hybrid plug-in EV (2012 Toyota Prius Plug-in Hybrid) to more than 100 kWh in a long-range pure EV (2012 Tesla Model S and 2015 Tesla Model X). Based on the report of 176 EV models from all kinds of manufactures available online on ev-database.org (EV-database, 2021), the stochastic of the EV's battery capacity can be represented as a truncated normal distribution with mean of $\mu_{cap} = 63.2$ kWh and standard deviation of $\sigma_{cap} = 20$ kWh with assumption of the market share of all EV models are equal.

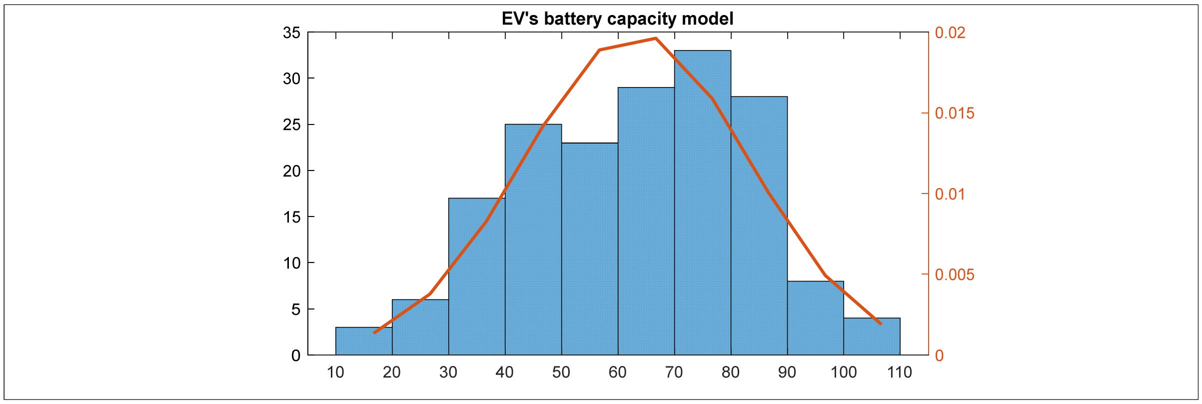

Figure 2.4 Fitting EV's battery capacity data as a normal distribution function

The Monte Carlo Simulation-based method is casted to use in this application to predict the aggregate power and energy boundaries of the EV fleet is illustrated in the algorithm diagram, Figure. 2.5.

- Initialization: Generating randomly a data pool of EV's charging tasks, each charging task is denoted by an 8-tuple $\left(i, ta_i, td_i, sa_i, sd_i, c_i, pc_i^{\max}, pd_i^{\max}\right)$ given the probability distributions of the stochastic variables i.e., arrival time, parking duration, and initial SOC, battery capacity, charging/discharging rate, for a period of 24 hours.
- Initialization: Generating randomly a data pool of EV's charging tasks, each charging task is denoted by an 8-tuple $\left(i, ta_i, td_i, sa_i, sd_i, c_i, pc_i^{\max}, pd_i^{\max}\right)$ given the probability distributions of the stochastic variables i.e., arrival time, parking duration, and initial SOC, battery capacity, charging/discharging rate, for a period of 24 hours.

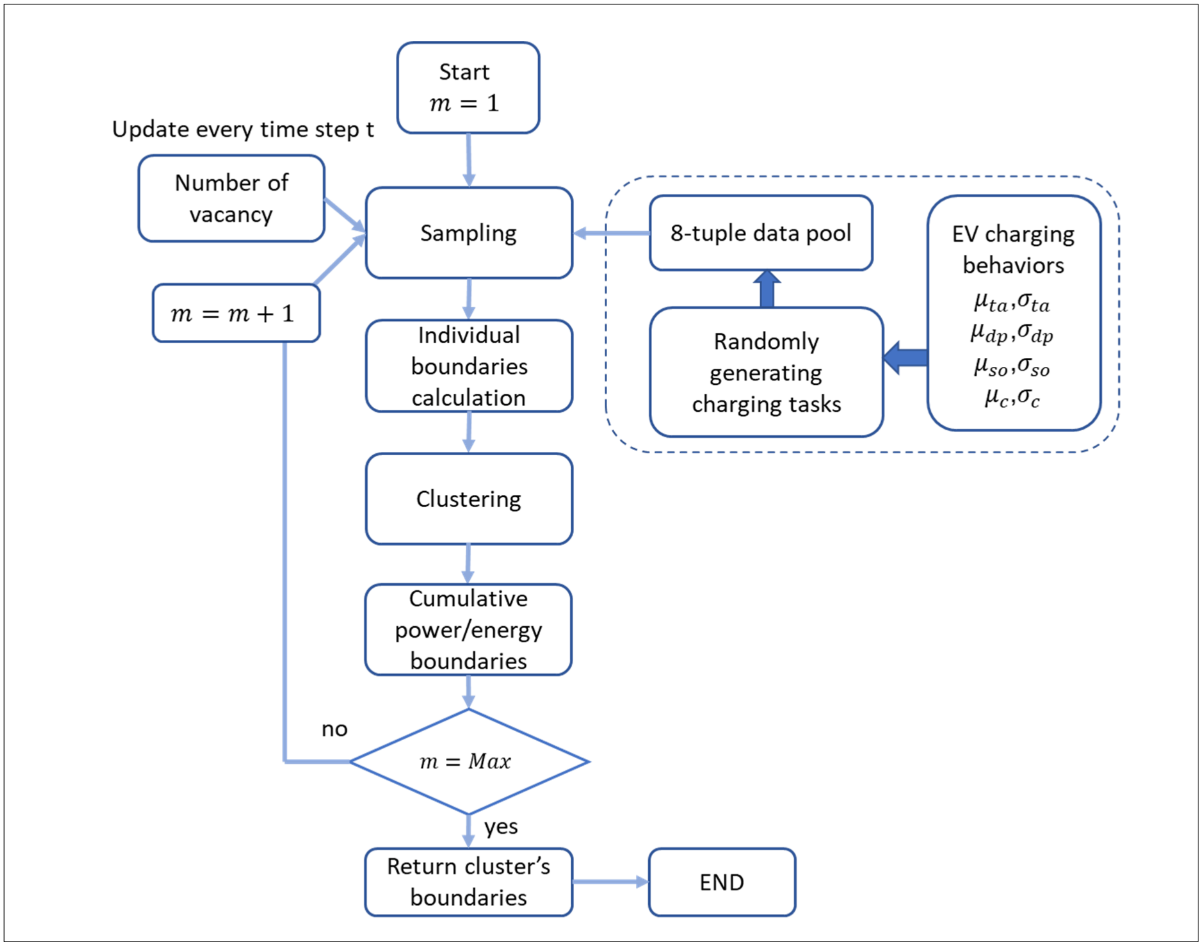

Figure 2.5 MCS-based forecast algorithm

- Step 1: at time t_0^- right before time step t_0, $(t_0 - 1 < t_0^- < t_0)$, the number of vacant charging lots (*Nv*) is updated. Initializing the iteration counter for MCS process $m = 1, (1 \le m \le M)$, with M is the maximum number of iterations for MCS sampling process.
- Step 2: Nv samples will be randomly withdrawn from the data pool.
- Step 3: Calculate the power and energy boundaries of three EV's clusters
- Step 4: Calculate the average of each boundary, return the average power and energy boundaries if $m = M$, else, go back to step 2.

The average power and energy boundaries are fed as predicted data of the aggregate EV fleets into the charge/discharge scheduling optimization problem.

2.3.4 PV system and building loads

In this study, to focus on the stochastic behavior of the EV fleet, we assume to have 24-hour PV generation predicted based on the historical data. To simulate the intermittency of PV power output, random noise will be added into forecast data and sunny and cloudy day data are mixed to account for highly stochastic characteristics.

Besides, the electricity demand in the building is also considered a stochastic variable that depends on the user's behavior defined by the functions of the building. For example, an office building requests more energy during working hours yet only a small amount during nighttime to supply the essential loads such as security system and data center. Whereas, in a residential building, two peaks in its power curve are seen in the morning and evening yet the PV generation is only available during the daytime. In this study, while the focus is on the stochastic behavior of EV charging tasks, the real load profiles in functional buildings are reused by adding certain noises to replicate the uncertainty. Then they will be fed into the optimization model as a predicted data. The effect of different load profiles on the performance of the charge/discharging scheduling optimization problem will be discussed further in the simulations and results section.

2.3.5 Stationary BESS

We assume that a BESS is already installed in the building and have limited capacity Cb due to the high capital cost. Its power charging/discharging rate is limited to be lower than the maximum values $Pc_{\max}, Pd_{\max}$, respectively. The BESS can be discharged to as low as $E_{\min} = 0.2Cb$ and charged up to $E_{\max} = 0.95Cb$ to avoid a fast degradation.

Considering the high-level need of the EV charging management, a mathematical model based on the discrete-time energy balance, has been applied in many studies (Irshad, Nizami, Rafique, Hossain, & Mukhopadhyay, 2020; Mahmud, Hossain, & Town, 2018; J. Wu, Xing, Liu, Guerrero, & Chen, 2018), is represented as follows:

$$Eb(t+1)=\begin{cases} Eb(t)+\eta b_c.Pb_c(t).\Delta t & \text{charging mode} \\ Eb(t)-1/\eta b_d.Pb_d(t).\Delta t & \text{discharging mode} \end{cases} \quad (2.10)$$

Where, $Eb(t)$ and $Eb(t+1)$ are BESS's energy levels at two consecutive intervals t and $t+1$. $Pb_c(t), Pb_d(t)$ denote the charging/discharging power of BESS at time t. charging/discharging efficiencies are represented by $\eta b_c, \eta b_d$, respectively.

2.4 Multi-stage day-ahead market-based charge/discharge scheduling framework (M3)

To achieve the operating goals, a multi-stage operating BCM charge/discharge scheduling optimization problem is proposed, which is illustrated in Figure 2.6. The day-ahead scheduling optimization problem is formulated in the first stage. It takes the forecast data of EV charging behavior, PV generation, load, and day-ahead electricity price provided by the distribution system operators (DSOs) as inputs, then a deterministic optimization problem is formulated and solved to achieve the day-ahead power exchange with the utility, P_{grid_DA}.

The second stage starts before each time step, t^{-}, during the operating day. When the realization of EV's charging tasks at time t is assumed to be known, and prediction of upcoming EV's charging tasks for the rest of the day is available, a rolling horizon optimization problem is formulated. Its goals are to minimize the operating cost, flatten the power curve and balance the power output from the PV system while following the scheduled day-ahead energy buying/selling from/to the main grid.

In the first and second stages, the aggregate EV modeling approach is used to reduce the computational complexity caused by the increase in the number of EVs in a large-scale CS. The EV population in the CS is divided into three different clusters based on their time-flexibility and V2G capability, which will be discussed in detail in the subsequence sections. The uncertainty and data forecast problems in these stages are handled by applying the Monte Carlo Simulation method based on the knowledge of the stochastic variables' probability distribution functions.

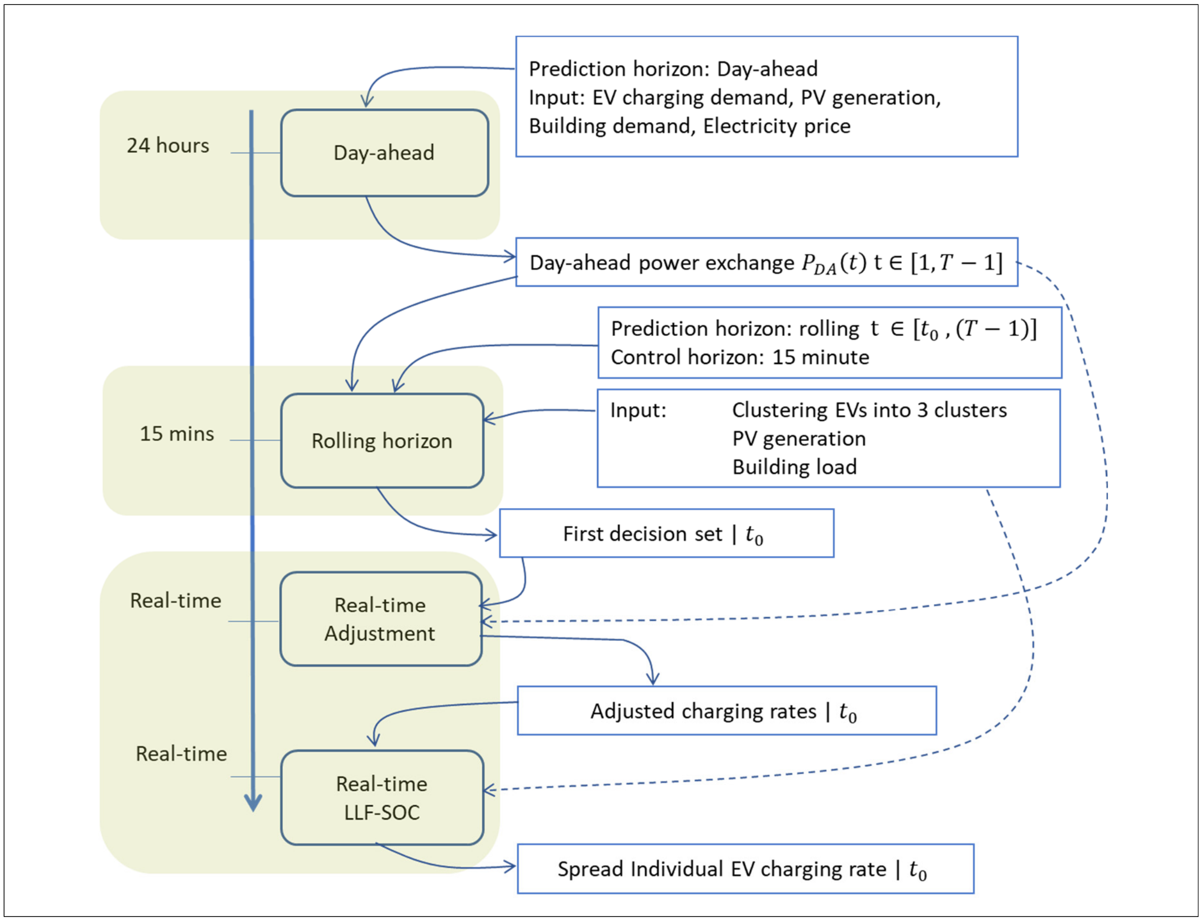

Figure 2.6 Overall the day-ahead market-based charge/discharge scheduling algorithm

In the real-time control stage, power charging rates assigned to the cluster of EVs are divided and spread to individual EVs in the CS. However, the PV generation and loads are subjected to change and cannot be predicted accurately. In this stage, the EV charging flexibility is investigated providing adjustments to the real-time charging/discharging following the fluctuation of the stochastic PV generation and building's load.

2.4.1 Day-ahead scheduling problem

The proposed day-ahead charge/discharge scheduling (DACS) model aims at finding an optimal power trading schedule with the utility over 24-hour ahead, that minimizes the average operating costs for the entire building charging station microgrid, flattens the net load profile at the interface with the utility, and balances the PV generation fluctuation, given the grid limits, stationary BESS limits, predicted PV output and building demand, and forecast data of the EV charging demands a day ahead.

Before the electricity market closes, BCMOs schedule the charging/discharging power rates for BESS, $Pc_b(t), Pd_b(t)$, and $Pc_1(t), Pc_2(t), Pc_3(t), Pd_3(t)$ for 'urgent', 'deferrable', 'controllable' groups, respectively, given the forecast data about the EV charging behavior, PV generation, building load, and day-ahead electricity price. The details of all decision variables and parameters are given in Table. 2.2 and 2.3. Then the exchange power with the main grid over 24-hour ahead can be calculated as $P_{DA}(t) = Pb(t) - Ps(t)$. It is defined as an output of the day-ahead scheduling problem which will be submitted to the DSOs before the operating day.

2.4.1.1 Problem formulation

The day-ahead battery and EV charging scheduling problem is formulated in problem P1, as a mixed-integer nonlinear programming model:

P1:

$$\min_{X_{DA}} f_1 = \sum_{t=1}^{T-1} \left[\begin{array}{l} c_b(t).Pb(t).\Delta t - c_s(t).Ps(t).\Delta t \\ +c_{bat}.\left(Pc_b(t) + Pd_b(t)\right).\Delta t + c_{V2G}.Pd_3(t).\Delta t \\ +\lambda_1.\left(Pb(t) - Ps(t)\right)^2 \\ +\lambda_2.\left(\left(\sum_{j\in\{b,1,2,3\}} Pc_j(t) - \sum_{l=\{b,3\}} Pd_l(t)\right) - Pv(t)\right)^2 \end{array} \right] \tag{2.11}$$

with

$$X_{DA}(t) := \left(Pc_b(t), Pd_b(t), Pc_1(t), Pc_2(t), Pc_3(t), Pd_3(t), \delta b(t), \delta g(t), \delta(t)\right), \forall t \in (1, T-1)$$

Subject to,

grid limits

$$0 \le Pb(t) \le Pb_{\max}.\delta g(t) \tag{2.12}$$

$$0 \le Ps(t) \le Ps_{\max}.\left(1 - \delta g(t)\right) \tag{2.13}$$

$$\delta g(t)=\begin{cases}1 & buying\left(Pb(t)\geq 0, Ps(t)=0\right)\\ 0 & selling\left(Pb(t)=0, Ps(t)\geq 0\right)\end{cases} \quad (2.14)$$

BESS limits $0\leq Pc_b(t)\leq Pc_{\max}.\delta b(t)$ (2.15)

$$0\leq Pd_b(t)\leq Pd_{\max}.\left(1-\delta b(t)\right) \quad (2.16)$$

$$\delta b(t)=\begin{cases}1 & \text{charging}\left(Pc_b(t)\geq 0, Pd_b(t)=0\right)\\ 0 & \text{discharging}\left(Pc_b(t)=0, Pd_b(t)\geq 0\right)\end{cases} \quad (2.17)$$

$$E_{\min}\leq E_b(t)\leq E_{\max} \quad (2.18)$$

$$E_b(t+1)=E_b(t)+\eta c.Pc_b(t)-{}^{1}\!/_{\eta d}.Pd_b(t) \quad (2.19)$$

EV fleets $Pl_i(t)\leq Pc_i(t)\leq Pu_i(t), i\in\{1,2\}$ (2.20)

$$0\leq Pc_3(t)\leq Pu_3(t).\delta(t) \quad (2.21)$$

$$Pl_3(t).\left(1-\delta(t)\right)\leq -Pd_3(t)\leq 0 \quad (2.22)$$

$$El_j(t)\leq E_j(t)\leq Eu_j(t), j\in J \quad (2.23)$$

$$E_j(t)=\sum_{k=1}^{t}Pc_j(k).\Delta t, j\in\{1,2\} \quad (2.24)$$

$$E_3(t)=\sum_{k=1}^{t}\left(Pc_3(k)-Pd_3(k)\right).\Delta t \quad (2.25)$$

$$\delta(t)=\begin{cases}1 & \text{charging}\left(Pc_3(t)\geq 0, Pd_3(t)=0\right)\\ 0 & \text{discharging}\left(Pc_3(t)=0, Pd_3(t)\geq 0\right)\end{cases} \tag{2.26}$$

Power balance

$$Pb(t)+Pv(t)+Pd_b(t)+Pd_3(t)=Ps(t)+\sum_{j\in\{b,1,2,3\}}Pc_j(t)+Pload(t) \tag{2.27}$$

There are two main costs contributing to the operating cost of the entire BCM system, i.e., the energy purchase cost and degradation cost of the batteries including BESS and participated V2G from the 'controllable' EV group. The first row in the objective function of problem P1 (2.11), represents the net cost of energy purchase from the main grid with different purchasing and selling prices $c_b(t), c_s(t)$. It is often set by the distribution system operators (DSOs) such that $c_b(t)>c_s(t)$ to prevent arbitrage activity. The second row denotes the cost associated with the battery degradation causing by charging/discharging in the BESS and extra discharging circles for providing V2G service from EV's battery. In this study, we approximate the degradation cost to be proportional to the amount of charging/discharging energy in the battery, as be used in (Zhang et.al., 2017).

The last two terms in the objective (2.11) account for the load flattening and RES balancing goals. In which, $\left(Pb(t)-Ps(t)\right)^2$ prevent the fluctuation in the net load profile at the PCC, while $\left(\left(\sum_{j\in\{b,1,2,3\}}Pc_j(t)-\sum_{l\in\{b,3\}}Pd_l(t)\right)-Pv(t)\right)^2$ reduces the imbalance between EV, BESS load and PV generation (Sadeghianpourhamami et al., 2018). $j\in\{b,1,2,3\}$ are indices to denote the BESS (b), 'urgent' cluster (1), 'deferrable' cluster (2), and 'controllable' cluster (3). Two coefficients λ_1, λ_2 control the contribution of each term in the effectiveness of the optimal schedule via a trade-off between cost-saving and flattening or balancing.

Equations (2.12-2.14) ensure the grid limits to be maintained at all times. The binary variable $\delta g(t)$ is introduced to separate selling from purchasing energy at the PCC. It allows to apply different selling/purchasing energy prices $c_b(t), c_s(t)$ and prevents selling and purchasing simultaneously. The stationary BESS's constraints are represented in equations (2.15-2.19).

They include charging/discharging power limit in equation (2.15), (2.16); energy limits in equation (2.18); the discrete energy balance model of the BESS in (2.19). The binary variable $\delta b(t)$ denotes the charging status of the BESS. The cumulative power and energy of three EV fleets are bounded in the feasible set defined by the equations (2.20 – 2.26). The lower boundaries of 'urgent' and 'deferrable' EV groups are greater or equal to zero while that of the 'controllable' EV group is allowed to be negative to provide discharging power back to the grid and building. The charging, discharging variables of the 'controllable' EV group are separated in order to apply the payback for their V2G support. Finally, the power flows in the entire building-charging station microgrid are balanced at all times, equation (2.27).

2.4.1.2 Solving the day-ahead optimization problem

An hour before the electricity market closing, the MCS algorithm obtains the average cumulative power and energy boundaries of the EV fleets. That information is fed into the DACS optimization problem. The day-ahead problem becomes deterministic under the assumption of the knowledge about the probability distribution function of the stochastic arrival time, parking duration, initial SOC, battery's capacity, and charging rate along with the prediction of PV generation, building load, and day-ahead electricity price. It is formulated as mixed-integer nonlinear programming with the quadratic parts in the objective function. Thanks to the fleet-based aggregation technique, the number of variables is reduced significantly, which makes the problem effectively tractable using any off-the-shelf solver like CPLEX, Matlab optimization toolbox, and Gurobi. By solving the DACS optimization problem, the optimal power exchange with the utility is determined and submitted to the DSOs as the first settlement. Noted that the BCM plays as a price-taker in the electricity market and can receive the prediction of day-ahead pricing from the DSOs. Its capacity is small enough to not affect the locational marginal pricing so that the regulation reserve service is not considered in the operation of the BCM.

2.4.2 Rolling horizon control problem

During the operating day, when the realization of EV availability at the CS, demand of the building, PV power output are available, BCMOs process to charge/discharge the EV fleets, stationary BESS, and decide the real-time power exchange with the utility in an adaptive manner. That aims to minimize the expected cost for the rest of the day subject to the scheduled day-ahead $P_{DA}(t)$, the EV charging flexibility and BESS capacity limitations. If the day-ahead power $P_{DA}(t)$ is greater than actual power $P_g(t)$, the BCMOs must cancel the overscheduled energy and pays a certain cancelation fee. When the scheduled power is less than the actual used power, $P_{DA}(t) < P_g(t)$, the excess energy will be purchased in the time-of-use electricity price, which is usually higher than day-ahead price. The charge/discharge scheduling optimization problem aims to minimize the operating cost of the entire building. Therefore, following the scheduled day-ahead power plan to make use of the wholesale electricity price using the flexibility of EV and ESS may reduce the overall operating cost.

2.4.2.1 Problem formulation

In this second stage, right before any time step t_0, at t_0^- with ($(t_0 - 1) < t_0^- < t_0$) the EVs arrival during the time period $[(t_0-1)^+, t_0^-]$ are known, and the parked EVs charging status is updated. The expected EV charging tasks which are coming to CS during the rest of the day $(t_0, T-1)$, are predicted using MCS method. The second stage charge/discharge scheduling optimization problem is formulated to minimize the average cost over the period $(t_0, T-1)$. The second-stage objective function is presented as below.

P2:

$$\min_{X_{t0}} f_2 = \sum_{t=t_0}^{T-1} \begin{bmatrix} c_b(t).Pb(t).\Delta t - c_s(t).Ps(t).\Delta t \\ +c_{bat}.\left(Pc_b(t) + Pd_b(t)\right).\Delta t + c_{V2G}.Pd_3(t).\Delta t \\ +\lambda_2.\left(\left(\sum_{j\in\{b,1,2,3\}} Pc_j(t) - \sum_{l=\{b,3\}} Pd_l(t)\right) - Pv(t)\right)^2 \\ +\lambda_3.\left(Pb(t) - Ps(t) - P_{DA}(t)\right)^2 \end{bmatrix} \tag{2.28}$$

The second stage objective function is similar to the objective function of the first stage. However, there are some differences accounting for the change of the prediction horizon from t_0 to T–1instead of the entire 24-hour period. This aims to follow the day-ahead schedule, $P_{DA}(t)$ with the new term, $\lambda_3.(Pb(t) - Ps(t) - P_{DA}(t))^2$ in the objective function. As long as it tracks the day-ahead $P_{DA}(t)$, the aim of flattening the power curve is no longer needed. The second stage optimization problem also follows the constraints (2.12) – (2.27).

The second stage optimization problem is repeated before every time step with the rolling prediction horizon. Only the first decision set is adopted to the operation at time step t_0, the rest are discarded. Thus, the output of the second stage optimization is the set $X_{opt}(1\,|\,t_0^-)$ of power charging/discharging rates $Pc_1\left(1\,|\,t_0^-\right), Pc_2\left(1\,|\,t_0^-\right), Pc_3\left(1\,|\,t_0^-\right), Pd_3\left(1\,|\,t_0^-\right)$ for three EV clusters, respectively, and the charging/discharging decisions for stationary BESS, $Pc_b(1\,|\,t_0^-), Pd_b(1\,|\,t_0^-)$. In which, $(1\,|\,t_0)$ denotes for the decision at the first step of the optimal results which is calculated at time t_0.

2.4.2.2 Solving the rolling-horizon optimization problem

Similar to the day-ahead optimization problem, rolling-horizon is modeled as and Mixed-Integer Quadratic Programming (MIQP) problem. The problem is formulated every 15 minutes, and right before the operating point over the rest of the day. The rolling horizon MIQP problem can be solved using a commercial solver as mentioned in 2.4.1.2. However, the large-scale EV fleet and shorter time steps make the problem more complex. Thus, the proposed cluster-based integrated EV model helps reduce the number of variables significantly, which speeds up the calculation speed. In this study, we use Matlab Optimization toolbox to solve both day-ahead planning and rolling-horizon problems.

2.4.3 Real-time control problem

By solving problem P2, we obtain a series of optimal decision sets $X_{opt}(t), \forall t \in (t_0, T)$, then the decision in the first step $X_{opt}(1 \mid t_0^-)$ is applied to the next operation interval. The aggregate power charging rate $Pc_1\left(1 \mid t_0^-\right), Pc_2\left(1 \mid t_0^-\right), Pc_3\left(1 \mid t_0^-\right), Pd_3\left(1 \mid t_0^-\right)$ will be divided and spread to individual EVs. The 'urgent' demands need to be satisfied at all times so that EVs in the 'urgent' fleet are charged at their possible maximum rate $pc_i(t_0) = \min(pc_i^{\max}, e_i(t_0)/\Delta t)$. While the charging/discharging rates $Pc_2\left(1 \mid t_0^-\right), Pc_3\left(1 \mid t_0^-\right), Pd_3\left(1 \mid t_0^-\right)$ need to be divided for spreading to individual EVs in the 'deferrable' and 'controllable' clusters. A real-time adjustment may be required in the 'deferrable' and 'controllable' clusters before the dividing process. The adjustment is based on the EV flexibility of the 'deferrable' and 'controllable' fleets to compensate for the deviation from the planned day-ahead schedule caused by the uncertainty of the PV and building's loads.

2.4.3.1 Real-time LLF_SOC control algorithm

In this work, we adopt a heuristic real-time control technique named Least-Laxity-First-SOC (LLF-SOC) (H. Zhang et al., 2017) to determine the individual charging rate for each EV in the fleets. Based on both their laxity and SOC, EVs in 'deferrable' and 'controllable' fleets are separated into G groups with indices $g \in \{1, ..., G\}$. EVs with the lowest group index will be charged first, in contrast, the highest indexing group will be able to discharge first. The LLF-SOC algorithm is illustrated in Figure 2.7 and presented in detail as follows.

The EVs in the 'deferrable' fleet are only be charged, $Pc_2\left(t_0\right) > 0$, or idled, $Pc_2\left(t_0\right) = 0$, while EVs in 'controllable' fleet will be charged if scheduled power rate

$P_3(t_0) = Pc_3(t_0) - Pd_3(t_0) > 0$, idled if $P_3(t_0) = 0$, or discharged if $P_3(t_0) < 0$. EVs in each fleet, first, are divided into G L-sharp groups based on their current laxity and SOC.

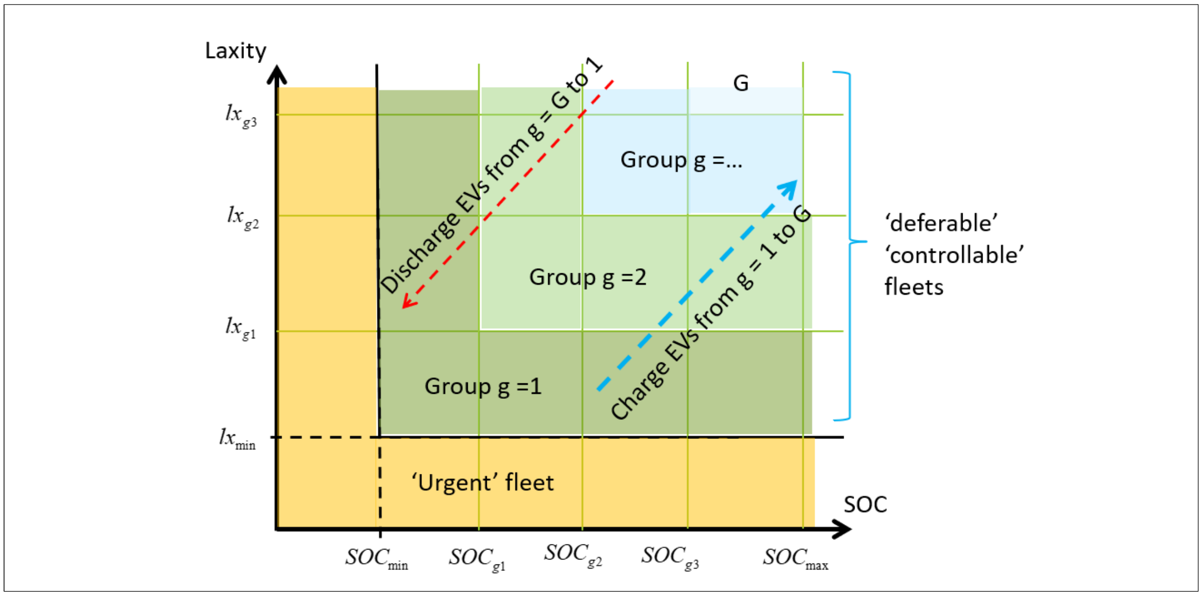

Figure 2.7 LLF – SOC algorithm illustration

In 'deferrable' fleet, EVs will be charged by the sequence of the group indices $g \in \{1, 2, ..., G\}$. Starting from $g = 1$, if the total maximum charging rates of EVs in the group g, $Pu_{2,g}(t_0) \le P_2(t_0)$, then all EVs in such group will be charged at their rate, then the residual of the schedule power rate $P_2(t_0) = P_2(t_0) - Pu_{2,g}(t_0)$ will be assigned to the next group $(g+1)$. This procedure continues until $Pu_{2,g}(t_0) > P_2(t_0)$, then EVs in this group will get the charging power $p_i^{\max}.\left(P_2(t_0)/Pu_{2,g}(t_0)\right)$.

The procedure is the same as above for the charging process in the 'controllable' group if $P_3(t_0) \ge 0$, while discharging is processed in the opposite direction (starting to discharge from group G^{th} to group 1^{st}) if $P_3(t_0) \le 0$.

2.4.3.2 Real-time adjustment and EV flexibility exploitation

In the real-time market control manner, BCMOs receive an optimal charging schedule right before the operating time step, that based on the measurements and forecast at time t_0^- after time t_0-1 and right before t_0. EVs which arrive during the period from t_0^- to $(t_0+1)^-$ are assumed to wait until time t_0+1 to be charged. Thus, the number of available EVs involve in the charging/discharging process during calculation time, from the data collecting time point t_0^- to the next assessment time $(t_0+1)^-$, remains unchanged. Therefore, the power and energy boundaries of the EV clusters stay the same. That allows evaluating the flexibility of the EV cluster which is valid for at least a duration of Δt from t_0^- to $(t_0+1)^-$ and covers the operating point t_0. However, building loads and PV generation could vary significantly during this evaluation period. The realization of the stochastic variables potentially increases the requested power from the main grid, causing overload and jeopardizing the stability of the distribution network. The EV's flexibility comes into play to handle this issue. That requires to be evaluated before the operating point to find how much energy (power) can be adjusted without scarifying the customer's convenience.

The flexibility of the EV fleet is defined as its ability to accommodate the variability and uncertainty in the charging/discharging balancing while maintaining satisfactory levels of EV's demands for any time scale. However, there is no uniform definition of flexibility. In our work, the EV's flexibility is defined as the ability of EV fleets to take the charging power adjustment to support building-microgrid in case of overloading at the point of common coupling (PCC) and compensate the mismatch between scheduled decision and real-time realization. There are two types of EV charging flexibility that need to be separated to use in different time scale: expected EV flexibility and real-time EV flexibility.

The expected flexibility of an EV fleet is reflected through its power and energy boundaries over the predicting horizon as analyzed in section 2.2.2. It relies on the expected EV arrival in the future and strongly depends on the probability distribution function of the stochastic variables. The expected flexibility is useful for day-ahead planning in the first stage and rolling horizon optimization scheduling in the second stage.

In the real-time control stage, the realization of the EV fleet at the operating point t_0 is known, so that the real-time EV flexibility can be assessed to provide real-time adjustment before dividing power charging rates to individual EVs in the 'deferrable' and 'controllable' cluster applying the LLF-SOC algorithm as presented in the previous section.

The 'deferrable' EV fleet can be able to reduce its charging power from the scheduled value $Pc_2(1|t_0^-)$ to its lower boundary, $Pl_2(t_0)=0$, or increase to the upper boundary, $Pu_2(t_0)$. Similarly, the 'controllable' EV fleet can increase the charging rate $P_3(1|t_0^-)$ up to its upper bound $Pu_3(t_0)$, or discharging up to $Pl_3(t_0)$. We denote the maximum adjustment up as $\Delta P_{up}(t_0)$ and maximum adjustment down as $\Delta P_{down}(t_0)$ which are evaluated at time t_0 as a metric to assess the real-time EV flexibility. That can be calculated as follows:

$$\Delta P_{up}(t_0) = \Delta P_{2\_up}(t_0) + \Delta P_{3\_up}(t_0)$$
$$\begin{cases} \Delta P_{2\_up}(t_0) = \min\left(Pu_2(t_0), Eu_2(t_0)/\Delta t\right) - Pc_2(1|t_0^-) \\ \Delta P_{3\_up}(t_0) = \min\left(Pu_3(t_0), Eu_3(t_0)/\Delta t\right) - P_3(1|t_0^-) \end{cases} \tag{2.29}$$

$$\Delta P_{down}(t_0) = \Delta P_{2\_down}(t_0) + \Delta P_{3\_down}(t_0)$$
$$\begin{cases} \Delta P_{2\_down}(t_0) = \max\left(0, Pc_2(1|t_0^-)\right) \\ \Delta P_{3\_down}(t_0) = \max\left(0, \min\left(P_3(1|t_0^-) - Pl_3(t_0), El_3(t_0)/\Delta t\right)\right) \end{cases} \tag{2.30}$$

At t_0^- advance to time t_0, the set of decision, $Pc_1\left(1|t_0^-\right), Pc_2\left(1|t_0^-\right), P_3\left(1|t_0^-\right)$ are achieved by solving the rolling horizon optimization P2. The EVs which arrive between the time t_0^- and t_0 do not involve in the charging process, then do not contribute to the EV charging flexibility assessment at time t_0. The BCMOs, first, charge the 'urgent' EV fleet up to the charging rate $Pc_1(t_0) = Pc_1\left(1|t_0^-\right)$. Because of the deviation from the forecast PV output and building's demand, the mismatch between the real-time, $P_g(t_0)$, and day-ahead , $P_{DA}(t_0)$ power exchange with the utility at time t_0 is calculated as $\Delta P_g(t_0) = P_g(t_0) - P_{DA}(t_0)$. The real-time adjustment is presented as a heuristic logic adjustment algorithm in Figure 2.8.

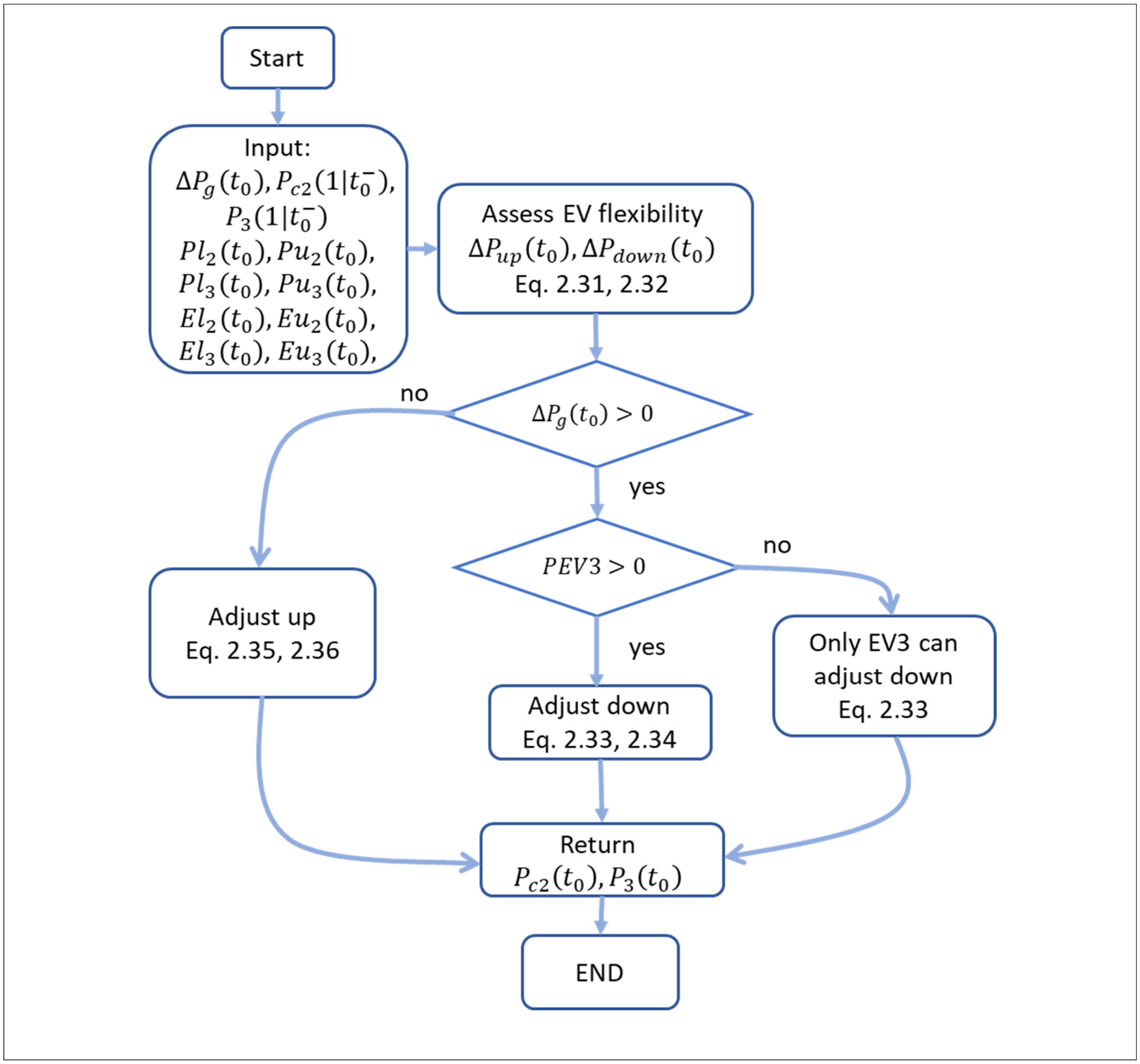

Figure 2.8 Real-time adjustment algorithm

The inputs are the grid power deviation $\Delta P_g(t_0)$, charging rates $Pc_2(1|t_0^-), P_3(1|t_0^-)$, and the power and energy boundaries of EV fleets assessed at time t_0. The algorithm starts to check if the adjustment is up or down. If the real-time power, $P_g(t_0)$ is larger than the scheduled day-ahead market, $P_{DA}(t_0)$, i.e., $\Delta P_g(t_0) > 0$, an adjustment down is made. If 'controllable' fleet is in the discharging mode, $P_3(1 \mid t_0^-) \leq 0$, the only 'deferrable' fleet can reduce their charging rate to process the adjustment down, otherwise, if $P_3(1 \mid t_0^-) > 0$, both 'deferrable' and 'controllable' fleet can be adjusted down, equation 2.31 and 2.32.

$$Pc_2(t_0) = \max\left(\begin{array}{l} 0, \\ Pc_2(1 \mid t_0^-) - \min\left(\begin{array}{l} \Delta P_{2\_down}, \\ \dfrac{\Delta P_{2\_down}}{\Delta P_{2\_down} + \Delta P_{3\_down}} \Delta P_g(t_0) \end{array}\right) \end{array}\right) \tag{2.31}$$

$$Pc_3(t_0) = \max\left(\begin{array}{l} \dfrac{El_3(t_0)}{\Delta t}, \\ Pl_3(t_0), \\ Pc_3(1 \mid t_0^-) - \min\left(\begin{array}{l} \Delta P_{3\_down}, \\ \dfrac{\Delta P_{3\_down}}{\Delta P_{2\_down} + \Delta P_{3\_down}} \Delta P_g(t_0) \end{array}\right) \end{array}\right) \tag{2.32}$$

When the real-time power is insufficient, $\Delta P_g(t_0) < 0$, an adjustment up is processed as follows.

$$Pc_2(t_0) = \min\left(\begin{array}{l} \dfrac{Eu_2(t_0)}{\Delta t}, \\ Pc_2(1 \mid t_0^-) - \min\left(\begin{array}{l} \dfrac{\Delta P_{2\_up}(t_0)}{\Delta P_{2\_up}(t_0) + \Delta P_{3\_up}(t_0)} \Delta P_g(t_0), \\ \Delta P_{2\_up}(t_0) \end{array}\right) \end{array}\right) \tag{2.33}$$

$$Pc_3\left(t_0\right)=\min\left(\begin{array}{l}\dfrac{Eu_3(t_0)}{\Delta t},\\ Pl_3(t_0),\\ Pc_3\left(1\,|\,t_0^-\right)-\min\left(\begin{array}{l}\dfrac{\Delta P_{3\_up}(t_0)}{\Delta P_{2\_up}(t_0)+\Delta P_{3\_up}(t_0)}\Delta P_g\left(t_0\right),\\ \Delta P_{3\_up}(t_0)\end{array}\right)\end{array}\right) \tag{2.34}$$

Subsequently, the adjusted charging/discharging power rates will be divided and spread to the individual EVs in ‘deferrable’ and ‘controllable’ clusters. The real-time LLF-SOC and real-time adjustment are based on a heuristic logical control algorithm, the computational time is sufficient to implement in a real-time manner.

2.5 Summary

In this chapter, we model the BCM system and present a solution for our stated research questions. The operating problem in the aggregator (BCMOs) perspective is clearly stated which follows the day-ahead electricity market to schedule and control the charging/discharging processes of the EVCS and BESS for minimizing the average operating cost, balancing the renewable energy generation, flattening the power curve at the PCC, given the knowledge about probability distribution function of the EV charging behavior, forecast data of PV generation, building load, and day-ahead electricity price. First, the individual EV charging model is presented followed by the cluster-based aggregate EV charging model. Then the multi-stage charge/discharge scheduling optimization problem is formulated in different time scales, i.e., day-ahead, 15-minute, and real-time. Finally, an EV charging flexibility assessment for a real-time adjustment algorithm is introduced.

CHAPTER 3

NUMERICAL RESULTS AND DISCUSSIONS

3.1 Simulation set up and parameters

In this chapter, a series of numerical simulations are carried out to demonstrate the efficiency of the proposed algorithm using real-world data. The BCM in Figure 2.1 is connected to the main grid at the PCC with limited power exchange, $Pb_{\max} = Ps_{\max} = 3000\ kW$. A solar system comprises $A^{PV} = 5000$ m^2 PV panels on the building's roof and the parking canopy with energy conversion efficiency is $\eta^{PV} = 0.3$. The solar radiation intensity data adopted from high-resolution solar radiation datasets at Alderville, ON (available online on nrcan.gc.ca). The solar irradiance will be modified to create the condition of two typical days i.e., cloudy, and clear days. To address uncertainty, random noise is added to the real data with a random mix between cloudy and clear data to obtain a highly stochastic PV power output as illustrated in Figure 3.1. A stationary BESS is considered in the BCM system with 1500 kW / 5000 kWh power/capacity. Its operating range is from 20% to 95% of its capacity to avoid fast degradation because of overcharging/discharging. In this simulation, we neglect the BESS's charger/inverter losses, with $\eta_c^b = \eta_d^b = 1$.

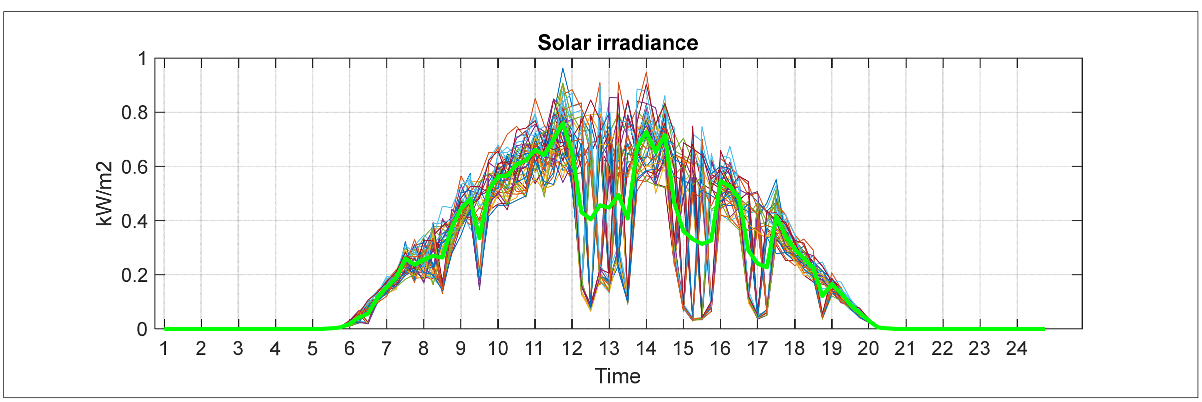

Figure 3.1 Solar irradiance simulated data

Our experimental scenario is based on the open energy data achieved from the Open EI website (Open-EI) with data tailored to meet the larger scale of the building. Three types of loads are adopted representing the specific consumption profiles in office, residential, and commercial buildings. The high resolution (15-minute interval) electricity price is simulated base on the hourly day-ahead electricity price data achieved from the ISO New England website (https://www.iso-ne.com/markets-operations). Instead of using a time-of-use price scheme, we apply the penalty fee on both cancel and excess energy used during the real-time operating at a fixed value of 0.027 $/kWh (D. Wu et al., 2017).

Table 3.1 Parameters and coefficients of BESS-PV-MG

BCM's Elements	**Parameters**	**Value**	**Unit**
PV generator	A^{PV}	5000	m^2
	η^{PV}	0.3	
BESS	E_{cap}	5000	kWh
	$E_{\min}$	$20\%.E_{cap}$	kWh
	$E_{\max}$	$95\%.E_{cap}$	kWh
	$Pd_{\max}$	1500	kW
	$Pc_{\max}$	1500	kW
	E_0	$50\%.E_{cap}$	kWh
	$\eta c, \eta d$	1	
	Cb	8	$cent/kWh
PCC	$Pb_{\max}$	3000	kW
	$Ps_{\max}$	3000	kW
EVCS	N	1000	Parking lots
	Level	I, II, III, fast charging	Charing levels

The statistical knowledge of the EV fleets parking behaviors is achieved from the related works that are analysed in section 2.2.3. The probability distribution parameters of the EV's behaviors are listed in Table 3.2 and then illustrated in Figure 3.2 and Figure 3.3 with the samples of 1000 EV charging tasks.

Table 3.2 Probability distribution parameters for three difference type of parking stations

Probability Distribution		**Office**	**Residence**	**Commercial**	**Reference**
Arrival time (h)	μ_{ta}	9	18.5	12	Gao et al., 2019
	σ_{ta}	2	2	4	
Parking duration (h)	μ_{dp}	7	10.5	2.5	Zhou. Y et al., 2018
	σ_{dp}	2	2	2	
Initial SOC	μ_{so}	0.6	0.6	0.6	Islam et al., 2018
	σ_{so}	0.2	0.2	0.2	
Capacity (kWh)	μ_c	75	75	75	EV-database, 2021
	σ_c	10	10	10	

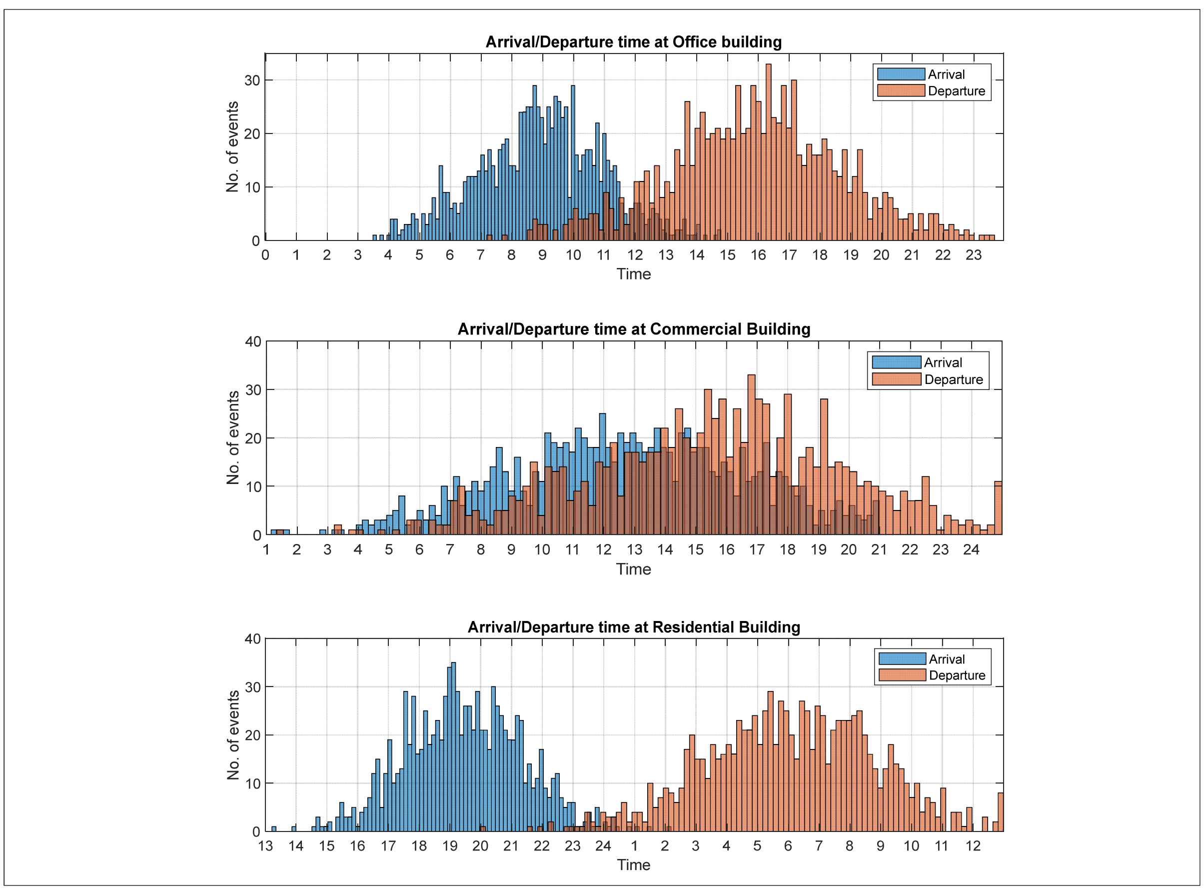

Figure 3.2 Arrival/departure pdf in three different parking station – office, commercial and residential building

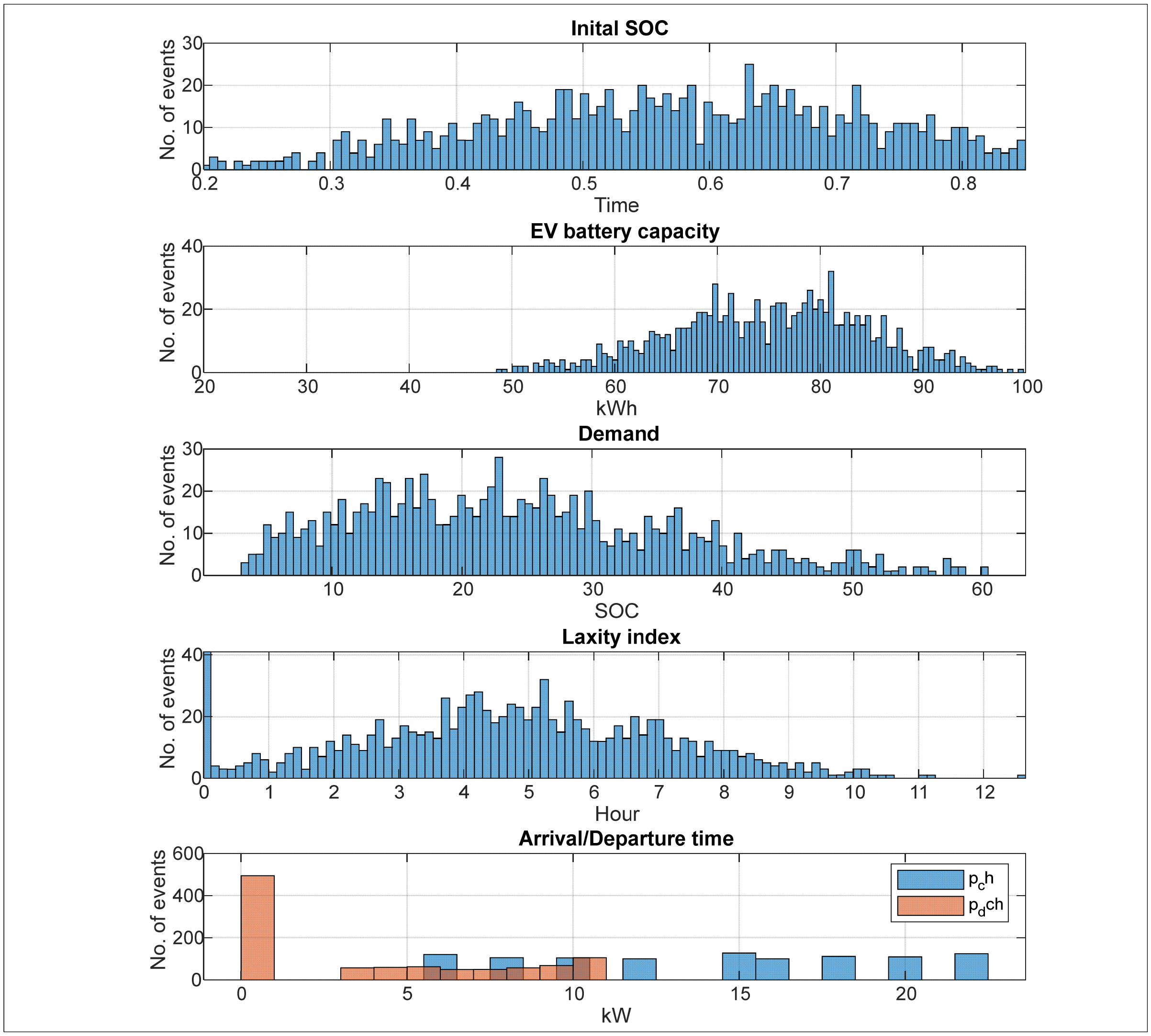

Figure 3.3 Cumulative distribution functions of the stochastic behaviors - sample of 1000 charging events withdrawn from the 8-tuple data pool at an Office BCM

In the real-time LLF-SOC algorithm, the EVs in the ‘deferrable’ and ‘controllable’ clusters are divided into G = 10 groups. We choose a sampling time of 15 minutes then simulations are performed over a 24-hour horizon. The simulations have been implemented in the MATLAB environment in a computer with an Intel Core i7 CPU 3GHz, 24 Gb of RAM.

3.2 Results and discussions

To investigate the performance of the proposed algorithm, we compare it with a baseline algorithm that is also a multi-stage charge/discharge scheduling optimization but without real-time adjustment. We ensure the EV's characteristics as well as PV generation, building load, and electricity price are identical for both algorithms in each run. The algorithms are tested in three different types of BCM multiple times.

The results of the proposed multi-stage DACS optimization problem are represented in Figures 3.4 – 3.6 for and office, residential, and commercial BCM, respectively. Figure 3.4 shows the charge/discharge schedule for an office BCM, in which, the EV charging power achieves a peak around 11:00 when most of employees arrived their office. The actual exchanging power with the utility in real-time market (the red line) follows closely the day-ahead schedule (violet dashed line). Whereas the larger deviations are shown in the results of a commercial and residential BCM. In the residential BCM (Figure 3.5), the deviations are greatest during the daytime without the support from the EV fleets, the power exchange with the utility is strongly influenced by the fluctuation of PV power output. As seen in three Figures 3.4 – 3.6, although the actual power used during the operating day strictly follows the day-ahead curves in almost every time steps, two large excesses can be realized in a commercial BCM around 19:00 to 21:30 and in residential BCM from 4:00 to 7:00.

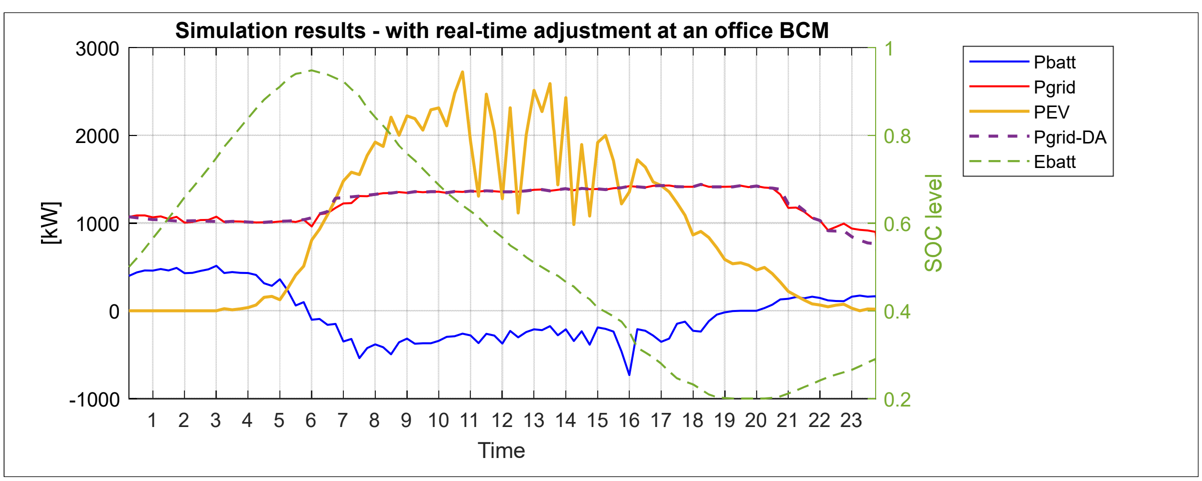

Figure 3.4 Simulation results – proposed algorithm for an office BCM

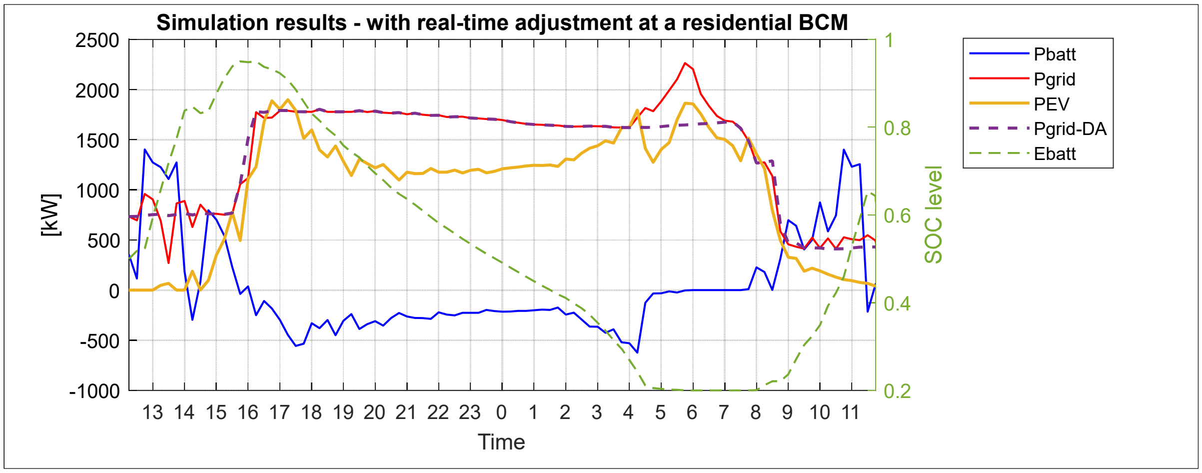

Figure 3.5 Simulation results – proposed algorithm for a residential BCM

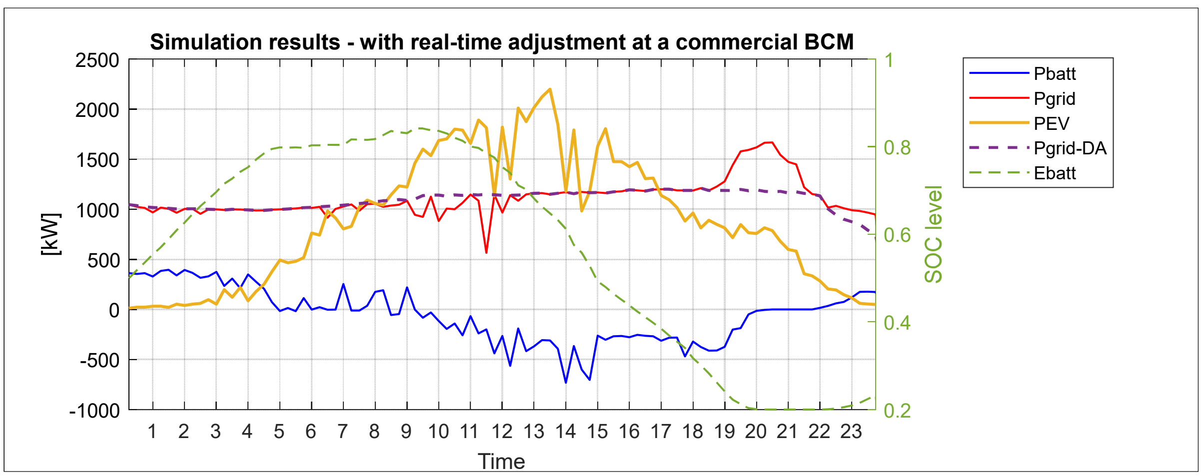

Figure 3.6 Simulation results – proposed algorithm for a commercial BCM

3.2.1 Assessment of EV Flexibility

From equations 2.31 and 2.32, the flexibility of the EV fleets can be assessed and lasts for at least one interval (Δt). It can be seen illustratively in Figures 3.7 to 3.9. The results show the greater flexibility corresponds to the longer parking duration EV fleet. In office and residential BCMs, EVs are usually parked for much longer than needed to fully charge their battery. They potentially provide higher flexibility to cooperate the operation of the BCM, with about 10,000 kW of power flexibility. Whereas EVs parked at a commercial BCM have shorter parking durations while still request a high demand. They are less flexible and provide less than 2,000 kW of power flexibility most of the time (Figure 3.9). However, the performances of the three BCMs are not significantly different because the maximum deviation from the schedule day-ahead power is only about 600 kW. Thus, the EV flexibility is sufficient to eliminate the power deviation most of the time.

The EV flexibility in a residential BCM is illustrated in Figure 3.8. EVs are mostly available at a residential parking during the nigh time while most of deviation caused by the intermittence of the PV generation during the daytime when BCMOs need the EV flexibility the most. Interestingly, in a residential BCM, there is not enough flexibility to adjust down at the end of the parking period from 5:00 to 6:45. It is caused by the error in the day-ahead forecast. Therefore, most of EVs are becoming 'urgent' before departure in the morning while other EVs in the 'controllable' cluster are in the discharging mode (Figure 3.10), which does not allow them to provide the real-time adjustment down.

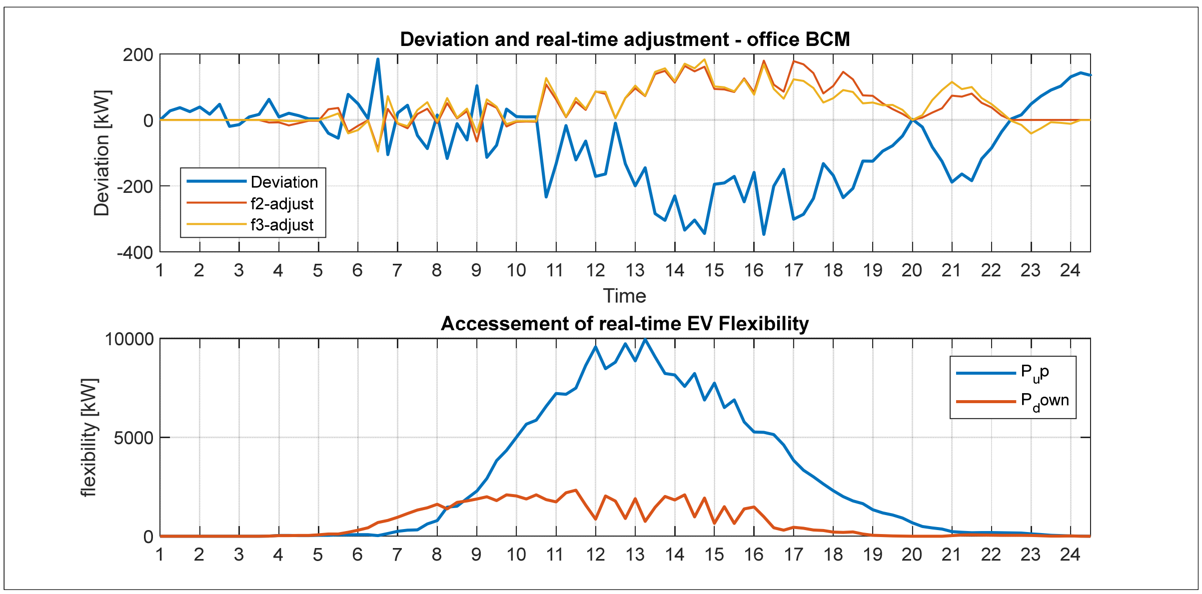

Figure 3.7 Real-time flexibility boundaries of the EV fleet and adjustment against the deviation from day-ahead planning in Office BCM

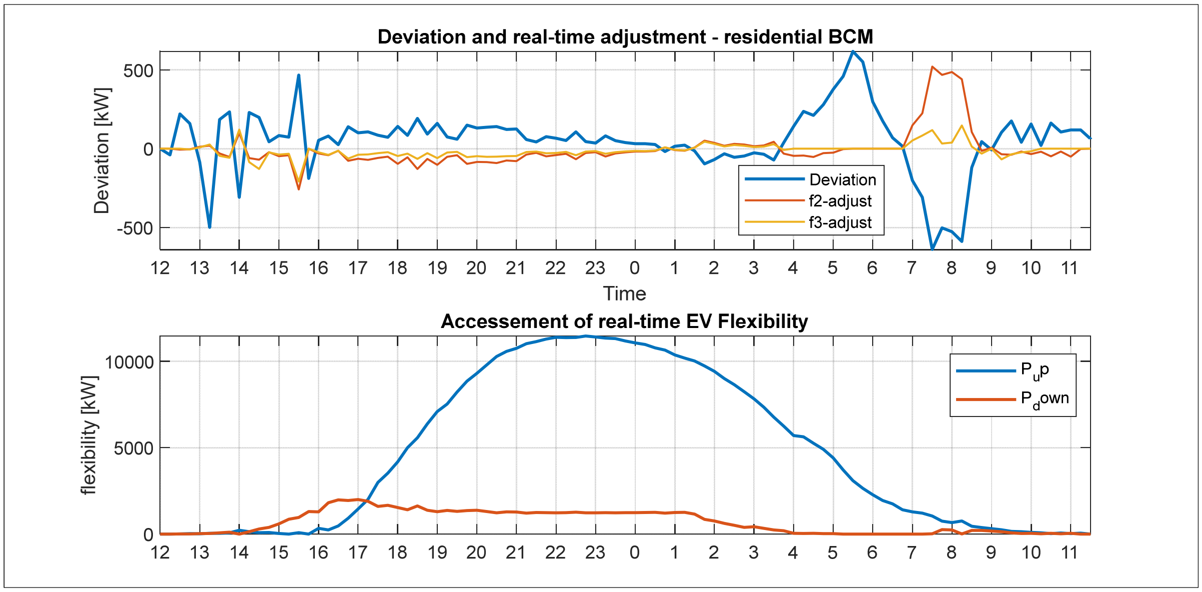

Figure 3.8 Real-time flexibility boundaries of the EV fleet and adjustment against the deviation from day-ahead planning in Residential BCM

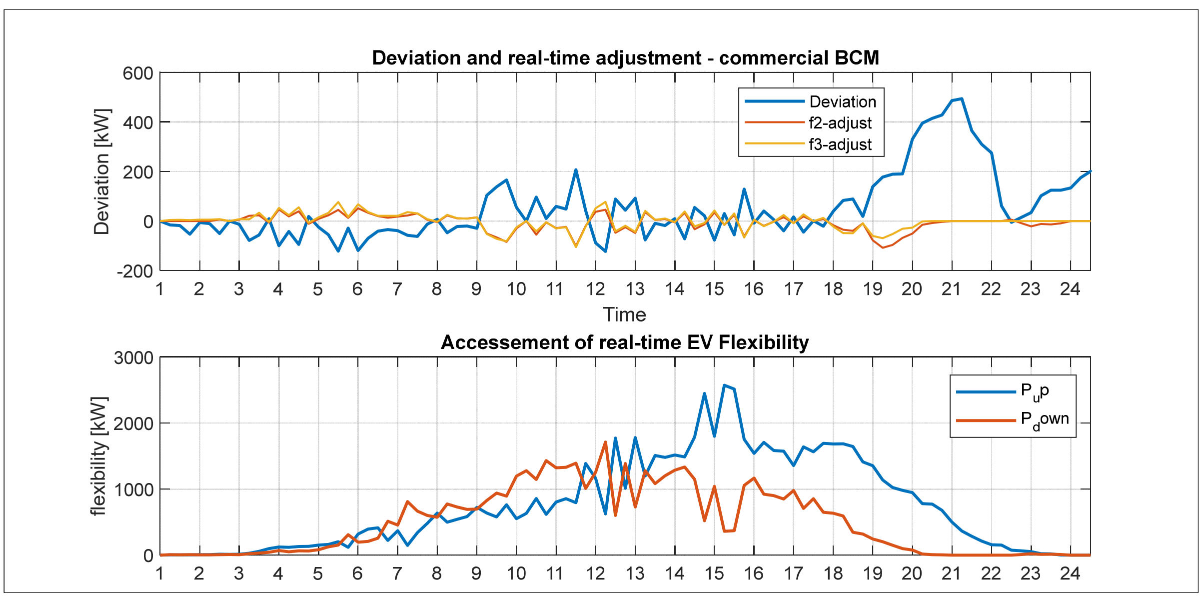

Figure 3.9 Real-time flexibility boundaries of the EV fleet and adjustment against the deviation from day-ahead planning in Commercial BCM

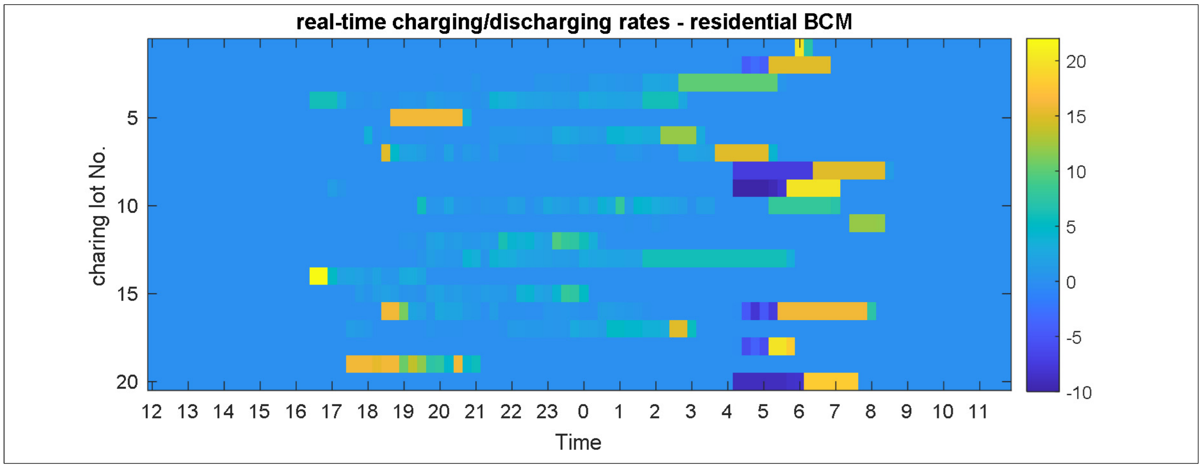

Figure 3.10 Real charging/discharging rates [kWh] assigned to EVs at the first 20 charging lots – residential BCM

It is worth noting that real-time adjustment may cause more delay or immature full charge. The delay caused by the real-time adjustment will reduce the ability to provide adjustment down at the end of the parking period since those charging tasks become 'urgent' and cannot be adjusted down. The immature full charge means that the EV is unable to provide the adjustment down during the rest of the parking period. This results in larger deviations as we can see at the end of the parking period in both three BCMs.

Thanks to the cluster-based modeling strategy, the 'urgent' charging tasks are kept track by the rolling-horizon optimization every time step so that EVs in this cluster will be charged as soon as their task becoming 'urgent'. In addition, the real-time adjustment algorithm utilizes only the free flexibility capacity of the EV fleets to keep track of the day-ahead schedule. It avoids requesting discharging from the EVs in the 'controllable' cluster for real-time adjustment purposes. Thus, there is no additional fee added to the operating cost during the adjustment processes while it well adapts to the volatile of the PV generation and building demand.

3.2.2 EV user's satisfaction

EV's user satisfaction is the primary goal of a charging station. It can be represented as a ratio of the amount of charged energy over the total requested demand in percentage. We denote the satisfaction index as s_index, then its calculation is represented as bellow.

$$s\_index = \left(1 - \frac{\sum_{i=1}^{N} D_i(td_i)}{\sum_{i=1}^{N} D_i(ta_i)}\right).100\% \tag{3.1}$$

In which, $D_i(td_i)$ is the demand of EV i^{th}, remaining at the departure time td_i. $D_i(ta_i)$ is the demand of EV i^{th}, requested at the arrival time ta_i.

The simulation results show that the proposed algorithm can ensure at least 97% of the EV satisfaction. We run the simulation multiple times and the EV satisfaction is presented in Figure 3.11. The least satisfaction index can be seen in residential BCM with the lowest point is above 97%, and the average number of EVs that leaving with lower energy level than the designed value is only 15 over 977 arrival EVs at the CS during the operating day.

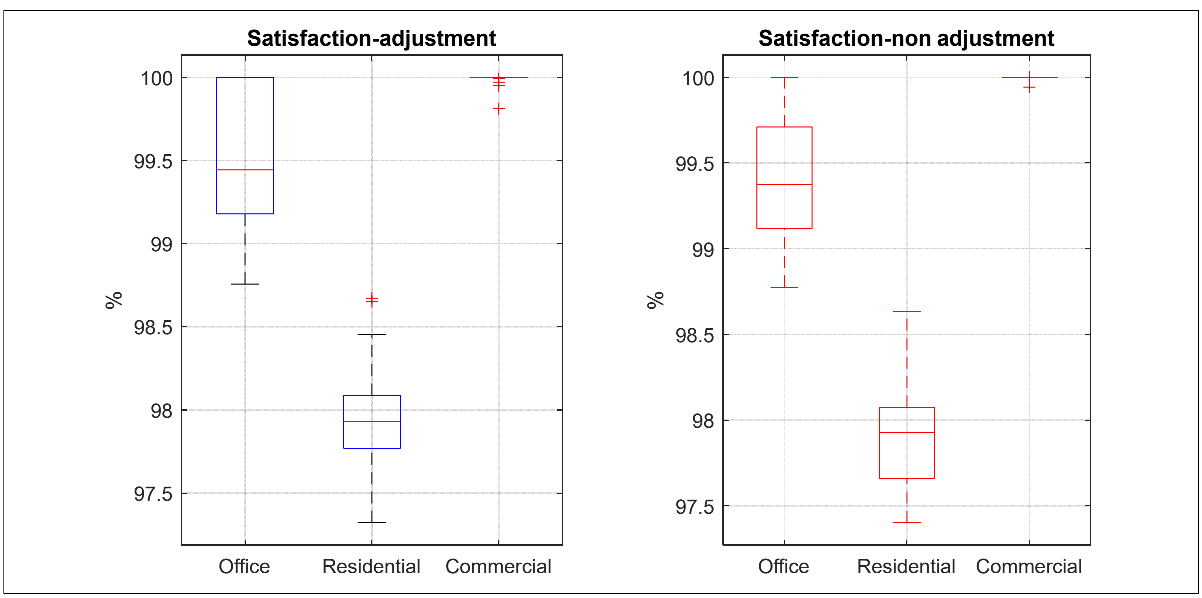

Figure 3.11 EV satisfaction index

The real-time adjustment, as discussed above, may cause more delay or immature full charge which affects the optimal schedule at the end of the period. However, the results show that the effect of the real-time adjustment does not reduce the satisfaction of EV users considerably. Remarkably, the satisfaction index achieved in the case of a commercial BCM is almost 100% while it shows the lowest in providing real-time flexibility as analysed in the previous subsection. That means that the real-time adjustment may reduce the satisfaction index of EV users yet still keep it at an acceptably high level, above 97% in most of the running cases.

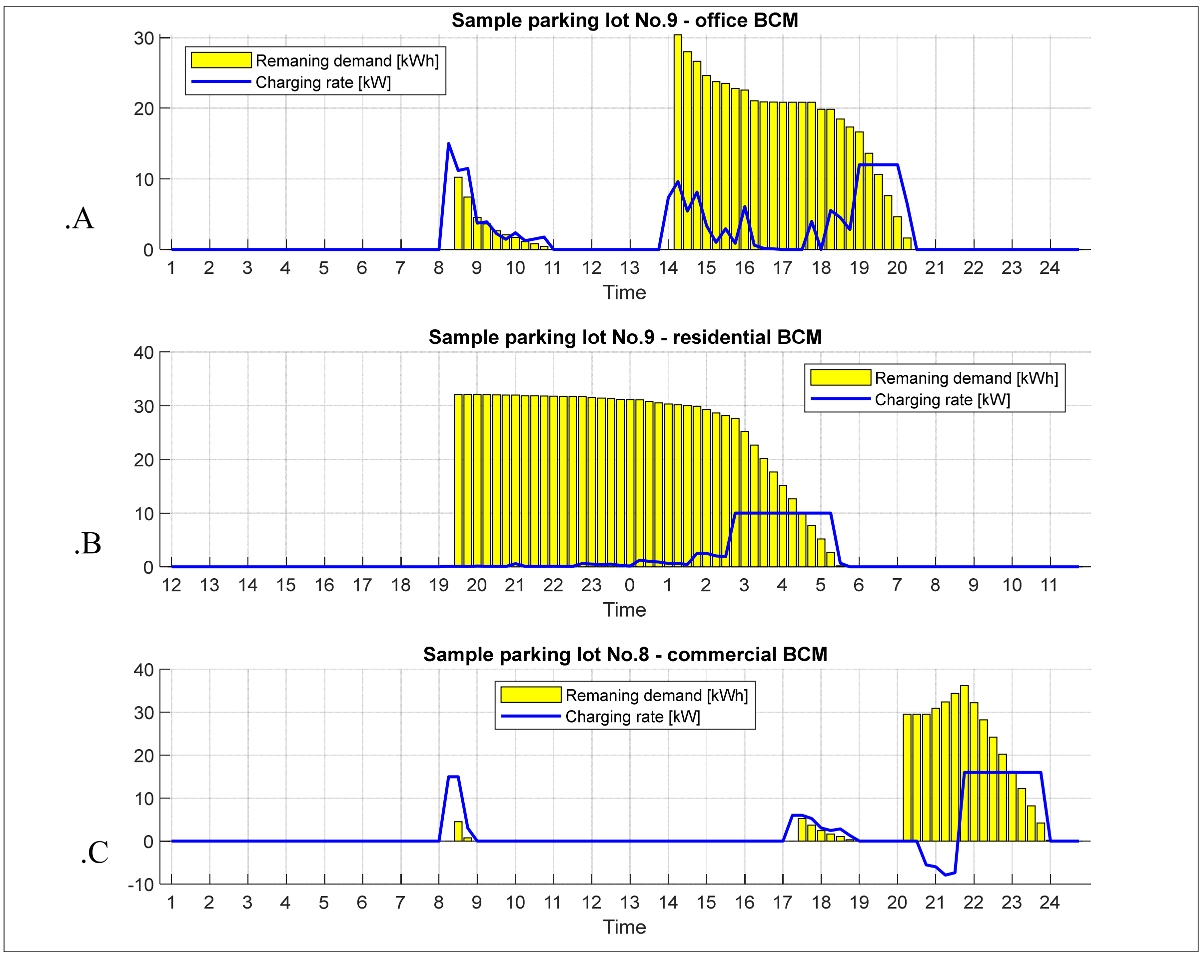

Figure 3.12 Examples of the power charging/discharging rates at specific parking lots

For a more intuitive display, Figure 3.12 shows the charging/discharging power rates in some specific parking lots. At parking lot No. 9 in office BCM (Figure 3.12.A), there are two EVs plugged in this lot during the operation day. The first EV arrived at 8:15. Its charging demand is quite 'urgent' so that the battery is fulfilled continuously throughout the parking period. Whereas the second EV arrived at 14:00, which stayed for a longer period. The charging rates assigned for this EV are discontinuous and have some delay periods, yet the charging demand finally is fulfilled at the end of its parking period at 20:15.

Figure 3.12.B shows the long parking duration overnight in the residential parking lot. Its battery is gradually charged up over the period and when it becomes an 'urgent' charging task at 2:45, the maximum charging rate is assigned to this EV until fully charged before its designed departure time at 5:30.

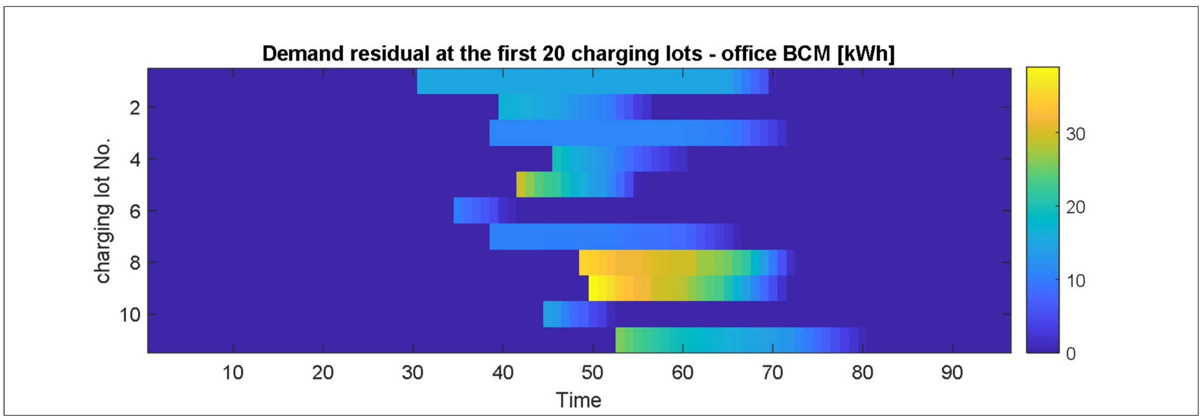

Figure 3.13 Demand residual at some parking lots in an office parking station

Figure 3.12.C illustrates several very short charging tasks in commercial parking lot No.8. However, the third EV which arrives at 20:00 and stays until midnight can contribute by discharging its energy to the BCM during the evening peak demand period. As a result, the maximum charging rate is applied to charge up its battery from 21:45 to meet the desired energy level before departure.

In Figure 3.13, the remaining charging demand of each EV is reduced to zero at the end of the parking period. The figure shows the fulfillment and high satisfaction of the EV's users under the proposed control algorithm.

3.2.3 Operating cost efficient

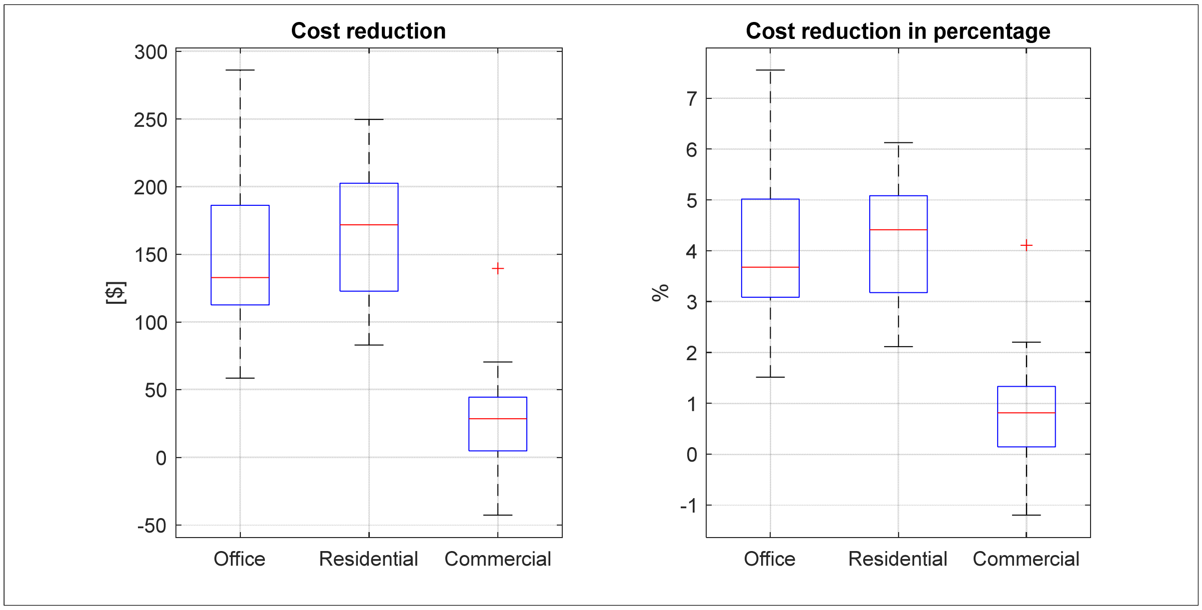

Figure 3.14 Daily operating cost reduction results

We run 50 experiments with different values of the stochastic variables in each type of BCMs with the identical EV' behaviors and forecast data in both algorithms. The results are presented briefly in Figure 3.14. In comparison with the baseline algorithm, the proposed real-time adjustment shows a significant reduction in operating costs. Especially, in an office BCM, the daily operating cost reduces 132.79 $ on average with the highest point at 286.11 $ and minimum at 58.58 $, while better performance can be seen in residential BCM with an average reduction of 171.81 $. The time-adjustment algorithm is less effective in the case of commercial BCM. It can be explained by a shorter parking duration so that the flexibility of EV fleets is low. Consequently, EVs are less likely to be able to provide support during real-time adjustment. The average reduction, in this case, is 28.50 $, or only 0.81%, which is much lower than 3.67% in office BCM and 4.42% in residential BCM.

3.3 Summary

This chapter presents the case studies with a series of numerical simulations based on the real-world as well as simulated data. The simulations consider three types of BCM i.e., office, commercial, and residential buildings. The proposed multi-stage charge/discharge scheduling optimization algorithm is compared with other algorithms. We consider three comparison criteria, namely user satisfaction index, EV flexibility, and operating cost-effectiveness. The results are promising to prove the performance of the proposed algorithm with real-time adjustment using the EV flexibility assessment method. Specifically, the operating cost reduces up to 4.42% corresponding to 171.81 $/day. The EV flexibility is successfully evaluated for the real-time adjustment process, clearly improving the operating cost efficiency. The adjustment may lead to a longer delay or immature full-charged, however, proper cluster-based EV fleet modeling technique always takes the ‘urgent’ charging tasks into consideration that helps to keep the satisfaction of the EV users at a high level of above 97%.

CONCLUSION

Though EV charge/discharge scheduling optimization is an old topic in the literature, it still looks for better solutions. The aggregating model of the EV fleet can reduce the computational burden to adopt a large-scale charging station while running in high time resolution. In this study, we consider one of such EV aggregators, a BCM. The main purpose of BCMOs is to economically operate the charging station arming at operating cost reduction, provide demand-response to the utility by following the day-ahead planning, and balancing their PV power output under the limits of the utility connection, the BESS, and satisfy the EV user demands. To achieve those goals, the BCMOs, first, require knowing better about the day-ahead EV parking behavior for day-ahead planning upfront of the operating day. Second, the rolling horizon optimization problem during the operating day requires to be solved in a short time for higher time resolution operation. Third, EV fleets can act as a flexible load and provide a wide range of power flexibility. The EV flexibility assessment is vital to provide real-time adjustment against the uncertainty of PV generating and building demand. Our work covers all these matters by proposing a multi-stage day-ahead charge/discharge scheduling optimization algorithm. The proposed algorithm includes three main stages: the day-ahead planning that happened before the starting of the operating day; the rolling horizon optimization performed every 15 minutes to keep track of the day-ahead schedule during the operating day; the real-time control executed a moment before the point of operation. The real-time control stage consists of a real-time heuristic LLF-SOC algorithm to assign charging rates to individual EVs in each cluster, and a real-time adjustment exploiting the real-time EV flexibility.

Our contributions are summarised as follows:

- We propose a new clustering method for modeling a large-scale EVs charging load avoiding the potential of the unfulfillment of the EV with ‘urgent’ demand caused by circulation charge/discharge effects among the aggregate EVs fleet that was not investigated thoroughly in the literature. The ‘urgent’, ‘deferrable’, and ‘controllable’ EVs are clustered in different groups or clusters. Each cluster acts as an independent aggregator, which involves the optimization problem to achieve the optimal charging rate for the entire cluster. That will be divided and spread to the individuals later in the real-time control stage.

- We capture the stochastic of the battery capacity and charging rate into the stochastic model of EV fleets. Based on the probability distribution function of arrival time, parking duration, initial SOC, as well as battery capacity and charging rate of EVs, achieved from real-world data, multiple EV charging tasks are generated. The average power and energy boundaries of three EV clusters, subsequently, be calculated using the MCS method. This is the first time EV battery capacity and charging rate are considered in the stochastic model of EV fleets. This improves the model accuracy and differs from other works in the literature where the authors usually assume one or few types of EVs with specific charging rate and battery capacity.
- We propose a low complexity multi-stage charge/discharge scheduling algorithm using mixed-integer quadratic programming for day-ahead planning and rolling horizon optimization problem, and real-time heuristic control algorithm so that the problem can be solved effectively using Quadratic Optimization toolbox in MATLAB. The EV-size-independent optimization algorithm allows recursively computing the optimal charging/discharging decision to every EV in a time resolution of 15-minute intervals.
- Multiple simulations based on real-world as well as simulated data are carried out. The results prove the performance of the proposed scheduling algorithm with an operating cost reduction of up to 4.42% or 171.81 $/day in a residential BCM. The real-time adjustment keeps the actual power at PCC along with the day-ahead power while remains a high level of satisfaction for EV users, above 97%.

Future works

Our current simulations rely heavily on the simulated dataset and simulation techniques such as MCS. The future research opportunity is to investigate deeply the parking and driving behaviors to better represent the stochastic nature of EV fleets when real large-scale datasets will be available thanks to the spread of EVs all around the world.

APPENDIX I

ARTICLES PUBLISHED IN CONFERENCES

Two peer-reviewed conference papers have been published, namely:

V. Q. Ngo, K. Al-Haddad and K. K. Nguyen, "Particle Swarm Optimization – Model Predictive Control for Microgrid Energy Management," *2020 Zooming Innovation in Consumer Technologies Conference (ZINC)*, Novi Sad, Serbia, 2020, pp. 264-269.

V. Q. Ngo, K. Khoa Nguyen and K. Al-Haddad, "Optimal Dynamic Pricing and Rewarding for Electric Vehicle Charging Scheme in High Penetration Photovoltaic Microgrid," *IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society, Singapore*, 2020, pp. 3697-3702.

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Jin, C., Sheng, X., & Ghosh, P. (2014). Optimized Electric Vehicle Charging With Intermittent Renewable Energy Sources. *IEEE Journal of Selected Topics in Signal Processing, 8*(6), 1063-1072.

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