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ENERGY MANAGEMENT OF MICROGRIDS

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ENERGY MANAGEMENT OF MICROGRIDS

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

2018

Statement of Originality

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

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Date

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Student Name

Acknowledgement

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Abstract

The innovative shape of traditional power systems has been developing towards more intelligent, flexible and efficient entities. In the name of microgrids, the transformation of physical structure has gradually blurred the boundaries between generation, transmission and distribution network from centralization to decentralization topologies. With much smaller scales, microgrids are comprised of local distributed generation, energy storage systems (ESSs) and load, making it quite possible to enhance reliability with distributed generation, increase efficiency with reduced transmission distance, and implement capability in ease use of alternative energy resources and storages. However, public concern has been raised due to progressive stability and reliability issues regarding different aspects related with fast developing system infrastructure and emerging electricity market. On the other hand, it might sometimes become a serious issue for microgrids on the trade-off between economy and reliability, since operating reserves are much incomparable to variations from both generation and consumption sides in most cases.

Against the background of exploring better configuration for microgrids to be not only reliable but also economic, many conducted research has mainly focused on autonomous operation, droop control, hierarchical control, low-voltage protections, state estimations and power electronics studies and so forth. In terms of modeling and control strategy, this thesis gives an overall comprehensive methodology about effective planning and efficient operation of microgrids. Firstly, optimal power flow algorithms are investigated in a novel way that provides the minimum operating cost and maintains the highest possible reliability levels. In order to deal with stochastic behaviors of RESs and loads in microgrids,

scenario reduction techniques are extended by imposing auxiliary constraints so that the optimal solution space is narrowed down. By implementing the fine-tuned algorithm, case studies with benchmarks have well validated the reliability has been significantly enhanced at little cost of additional expenditure.

Large-scale energy storage systems have provided promising potentials for multiple applications in microgrids by providing additional spinning reserve, regulating voltage, frequency and power factors, as well as offering economic benefits by participating into demand response and facilitating the integration of renewable energy sources (RESs). A dynamic optimal power flow (OPF) model with adaptive operation costs is thus proposed to address influential consequences of ESS implementation in microgrids, specifying the dynamic characteristics of energy storage in multiple time periods. Conclusive results have shown that the proposed model and algorithm can be utilized not only to meet system ramping requirements, but also to help flatten the load profile in peak hours.

In microgrids, participation of renewable energy sources in combination of ESSs has further expanded the potential benefits to end uses as well as to system operators. In consideration of economic operation, a two-layer predictive energy management system (EMS) for microgrids with hybrid ESS is proposed incorporating respective degradation costs, so that high system robustness at minimum operational cost is well maintained. The hierarchical dispatch model is well designed, that total operational cost is achieved in the upper layer EMS while the lower layer EMS deals with more cumbersome tasks resulted in intermittencies and forecast errors. The novelty of the proposed algorithm has been demonstrated by intensive scenario tests incorporating different pricing schemes, prediction horizon lengths and forecast accuracies.

Clustering microgrids in different distribution networks, microgrid community has enabled individual members to be more operationally flexible by resource sharing with minimizing dependency on the main power grid during normal

conditions and more self-sustainable with enhanced power system reliability under extreme events. This thesis further investigated the hierarchical EMS in the context of interconnected microgrid community, in which pairing strategy is proposed so that community-level EMS to explicitly determine the power flow between microgrids and with the upstream distribution grid. Such the profit can be fairly shared by each participating microgrid in the community, without user privacy being compromised.

All the proposed methodologies and algorithms throughout the research have been verified in MATLAB, with regards to different system topologies involving multiple data of RESs, ESSs and loads.

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List of Abbreviation

AC	Alternating Current
DC	Direct Current
DER	Distributed Energy Resources
DG	Distributed Generation
DOD	Depth of Discharge
EENS	Expected Energy Not Supplied
EMS	Energy Management System
ES	Energy Storage
EV	Electric Vehicle
MCS	Monte Carlo simulation
OPF	Optimal Power Flow
PCC	Point of Common Coupling
PV	Photovoltaic
RES	Renewable Energy Source
RMS	Root Mean Square
SOC	State of Charge
TOAT	Taguchi orthogonal Array Tables
TOU	Time of Use

Chapter 1

Introduction

This chapter starts with the backgrounds of the related research work, and the current barriers of existing developments. Following with the objectives to be explored, in a receding sequence, the theme of the thesis is to investigate and design efficient energy management systems of microgrids with renewable penetrations and energy storage participations. Research contributions and the organization of this thesis are presented as well.

1.1 Background and Motivation

Major problems of fossil fuel depletion, environmental pollution and low energy efficiency have gained serious concerns in terms of development of future power systems [1]. In place of coal and oil which have been most fundamental energy resources since the industrial revolution, shale gas has become an increasingly important source of natural gas in the US since 2010 [2]. China has made a big breakthrough recently on extracting flammable ice, another form of natural gas stored deep under the seafloor, leading to a global energy revolution [3]. It seems to be an ideal substitute in dealing with energy crisis, however, improper extraction may lead to severe consequences that would significantly fasten greenhouse effects [4]. With so many innovative technologies being prompted through, it is indeed of high risk to put the future of all humankind heavily on conventional fossil fuel resources.

The new trend of using local generation by using low-carbon and unconventional renewable energy sources (RESs), such as photovoltaic (PV), micro-turbines, fuel cell and wind power, etc., has gained a lot of public expression. New-type generation units are termed distributed generation (DG) units, being versatile for future green energy development. With increasing RESs being penetrated in existing traditional networks, the boundaries between generation, transmission and distribution sites have been gradually blurred. Microgrids provide a closer proximity between generation and consumption by incorporating flexible and intelligent control schemes with distributed energy resources (DERs). Transition from passive, centralized and unidirectional networks to active, distributed and bidirectional networks has emphasized future technologies towards more intelligent, flexible and efficient entities.

Microgrid, defined as a cluster of small-size generation units and local loads [5], can interact in parallel to the utility grid and operate as single entities

independently without affecting integrity of upstream networks. In practice, microgrids have much potential to maximize overall system efficiency and power quality, perform dynamic control over generation units and loads, and enable autonomous operations [6]. Microgrids have offered a range of benefits in terms of environmental friendliness, economic advantages and efficiency improvements. From grid point of view, microgrids are treated as aggregated individuals in compliance with grid regulations without hampering the reliability and security of the power utility [5], [7]. From end users' point of view, microgrids are beneficial to improve local reliability, reduce transmission losses and provide economic arbitrage supports.

Intermittency and non-dispatchability of RESs may result into system robust problems, that fluctuating generation outputs may not guarantee the constant power supply due to stochastic and intermittent behaviors [8], [9]. As a key solution, Energy storages (ESs) are integrated to compensate power mismatches to improve microgrid reliability and dynamic stability. ESs including batteries, supercapacitors, flywheels, etc., have been widely deployed to facilitate the integration of RESs, as well as offer economic benefits by participating into demand response. ESs can also act as bidirectional mediators with the utility grid to store and export energy, providing auxiliary services and financial benefits for end-users based on various control strategies [10].

To meet different operation requirements, hybrid ES that combines different types of ESs inherits advantages for each individual as an effective and reliable solution. Researches working on hybrid ES in microgrids have covered from real-time operations that account for instant power sharing [11], [12] and frequency regulation [13], to scheduling problems that manifest charging strategies [14] and operational optimization in the long term [15], [16] in microgrids.

Regarding fast development of system infrastructure and emerging electricity market, several technical issues need to be addressed carefully before real

implementation in microgrid environments. The trade-off between economy and reliability may become a serious concern since operating reserves are much incomparable to variations from both generation and consumption sides in most cases. These two effects have narrowly been considered in most existing works with respect to real-time operation under different resources, load and environment conditions. For microgrid community typically, distinct power flow has not yet been addressed, and iterative algorithm may result into intensive computation stress and convexity issues, especially for the microgrid community with a large number of microgrid partners.

In view of the above challenges, one technical challenge is to design highly efficient and reliable management schemes to accommodate accurate monitoring, supervisory control and secured protection for various types of microgrids, and a balance of economy and reliability always plays a significant role on controlling strategies.

1.2 Objectives

The main objective of this thesis is to develop a novel infrastructure of the energy management system (EMS) of microgrids to assess and optimize the operation involving RESs and ESs. Main objectives of the research work are described as follows:

- Reliability reinforcement with economic evaluation;
- Analysis on costs of energy storage systems;
- Assessment on interactions of hybrid energy storage systems;
- Hierarchical energy management for single microgrids; and
- Development on power flow management for interconnected microgrids.

1.3 Contributions

In view of the above objectives, several major contributions of the PhD work have been achieved as described in the following.

a. OPF with Worst-case Scenarios considering Uncertainties of Loads and Renewables

A DC OPF algorithm considering worst-case scenarios is proposed. It accounts for uncertainties caused by loads and RES, and maintains the highest system reliability level.

b. Dynamic OPF including ESs

The OPF model considering ESs with adaptive operation costs is proposed to optimize power generation and storage scheduling in multiple time periods. Operation cost coefficients of ESs are auto-adjusted according to SOC and TOU price, specifying the dynamic characteristics of ESs.

c. Two-layer EMS for Microgrids with Hybrid ES Degradation Costs

A two-layer EMS with hybrid ESs consisting of batteries and supercapacitors is proposed, in which long-term costs of hybrid ESs are modeled and transformed to short-term costs related to real-time operation. To guarantee system robustness and economic operation, the upper layer EMS minimizes the total operational cost, and the lower layer EMS eliminates fluctuations induced by forecast errors.

d. Coordinated EMS of Regional Residential Community with Multiple Microgrids

A novel two-level EMS with multiple small-scale microgrids in a regional community is proposed to minimize the total operational cost of the entire community and maximize the individual benefit of each microgrid. A novel pairing algorithm is introduced to find the microgrid pairings with surplus and deficit explicitly. The local EMSs inside microgrids aim to minimize the individual operational cost,

while the central EMS determines specific power transactions inside the microgrid community by using the pairing algorithm to further reduce individual operational costs and transmission losses. The proposed method has its distinguishing advantages on modeling generality, computational complexity and customer privacy protection.

1.4 Thesis Organization

This chapter presents the general background and motivation of developing the EMS for microgrids. Objectives and main contributions of the research work are introduced.

Chapter 2 provides literature review of current research topics on optimal power flow algorithms, microgrids and energy management systems are discussed.

Chapter 3 proposes a DC OPF algorithm considering worst-case scenarios. Auxiliary constraints represent uncertainties are implemented to deal with trade-offs between reliability and economy. The proposed algorithm ensures highest operational reliability levels in a cost saving fashion. The detailed simulation results of IEEE 14-bus and IEEE 57-bus system with the proposed algorithm are provided by comparison two cases.

Chapter 4 proposes a novel OPF model considering ESs with adaptive operation costs to achieve the optimal scheduling in multiple time periods. The proposed model effectively reflects the sensitivity of the system to price signals, as well as the responsiveness to sudden load changes. Simulation results show the total generation cost of the system has decreased with the implementation of ESs.

Chapter 5 proposes a two-layer EMS with hybrid ESs consisting of batteries and supercapacitors to minimize the operational cost with high system robustness. A hierarchical dispatch model is introduced in which the upper layer EMS minimizes the total operational cost and the lower layer EMS eliminates fluctuations

induced by forecast errors. Simulation studies demonstrate that different types of energy storages can be utilized at two control layers for multiple decision-making objectives. Scenarios incorporating different pricing schemes, prediction horizon lengths and forecast accuracies also prove the effectiveness of the proposed EMS structure.

Chapter 6 proposes a coordinated two-level EMS model for multiple small-scale microgrids in a regional community to account for minimization of the community-level operational cost and maximization of individual microgrid-level benefits simultaneously. The proposed EMS has been applied into two case studies with different scales of microgrid community. Simulation results have demonstrated that the optimization time has been reduced significantly by the non-iterative algorithm, and privacy issues have been eliminated by minimal information exchange.

Chapter 7 concludes the research findings presented in this thesis. Moreover, prospective areas for further investigation are proposed.

Chapter 2

Literature Review

In this chapter, a comprehensive review of the related research works on energy management systems of microgrids is presented in detail. The concept of microgrid is introduced, followed by the brief introduction of various components that a microgrid is comprised of. OPF as one of the most traditional evaluation tools is firstly introduced. Energy management system related with microgrids are investigated. Existing research status and barriers are presented at last.

2.1 Microgrid

There is no unified description to exactly define microgrid at this time. For example, how small a microgrid should be in terms of geographic area or energy use still remains a debate [17]. However, microgrids should be regarded to have capabilities of autonomous operation isolated from the main grid, and management of distributed assets independently. For any energy requirements and goals, there might exist certain specific solution forming optimal microgrids.

2.1.1 General Structure

Generally, a microgrid is defined as a group of DGs, loads and ESs [18]. Considering the size of microgrids, distributed generation is not always composed of RESs such as PV, wind turbines and fuel cells. A microgrid can include diesel generators as well, if the power supplied by RES cannot meet the demand when operating in the isolated mode.

When a microgrid is at sometime in lack of supply, ESs, such as batteries, super capacitors and flywheels (although the latter are not often used), can act as distributed generation and compensate power mismatch. ESs can also act as bidirectional mediators with the utility grid to store and export energy, providing auxiliary services and financial benefits for end-users based on various control strategies. In order to meet different operation requirements, the so-called hybrid ES which combines different types of energy storage inherits advantages for each individual to provide an effective and reliable solution. Researches working on hybrid ES in microgrids have covered from real-time operations that account for instant power sharing [11], [12] and frequency regulation [13], to scheduling problems that manifest charging strategies [14] and operational optimization in the long term [15], [16].

V2G schemes can be also deployed in microgrids where EVs are utilized

in which EVs are regarded as both DGs and loads [19]. Overall, there is no sharp demarcation among DG, load, ES, and EV in microgrids when general functionalities have been considered.

An efficient microgrid should be able to operate properly under both the grid-connected mode and the isolated mode [20]–[22]. A microgrid must have the ability to share information and exchange energy with the utility grid while operating in grid-connected mode, and must be able to conduct autonomous management when isolated [23], [24]. These requirements need flexible operating strategies and feasible communication capabilities in microgrids. Aside from basic objectives such as safe operation, fault handling, etc., microgrids should also be able to provide additional services including load sharing, demand response, power factor correction, risk-limiting dispatch and so forth [25], [26].

In recent years, DC grids are reviving because of the deployment of variable DC loads in industrial and commercial applications. However, some AC sources, like wind turbines, have to be converted to DC before connected to DC microgrids. Even for conventional AC generators and loads connected to DC microgrids, AC/DC inverters are always required for power conversions. Such the existence of multiple conversions may not merely reduce the efficiency of energy utilization, but increase the expenses for grid construction and maintenance, even undermine the system reliability due to the growing number of the converters. To avoid the unnecessary multiple conversion, the concept of the hybrid AC/DC microgrid has been introduced in [21], [27], with discussions around its structure and operation [28]–[30].

2.1.2 Microgrid Community

The microgrid community, such as residential area, university campus, industrial park, etc., clusters a group of microgrids under the single PCC to consolidate system reliability and economy requirements. In normal conditions, microgrid

community helps individual microgrids reduce transmission loss and enhance system reliability by sharing resources internally [31]. Under extreme circumstances, microgrid community can also operate as an autonomous entity from the upstream power grid to maintain its integrity and security [32]. Several representative studies on microgrid community in terms of power quality and system reliability have been presented recently in [33]–[36]. The EcoCampus flagship program, as a leading example, has been conducted in Nanyang Technological University, Singapore since 2011, aiming to develop a novel campus-wide energy efficient and sustainable microgrid community by 2020 [37].

2.2 Review of Energy Management of Microgrids

Growing interest in RES has prompted microgrids to develop towards more intelligent and modernized entities. Microgrids integrate DGs including conventional and renewable sources to supply predicted load of end-users in a decentralized manner [38]. However, integration of RES has brought intermittency and non-dispatchability issues, which may affect system robustness. Energy from RES might be unavailable due to bad weather conditions when electricity is needed [39]. To solve this problem, effective energy management system (EMS) is needed to coordinate operations to maintain the supply-demand balance [40]. It becomes more challenging when microgrids are involved, since generation and reserves are quite limited compared with larger power grids.

As a prerequisite key step, EMS should be able to address the reliable models of microgrids that describes the underlying physics accurately. The most fundamental objectives of EMS in microgrids are to optimize economy, to enhance efficiency and to increase reliability, which can be further described as follows [41]:

- Ensure the coordinated operation of DGs, ESs and loads;

- Ensure the stable operation of the system;
- Maximize the utilization of RESs and minimize the usage of non-RESs;
- Maximize the profits or minimize the costs of operation; and
- Maximize satisfaction of microgrid operators during normal operation and Minimize losses during system contingencies.

In general, a sophisticated microgrid EMS must be able to operate and coordinate a variety of DGs, ESs, and loads in order to provide high-quality, reliable, sustainable, and environmental energy in a cost-effective way [42].

2.2.1 Optimal Power Flow

The optimal power flow (OPF) study, firstly introduced in 1960s by Carpentier [43], is widely employed in view of system design planning, operation, management and power flow algorithms [44]–[46]. The OPF technique is a useful tool to analyze power systems in steady-state operation [47], [48]. The objective of an OPF algorithm is to find the operation point which minimizes generation cost and loss or maximizes social welfare, while an acceptable system performance is maintained in terms of constraints [41, 42]. The existing OPF techniques are classified into AC OPF and DC OPF.

a. Deterministic AC OPF

In AC power systems, normal operation requires the balance between power generation and consumption. The power balance equations for each bus can be written for real and reactive power as follows [49]:

$$P_i = V_i \sum_{j \in i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}), \quad i, j \in N_B \quad (2.1)$$

$$Q_i = V_i \sum_{j \in i} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}), \quad i, j \in N_B \quad (2.2)$$

The line power flow equations are:

$$P_{ij} = V_i V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) - t_{ij} G_{ij} V_i^2, \quad i, j \in N_B \quad (2.3)$$

$$Q_{ij} = V_i V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) - B_{ij} V_i^2 + G_{ij} V_i^2, \quad i, j \in N_B \quad (2.4)$$

where P_i and Q_i are the active and reactive power injected into the system at bus i , respectively, P_{ij} and Q_{ij} are the active and reactive power flowing from bus i to j , respectively, V_i and V_j are voltage magnitudes of bus i and j , respectively, G_{ij} and B_{ij} are the conductance and susceptance values between bus i and j , respectively, θ_{ij} is the voltage angle difference between bus i and j , and N_B is the number of buses. These balance conditions from (2.1) to (2.4) must be satisfied for system reliable operation.

The most common OPF objective is to minimize the total generation cost in consideration of various network and generation constraints. Aside from it, the objective function can be in other forms, such as the minimization of transmission losses [50], [51], or the maximization of system reliability [52], [53]. The OPF constraints can be categorized into equality constraints and inequality constraints. The equality constraints are the power flow network equations. The inequality constraints are minimum and maximum limits on variables, such as transmission line capacities, bus voltages and generation output limits.

When the objective function is to minimize the total generation cost, the AC OPF model is formulated as follows:

Objective function:

$$\min \sum_{i \in N} F(P_{Gi}) \quad (2.5)$$

subject to power flow constraints:

$$P_{Gi} - P_{Li} - V_i \sum_{j \in i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0, \quad i, j \in N_B \quad (2.6)$$

$$Q_{Gi} - Q_{Li} + V_i \sum_{j \in i} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0, \quad i, j \in N_B \quad (2.7)$$

transmission line constraints:

$$\underline{P}_{ij} \leq P_{ij} = V_i V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) - t_{ij} G_{ij} V_i^2 \leq \overline{P}_{ij}, \quad i, j \in N_B \quad (2.8)$$

bus voltage constraints:

$$\underline{V}_i \leq V_i \leq \overline{V}_i, \quad i \in N_B \quad (2.9)$$

generation constraints:

$$\underline{P}_{Gi} \leq P_{Gi} \leq \overline{P}_{Gi}, \quad i \in N_G \quad (2.10)$$

$$\underline{Q}_{Gi} \leq Q_{Gi} \leq \overline{Q}_{Gi}, \quad i \in N_G \quad (2.11)$$

where $F(P_{Gi})$ is the operation cost function for generator i . P_{Gi} and Q_{Gi} are the active and reactive power of generator at bus i , respectively. P_{Li} and Q_{Li} are the active and reactive power of load at bus i , respectively. $\underline{P}_{ij}$ and $\overline{P}_{ij}$ are the lower and upper limit of transmission line rating from bus i to j , respectively. $\underline{V}_i$ and $\overline{V}_i$ are the lower and upper limit of voltage at bus i , respectively. $\underline{P}_{Gi}$ and $\overline{P}_{Gi}$ are the lower and upper limit of the active power of generator at bus i , respectively. $\underline{Q}_{Gi}$ and $\overline{Q}_{Gi}$ are the lower and upper limit of the reactive power of generator at bus i , respectively. N_G is the number of generation units.

b. Deterministic DC OPF

OPF formulations incorporating AC power flow equations are both nonlinear and non-convex [54]. In many cases, the AC OPF model is not feasible to analyze large power systems due to nonlinearity.

The DC power flow extends the decoupling principle to form linear constraint sets [54]. The DC power flow is a simplification of the AC power flow, since only the active power flow equations are considered [55]. Compared with the AC

power flow model, the DC power flow model requires less computational time but achieves less accuracy [56].

The DC power flow equations are based on three assumptions: the line resistance G_{ij} is much smaller than the line reactance B_{ij} , the difference of voltage angles at adjacent buses θ_{ij} is small, and all bus voltage magnitudes are approximated as 1. Under these assumptions, we have [56] as follows:

$$G_{ij} + jB_{ij} = \frac{-r_{ij}}{r_{ij}^2 + x_{ij}^2} + j \frac{-x_{ij}}{r_{ij}^2 + x_{ij}^2} \approx jB_{ij} \quad (2.12)$$

$$\sin \theta_{ij} \approx \theta_{ij} = \theta_i - \theta_j \quad (2.13)$$

Power balance equations (2.1) and (2.3) are thus presented as follows:

$$P_i = \sum_{j \in i} B_{ij} \theta_{ij} \quad (2.14)$$

$$P_{ij} = B_{ij} \theta_{ij} \quad (2.15)$$

where B_{ij} is the susceptance between bus i and j, respectively.

These two equations can be written in the matrix form as:

$$\mathbf{P}_{bus} = \mathbf{B}_{bus} \boldsymbol{\theta} \quad (2.16)$$

$$\mathbf{P}_{line} = \mathbf{B}_{line} \boldsymbol{\theta} \quad (2.17)$$

where $\mathbf{P}_{bus}$ is the array of active power injected into the system at all buses. $\mathbf{P}_{line}$ is the array of active power flowing at all lines. $\mathbf{B}_{bus}$ and $\mathbf{B}_{line}$ are susceptance matrices of buses and lines, respectively. $\boldsymbol{\theta}$ is the array of voltage angle differences between all adjacent buses.

Equation (2-16) and (2-17) can be rewritten as

$$\mathbf{P}_{line} = \mathbf{B}_{line} \mathbf{B}_{line}^{-1} \mathbf{P}_{bus} = \mathbf{B} \mathbf{P}_{bus} \quad (2.18)$$

where $\mathbf{B}$ is the $N_{line} \times N_{bus}$ transfer matrix. When the objective function is to minimize the total generation cost, the DC OPF model is formulated as follows:
Objective function:

$$\min \sum_{i \in N} F(P_{Gi}) \quad (2.19)$$

Subject to power flow constraints:

$$\mathbf{P}_{bus} = \mathbf{P}_S - \mathbf{P}_D \quad (2.20)$$

generation constraints:

$$\underline{P_{Gi}} \leq P_{Gi} \leq \overline{P_{Gi}} \quad (2.21)$$

transmission line constraints:

$$\underline{P_{line}} \leq \mathbf{B}\mathbf{P}_{bus} \leq \overline{P_{line}} \quad (2.22)$$

where $F(P_{Gi})$ is the operation cost function for generator i . $\mathbf{P}_S$ and $\mathbf{P}_D$ are the arrays of total supply and demand, respectively. P_{Gi} is the active power of generator at bus i . $\underline{P_{Gi}}$ and $\overline{P_{Gi}}$ are the lower and upper limit of the active power of generator at bus i , respectively. $\underline{P_{line}}$ and $\overline{P_{line}}$ are the arrays of the lower and upper limit of transmission line rating, respectively. N_G is the number of generation units.

c. Probabilistic DC OPF

With the penetration of distributed generation and development of RES, more uncertainties have been brought into power systems, which make operation conditions more unpredictable. Deterministic OPF analysis cannot accurately represent the stochastic nature of generation outputs and random loads. On the other hand, deterministic OPF models are unable to meet the needs of power systems in fast expansion. Therefore, it is important to consider uncertainties in the OPF formulation.

Probabilistic OPF has been proposed to address uncertainties inherent to power systems [57]. In the probabilistic OPF formulation, the traditional generators are considered as certain and controllable variables, and the RES and loads are regarded to be uncertain and uncontrollable. These uncertain factors are modeled as probabilistic distributions, as well as the final results [58]. Under such considerations, the probabilistic DC OPF model is formulated as:

Objective function:

$$\min \sum_{i \in N} F(P_{Gi}) \quad (2.23)$$

subject to power flow constraints:

$$\widetilde{P}_{bus} = \widetilde{P}_G + \widetilde{P}_R + \widetilde{P}_D \quad (2.24)$$

generation constraints:

$$\underline{P_{Gi}} \leq P_{Gi} \leq \overline{P_{Gi}} \quad (2.25)$$

transmission line constraints:

$$\underline{P_{line}} \leq \widetilde{P}_{line} = B\widetilde{P}_{bus} \leq \overline{P_{line}} \quad (2.26)$$

where the tilde superscript means uncertain variables. $F(P_{Gi})$ is the operation cost function for generator i . $\widetilde{P}_{bus}$ is the array of active power injected into the system at all buses. P_G and $\widetilde{P}_R$ are the arrays of conventional generator and renewable generation outputs, respectively. $\widetilde{P}_D$ is the array of demand. P_{Gi} is the active power of generator at bus i . $\underline{P_{Gi}}$ and $\overline{P_{Gi}}$ are the lower and upper limit of the active power of generator at bus i , respectively. $\widetilde{P}_{line}$ is the array of active power flowing at all lines. $\underline{P_{line}}$ and $\overline{P_{line}}$ are the arrays of the lower and upper limit of transmission line rating, respectively. B is the transfer matrix. N_G is the number of conventional generators.

d. Development on OPF Techniques

From the 1970s, a number of analytical computing algorithms of probabilistic OPF has been developed, including nonlinear programming (NLP), linear programming (LP), mixed integer programming (MIP), quadratic programming (QP), interior point algorithm and so forth [59], [60]. Proposed by Karmarkar in 1984 [61], interior point algorithm is a novel programming method compared with NLP and LP algorithms, which does not follow points on the constraints boundary to find optimum, but sets points through the interior of the constraints directly toward the optimal solution [56].

Many recent works have focused on improvement of probabilistic OPF methodologies. Monte Carlo simulation (MCS) has been widely used as an numerical evaluation method for different algorithms. However, when conventional analytical methods cannot deal with the correlation and randomness of multiple uncertainties, MCS can be also used to present the intrinsic characteristics of systems [62]. Two-point-estimate-method (2PEM) algorithm is introduced in [57] to account for uncertainties in OPF against the background of competitive electricity markets. In [63], forecasting errors of RES in distributed networks is considered by using a chance-constrained multi-objective probabilistic OPF model. In [64], a probabilistic approach based on the convolution method is proposed to evaluate the operation of a hybrid solar-wind system in long term. A hybrid solar-wind power system has also been discussed in [65], in which the correlation of uncertain variables has been considered by using a modified 2PEM technique.

Robust control strategies have also been considered to deal with uncertain variations in the literature. Robust OPF is defined in [66] as a formulation in which some control constraints are allowed to be violated with limits by penalty functions. Robust OPF is able to give an accurate specification for decision making under various uncertainty [67], [68]. In [69], a robust optimization model considering uncertainties of loads is proposed for planning system expansion. In [70], the probabilistic OPF is proposed so that the optimized result is robust

to uncertain fluctuations, in which the Taguchi orthogonal array tables (TOAT) method is used to pick up representative scenarios.

2.2.2 EMS for Individual Microgrids

For individual microgrids, wind-range control algorithms are always needed to ensure system security, optimal operation, emission reduction requirements. Seamless transition among various operational modes are also required without violating system constraints [6]. Usually, such functions are fulfilled by a local central controller, which mainly deals with local objectives, such as maintain power quality and reliability through frequency control, voltage control and protection coordination. Most of the time, the local controller also takes care of economic scheduling for microgrid owners [6], [71].

Centralized hierarchical structures for EMS are often applied for stand-alone microgrids [72]–[74]. In [75], a hierarchical EMS with dynamic demand response and distributed energy resource scheduling is proposed, in which the users' preference and varying external information are adapted with a dynamic update mechanism. In [29], a hierarchical EMS is implemented in a microgrid to control multiple DC source and energy storages. The proposed coordination control is further considered to target the trade-off between maximum power harvest and effective battery management. [76] also presents a centralized EMS to coordinate charging of plug-in EVs in which both peak loads in the network and EV charging costs of end users are reduced. Research in [77] decomposes the microgrid energy management into a unit commitment problem to account for voltage and frequency regulation and an optimal power flow problem to provide reactive power support. In [78], a heuristic method combined with a centralized EMS and local EMSs is proposed to determine ES cycling operation at the household level.

2.2.3 EMS for Microgrid Community

EMS of the microgrid community is the core ingredient to improve energy efficiency, increase economic benefit and maintain operation reliability. Based on the framework and control strategy, EMS can be classified into centralized and decentralized forms. Centralized EMS gathers full information from dispatchable components and makes operating decisions for all individual microgrids [12], [79]. In [80], a centralized EMS for microgrids is proposed to optimize the operation of the microgrid during interconnected operation. In [81], a centralized home-based energy management scheme is addressed to minimize the total aggregated load deviation in the regional area. In [82], a two-stage robust optimization model is proposed to address the coordination problem with guaranteed robustness against the uncertainties of RES and load demands.

On the other hand, decentralized EMS has also been investigated in the existing literature considering the distributed infrastructure of microgrid community [83]–[85]. A cooperative control for a smart network of residential buildings has been developed in [86] to manage energy exchange with the upstream grid. Cost minimization problems are addressed by the decentralized Lyapunov-based algorithm based on dual decomposition in [87]. An operation model incorporated with electric vehicles has been derived to minimize the procurement cost of neighboring smart households in [88]. In [89], power exchange in a microgrid community has been discussed, in which economic efficiency has been improved by coalitional transaction. A market clearing model involving multiple microgrids with critical loads has been proposed in [90] to account for normal and disruptive operating scenarios, in which loads are effectively responsive to vigorous market change.

2.3 Research Limitations in Literature

Existing research have provided broad and innovative concepts in the field of energy management of microgrids. However, there are several major drawbacks listed below as references for research directions.

1. In terms of OPF algorithms, the full set of state spaces cannot be usually provided, which may end up with local optimal solutions. Particularly for large systems with multiple constraints at buses and transmission lines, the problem may become prominent where global optimum cannot be reached. Next, reliability issues have been barely concerned, in which most of the existing algorithms do not utilize the effects of uncertainty into robust operation. Furthermore, the new problems have appeared with the implementation of ESs into the system. Most existing OPF techniques have merely made optimal scheduling within single time periods in a static way, ignoring dynamic behaviors of ESs highly correlated with time. Neglect of operational costs related with ESs may fail to achieve the global optimum.

2. Previous studies for microgrids have mostly featured on the design of EMS to improve energy efficiency and operation reliability of microgrids. For ES as a key component of microgrids, however, existing works have narrowly considered economic effects of the real-time ES operation under different resources, load and environment conditions, and ignored or merely assumed a fixed price as the operational cost. Different from generation resources, the short-term dispatch for ES has a significant impact on its lifetime in the long term. For example, battery life would be considerably deteriorated by frequent charging and discharging. On the other hand, the conflict of economy and security further complicates the desired energy management in microgrids. Increasing the ES capacity size will provide larger operating reserves to reduce the probability of loss of load, however at the expense of extra capital investment. The two-fold requirements enforce the

ES operational cost to be accurately related to the long-term degradation process in real-time operation. However, the degradation cost of ES was either neglected or modeled on a very rough and general basis in previous literature.

3. For EMS in microgrid community, individual microgrids are usually self-interested entities, whose optimization objectives may be inconsistent with other microgrids. Various infrastructures and geographic locations of microgrids would challenge the implementation of EMS in the sense of complexity on operational strategies, whereas such the problem would be more noticeable for centralized EMS to handle computational burden due to size expansions. Intensive computation stress and convexity issues, especially for the microgrid community with a large group of individual microgrids, have made optimal solutions much less practical. Furthermore, requirements for full observability in centralized EMS and inter-communication in decentralized EMS would introduce microgrid security and customer privacy issues. Finally, specific power flows in the microgrid community specifying distinct characteristics for individual microgrids have not been yet considered.

2.4 Summary

In this chapter, the background literatures in our studies are summarized. The background of microgrid is introduced, including the basic concept, its advantages and research barriers. Energy management of microgrids in terms of different scales are discussed. OPF analysis is introduced as an important tool for determination of the optimal operation for microgrids. The methodologies are used in modeling in Chapter 3 and 4. Current ongoing research on EMS of single microgrid is investigated. The fundamental rationale is used in Chapter 5. Finally, EMS of interconnected microgrids, also known as microgrid community, are also discussed, whose substantial improvements are presented in Chapter 6.

Chapter 3

OPF with Worst-case Scenarios considering Uncertainties of Loads and Renewables

The growing interest on RES gives traditional power systems an opportunity to evolve towards more sustainable and environmental entities, however the viability of RES have brought stability and reliability issues in power systems. A DC OPF algorithm considering worst-case scenarios is proposed in this chapter that accounts for uncertainties brought by loads and RESs. In the meantime, the highest reliability level can be achieved for the whole system. By assigning selected values with largest probabilities to random variables, the probabilistic OPF formulation is converted into a set of deterministic OPF problems in which the additional auxiliary constraints are implemented to represent the uncertain influences. The proposed OPF with worst-case scenarios is applied into an IEEE 14-bus and 57-bus benchmark power system. The results in the simulation along with other OPF techniques shows the validity and robustness of the algorithm.

3.1 Introduction

To address the shortcomings mentioned in Chapter 2, a DC OPF algorithm considering worst-case scenarios is proposed to provide the minimum operating cost and maintain the highest possible reliability levels sententiously. Inspired by [70] and [91], the probabilistic OPF problem is transformed into a set of deterministic OPF formulations based on selected scenarios representing RES and load uncertainties, and additional auxiliary constraints are imposed into the scenarios to narrow down the optimal solution space.

3.2 System Modeling

3.2.1 Formulation of DC OPF

AC OPF may be not applicable to appropriately analyze the operation of large power systems due to nonlinearity and non-convexity [54]. In this research, DC OPF is introduced since only active power flow equations are considered to extend the decoupling principles for linear constraint sets [55], [56]. Simplified from AC OPF, DC power flow model is adopted only based on three observations:

- a) the line resistance G_{ij} is much smaller than the line reactance;
- b) the difference of voltage angles at adjacent buses is small; and
- c) all bus voltage magnitudes are approximated as nominal values in per-unit system.

The objective of the optimization problem is to minimize the total operational cost of all generators, which can be expressed as follows:

$$F(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i, \quad i \in N_B \quad (3.1)$$

where a_i , b_i and c_i are cost coefficients and N_B is the number of buses.

θ_i is denoted to be the power angle at bus i . Correspondingly, B_{ij} is denoted to be the susceptance between bus i and j . Thus, the real power flow at all buses can be written as:

$$P_{Bi} = \sum_{\substack{j \in N_B, \\ j \neq i}} B_{ij}(\theta_i - \theta_j), \quad i, j \in N_B \quad (3.2)$$

Similarly, the real power flow between transmission lines can be written as:

$$P_{Tij} = B_{ij}(\theta_i - \theta_j), \quad i, j \in N_B \quad (3.3)$$

These two equations can be transformed into matrix formats as follows:

$$\underbrace{\mathbf{P}_B}_{N_B \times 1} = \underbrace{\mathbf{B}_B}_{N_B \times N_B} \theta \quad (3.4)$$

$$\underbrace{\mathbf{P}_T}_{N_T \times 1} = \underbrace{\mathbf{B}_T}_{N_T \times N_B} \theta \quad (3.5)$$

where N_T is the number of transmission lines, $\mathbf{B}_B$ and $\mathbf{B}_T$ are corresponding susceptance matrices.

3.2.2 Uncertainties and Constraints

Uncertainties introduced by the implementation of RES make system operation more unpredictable. In order to address the uncertain parameters, in the proposed probabilistic OPF, variables related with RES and loads are treated as uncertain variables, while traditional generators are considered as certain and controllable variables. It is noted that the specific probabilistic distributions can be defined by using proper forecast techniques [58], therefore, parameters of RES and loads can be presented by several probability density functions.

The power balance equality constraint at each bus can be formulated as follows:

$$\tilde{P}_{Bi} = P_{Gi} + \tilde{P}_{Ri} - \tilde{P}_{Li}, \quad i \in N_B \quad (3.6)$$

where the tilde superscript refers to the corresponding probability density functions for uncertain variables. Taking (3.4) and (3.5) into consideration, (3.6) can be written in the matrix form as follows:

$$\tilde{\mathbf{P}}_B = \mathbf{P}_G + \tilde{\mathbf{P}}_R - \tilde{\mathbf{P}}_L = \mathbf{B}_B \mathbf{B}_T^{-1} \mathbf{P}_T \quad (3.7)$$

The power flow of each transmission line is restricted by the maximum limits. In combination with (3.7), the inequality constraints for transmission lines can be reformulated as:

$$\underline{\mathbf{P}}_T \leq \tilde{\mathbf{P}}_T = \mathbf{B}_T^{-1} \mathbf{B}_B (\mathbf{P}_G + \tilde{\mathbf{P}}_R - \tilde{\mathbf{P}}_L) \leq \overline{\mathbf{P}}_T \quad (3.8)$$

The output of each generator unit is limited by its power ratings, which is formulated as follows:

$$\underline{P}_{Gi} \leq P_{Gi} \leq \overline{P}_{Gi}, \quad i \in N_B \quad (3.9)$$

3.2.3 Objective Function of Optimization Problem

The overall probabilistic OPF problem is formulated as follows:

$$\begin{aligned} f : \min & \sum_{i \in N_B} F(P_{Gi}) \\ \text{s.t.} & (3.1), (3.4), (3.5), (3.7) - (3.9) \end{aligned} \quad (3.10)$$

It should be noted that the objective function is with quadratic forms, while all the constraints are linear equations. Hence the optimization problem can be solved by using quadratic programming or linear programming incorporated with linearization techniques. Nevertheless, (3.7) and (3.8) include random variables of RES and loads, since their distribution probability functions are not explicitly shown. This might be the obstacle to finding the optimal solution.

3.3 Worst-case Scenarios

Worst-case scenarios are selected by aggregating load variables and selecting representative values of RES. The original probabilistic OPF is transformed into several deterministic OPF formulations with additional constraints manifesting uncertainties of loads and RES.

3.3.1 Uncertainties Modeling of Loads and RES

Loads fluctuations and RES forecasting errors would introduce uncertainties in the system. [65]. Uncertainties of loads and RES are regarded as independent with each other considering the weak correlations. Generally, the loads are modeled to follow the normal distribution [92] as follows:

$$P_{Li} \sim N\left(\mu_i, \sigma_i^2\right), i \in N_B \quad (3.11)$$

It is assumed that wind turbines provide majority of RES power in the system. The generation of wind turbines is modeled to follow the general Weibull distribution [93]:

$$\rho(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} e^{-\frac{v^k}{c}} \quad (3.12)$$

where k and c are the shape and scale parameter, respectively. v is the wind speed. The outputs of RES can be approximated in relation with v as follows [64], [65]:

$$P_{Ri} = \begin{cases} P_{Ri_r}^i \frac{v - v_{cin}^i}{v_{rated}^i - v_{cin}^i}, & v_{cin}^i \leq v \leq v_{rated}^i \\ P_{Ri_r}^i, & v_{rated}^i \leq v \leq v_{cout}^i \\ 0, & otherwise \end{cases}, i \in N_B \quad (3.13)$$

where $P_{Ri_r}^i$ is the power rating of i th wind turbine, v_{cin}^i , v_{cout}^i and v_{rated}^i are the rated speed, cut-in speed and cut-out speed, respectively.

Note that all the RES are chosen to be wind turbines just for the simplicity of modeling. There are indeed various types of RES such as photovoltaics and micro hydros, however, they do not have any intrinsic difference with wind turbine models except that they have different probability density functions. Therefore, implementation of different type of RES will not consume additional constitutionality of the whole system.

3.3.2 Aggregation of Load Variables

The computational burden would be alleviated if the number of random variables are reduced. It is assumed that the load variables are linearly independent [71]. Thus at each transmission line, random variables of loads can be combined into one variable.

$\tilde{P}_{L-agg}$ is denoted to be the array of the aggregation of all loads as follows:

$$\tilde{P}_{L-agg} \tilde{P}_{L-agg} = B_T^{-1} B_B \tilde{P}_L \quad (3.14)$$

Since the load variables at different buses are independent [94], recalling (3.8), the term including loads forms the following normal distribution:

$$\tilde{P}_{L-agg} \sim N(B_T^{-1} B_B \mu, \sigma^T (B_T^{-1} B_B)^T B_T^{-1} B_B \sigma) \quad (3.15)$$

where μ and σ refers to the mean value and stand deviation array of the load variables, respectively.

For each transmission line, the term including $\tilde{P}_L$ with N_B random variables in (3.8) is transformed into one aggregated variable representing effects of all loads. In total, the number of random variables is reduced from $N_L + N_B$ to $1 + N_B$. As a consequence, the computational burden has been alleviated.

3.3.3 Representative Values for Random Variables

The number of representative values for random variables in loads and RES also has significant influences on the computational complexity. Apparently, a smaller number of representative values lead to the faster processing time. In this chapter, two representative values are selected for the aggregated load and RES variables [57], [65]. For the aggregated load $\tilde{P}_{L-agg}$, two representative vectors are selected as follows:

$$P_{L-agg} \in \{B_T^{-1}B_B\mu + \sigma^T(B_T^{-1}B_B)^T B_T^{-1}B_B\sigma, \\ B_T^{-1}B_B\mu + \sigma^T(B_T^{-1}B_B)^T B_T^{-1}B_B\sigma\} \quad (3.16)$$

For RES variables $\tilde{P}_R$, zero and the rated capacity are adopted respectively since the outputs of RES are always in this zone. The selected values are presented as follows:

$$P_R \in \{0, P_{R_rated}\} \quad (3.17)$$

3.3.4 Selection of Worst-case Scenarios

After selection of representative values for each random variable, a total number of 2^{1+N_B} possible scenarios are formed. Among all the scenarios, the constraints on transmission lines must be determined for each scenario. (3.8) can be presented as a set of the following formulations:

$$\begin{cases} \underline{P}_T - B_T^{-1}B_BP_G \leq B_T^{-1}B_B\tilde{P}_R - \tilde{P}_{L-agg} \\ \overline{P}_T - B_T^{-1}B_BP_G \geq B_T^{-1}B_B\tilde{P}_R - \tilde{P}_{L-agg} \end{cases} \quad (3.18)$$

Suppose the total number of M scenarios based on representative values of random variables have been selected. The constraint for each transmission line

can be thus formulated as follows:

$$\begin{cases} \underline{P_{Ti}} - \mathbf{B}_{Ti}^{-1} \mathbf{B}_{Bi} \mathbf{P}_G \leq \min_{m \in M} (\mathbf{B}_{Ti}^{-1} \mathbf{B}_{Bi} \widetilde{\mathbf{P}}_{R,m} - \widetilde{P}_{L-agg,i,m}) \\ \overline{P_{Ti}} - \mathbf{B}_{Ti}^{-1} \mathbf{B}_{Bi} \mathbf{P}_G \geq \max_{m \in M} (\mathbf{B}_{Ti}^{-1} \mathbf{B}_{Bi} \widetilde{\mathbf{P}}_{R,m} - \widetilde{P}_{L-agg,i,m}) \end{cases}, i \in N_T \quad (3.19)$$

where the subscript i denotes the i th row of the corresponding matrix.

The scenarios with the max/min constraints are regarded as worst-case scenarios, because they provide the strictest line constraints for the OPF that has the highest reliability levels. As all the random variables are independent, the additions of the right terms in (3.19) are linear and can be further written as follows:

$$\underline{P_{Ti}} - \mathbf{B}_{Ti}^{-1} \mathbf{B}_{Bi} \mathbf{P}_G \leq \sum_{k \in N_B} \min_{m \in M} \left(\mathbf{B}_{Ti,k}^{-1} \mathbf{B}_{Bi} \widetilde{P}_{R,m} \right) - \max_{m \in M} \left(\widetilde{P}_{L-agg,i,m} \right) \quad (3.20)$$

$$\overline{P_{Ti}} - \mathbf{B}_{Ti}^{-1} \mathbf{B}_{Bi} \mathbf{P}_G \geq \sum_{k \in N_B} \max_{m \in M} \left(\mathbf{B}_{Ti,k}^{-1} \mathbf{B}_{Bi} \widetilde{P}_{R,m} \right) - \min_{m \in M} \left(\widetilde{P}_{L-agg,i,m} \right) \quad (3.21)$$

The process of selecting worst-case scenarios is illustrated in Fig. 3.1. For random variables of RES, the corresponding terms $\max_{j \in M} \{-B_{i,k}, P_{R,k,j}\}$ are independent with other variables. Thus, the max/min worst-case scenarios of each transmission line can be obtained by selecting maximum and minimum values for each random variable and adding each corresponding terms.

3.3.5 Proposed DC OPF Formulation

The additional auxiliary constraints are added into the proposed probabilistic OPF formulation with worst-case scenarios, which is obtained as follows:

$$\begin{aligned} F : \min & \sum_{i \in N_B} F(P_{Gi}) \\ \text{s.t.} & (3.1), (3.4), (3.5), (3.7) - (3.9), (3.16), (3.17), (3.20), (3.21) \end{aligned} \quad (3.22)$$

Figure 3.1: Flowchart of selecting the worst scenario.

3.4 Case Study

In this section, an IEEE 14-bus and IEEE 57-bus benchmark system are simulated. The simulations are conducted with MATPOWER in the MATLAB environment [95]. In order to show the effectiveness of the proposed method, a deterministic formulation with conventional transmission line constraints and a probabilistic OPF based on Taguchi orthogonal array tables (TOAT) in [70] are simulated as well.

3.4.1 Validation Indices

The validation process needs to be conducted in order to appropriately compare and evaluate the performances of different methods. Monte Carlo simulation (MCS) is adopted to generate a series of random scenarios [96], since it is capable of manipulating a large number of random samples with different combinations

of uncertain values [97]. Random variables of load and RES are sampled based on their distribution characteristics mentioned in Section III. Meanwhile, the generator outputs are set as the optimized results except for those at the slack bus. In each scenario generated by MCS, the generation constraints and transmission line constraints are investigated. If all the constraints are within their limits, the tested scenario will be identified as a feasible scenario; otherwise, it is identified as unfeasible [98]. After all the scenarios generated by MCS are examined, the robust degree of the optimized results can be calculated as follows:

$$d_f = \frac{n_v}{n_{MCS}} \times 100\% \quad (3.23)$$

where n_v and n_{MCS} are the number of all feasible and tested scenarios, respectively.

The other confirmatory parameter to evaluate the generation insufficiency is expected energy not supplied (EENS). It is defined as the average of differences between the optimized generation outputs and the variable demand values when the scenario is unfeasible. In scenarios with feasible solutions, EENS is counted as zero. In two case studies, n_{MCS} is set to be 10000. The standard deviation for the aggregated loads is set to be 5%. The RES distribution is set as the Weibull distribution with $k=1.72$ and $c=1.91$.

3.4.2 IEEE 14-bus System

The diagram of the IEEE 14-bus benchmark power system is presented in Fig. 3.2. The transmission network parameters are presented in [99]. In addition, two 30 MW wind turbines are added at bus 2 and 3, respectively. For all generation units, including RES and generators, their output limits and cost parameters are presented in TABLE 3.1, in which traditional generators follow the quadratic cost formulation and RES are assumed to have no operational cost. The transmission line constraints are shown in TABLE 3.2. There are 11 loads in the IEEE 14-bus system, which can be aggregated into one uncertain variable based on

Figure 3.2: Schematic diagram of IEEE 14-bus power system.

Table 3.1: Generation Parameters in IEEE 14-bus System

Type	Bus number	Power limits (MW)		Cost parameter		
		P_{max}	P_{min}	a_i	b_i	c_i
generators	1	100	0	0	25	0
	2	80	0	0.25	20	0
	3	80	0	0.01	40	0
	6	60	0	0.01	40	0
	8	60	0	0.01	40	0
RES	2	30	0	0	0	0
	3	30	0	0	0	0

(3.14). Therefore, there exists three random variables including an aggregated load variable and two RES variables.

The process time, robust degree, EENS and operating cost of the traditional deterministic OPF, the probabilistic OPF with TOAT and the proposed OPF with worst-case scenarios are presented in TABLE 3.3 respectively. The optimized generation outputs of three methods are also shown in TABLE 3.4.

The results indicate that the traditional OPF achieves the lowest generation

Table 3.2: Transmission Line Parameters

From	To	Resistance (p.u.)	Reactance (p.u.)	Susceptance (p.u.)	Rated Capacity (MW)
1	2	0.01938	0.05917	0.0528	80
1	5	0.05403	0.22304	0.0492	40
2	3	0.04699	0.19797	0.0438	50
2	4	0.05811	0.17632	0.034	40
2	5	0.05695	0.17388	0.0346	40
3	4	0.06701	0.1710	0.0128	50
4	5	0.01335	0.04211	0	80
4	7	0	0.20912	0	40
4	9	0	0.55618	0	40
5	6	0	0.25202	0	40
6	11	0.094989	0.1989	0	40
6	12	0.12291	0.25581	0	40
6	13	0.06615	0.13027	0	40
7	8	0	0.17615	0	40
7	9	0	0.11001	0	40
9	10	0.03181	0.0845	0	40
9	14	0.12711	0.27038	0	20
10	11	0.08205	0.19207	0	20
12	13	0.22092	0.19988	0	20
13	14	0.17093	0.34802	0	20

Table 3.3: Simulation Results of IEEE 14-bus System

	Process time(s)	Robust degree	EENS (MW/h)	Generation cost (10^3 \$/h)
Traditional	0.022249	4.29%	57.0683	6.0715
TOAT	0.045919	73.92%	15.2941	6.6863
Worst case	0.028087	89.92%	5.9574	6.8649

Table 3.4: Optimized Generation outputs of IEEE 14-bus System

Type	Bus number	Generation outputs (MW)		
		Traditional	TOAT	Worst case
generators	1	100	60.4041	49.0166
	2	40.7763	40.2556	42.5230
	3	19.4078	30.6494	34.3694
	6	19.4079	35.7711	35.6472
	8	19.4078	31.9196	37.4435
RES	2	30	30	30
	3	30	30	30

cost, whereas its robust degree is low compared with other OPF methods. In the traditional OPF, the generator with the least marginal cost (i.e. generator at bus 1) produces the most power in order to achieve the minimum operational cost, reaching its maximum capacity. In real situation, however, generators which have low costs do not always operate at their full capacity due to system constraints and reserve requirements. Therefore, the result in traditional OPF provides an extreme operation strategy. When the fluctuations on loads and RES occur, there is a large probability that the transmission lines are overload at the risk of failure. On the contrary, when the uncertainties of loads and RES are considered in the proposed OPF with worst-case scenarios, part of transmission capability is reserved by additional auxiliary constraints, resulting into more averaged power dispatch strategies. Therefore, the OPF with worst-case scenarios achieves higher robust degrees and lower EENS at the expense of the increased generation costs.

Compared with the proposed OPF with worse-case scenarios, the main drawbacks of the OPF with TOAT includes the decision making on scenarios selection and computational time. The TOAT method is unable to cover the strictest conditions for three random variables include the aggregated load and two RES, since it selects three scenarios out of eight combinations. Therefore, its robust degree is less than the proposed OPF. On the other side, large computational time is consumed to produce orthogonal arrays. Hence, the computation time would be

Table 3.5: Generation parameters in IEEE 57-bus system

Type	Bus number	Power limits(MW)		Cost parameter		
		P_{max}	P_{min}	a_i	b_i	c_i
generators	1	200	0	0	20	0
	2	100	0	0.01	40	0
	3	100	0	0.25	20	0
	6	100	0	0.02222	40	0
	8	400	0	0.01	20	0
	9	100	0	0.01	40	0
	12	350	0	0.0323	20	0
RES	8	50	0	0	0	0
	9	50	0	0	0	0
	12	50	0	0	0	0
	43	50	0	0	0	0

drastically reduced if the arrays are preprocessed prior to the problem formulation.

3.4.3 IEEE 57-bus System

In the IEEE 57-bus benchmark power system, four wind turbines with the capacity of 50 MW are connected to bus 8 and 9, 12 and 43, respectively. The parameters of all generation units are presented in TABLE 3.5. Similarly, with an aggregated load, there are five random variables including one aggregated load and four RES variables. The process time, robust degree, EENS and operating cost of three cases are presented in TABLE 3.6, respectively. The optimized generation outputs of three methods are also shown in TABLE 3.7.

TABLE 3.7 shows a similar result that the traditional OPF achieves the lowest generation cost compared with the OPF with worst-case scenarios, whereas its robust degree and EENS is quite poor. It is also illustrated in TABLE 3.7 that the generator with the least marginal cost (i.e. generator at bus 1) operates at its maximum capacity in the traditional OPF. In the OPF with worst-case scenarios,

Table 3.6: Simulation results of IEEE 57-bus system

	Process time(s)	Robust degree	EENS (MW/h)	Generation cost (10^4 \$/h)
Traditional	0.026893	1.20%	171.0055	2.9095
TOAT	0.533138	69.00%	44.8387	3.164
Worst case	0.043113	93.91%	10.9609	3.2538

Table 3.7: Optimized generation outputs of IEEE 57-bus system

Type	Bus number	Generation outputs (MW)		
		Traditional	TOAT	Worst case
generators	1	250	150.3943	87.9669
	2	15.1642	0	0
	3	40.6065	40.5084	45.8984
	6	15.1642	80.1814	100
	8	400	400	400
	9	15.1642	99.9999	100
	12	314.7005	279.7157	316.9346
RES	2	30	30	30
	8	50	50	50
	9	50	50	50
	12	50	50	50
	43	50	50	50

the generator output at bus 1 has been decreased due to the additional auxiliary constraints on the transmission lines. As a consequence, the robust degree and EENS has been increased.

In the IEEE 57-bus system, five random variables come from the aggregated load and four RES, resulting in a drastic decrease on the robust degree and EENS in the OPF with TOAT. In the meantime, the proposed OPF holds a high reliability level. It can be thus concluded that for the OPF with TOAT, it is very dependent on the size of random variables, whereas the proposed OPF with worst-case scenarios

can always provide the strictest conditions to maintain the system reliability.

3.5 Summary

This chapter presents a novel DC OPF algorithm that accounts for the uncertainties brought by RES and loads. With the consideration of worst-case scenarios, the highest operational reliability is provided while the traditional generators are scheduled in a cost saving fashion. In the formulation, assigning values with largest probabilities to random variables, the probabilistic OPF is transformed into a set of deterministic OPF formulations with auxiliary constraints, whose upper and lower boundaries are determined by the max and min worst-case scenarios in a finite set of selections. The proposed OPF algorithm is tested in an IEEE 14-bus and an IEEE 57-bus power system. By comparing with other methods provided in the literature, validation indices have shown the effectiveness of the proposed OPF with worst-case scenarios.

Chapter 4

Dynamic OPF Including Energy Storages

In past few years, ESs have greatly catalyzed the evolution of energy management in power system. The availability of storage techniques makes it possible to integrate large-scale ESs to mitigate supply/demand variation and fluctuations brought by renewables. This chapter proposes an OPF model considering ESs with adaptive operational costs to optimize power generation and storage scheduling in multiple time periods. The objective of the proposed model is to minimize the total generation cost of generators and the operational cost of ESs. The operational cost coefficients of ESs are auto-adjusted according to SOC and TOU cost of generators, specifying the dynamic characteristics of ESs. The effectiveness of the proposed OPF model is validated by the IEEE 14-bus system that in optimal scheduling the operation of ESs is not only price-sensitive but also responsive to the sudden load change.

4.1 Introduction

Conventional power systems are developing towards more intelligent, reliable and efficient entities [100], and innovative operation strategies for utility scheduling are required, however time coupling effects and ES operational costs have been ignored in most research works. In view of this situation, a dynamic OPF model including ESs with adaptive operational costs is proposed in this chapter to the above problems. In the proposed model, the scheme for adaptive operational costs of ESs is firstly introduced with respect to generation costs considering marginal cost effects. A mathematical model including ESs with cost functions for OPF is then formulated, in which the characteristics of ESs are specified. The operational cost coefficients of ESs are adjusted automatically according to SOC and TOU generation costs, specifying the dynamic characteristics of ESs.

4.2 Adaptive Operational Costs of ESs Considering TOU and SOC

Generally, the generation costs of conventional generators are described with the quadratic function as follows:

$$F(P_{Gi}) = c_{Gi}^2 P_{Gi}^2 + c_{Gi}^1 P_{Gi} + c_{Gi}^0 \quad (4.1)$$

The cost coefficients of conventional generators in (4.1) are fixed and dependent on the manufacturing specifications, maintenance scheduling and fuel prices. Recently, TOU pricing has been greatly prompted, encouraging electricity consumers to change their usage patterns in response to demand stress in peak hours. Accordingly, the electricity prices of typical generators can be determined in advance during different time periods, and their cost coefficients become time-based parameters. Consider a single-line system, which consists of load and two generators with quadratic cost functions. The marginal costs of generators can be

derived by differentiating the cost functions, which is shown as follows:

$$f(P_{Gi}) = \frac{dF(P_{Gi})}{dP_{Gi}} = 2c_{Gi}^2 P_{Gi} + c_{Gi}^1 \quad (4.2)$$

Within the system constraints, in order to minimize the total generation cost in the dispatch problem, the generator with low generation costs should produce as much power as possible, while the generator with higher costs should then compensate the remaining power. This means the generators endeavor to operate at the same marginal cost as shown by the red horizontal lines in Fig. 4.1a. If the generation cost of one generator is flat, for example, c_{G1}^2 is zero, the output power of the other generator would be restricted at the crossing point of marginal costs, as shown in Fig. 4.1b.

Figure 4.1: Marginal costs of generators: (a) two generators with quadratic costs; and (b) one generator with the quadratic cost and the other with the fixed cost.

Let us consider another single-line system including one generator with the flat generation cost and the ESs. In order to mimic the operational behavior of generators, the operational cost of the ESs is set as a quadratic function similar to that of conventional generators. It should be noted that except for the loss caused by charge and discharge cycles, the ESs should not have any practical operational costs since it does not actually produce or consume energy by themselves. Therefore, defining the virtual operational costs for ESs is just for

optimal scheduling in multiple time periods. The operational costs of ESs can be written as follows:

$$F(P_{Si}) = c_{Si}^2 P_{Si}^2 + c_{Si}^1 P_{Si} + c_{Si}^0 \quad (4.3)$$

Since the ESs can do both charging and discharging, the operational cost of ESs with the negative power determines the charging cost.

Figure 4.2: Marginal costs of the generator with the flat cost and ESs in which the crossing point is: (a) positive; (b) negative.

Fig. 4.2 shows a similar principle that if the marginal cost of ESs is lower than the generator, ESs will be discharged with the power below the crossing point. When the demand is stressed, ESs will operate at the crossing point of marginal points. On the other hand, if the crossing point of marginal costs is on the left of y axis, then ESs will be charged by the generator at the crossing point in spite of the load conditions.

Expanding the above application into power system, the cost coefficients of ESs can be adjusted based on different control variables, such as generation outputs at typical buses, load values and real-time electricity prices and so on. Therefore, setting variable marginal cost coefficients for ESs can be used to determine the value of the exchange power with the grid. When the generation cost of the generator is time-variant, which means the marginal cost of the generator is

floating up and down, the exchange power of ESs is then closely correlated with its cost coefficients c_{Si}^2 and c_{Si}^1 .

Defining the cost coefficients of ESs should also have to consider the SOC of ES in each time period as well to avoid ESs from over-charging and over-discharging. ESs should be more likely to discharge than charge at high capacity, and it intends to charge when its capacity is low. Suppose the marginal cost of the generator is varying between $\underline{c_{Gi}^1}$ and $\overline{c_{Gi}^1}$, and the references of c_{Si}^2 and c_{Si}^1 are $c_{Si_ref}^2$ and $c_{Si_ref}^1$ at the medium SOC, correspondingly, then the cost coefficients of ESs can be written as functions of $E_{Si}(t)$, which are shown (4.4) and (4.5):

$$c_{Si}^2 = \begin{cases} c_{Si_ref}^2 \left[1 + \left(\frac{E_{Si}(t) - E_{Si_ref}}{\overline{E_{Si}} - E_{Si_ref}} \right)^{K_{Si}} \right], & E_{Si}(t) > E_{Si_ref} \\ c_{Si_ref}^2 \left[1 + \left(\frac{E_{Si_ref} - E_{Si}(t)}{E_{Si_ref} - \underline{E_{Si}}} \right)^{K_{Si}} \right], & E_{Si}(t) < E_{Si_ref} \end{cases} \quad (4.4)$$

$$c_{Si}^1 = \begin{cases} c_{Si_ref}^1 + (\overline{c_{Gi}^1} - c_{Si_ref}^1) \left(\frac{E_{Si}(t) - E_{Si_ref}}{\overline{E_{Si}} - E_{Si_ref}} \right)^{L_{Si}}, & E_{Si}(t) > E_{Si_ref} \\ c_{Si_ref}^1 + (\underline{c_{Gi}^1} - c_{Si_ref}^1) \left(\frac{E_{Si_ref} - E_{Si}(t)}{E_{Si_ref} - \underline{E_{Si}}} \right)^{L_{Si}}, & E_{Si}(t) < E_{Si_ref} \end{cases} \quad (4.5)$$

(4.4) and (4.5) show that cost coefficients of ESs are highly correlated with the SOC and the generation cost. When the SOC of ES is low, c_{Si}^2 is close to $2c_{Si_ref}^2$ and c_{Si}^1 is close to $\overline{c_{Gi}^1}$. These changing coefficients force the crossing point of marginal costs on the higher generation cost moving towards zero, limiting the maximum discharging power, while the crossing point on the lower generation cost allows the charging power to its maximum. In this way, ESs are able to charge with a large rate when the TOU cost of the generator is low, but constrained to discharge when the TOU cost is high. Likewise, when ESs are at high capacity, the adaptive coefficients will limit the charging and enable the discharging. Therefore, it can be concluded that the charging and discharging power of ES with adaptive operational costs can be regulated by both TOU price and SOC in the finite time

horizon.

4.3 Mathematical Model for Optimal Power Flow

In this section, a DC OPF model based on DC power flow including ESs with adaptive operational costs is formulated, in which the dynamic behaviors of ESs and TOU generation costs are both considered. An adaptive cost model for ESs is integrated to adjust and control its exchange power in multiple time periods. The model is to determine the output power of generators and ESs, so that the total operational cost can be minimized.

4.3.1 Objective Function

With ES, all the OPF variables and parameters should be considered in the time domain. The objective function of the modified OPF is the minimization of the total operational cost in each time period, which can be described as follows:

$$f = \min \sum_{i \in N_{bus}} F(P_{Gi}) + F(P_{Si}(t)) \quad (4.6)$$

As mentioned in Chapter 4.2, different from the generation cost of generators, the second term in (4.6), which represents the operational cost of ES, also has meaning when the output power of ES is negative.

4.3.2 Constraints

1) Bus constraints

In DC power flow, only the active power flow equations are considered. For each bus, the power flow constraints can be written as:

$$P_{Gi}(t) + P_{Si}(t) - P_{Di}(t) = \sum_{j=1}^{N_{bus}} B_{ij} \theta_{ij}, \quad i \in N_{bus} \quad (4.7)$$

2) *Transmission line constraints*

Similarly, the transmission line power constraints can be written as:

$$\underline{P_{ij}(t)} < P_{ij}(t) = B_{ij}\theta_{ij} < \overline{P_{ij}(t)}, \quad i, j \in N_{bus} \quad (4.8)$$

3) *Generator constraints*

The generator output power is restricted by its rating limits:

$$\underline{P_{Gi}(t)} \leq P_{Gi}(t) \leq \overline{P_{Gi}(t)}, \quad i \in N_{bus} \quad (4.9)$$

Since the OPF model is formulated across the time horizon, the limits on ramp rates of conventional generators should be also considered to protect generators from overload when the load change is sharp. The ramp limits can be written as:

$$\underline{R_{Gi}(t)} \leq P_{Gi}(t) - P_{Gi}(t-1) \leq \overline{R_{Gi}(t)}, \quad i \in N_{bus} \quad (4.10)$$

4) *ES constraints*

The performance of ES at each time period can be described by two parameters: SOC, i.e., the available capacity by each end of the time period $E_{si}(t)$, and the exchange power with the system in each time period $P_{si}(t)$. Since ES is considered as load when it is charging, and as generator when discharging, the value of $P_{si}(t)$ can be both positive and negative. If the efficiency of ES is 1, the limits of $P_{si}(t)$ should be equal to the charging and discharging power of ES. However, considering the charging and discharging efficiency of ES, $P_{si}(t)$ should be limited as follows:

$$\frac{P_{SCi}(t)}{\eta_{Ci}} \leq P_{Si}(t) \leq P_{SDi}(t) * \eta_{Di} \quad (4.11)$$

At the end of period t, the capacity of ES is updated based on the exchange power:

$$\underline{E_{Si}} < E_{Si}(t) < \overline{E_{Si}} \quad (4.12)$$

$$E_{Si}(t) = \begin{cases} E_{Si}(t-1) + P_{Si}(t)\Delta t * \eta_{Ci}, & P_{Si}(t) < 0 \\ E_{Si}(t-1) + P_{Si}(t)\Delta t / \eta_{Di}, & P_{Si}(t) > 0 \end{cases} \quad (4.13)$$

4.4 Case Studies and Results

In this section, an IEEE 14-bus system is used to validate the effectiveness of the proposed OPF model, that in the optimized scheduling ES can be both sensitive to the TOU price and responsive to the ramping load change. The parameters of this benchmark can be found in [101]. Additionally, a 100-MWh ES unit with the initial 30% SOC is connected to bus 1. The charging and discharging efficiency, η_{Ci} and η_{Di} , are both set to 95%. The maximum charging and discharging power are 15MW. The hourly load profile is generated by utilizing the load data in March 2014 retrieved from Energy Market Company, Singapore. The optimization problem is solved using the interior point solver with MATPOWER [95] in the MATLAB environment.

4.4.1 Case I: TOU Generation Cost without Ramp Rate Limits

In Case 1, according to the load profile, the generation cost of the generator at bus 1 is considered to be the TOU price with peak, valley and flat values. Its coefficients c_{G1}^2 and c_{G1}^0 are set to zero, and c_{G1}^1 variant with time as follows:

$$c_{G1}^1 = \begin{cases} 2.0 \text{ \$/MWh}, & t = 1, 8 \sim 15, 23 \sim 24h \\ 2.5 \text{ \$/MWh}, & t = 2 \sim 7h \\ 3.0 \text{ \$/MWh}, & t = 16 \sim 22h \end{cases} \quad (4.14)$$

The generation costs of other generators are presented in TABLE 4.1. For ES at bus 1, the coefficients of its operational cost are considered according to (4.4) and (4.5). E_{Si_ref} is given as 60% of SOC, and $c_{Si_ref}^1$ is equal to the flat price of the generation cost as 2.5\$/MWh. $c_{Si_ref}^2$ is calculated in such a way that the charging and discharging power of ES can reach their maximum at medium SOC. In this case, the value of $c_{Si_ref}^2$ is 0.015\$/MWh² when the SOC is 60%.

The ramp rates of all generators are neglected in case I, thus the effects of

Table 4.1: Cost Coefficients of Generators

Bus number	Power limits (MW)		
	c_{Gi}^2 (\$/MWh ²)	c_{Gi}^1 (\$/MWh)	c_{Gi}^0 (\$)
2	0.025	3.0	0
3	0.001	4.0	0
6	0.001	4.0	0
8	0.001	4.0	0

Figure 4.3: Load profile, generators output and ES output in Case I.

Table 4.2: Comparison on Average cost in 24 hours in Case I

Scenario	With ES	Without ES	Improvement
Average operational cost (\$)	3811.01	3856.11	1.18%

ramping limits can be removed. The simulation results of the load profile, the aggregated generator output and the exchange power of ES in 24 hours are shown in Fig. 4.3. The SOC of ES in 24 hours is shown in Fig. 4.4.

It is observed that ES is charging when the load demand is low at hour 1 to 4. When the demand is high at hour 16 to 21, ES is discharging as the generator. The reason that ES is able to realize the peak shaving by following the TOU generation cost can be explained by the difference on marginal costs of ES and the generator at bus 1. When the marginal cost of the generator is higher than the discharging cost of ES, ES will be scheduled to supply load with a cheaper price. On the contrary, when the marginal cost of the generator is lower, ES will be charged with extra energy from the system, profiting from cost disparities.

Figure 4.4: ES output and SOC in Case I.

Figure 4.5: Operational Cost in Case I.

It can be also seen in Fig. 4.4 that the maximum charging and discharging power can be regulated by both the TOU generation cost and the SOC. For example, at hour 20 and 21, although the TOU generation cost is still high, the exchange output of ES has been significantly decreased, because its SOC is near the lower boundary. In this situation, the marginal costs of ES and the generator are so close that the maximum output power of ES is restricted.

Fig. 4.5 shows the optimized operational cost in 24 hours with ES and without ES. It can be seen that the operational cost with ES is lower during the whole time horizon compared with that without ES, whenever ES is charged or discharged. Consequently, its averaged operational cost in 24 hours is lower by 1.18%, which is illustrated in TABLE 4.2.

Table 4.3: Ramp rate limits of generators

Bus number	Ramp rate limits	
	<i>Ramp – up (MW/hour)</i>	<i>Ramp – down (MW/hour)</i>
1	15	15
2	15	15
3	10	10
6	10	10
8	10	10

Figure 4.6: Load profile, generators output and ES output in Case II.

4.4.2 Case II: TOU Generation Cost with Ramp Rate Limits

In Case II, The costs of ES and generators remain the same as in Case I. However, the ramp rate limits of generators are considered, which are presented in TABLE 4.3. The simulation results are shown in Fig. 4.6, and the comparison of ES output and SOC between Case I and Case II is given in Fig. 4.7.

Fig. 4.6 shows the similar outcome as in Case I, that when the generators have no ramp rate limits, ES can still provide peak shaving along with cost variations. Nevertheless, the differences between two cases are mainly at hour 5, hour 10, hour 16 and hour 17, where the ramp rate limits have considerable influences on the system operation. For example, in Case II, the load has suddenly increased at hour 10, however the output power of the base generator at bus 1 is restricted by its ramp-up limit. As a consequence, a part of demand surplus will be filled up by ES as well as other generators with higher generation costs.

Figure 4.7: Comparison of ES output and SOC between Case I and Case II.

4.4.3 Case III: Fixed Generation Cost with Ramp Rate Limits

In Case III, the generation cost of the generator at bus 1 is assumed to be constant at all times, i.e., c_{G1}^2 and c_{G1}^0 are set to zero and c_{G1}^1 is $2.5\$/MWh$. In this way the effects of TOU generation cost are ruled out, so that the direct effect of ramp rate limits on ES can be investigated. The optimization results are shown in Fig. 4.8.

It can be observed that, ES with the proposed operational cost can still respond to the sudden load increase in hour 10 due to the ramp-up limit of the generator at bus 1. In other time periods when the output power of generators is sufficient within network constraints, however, ES does not respond to the load change since the generation cost is constant.

It is worth noting that with the fixed generation cost in this case, the generators do not reach their maximum outputs in most of the time periods. This leads to the fact that at some hours such as hour 18 and hour 23, even though the load is changing significantly, due to the transmission line constraints, however, more expensive generators rather than the base generator or ES would commit to meet the demand, at the expense of higher generation costs nevertheless.

Figure 4.8: Load profile, generators output and ES output in Case III.

4.5 Summary

A mathematical model for DC OPF considering ES with adaptive operational costs is proposed in this chapter to optimize the generation and ES scheduling in multiple time periods. The operational cost coefficients of ES are adjusted automatically according to SOC and TOU generation costs, specifying the dynamic characteristics of ES. An IEEE 14-bus benchmark system is simulated to show the effectiveness of the proposed OPF model, whose objective is to minimize the system operational cost of generators and ESs. The simulation results validate that with the proposed method, the operation of ES is not only price-sensitive but responsive to the ramping load change. It is concluded that ES with adaptive operational costs can be utilized not only to meet system ramping requirements, but also to help flatten the load profile in peak hours.

Chapter 5

Energy Management System for Microgrids with Energy Storage Degradation Costs

The integration of RES and ES in microgrids has provided potential benefit to end users and system operators. However, intermittent issues of RES and high cost of ES need to be placed under scrutiny for economic operation of microgrids. This chapter presents a two-layer predictive EMS for microgrids with hybrid ES consisting of batteries and supercapacitors. Incorporating degradation costs of the hybrid ES with respect to the DOD and lifetime, long-term costs of batteries and supercapacitors are modeled and transformed to short-term costs related to real-time operation. In order to maintain high system robustness at minimum operational cost, a hierarchical dispatch model is proposed to determine the scheduling of utilities in microgrids within a finite time horizon, in which the upper layer EMS minimizes the total operational cost and the lower layer EMS eliminates fluctuations induced by forecast errors. Simulation studies demonstrate that different types of energy storages can be utilized at two control layers for multiple decision-making objectives. Scenarios incorporating different pricing schemes, prediction horizon lengths and forecast accuracies also prove the effectiveness of the proposed EMS structure.

5.1 Introduction

Hybridization of ES urges different dispatch decisions to be made given various operation targets and ES characteristics. ESs with large energy densities such as batteries are committed to exchange excess energy with other components and the utility grid, and those with large power ratings such as supercapacitors are used to compensate the instant power mismatch. Hence, in the face of different devices in the hybrid ES, different time resolutions are required for the comprehensive design of EMS: the long-term time horizon manifests operational economy and the short-term time horizon reflects system security.

A novel two-layer EMS for microgrid including the hybrid ES is proposed in this chapter, in which the upper layer schedules the power dispatch to minimize the operational cost while the lower layer minimizes forecast uncertainties and power fluctuations. The degradation cost models of battery and supercapacitor are developed to accurately reflect the explicit degradation process, bridging the long-term capital cost and the short-term operational cost for real-time economic dispatch, so that various types of ESs can be dispatched at different control layers for multiple decision-making objectives.

5.2 Microgrid Modeling

5.2.1 Microgrid Structure

The schematic diagram of a typical microgrid is depicted in Fig. 5.1. It is comprised of the PCC to the utility grid, a hybrid ES, a RES system and the aggregate load. Practically, the microgrid can operate either in the grid tied mode or independently as an islanded grid, depending on system requirements, RES conditions and electricity market. Unless specified otherwise, we will focus on the grid connected mode in the following discussion.

Figure 5.1: System model of the microgrid.

5.2.2 Dynamic pricing

The utility grid is operated in an electricity market, where the electricity price is usually determined by the upper-level system operator in a static or dynamic way [102]. Static pricing schemes, such as fixed prices and time-of-use prices, are often set in advance and do not change with network conditions. Fixed prices do not usually influence user patterns in microgrid since the electricity cost does not change with the quantity of use, whereas time-of-use prices announced by the market authorities prompt more electricity to be used in off-peak hours considering relatively lower rates per kWh. Dynamic pricing schemes, such as the real-time pricing, are sensitive to locational marginal prices and are often announced hours ahead, allowing users to make advanced scheduling so that the operational cost can be minimized [102]. When the bidirectional communication is allowed, microgrids can make profits by selling part of excess electricity to the utility grid.

Two pricing schemes, which are time-of-use pricing and dynamic real-time pricing, are adopted in this chapter. In the time-of-use pricing model, the electricity price corresponds to a two-level model which has an off-peak value and an on-peak value. The specific values will be provided in Section V. In the dynamic real-time pricing model, the price is determined by the system operator according to the bidding of the market participants. In this chapter, the half-hourly price data in EMA over a year is adopted to form the hourly data, starting

from May 2013 to April 2014 [103]. Moreover, the selling price is also set in both pricing models, indicating the price per kWh that the microgrid sell extra generation back to the utility grid, which is lower than the buying price.

5.2.3 ES Hybridization

Design features of the hybrid ES vary in terms of power density, energy density, lifetime and cost [104]. In this chapter, the hybrid ES in the microgrid is comprised of the battery and supercapacitor given their complementary characteristics. The battery is able to store a large amount of electrical energy for the sake of high energy density, while the supercapacitor has high power density to give fast response for charging and discharging events. The main functions of the hybrid ES include maintaining the instantaneous power balance and minimizing the operational cost over a period of time. Hence, the battery and supercapacitor should target different objectives, that the battery is scheduled to operate as the distributed generation unit for economic dispatch while the supercapacitor should make up the instant power mismatch.

5.2.4 Renewable Power Generation

The implementation of RES in the microgrid gives the EMS a more cumbersome task to track the instantaneous supply/demand balance. The microgrid is modeled with two RES systems including PV panels and wind turbines. PV generation is considered to have a great variation due to passing clouds. Wind power is closely correlated with wind speed, which follows different patterns on seasons and even days. RES forecast error is considered to have a close relationship with the prediction lead time. Solar power ranges from 20% to 35% RMS error depending on different irradiance forecast techniques. Day-ahead wind forecast currently averages at more than 10% RMS error of the capacity, and progressively

reduces half to 5%-6% for one hour-ahead forecast [105]. Based on this fact, the RES output in this chapter is modeled with a gradient uncertainty level, in which the forecast error increases when the receding horizon becomes larger. There are many existing and ongoing studies on RES forecasting methodologies, however, they will not be further discussed since different forecasting techniques are not within the scope of this chapter.

5.3 Degradation Cost Modeling

The degradation of ES is very important to evaluate economic operation of microgrid analytically [106]. In order to accurately model the cost properties for microgrid energy management, the degradation cost of the hybrid ES is discussed and mathematically formulated in this section, especially for the battery and supercapacitor.

5.3.1 Modeling of Battery Degradation Cost

The degradation on battery lifetime features on two main factors, namely, the aging of cycle life that reflects the total achievable cycle count of a battery unit, and the capacity wear that accounts for the usable energy [107]. Cycling conditions, such as the number of frequent charging and discharging, charging and discharging rates and maintenance scheduling, have a great impact on the battery lifetime [108]. Improper cycling may cease to battery failure due to accelerated degradation. Apart from cycling conditions, state parameters also have significant influences on battery lifetime. Excessive high or low SOC would drastically deteriorate battery charging and discharging performance. Temperature may have a negative impact on the battery life as well, that at high temperatures the decay process will be accelerated. In practice, the temperature controller is often included in the battery management system. Therefore, it is assumed that the battery degradation

Figure 5.2: Different definitions on DOD.

due to ambient factors can be neglected. As for the effect of charging rate, its direct impact on battery lifetime is negligible in comparison of other parameters when battery is operating within a certain degree of rated current [109].

To this end, the primary determinants on battery lifetime are the actual full capacity and the DOD. There are two main DOD definitions in the literature in accordance with different cycling events, as shown in Fig. 5.2(a) and (b). The first is the discharged energy from the full capacity (100% SOC), and the second refers to a full cycle consisting of one charging and discharging event [110]. Unless other specified in this chapter, SOC is defined as the leftover energy compared to the full capacity, and DOD is defined as the energy in one charging or discharging event with respect to the full capacity, as illustrated in Fig. 5.2(c). We also define the actual full capacity of the battery as the amount of energy that can be stored at 100% SOC. Note that a cycle event is counted whenever the operating modes (charging and discharging) switch to the opposite sides.

Fig. 5.3 shows a relationship between the number of life cycles and the DOD of Ni-Cd batteries [109]. The battery lifetime has the best fitting in the following expression with $DOD=d_B$:

$$L_B(d_B) = a \times d_B^{-b} \times e^{-cd_B} \quad (5.1)$$

where $a, b, c > 0$ are curve-fitting coefficients. As expected, the number of life cycles decreases with the increasing DOD. Without loss of generality, this expression is also applied for other types of batteries with different parameters

Figure 5.3: Relationship of number of lifecycles and DOD of a Ni-Cd battery.

such as Lithium-Ion and Lead-Acid batteries [111]. The statistical data is usually identified and provided by manufacturing specifications, however all charging and discharging cycles in the statistical data are assumed under conditions with constant DOD, which is apparently impractical in real-time operation. Therefore, estimation of battery degradation cost by using the above information would introduce gross errors. To the best of our knowledge, however, there is unfortunately no previous work featuring on direct relationships of variable DODs and battery lifetime. Therefore, in order to take the battery degradation cost model in a practical fashion, it is reasonably assumed that the empirical data of life cycles is accurate enough to estimate the long-term degradation effect, in other words, the effect of each charging and discharging cycle event on the lifetime is irrelevant with the historical charging and discharging profiles.

Given the actual capacity and DOD as two factors, the battery degradation model is based on the moderate assumptions:

- a) The degradation process is considered to be time-linear throughout the whole battery life [112]; and
- b) The degradation cost of each charging and discharging cycle event with the same level of DOD is the same at different levels of SOC.

The battery degradation cost model represents a direct depreciation on its

actual capacity and lifetime. Considering a discharging event starting at time t with the average power $P_B(t)$ for a time interval Δt , the DOD during this interval, $d_B(\Delta t)$, can be expressed as:

$$d_B(\Delta t) = \frac{P_B(t)\Delta t}{E_{BA}(t)} \quad (5.2)$$

where $E_{BA}(t)$ is the actual capacity at time t . With the coefficients of charging/discharging efficiencies η_{Bc} and η_{Bd} , the average degradation cost per unit energy in this event in accordance with Fig. 5.3 can be formulated as follows [113]:

$$C_{BAC}(t, d_B(\Delta t)) = \frac{C_B \Delta t}{2L_B(d_B(\Delta t))E_{BA}(t)d_B(\Delta t)\eta_{Bc}\eta_{Bd}} \quad (5.3)$$

Note that it is a levelized degradation cost for each charging and discharging event with $DOD=d_B$. Therefore, we can get the corresponding battery degradation cost for this discharging event by simply multiplying the energy exported from the battery:

$$\begin{aligned} C_{BDC}(t, d_B(\Delta t)) &= C_{BAC}(t, d_B(\Delta t)) P_B(t) \\ &= \frac{C_B P_B(t) \Delta t}{2L_B(d_B(\Delta t))E_{BA}(t)d_B(\Delta t)\eta_{Bc}\eta_{Bd}} \end{aligned} \quad (5.4)$$

After the cycling event, the actual capacity of the battery at $t+\Delta t$ is proportionally deprecated, which can be calculated as follows:

$$E_{BA}(t + \Delta t) = E_{BA}(t) - \frac{E_{B.rated}}{L_B(d_B(\Delta t))} \quad (5.5)$$

where $E_{B.rated}$ is the rated battery capacity.

In order to address the same degradation effect on the battery, we consider the cost of the charging event equal to that of the discharging event. Note that operation at too high or low SOC for a long time would in fact rise the internal impedance and decompose electrolyte in the battery, leading to capacity loss and power fade, however such fade in a short term would be insignificant compared with the degradation caused by chronic charging and discharging events. It is also noted that the effect of the charging and discharging rate on battery life will not

be considered as a long-term effect as long as its current does not exceed the limit defined by manufacturer specifications, so as for other external parameters such as temperature and maintenance scheduling [113].

5.3.2 Modeling of Supercapacitor Degradation Cost

The lifetime of supercapacitor depends mostly on evaporation rate of liquid electrolyte, which is a principal function of temperature and terminal voltage [114]. In general, the lifetime of supercapacitor decreases with increasing central temperature. Supercapacitor is capable of undergoing thousands of deep cycles much more than battery and exhibits a much longer lifetime for more than ten years which is not limited by cycling stress [115]. Calendar ageing effects of supercapacitor are mainly resulted from voltage and temperature effects [116]. In particular, thermal conditions may have great influences on performance of supercapacitor, that capacitance degradation would be accelerated when the temperature is too high [117]. On the other hand, charging and discharging rates have little effect on supercapacitor degradation [118].

Since the supercapacitor lifetime at the maximum working temperature with proper voltage ranges is always given by manufacturing specifications, it can be reasonably assumed that supercapacitor is expected to last for the estimated life within normal operating conditions. Therefore, the supercapacitor degradation cost can be considered as a linear function of time despite of DOD of each charging/discharging event. Given the estimated supercapacitor lifetime L_{SC} and the replacement cost C_{SC} , the supercapacitor degradation cost for any time interval Δt can be simply presented as follows:

$$C_{SCDC}(t) = \frac{C_{SC}\Delta t}{L_{SC}} \quad (5.6)$$

(5.6) shows that different from the battery degradation cost, the supercapacitor degradation cost is constant irrespective of cycling conditions. Thus, the supercapacitor degradation cost is time-linear as long as it is utilized into microgrid.

Figure 5.4: Structure of the proposed two-layer EMS.

Therefore, it is more suitable for frequent charging/discharging to fill instantaneous power imbalance.

5.4 Proposed Two-layer EMS

Based on the complementary characteristics of the battery and supercapacitor, in this section, a two-layer EMS is proposed to optimize the microgrid operation. Different from the two-layer structure formulated in the literature, such as in [119] that aims for energy loss minimization and in [120] which minimizes the averaged long-term cost, our proposed EMS achieves the minimal operational cost with the incorporation of the degradation model of hybrid ES.

The objective of the proposed two-layer EMS is to optimize the power dispatch of power sources and energy resources in a finite period of time, so that the microgrid operates economically while satisfying operational limits under RES uncertainties. We consider a discrete-time optimization problem incorporated with the model predictive control framework, since the forecast uncertainty can be potentially compensated due to feedback mechanism [121], [122]. Fig. 5.4 illustrates the hierarchical structure of the proposed two-layer EMS, in which T_u

and T_l denote the length of prediction horizon in the upper and lower layer, respectively. The upper layer EMS consists of a nonlinear receding model predictive controller with the time horizon $t_l \in \{1, \dots, T_l\}$, and the lower layer EMS is a quadratic model predictive controller with the time horizon $t_u \in \{1, \dots, T_u\}$. Δt_u and Δt_l indicate the time intervals in the upper and lower layer, respectively. Control actions in each time interval are obtained by solving its own objective function in each layer that the decisions of one layer influence those of the other. At current time, the optimal scheduling is formulated for T_u in the upper layer based on the predictions of the upcoming load profile, renewable outputs and electricity prices, however only the dispatch within the time frame $T_l \Delta t_l + \Delta t_u$ will be implemented as the reference values to control dispatch actions at the lower layer. Then, the lower layer EMS makes its own optimization with the implementation of supercapacitor, which is to minimize power fluctuations after the realization of forecast errors in each ΔT_l within the low-layer horizon T_l . After time Δt_u , the lower layer EMS sends the updated state variables back to the upper layer, and the scheduling problem will start for the next ΔT_u .

5.4.1 Mathematical Model for State Dynamics and Constraints of ES

For both upper and lower layer, the power balance constraints must be meet at all times, which can be formulated as follows:

$$\underbrace{P_L(t)}_{\text{Load}} = \underbrace{P_M(t)}_{\text{Utility grid}} + \underbrace{P_B(t) + P_{SC}(t)}_{\text{ES}} + \underbrace{P_{PV}(t) + P_{WT}(t)}_{\text{RES}}, \quad t \in \{t_u, t_l\} \quad (5.7)$$

State dynamics must be specified for both the battery and supercapacitor in terms of capacities and charging/discharging power for two time horizons. Let $P_B(t)$ and $P_{SC}(t)$ denote the power of battery and supercapacitor, respectively. Considering charging and discharging efficiencies, the discrete-time capacity

difference equations of the battery and supercapacitor can be presented as follows, respectively:

$$E_B(t) = \begin{cases} E_B(t-1) - P_B(t)\Delta t\eta_{Bc}, & P_B(t) \leq 0 \\ E_B(t-1) - \frac{P_B(t)\Delta t}{\eta_{Bd}}, & P_B(t) > 0 \end{cases}, \Delta t \in \{\Delta t_u, \Delta t_l\}, t \in \{t_u, t_l\} \quad (5.8)$$

$$E_{SC}(t) = \begin{cases} E_{SC}(t-1) - P_{SC}(t)\Delta t_l\eta_{SC}, & P_{SC}(t_l) \leq 0 \\ E_{SC}(t-1) - \frac{P_{SC}(t)\Delta t_l}{\eta_{SCd}}, & P_{SC}(t_l) > 0 \end{cases} \quad (5.9)$$

The inequality constraints include power capacity limits of the utility grid, battery and supercapacitor as follows, respectively:

$$P_M^{\min}(t) \leq P_M(t) \leq P_M^{\max}(t), t \in \{t_u, t_l\} \quad (5.10)$$

$$P_B^{\min}(t) \leq P_B(t) \leq P_B^{\max}(t), t \in \{t_u, t_l\} \quad (5.11)$$

$$P_{SC}^{\min}(t_l) \leq P_{SC}(t_l) \leq P_{SC}^{\max}(t_l) \quad (5.12)$$

To prevent the battery from being overcharged and overdischarged, its SOC limit is expressed as follows:

$$S_B^{\min}(t) < \frac{E_B(t)}{E_{BA}(t)} < S_B^{\max}(t), t \in \{t_u, t_l\} \quad (5.13)$$

Accordingly, the supercapacitor SOC limit is expressed as follows:

$$S_{SC}^{\min}(t) < \frac{E_{SC}(t)}{E_{SC.rated}} < S_{SC}^{\max}(t), t \in \{t_u, t_l\} \quad (5.14)$$

Note that the scheduling of supercapacitor will not be actually included in the upper layer due to its low capacity, therefore, the state dynamic in (5.9) and the power constraint in (5.12) are only considered in the lower layer. The lower boundary of $P_M(t)$ is negative when the microgrid is allowed to sell electricity to the utility grid.

5.4.2 Mathematical Model for Upper Layer EMS

With the aforementioned models in Section III, the objective of the upper layer EMS is to optimize the decision variables $\{P_M(t_u), P_B(t_u)\}_{t_u=1}^{T_u}$ to minimize the total operational cost, including electricity cost of the utility grid and battery degradation cost.

The electricity cost $C_M^u(t_u)$ can be presented as follows:

$$C_M^u(t_u) = c_m(t_u)P_M^u(t_u)\Delta t_u \quad (5.15)$$

Since the battery degradation cost $C_B^u(t_u)$ in each time interval Δt can be determined only after when a charging or discharging event has ended, the power flow direction of the battery $P_B(t_u)$ must be specified. To this end, we firstly denote $g(t_u)$ to be an auxiliary binary variable to indicate the state transition on the charging and discharging events in two consecutive time intervals:

$$g(t_u) = \begin{cases} 1, & \text{if } P_B(t_u)P_B(t_u - 1) \leq 0 \\ 0, & \text{if } P_B(t_u)P_B(t_u - 1) > 0 \end{cases} \quad (5.16)$$

We also denote $E_a(t_u)$ as the accumulative energy in kWh before the cycling events have been changed. Correspondingly, the accumulative energy $E_a(t_u)$ can be written as follows:

$$E_a(t_u) = (1 - g(t_u))E_a(t_u - 1) + P_B(t_u)\Delta t_u \quad (5.17)$$

Therefore, the battery degradation cost in the consecutive time intervals can be presented by the state transition signal $g(t_u)$ the accumulative energy $E_a(t_u)$ as follows:

$$C_B^u(t_u) = C_{BDC}(t_u, \frac{E_a(t_u)}{E_B(t_u)}) - (1 - g(t_u))C_{BDC}\left(t_u, \frac{E_a(t_u - 1)}{E_B(t_u - 1)}\right) \quad (5.18)$$

Combining the electricity cost and the battery degradation cost in the objective function, the optimization problem in the upper layer EMS is a nonlinear

programming problem since the battery degradation cost is highly nonlinear. The optimization problem F_u can be formulated as follows:

$$\begin{aligned}
 F_u : \min \quad & \sum_{t_u \in \{1, \dots, T_u\}} C_M^u(t_u) + \sum_{t_u \in \{1, \dots, T_u\}} C_B^u(t_u) \\
 \text{s.t.} \quad & (5.7), (5.8), (5.10), (5.11), (5.13) - (5.18) \\
 \text{Decision variables : } & \{P_M(t_u), P_B(t_u)\}_{t_u=1}^{T_u}
 \end{aligned} \tag{5.19}$$

5.4.3 Mathematical Model for Lower Layer EMS

The objective of the lower layer EMS is to optimize the decision variables $\{P_M(t_l), P_B(t_l), P_{SC}(t_l)\}_{t_l=1}^{T_l}$ so that the variation resulted from forecast errors with the implementation of supercapacitor can be minimized. Considering (5.6) that the supercapacitor degradation cost is a function only related with time, the supercapacitor degradation cost $C_{SC}^l(t_l)$ can be writern as follows:

$$\sum_{t_l \in T_l} C_{SC}^l(t_l) = \frac{C_{SC}}{L_{SC}} T_l \tag{5.20}$$

It can be easily observed the supercapacitor degradation cost is independent with the charging/discharging power.

Accordingly, aside from the supercapacitor degradation cost, penalty costs that represent deviations from references provided by the upper layer EMS are added into the objective function. These penalty terms are denoted as $C_B^l(t_l)$ and $C_M^l(t_l)$ that represent the deviations on power references of the battery and utility grid due to forecast errors of RES in short-time scales. Given the power references from the upper layer, the penalty costs can be formulated as a quadratic function:

$$C_B^l(t_l) = (P_B^u(t_u) - P_B^l(t_l))^2 \tag{5.21}$$

and

$$C_M^l(t_l) = (P_M^u(t_u) - P_M^l(t_l))^2 \tag{5.22}$$

In addition, at the end of each prediction horizon, the SOC of supercapacitor should be maintained at a nominal value such that it is able to provide ramping services in the coming future. Hence, the penalty term $C_{SC}^l(T_l)$ that accounts for the capacity of supercapacitor in the prediction horizon terminal can be also presented as a quadratic function:

$$C_{SC}^l(T_l) = (E_{sc}^u(t_u) - E_{SC.rated})^2 \quad (5.23)$$

Combining the above quadratic factors in the objective function and convex constraints, the optimization problem in the lower layer can be formulated as a quadratic programming problem as follows:

$$\begin{aligned} F_l : \min & \left(\sum_{t_l \in \{1, \dots, T_l\}} C_{SC}^l(t_l) \right. \\ & + \sum_{t_l \in \{1, \dots, T_l\}} \left(\sigma_B^l C_B^l(t_l) + \sigma_M^l C_M^l(t_l) \right) \\ & \left. + \sigma_{SC}^l C_{SC}^l(T_l) \right) \\ \text{s.t.} & (5.8), (5.9), (5.10), (5.11) - (5.14), (5.20) - (5.23) \\ \text{Decision variables : } & \{P_M(t_l), P_B(t_l), P_{SC}(t_l)\}_{t_l=1}^{T_l} \end{aligned} \quad (5.24)$$

where σ_B^l , σ_M^l and σ_{SC}^l are cost weighting coefficients.

5.4.4 Remarks

In summary, the control strategy of the proposed two-layer EMS is outlined in Fig. 5.5. As illustrated in (5.19) and (5.24), the upper layer EMS minimizes the total operational cost including the electricity and degradation cost, and passes decision variables $[P_B(t_u), P_M(t_u)]$ to the lower layer as references. Considering load fluctuations and RES forecast errors, the optimization process is executed for each time interval ΔT_l , and the scheduling in the lower layer is made thereafter. After all the dispatch decisions within Δt_u have been made, the upper layer updates state variables $[E_B(T_l), E_{SC}(T_l)]$ and starts the scheduling for $t_u = t_u + 1$.

```

1: Initialize  $t_u = 1$ 
2: for  $t_u = 1$  to  $T_u$ , do
3:   Import the forecast data of load and renewables  $[P_L(t_u), P_{PV}(t_u), P_{WT}(t_u)]_{t_u}^{t_u+T_u}$ 
4:   Optimize  $F_u$  in upper layer
5:   Make decision variables  $[P_B(t_u), P_M(t_u)]_{t_u}^{t_u+T_u}$  within  $T_l\Delta t_l + \Delta t_u$  for the lower layer as set
       points
6:   for  $t_l = 1$  to  $T_l$ , do
7:     Import the forecast data of load and renewables  $[P_L(t_l), P_{PV}(t_l), P_{WT}(t_l)]_{t_l}^{t_l+T_l}$ 
8:     Optimize lower layer objective function  $F_l$ 
9:     Dispatch power of  $[P_M(t_l), P_B(t_l), P_{SC}(t_l)]_{t_u+t_l}$ 
10:  end for
11:  Return state variables  $[E_B(T_l), E_{SC}(T_l)]_{t_u+1}$  to the upper layer
12: end for

```

Figure 5.5: Algorithm of control strategy for two-layer EMS.

The optimization problem F_u in the upper layer is a nonlinear mixed-integer problem, as the cost function involved battery degradation cost $C_B^u(t_u)$ is nonlinear and includes integer terms. Similarly, the optimization problem F_l in the lower layer is a quadratic mixed-integer problem. There have already been many mature and advanced solvers with various algorithms so far that can handle to solve algebraic models with converged results, therefore comparison of their performances will not be further discussed since it is out of the scope.

It should be noted that in the lower layer, the supercapacitor may sometimes reach the capacity limit in the circumstances when the RES has increasingly excessive output. Since the upper layer EMS strives to maintain the battery output constant, it is necessary to conduct a new dispatch for all the components in the upper layer EMS in order not to violate the supercapacitor constraints.

5.5 Performance Evaluation

5.5.1 Simulation Setups

In this section, the proposed two-layer EMS associated with degradation cost models is demonstrated in three cases under different scenarios including pricing schemes, prediction horizons and forecast errors, and its performance is evaluated with several existing algorithms. The mathematical model described above as implemented in Matlab and optimization problem in the upper and lower layer is solved using the solver IPOPT [123] and Gurobi [124] integrated with Matlab, respectively.

The parameters in the case studies are listed in Table 5.1. The simulation is conducted for a 48h scheduling horizon, and the time intervals in the upper and lower layer are set to be 1h and 5min, respectively. The exact power of load, PV and wind turbine are shown in Fig. 5.6. The parameters of hybridized ES are shown in Table 5.2. The battery is set to have a capacity of 12kWh at 600\$ per kWh and the maximum power of 4kW. The charging and discharging efficiencies are both 95%, and the SOC operation range is set to be 10% to 90%. Its DOD-cycle curve is obtained so that the coefficient (a, b, c) takes the values of (4980, 1.98, 0.016), respectively [109]. The capacity and maximum power of supercapacitor is set to be 1kWh and 10kW, respectively, with its charging and discharging efficiency at 92% [125], [126].

In case 1, the time-of-use pricing and real-time pricing are implemented in two scenarios, respectively. In the time-of-use pricing, the electricity price is set as 0.1\$/kWh during off-peak hours (hour 0-8 and 18-23) and 0.25\$/kWh at on-peak hours (hour 9-17). In the real-time pricing, the hourly data is adopted by weighting the half hourly data from May 2013 to April 2014 in Energy Market Company of Singapore [103]. The selling price is set as 80% of the electricity price in both pricing schemes. In case 2, six time lengths of the prediction horizon in the upper

Figure 5.6: Exact power of load, PV and wind turbine in 48 hours.

Table 5.1: Parameters in case studies

Case	pricing scheme	forecast error	prediction horizon		time interval	
			T_u	T_l	Δt_u	Δt_l
1	time-of-use	5%-10%	48	12	1h	5min
	real-time					
2	time-of-use	5%-10%	6-96			
3	time-of-use	5%-(10%~40%)	48			

Time-of-use: the electricity price is set as 0.1\$/kWh during off-peak hours (hour 0-8 and 18-23) and 0.25\$/kWh at on-peak hours (hour 9-17).

Real-time: the hourly data is adopted by weighting the half hourly data from May 2013 to April 2014 in Energy Market Company of Singapore [103].

Table 5.2: Parameters of Hybridized ES

Type	Price (\$/kWh)	Capacity (kWh)	Power (kW)	S^{min}	S^{max}	η_c	η_d	Coefficients		
								a	b	c
battery	600	12	4	10%	90%	95%	95%	4980	1.98	0.016
supercap	3600	1	10	0%	100%	92%	92%	N.A.		

layer EMS from 6h to 96h are selected, respectively. In case 3, variable RES forecast errors are adopted with the standard deviation from 10% to 40% at the time terminal in the upper layer.

5.5.2 Case Studies

a. Different Pricing Schemes

(a) Optimal dispatch in time-of-use pricing

(b) Optimal dispatch in real-time pricing

Figure 5.7: Case 1: results of two scenarios with different pricing schemes.

The results of the optimal dispatch based on time-of-use pricing by the proposed EMS are shown in Fig. 5.7a. As expected, the operation of the battery is mainly scheduled by the electricity price in the upper layer EMS, in which the battery is charging during off-peak hours and discharging during on-peak hours. In addition, excessive energy generated by the RES at hour 11 to 13 is sold back to the utility grid since the electricity price is high. Similar results with the real-time pricing scheme are illustrated in Fig. 5.7b. In addition, it is observed that the battery has sensitive responses to high electricity prices at hour 16, 20 and 37 when the battery is quickly discharged. When the electricity price is relatively lower at hour 17 and 18, the battery is charged to ensure enough energy can be discharged in next following hours. On the other hand, it can be also observed in Fig. 5.7 that the lower layer EMS handles the fluctuation within each hour, that the power variations of the utility grid and battery have been stabilized within small ranges while the supercapacitor is frequently charged and discharged at a large rate to flatten the load uncertainties and forecast errors.

b. Impact of Prediction Horizons

Fig. 5.8 shows the results of six scenarios with different prediction horizons from 6h to 96h. It is indicated in Fig. 5.8a that the SOC of battery varies with the

(a) SOC of battery

(b) Operational cost

(c) Battery degradation cost

(d) Hourly average cost

Figure 5.8: Case 2: results of six scenarios with different prediction horizons.

changing prediction horizon. When it increases over 24h, the battery SOC change becomes much less significant. The operational cost and the battery degradation cost are depicted in Fig. 5.8b and Fig. 5.8c, showing that high levels of detail on prediction horizon result in less variation on costs. Typically, the variation on the system operational cost is reduced when the prediction horizon reaches 24h, because the load profile follows similar daily patterns. It is also illustrated in Fig. 5.8d that despite of the length of prediction horizon, the average operational cost in 48 hours does not have great changes with different prediction horizon, whereas a significant decrease on the battery degradation cost has taken place.

Table 5.3 shows the average computation time with different prediction horizons. It can be reasonably observed that with the larger prediction horizon setting the computation time of upper layer increases while that of lower layer remains nearly same. However, the two-layer EMS ensures the optimal results to be obtained before the next upcoming time slot, since the computation time is much shorter than the corresponding time interval. It is thus clearly shown that the computation ability is quite sufficient for the system needs.

c. Impact of Forecast Accuracies

Fig. 5.9 shows the results of four scenarios with increasing forecast errors from 10% to 40%. It is indicated in Fig. 5.9a that battery operation does not change very much with increasing forecast errors, whereas the supercapacitor output has been influenced to a great extent as shown in Fig. 5.9b. It can be also observed that the supercapacitor output is mainly affected in the daytime when solar energy is more abundant and intermittent, resulting into relatively more uncertainties on RES outputs. Since one major objective of the lower layer EMS is to smooth the battery output, it is reasonably explained that increasing forecast errors introduces more volatile variations on the supercapacitor output. On the other hand, the operation of supercapacitor is regulated by the lower layer EMS, which is responsible for instantaneous power mismatch, leading to the fact in Fig. 5.9c that neither the

Figure 5.9: Case 3: results of four scenarios with different forecast errors.

total operational cost nor the battery degradation cost has any significant change with increasing forecast errors.

d. Comparison with Benchmarks

In order to evaluate the performance and advantages of the two-layer EMS with the degradation cost models, several benchmark approaches and algorithms in the literature are analyzed. All the comparative scenarios are summarized in Table 5.4.

For comparison with the proposed nonlinear battery cost models, Four other

Table 5.3: Average computation time of different prediction horizons

prediction horizon	computation time (s)	
	upper layer	lower layer
6h	2.989	2.247
12h	6.732	2.263
24h	12.931	2.182
48h	20.688	2.239
72h	32.433	2.430
96h	50.978	2.305

Table 5.4: Comparison Benchmarks

Battery cost model	Algorithm
I: proposed battery degradation cost	A: proposed two-layer EMS
II: fixed battery degradation cost [109], [127]	B: single logic control
III: 5-level piece-wise linear cost	C: centralized EMS [77]
IV: 9-level piece-wise linear cost	
V: quadratic cost [128]	

scenarios are simulated arbitrarily for the case 1 with the time-of-use pricing scheme in Table 5.1. The fixed battery degradation cost per kWh is calculated from purple(5.3) by using the averaged DOD $d_B = 60\%$ as a regular basis (SOC from 80% to 20%) [109], [127]. The 5-level and 9-level piece-wise linear models are generated by averaging the battery degradation cost from 0% to 100%, respectively. The quadratic cost in [128] and is also incorporated for a more comprehensive comparison.

To further illustrate the advantages of the proposed two-layer operation structure, two different control algorithms with the the single-layer structure are added into the benchmarks. The single logic control is deployed in which the whole hybridized ES operates in just one layer. The battery will be charged or discharged as long as it is available, while the supercapacitor only accounts for mitigation of mismatches between load and PV outputs. The centralized EMS structure in [77] with the same solver of the proposed algorithm is tested as well.

Table 5.5: Results of Comparative Cases

Result	I-A	I-B	I-C	II-A	II-B	II-C
Operational cost (\$)	0.2935	0.4123	0.2946	0.2931	0.5011	0.3122
Batt degradation cost (\$)	0.00934	0.03432	0.01642	0.01462	0.06123	0.02046
Discharge ratio* (%)	66.34	172.62	89.12	92.36	201.63	111.36
Computation time [†] (s)	47.556	17.56	306.332	9.563	3.724	126.442
Result	III-A	III-B	III-C	IV-A	IV-B	IV-C
Operational cost (\$)	0.2983	0.4512	0.3129	0.3001	0.4339	0.3102
Batt degradation cost (\$)	0.01236	0.03985	0.01936	0.01132	0.03712	0.01712
Discharge ratio* (%)	73.26	182.46	94.17	74.12	181.29	81.99
Computation time [†] (s)	21.429	7.436	152.357	26.462	11.423	171.939
Result	V-A	V-B	V-C			
Operational cost (\$)	0.3123	0.4722	0.3270			
Batt degradation cost (\$)	0.01356	0.03832	0.01397			
Discharge ratio* (%)	86.42	182.93	101.12			
Computation time [†] (s)	31.437	16.443	193.462			

*: Discharge ratio is calculated by adding the DOD of all discharging events and then averaging in 24 hours.

[†]: Computation time is counted for searching the optimal results in the time interval of upper layer.

Table 5.5 shows the results of the comparative cases for all scenario combinations. It has been clearly shown that the proposed method is advantageous in all terms except for computation time. Cases with the fixed battery degradation cost lead to the worst results as its averaged degradation cost and the discharge ratio are both the highest, which means the battery may be inappropriately exploited. On the other side, cases with the piece-wise linear cost models produces very similar results with the proposed model with higher costs and discharge ratio and lower computation time, while cases with the quadratic cost merely takes the average result with even worse DOD ratio and computation time ratings.

Compared with the nonlinear model for degradation costs, one of the major shortcomings of fixed, piecewise linear and quadratic cost models is they cannot effectively reduce the charging and discharging frequency, as illustrated by row 4 (discharge ratio) in Table 5.5. This is because the cost is directly linked with the exchange power of ES as a constant approximation in spite of its operating conditions, resulting to the fact that SOC and DOD have little relationship with

the real-time degradation process. On the other hand, by comparing the results of scenario III and IV, it can be observed that the accuracy of such approximation methods is very dependent on the sampling points, which may in turn affect the optimization performance if the sampling points are not carefully selected. On the contrary, the nonlinear degradation model provides more levels of detail and ultimately reduces the charging/discharging frequency since it is derived directly from the characteristics of different ESs. Therefore, the nonlinear degradation cost model can provide the most accurate and effective results.

As for the algorithms, it can be also seen in Table 5.5 that the formulation of a single-layer optimization problem may be insufficient to make appropriate power dispatch for hybridized ES with distinctive characteristics, especially for battery and supercapacitor in this case. It can be seen that the single-layer model in I-C has encountered the computation issue since the optimization problem cannot be solved within the predefined time interval (5 min). It is difficult to make scheduling for supercapacitor in the long time scale such as one hour due to its lower energy density, and likewise, frequent charging and discharging for battery in short term deteriorate the lifetime dramatically, which may be not beneficial for long-term economic operation. To this end, the time interval for the single-layer model must be carefully selected to fit the need of hybridized ES, especially for the supercapacitor rather than battery. However, this may affect the result accuracy in turn. Therefore, one single layer optimization may not address the functionality of hybridization of energy storages, and its validity of single-layer optimization structure may be questioned by such the compromise between prediction horizon and computational burden. On the contrary, the design of such a two-layer structure in the chapter is specifically tailored to divide operation modes into variant time scales to deal with different characteristics of energy storages, at the expense of the computational time. With high-performance computer and more advanced solvers, the computation speed can be speed-up significantly.

5.6 Summary

In this chapter, a two-layer EMS for microgrids with the hybrid ES considering degradation cost models is proposed. We model the problem in the way that minimization of the operational cost is achieved while the power fluctuation by RES is accounted for. Degradation cost models of battery and supercapacitor are developed to convert the long-term capital cost into short-term operation problems. The two-layer EMS with hybrid ES is proposed in accordance with the degradation cost models, in which power dispatch is scheduled to minimize the operational cost in the upper layer and power fluctuations by RES forecast errors are minimized in the lower layer. The proposed EMS is applied to a microgrid which includes the PCC to the utility grid, a hybrid ES, a RES system and the aggregate load. Simulation studies successfully demonstrate that different types of energy storages including batteries and supercapacitors can be utilized at different layers for multiple decision-making objectives. Scenarios incorporating pricing schemes, prediction horizon lengths and forecast accuracies prove effectiveness of the proposed two-layer EMS structure.

Chapter 6

Coordinated Energy Management of Regional Residential Community with Multiple Microgrids

A novel two-level EMS with multiple small-scale microgrids in a regional community is proposed in this chapter. It aims both total operational cost minimization of the entire microgrid community and individual benefit maximization of each microgrid. At the local level inside each microgrid, with the detailed modeling of various energy resources including PVs, ESs, EVs and dispatchable loads, the individual optimization problem is formulated as a mixed-integer linear program. Local EMSs make power dispatch decisions to minimize the operational cost for individual microgrids. At the central level of the microgrid community, a novel pairing algorithm is proposed to find the microgrid pairings with surplus and deficit explicitly. The central EMS employs the pairing algorithm to determine specific power transactions among microgrids, and minimizes the power exchange with the upstream grid through the PCC. The operational cost of each individual microgrid is further reduced by additional economic benefits procured by the central EMS. The proposed method has its distinguishing advantages on modeling generality, computational complexity and customer privacy protection, and simulation results have verified its performance.

6.1 Introduction

As mentioned, four limitations have been manifest in literature involving energy mangement of microgrid community.

- Optimization problems of individual microgrids are inconsistent with each other;
- Intensive computation stress and convexity issues have become huge barriers to solving problems for microgrids with various infrastructures;
- Full observability in centralized EMS and inter-communication in decentralized EMS are hard to coordinate; and
- Lack of consideration of specific power flows in the microgrid community have long existed.

To overcome the above disadvantages, a hierarchical EMS model is proposed in this chapter to establish an effective mechanism of power dispatch for individual microgrids and energy exchange for the microgrid community. The main contributions are summarized as follows:

- 1) A coordinated two-level EMS for multiple small-scale microgrids in a regional community is developed. It aims to minimize the total operational cost of the microgrid community and maximize the individual benefit of each microgrid simultaneously.
- 2) For each individual microgrid, a local EMS is designed with detailed modeling of various energy resources including PVs, ESs, EVs and dispatchable loads. The local optimization problem aims to to decide optimal power dispatches for minimization of the operational cost.
- 3) In the community level, a novel pairing algorithm is proposed to find the microgrid pairings with surplus and deficit explicitly. The community-level central EMS employs the pairing algorithm to determine specific power

transactions among microgrids in a non-iterative way, minimizing the power exchange with the upstream grid through the point of common coupling (PCC). The operational cost of each individual microgrid is further reduced by additional economic benefits procured by the central EMS.

4) The proposed EMS has several distinguishing advantages on modeling generality, computational efficiency and customer privacy protection. Firstly, each local optimization problem is formulated as a mixed-integer linear program, which can be solved by using existing free/commercial solvers. Secondly, computational time has been reduced significantly by the proposed non-iterative coordination strategy. Lastly, no communication among local EMSs of individual microgrids is required, and communications between the central EMS and local EMSs only involve total energy exchanges of individual microgrids. Therefore, customer private information such as detailed scheduling inside microgrids can be well preserved.

6.2 Microgrid Community Structure

The network topology of the microgrid community is schematically illustrated in Fig. 6.1. The microgrid community can be described as a small regional distributed power system comprising a central EMS in the community level and multiple microgrids sited on different locations. Each microgrid has a direct connection with the upstream distribution grid through the point of coupling (PCC). Each microgrid is equipped with PV, ES, EV and different types of loads. The generalized microgrid model can be easily modified and utilized by changing these components to specify different system frameworks, e.g. building clusters, residential areas, etc.

Individual microgrids are supervised by the local EMSs, which only satisfies their self interests. Generally, these microgrid-level EMSs are responsible for

Figure 6.1: Network topology of a regional microgrid community with multiple microgrids.

optimizing local operations to decide power dispatches, such as minimization of local operational costs. Microgrids can also sell excess electricity back to the grid when the bidirectional transaction with the grid is allowed. On the other hand, the central EMS in the community level aims to manage the optimized operation for the entire microgrid community by coordinating individual microgrids. It is noted that cyber communication does not exist among individual microgrids. There is only interaction between each local EMS and the central EMS.

The dynamic electricity price is determined usually by the system operator from the utility grid. It is sensitive to locational marginal prices and often announced hours ahead, allowing users to make scheduling decisions in advance. For all microgrids inside the community, the same price scheme should be received since they are physically connected to the same bus. Typically, there is a difference on the purchasing and selling price at each time period to prevent from arbitrage.

For each microgrid which is only concerned on its self operation, however,

a part of microgrids may sell excessive electricity to the grid while the other part may need to purchase electricity due to deficit. For the entire microgrid community, this would lead to an undesirable result in terms of both power and economy efficiency. Frequent transactions among individual microgrids and the upstream grid would introduce additional power transmission losses. On the other side, uneconomic operation of the microgrid community would become an issue due to purchasing and selling price differences. To address the above problems, our proposed EMS aims to minimize such power exchanges that power efficiency and economic benefits for both individual microgrids and the entire community are maximized simultaneously. Details of the proposed two-level EMS will be elaborated in Chapter 6.3 and 6.4.

6.3 Local EMS in Individual Microgrid

As a self-interested entity, the local EMS in each individual microgrid aims to determine the optimized operation for local operational cost minimization.

6.3.1 Objective Function

Without loss of generality, the objective function in each individual microgrid can be formulated as follows:

$$\min \sum_{t \in T} \left\{ \begin{aligned} & p_{M,b}^{i,t} c_b^t \Delta t + p_{M,s}^{i,t} c_s^t \Delta t \\ & + \sum_{j \in \{N_G - i\}} (p_{C,b}^{ij,t} + p_{C,s}^{ij,t}) c_C^t \Delta t \\ & + \sum_{k \in ES^i} f_k[(p_{k,b}^{i,t} - \zeta_k^i p_{k,s}^{i,t}) \Delta t] \end{aligned} \right\}, \forall i \in N_G \quad (6.1)$$

The objective of the local EMS in each individual microgrid is to minimize the operational cost over an operation period of time T . The appropriate time horizon length T is determined by individual microgrids depending on their own

needs, which may not be necessarily correspondent with the central EMS in the community level. In our model, PV is considered as RES-based generation, which can be treated as negative loads. It is noted that investment costs of other appliances such as EV and PV are not considered, since the proposed method is focused on operational optimization of the microgrid, where investment cost in the planning stage is out of the scope of this work [129], [130].

The first line in (6.1) represents the electricity transaction cost with the upstream distribution grid, in which the purchasing price c_b^t is higher than the selling price c_s^t to prevent energy arbitrage from a dynamic electricity market. The time-varying dynamic pricing scheme provides economic incentives to microgrids by bilateral transaction schemes. The second line represents the transaction cost by energy exchanges in the microgrid community. The electricity transaction price c_C^t among microgrids is predefined as the average of c_b^t and c_s^t . The third line represents the degradation cost associated with ES. It is known that the degradation process of ES is nonlinear and highly related with its lifetime and operation mode [109], [111]. In order to take the degradation cost model in a practical fashion, the linearized form is defined from the nonlinear cost model in [131], as shown in Fig. 6.2. The degradation cost function f_k can be written in the inclining block function with special ordered set of type 2 (SOS-2) constraints [102] :

$$f_k(g_k^{i,t}) = \sum_{n \in N_k^i} \alpha_{k,n}^{i,t} F(G_{k,n}^i) \quad (6.2)$$

where

$$g_k^{i,t} = (p_{k,b}^{i,t} - \zeta_k^i p_{k,s}^{i,t}) \Delta t = \sum_{n \in N_k^i} \alpha_{k,n}^{i,t} G_{k,n}^i \quad (6.3)$$

$$\sum_{n \in N_k^i} \alpha_{k,n}^{i,t} = 1, \alpha_{k,n}^{i,t} \in [0, 1] \quad (6.4)$$

$$F(G_{k,n}^i) = F(G_{k,n-1}^i) + c_{k,n-1}^i (G_{k,n}^i - G_{k,n-1}^i), \forall n \in N_k^i - \{1\} \quad (6.5)$$

$$F(G_{k,1}^i) = 0 \quad (6.6)$$

Figure 6.2: Linearized degradation cost of k th ES in i th microgrid.

In (6.2), $\alpha_{k,n}^{i,t}$ is the element in SOS-2 N_k^i of k th ES in i th microgrid at time t , that only the adjacent elements can be nonzero. $c_{k,n}^i$ is the degradation cost coefficient of k th ES in microgrid i , and $G_{k,n}^i$ is the power level in which $c_{k,n}^i$ applies in N_k^i .

6.3.2 Constraints

The objective function (6.1) is subject to power balance, energy exchange, ES, EV and load constraints. Different components and their operational conditions have provided various requirements for mathematical modeling.

6.3.2.1 Power Balance

The power balance requirement is stated as follows that the total supply and demand must be equal:

$$\begin{aligned}
 & p_{M,b}^{i,t} + p_{M,s}^{i,t} + p_{PV}^{i,t} + \sum_{j \in \{N_G - i\}} (p_{C,b}^{ij,t} + p_{C,s}^{ij,t}) \\
 & + \sum_{k \in ES^i} (\zeta_k^i p_{k,b}^{i,t} + p_{k,s}^{i,t}) + \sum_{k \in EV^i} (\zeta_k^i p_{k,b}^{i,t} + p_{k,s}^{i,t}) \\
 & = p_{L_1}^{i,t} + \sum_{k \in L_1^i} p_k^{i,t} \lambda_k^{i,t} + \sum_{k \in L_2^i} p_k^{i,t} \lambda_k^{i,t}
 \end{aligned} \tag{6.7}$$

On the left side in (6.7), the first two terms denote the purchasing and selling power of the upstream grid, respectively. the third term denotes the PV power output. The fourth term denotes the transmitted power among individual microgrids. The last two terms denote the power of ES and EV, respectively. The right side includes the variables related with loads. It is noted that for the purpose of linearization, all the bidirectional power flow variables are split into two corresponding variables, which cannot have nonzero values at the same time.

6.3.2.2 Power Flow

The constraints on power flows to the upstream power grid and to other microgrids are presented as follows, respectively:

$$0 \leq p_{M,b}^{i,t} \leq \overline{p}_M^i u_M^{i,t}, \quad t \in T \quad (6.8)$$

$$\underline{p}_M^i (1 - u_M^{i,t}) \leq p_{M,s}^{i,t} \leq 0, \quad t \in T \quad (6.9)$$

$$0 \leq p_{C,b}^{ij,t} \leq \overline{p}_C^{ij} u_C^{ij,t}, \quad t \in T, j \in \{N_G - i\} \quad (6.10)$$

$$\underline{p}_C^{ij} (1 - u_C^{ij,t}) \leq p_{C,s}^{ij,t} \leq 0, \quad t \in T, j \in \{N_G - i\} \quad (6.11)$$

where the binary variables $u_M^{i,t}$ and $u_C^{ij,t}$ enforce the power flows to be unidirectional at each time interval.

6.3.2.3 ES and EV

The discrete-time state dynamic of ES is described in (6.12) that the charging/discharging efficiency coefficient ζ_k^i is imposed. (6.13) states the energy capacity limits for ES to avoid over-charging and over-discharging. Finally, (6.14) and (6.15) restricts the power limits, in which $u_C^{ij,t}$ is added for single power flow direction at each time interval. The constraints with ES can be written as follows:

$$E_k^{i,t+1} = E_k^{i,t} - p_{k,b}^{i,t} \Delta t - \zeta_k^i p_{k,s}^{i,t} \Delta t, \quad t \in T, \forall k \in ES^i \quad (6.12)$$

$$\underline{E}_k^i \leq E_k^{i,t} \leq \overline{E}_k^i, \quad t \in T, \forall k \in ES^i \quad (6.13)$$

$$0 \leq p_{k,b}^{i,t} \leq \overline{p_k^{i,t} \delta_k^{i,t}}, \quad t \in T, \forall k \in ES^i \quad (6.14)$$

$$\underline{p_k^{i,t}}(1 - \delta_k^{i,t}) \leq p_{k,s}^{i,t} \leq 0, \quad t \in T, \forall k \in ES^i \quad (6.15)$$

Similarly, the power and energy constraints for EV are stated in (6.16)-(6.19). Differently, T_k^i denote the parking time region, which means EV can be scheduled only when they are parked in microgrids. Besides, (6.20) states the minimum energy requirement when EV is at departure. The constraints with EV are written as follows:

$$E_k^{i,t+1} = E_k^{i,t} - p_{k,b}^{i,t} \Delta t - \zeta_k^i p_{k,s}^{i,t} \Delta t, \quad t \in T_k^i, \forall k \in EV^i \quad (6.16)$$

$$\underline{E_k^i} \leq E_k^{i,t} \leq \overline{E_k^i}, \quad t \in T_k^i, \forall k \in EV^i \quad (6.17)$$

$$0 \leq p_{k,b}^{i,t} \leq \overline{p_k^{i,t} \theta_k^{i,t}}, \quad t \in T_k^i, \forall k \in EV^i \quad (6.18)$$

$$\underline{p_k^{i,t}}(1 - \theta_k^{i,t}) \leq p_{k,s}^{i,t} \leq 0, \quad t \in T_k^i, \forall k \in EV^i \quad (6.19)$$

$$E_k^{i,t} \geq E_k^{i,dep}, \quad t = T_k^i, \forall k \in EV^i \quad (6.20)$$

6.3.2.4 Loads

Loads in microgrids can be classified into non-dispatchable and dispatchable loads. Non-dispatchable loads represent the basic and critical electricity consumption that is fixed and cannot be shifted over time. Non-dispatchable loads can be aggregated as one time-dependent variable $p_{L_1}^{i,t}$ in the model. On the other hand, dispatchable loads represent the electrical appliances that can be flexibly dispatched. Based on the operation modes, two categories of dispatchable loads are defined as type 1 and type 2 loads in our studies.

Type 1 loads include appliances which can be scheduled into several nonconsecutive time intervals, such as washing machines that can do the wash and spin processes in different time periods. The constraints of type 1 loads are formulated as follows:

$$\sum_{t \in T} p_k^{i,t} \lambda_k^{i,t} \Delta t = P_k^{i,t}, \quad \forall k \in L_1^i \quad (6.21)$$

$$\sum_{t \in T} \lambda_k^{i,t} = H_k^i, \forall k \in L_1^i \quad (6.22)$$

where (6.21) indicates that the scheduled operation of loads must meet the total energy requirement, and (6.22) imposes the constraint of the operation duration. The binary variable $\lambda_k^{i,t}$ indicates the operating status at time t , and H_k^i are defined as the operation duration during the entire scheduling horizon for type 1 loads.

Type 2 loads represent the appliances such as toasters and dishwashers that must be scheduled during consecutive times under users' discretion, since they usually have high power rating within short time duration. The constraints of type 2 loads are modeled as follows:

$$\sum_{t \in T} p_k^{i,t} \mu_k^{i,t} \Delta t = P_k^i, \forall k \in L_2^i \quad (6.23)$$

$$\sum_{t \in T} \mu_k^{i,t} = H_k^i, \forall k \in L_2^i \quad (6.24)$$

$$\sum_{t \in \{T-T\}} v_{k,s}^{i,t} = 1, v_{k,s}^{i,t} \in \{0, 1\}, \forall k \in L_2^i \quad (6.25)$$

$$\sum_{t \in \{T-T\}} v_{k,e}^{i,t} = -1, v_{k,e}^{i,t} \in \{0, -1\}, \forall k \in L_2^i \quad (6.26)$$

$$\mu_k^{i,t+1} - \mu_k^{i,t} = v_{k,s}^{i,t} + v_{k,e}^{i,t}, t \in \{T - T\}, \forall k \in L_2^i \quad (6.27)$$

where $\mu_k^{i,t}$ is defined operating status for type 2 loads similarly. In addition, two auxiliary integral variables $v_{k,s}^{i,t}$ and $v_{k,e}^{i,t}$ are modeled to address the feature of consecutive operation. $v_{k,s}^{i,t}$ and $v_{k,e}^{i,t}$ indicate the starting and ending time of k th type 2 load's operation at t , respectively. At last, (6.27) is added so that the type 2 loads must be operated consecutively in time series.

6.3.3 Overall Formulation

Combining the above factors, the optimization problem M_i for each individual microgrid i can be described as follows:

M_i : for $\forall i \in N_G$:

$$\min : \quad (6.1)$$

$$\text{subject to :} \quad (6.2) - (6.27)$$

The optimization problem is mixed-integer linear since the objective and all the constraints are linearized with some integral variables and parameter. There have already been many mature and advanced solvers with various algorithms so far that can handle to solve algebraic models with converged results such as CPLEX [132] and Gurobi [124].

6.4 Central EMS in Microgrid Community

In the community level, the central EMS aims to further reduce the operating cost of the entire microgrid community. It allocates the optimal power transactions among microgrids to minimize the power exchange with the upstream grid through PCC. In this section, a pairing algorithm is proposed to explicitly find the valid pairing of microgrids with the least power transmission distance (therefore, power loss). A non-iterative coordination strategy is presented with the pairing algorithm to determine specific power flows among microgrids with power surplus and deficit. Both the transmission loss with the upstream grid and among microgrids in the community are minimized. Consequently, the operational cost of each individual microgrid is further reduced by additional economic benefits procured by the central EMS.

6.4.1 Pairing Algorithm

The pairing algorithm identifies each distinct pair of microgrids with minimal power transmission losses, so that the pattern of exchanging energy inside the microgrid community can be established. To achieve this target, appropriate

weighting coefficients need to be addressed to decide the pairing priority among microgrids.

Electrical distances of microgrids are considered to be very close in the regional microgrids community compared to large power systems [101], [133], [134], whereas line resistance parameters are not precisely known in reality. Considering distances are approximately proportional to line resistances within the small regional area, geographical distances are used as weighting coefficients to indirectly reflect transmission losses induced by power exchange among microgrids in the community [135], [136]. The loss factor coefficient ε_{ij} is specified as well to present the linear transmission loss in a practical fashion.

Accordingly, the 2-D Cartesian coordinate system is formulated where the location of i th microgrid is expressed by the geographical coordinates (l_i^x, l_i^y) [137]. Hence, the weighting coefficient w_{ij} representing the transmission loss between microgrid i and j can be written by calculating the Euclidean distance as follows:

$$w_{ij} = \varepsilon_{ij} \sqrt{(l_i^x - l_j^x)^2 + (l_i^y - l_j^y)^2}, i \neq j, \forall i, j \in N_G \quad (6.28)$$

Note that for microgrid i and j with no physical connection, the corresponding weighting coefficient w_{ij} is set as a large positive number M . Similarly, $\{w_{ii} | \forall i \in N_G\}$ is set to be a large positive number M as well since no self connection is allowed.

The weighting matrix W is formulated to determine the pairing priority for the whole microgrid community, which is presented as follows:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1N_g} \\ w_{21} & w_{22} & \cdots & w_{2N_g} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N_g 1} & w_{N_g 2} & \cdots & w_{N_g N_g} \end{bmatrix} \quad (6.29)$$

From the above definition of w_{ij} , it can be recognized that W is a $N_g \times N_g$ symmetric matrix. Each row $r_i = [w_{i1}, w_{i2}, \dots, w_{iN_g}]$ in W comprises the

weighting coefficients from microgrid i to all other microgrids. Next, it can be proved that for the set of the microgrid community $i \in N_g$, there always exists a pairing of microgrids (w_{ij}, w_{ji}) for W in which the weighting coefficients to each other are minimal in their corresponding rows r_i and r_j .

Theorem 1 (Pairing Algorithm). *A pairing for the microgrid community can be always found, in which the weighting coefficients of two microgrids are minimal among those to all other microgrids.*

Proof. We denote $i, j \in N_G$ to be the index of corresponding rows and columns, respectively. The minimum value of each row in W can be expressed as follows:

$$w_i = \min_{j \in N_G} w_{ij}, \forall i \in N_G \quad (6.30)$$

Where w_i is the minimum element at row i in W . The set including all w_i can be further presented as:

$$\begin{aligned} \mathbf{R} &= \{w_i | w_i = \min_{j \in N_G} w_{ij}, \forall i \in N_G\} \\ &= \{w_{ic_i} | w_{ic_i} = \min_{j \in N_G} w_{ij}, \forall i \in N_G\} \end{aligned} \quad (6.31)$$

where $\mathbf{C} = \{c_i | i \in N_G\}$ is the column index set of the minimum elements.

In order to prove the original theorem, We firstly make its opposite proposition, that there exists no such pairing for all microgrids in N_G . Since $\mathbf{R}$ is the set of all minimum of each individual microgrid to others, another expression of this opposite proposition is that the elements in $\mathbf{R}$ are all different. Intuitively, all the elements $c_i \in \mathbf{C}$ are also different with each other. In the following discussion, we denote another index set as

$$\mathbf{K} = \{k_m \in \mathbf{C} | k_0 = 1, k_m = c_{k_{m-1}}, \forall m \in \{1, \dots, N_g\}\} \quad (6.32)$$

just for the symbol simplification. Considering W is a symmetric matrix, starting from the k_0 th row, we can get the following equation:

$$w_{1c_1} = w_{k_0 c_{k_0}} = w_{c_{k_0} k_0} = w_{k_1 k_0} \quad (6.33)$$

From (6.32), it is known that $w_{k_1 c_{k_1}}$ is the minimum element in the k_1 th row. Therefore, we have:

$$w_{k_1 k_0} > w_{k_1 c_{k_1}} = w_{c_{k_1} k_1} = w_{k_2 k_1} \quad (6.34)$$

Sequentially for $k_m \in \mathbf{K}$, the following formation must satisfy:

$$w_{k_0 c_{k_0}} > w_{k_1 c_{k_1}} > \cdots > w_{k_{N_g-1} c_{k_{N_g-1}}} = w_{k_{N_g} k_{N_g-1}} \quad (6.35)$$

For the last element $w_{k_{N_g} k_{N_g-1}}$, we can get:

$$w_{k_{N_g} k_{N_g-1}} > w_{k_{N_g} c_{k_{N_g}}} \quad (6.36)$$

It has been recognized that the elements $c_i \in \mathbf{C}$ are different, therefore, the elements $k \in \{\mathbf{K} - k_{N_g}\}$ are also different to each other. However, since $\mathbf{W}$ is a $N_g \times N_g$ symmetric matrix and the number, for $k_{N_g} \in \mathbf{K}$, the following formation must satisfy:

$$\{\mathbf{K} - k_{N_g}\} = \mathbf{K} \quad (6.37)$$

which means $w_{k_{N_g} c_{k_{N_g}}}$ must be equal to at least one element in the minimum row set $\mathbf{R}$:

$$w_{k_{N_g} c_{k_{N_g}}} \in \mathbf{R}, \quad k_{N_g} \in \{\mathbf{K} - k_{N_g}\} \quad (6.38)$$

This conclusion is contradictory to the opposite proposition. Hence, the pairing algorithm is proved that such the pairing for $\mathbf{W}$ can be always found. $\square$

By using the pairing algorithm, microgrid pairings with minimal transmission losses in the community can be always found, since pairings between microgrids with no connections and self-pairings have been excluded in prior. Accordingly, after acquiring the minimum at each row as in (6.31), such the microgrid pairing $x, y \in N_G$ for $\mathbf{W}$ can be determined as follows:

$$\{x, y\} = \{i, j\} | \{w_{ij} = w_{ji}, w_{ij} \in \mathbf{R}, \forall i, j \in N_G\} \quad (6.39)$$

6.4.2 Coordination Strategy in Microgrid Community

The pairing algorithm has demonstrated the pairing of two microgrids with the minimal transmission loss can be always located for the entire community. However, such a pairing is regarded to be valid only between two microgrids with different power flow directions. The coordination strategy in the central EMS recognizes all the valid pairings of microgrids with power surplus and deficits, and determines the specific values for corresponding power exchanges to minimize the total transmission loss inside the microgrid community. Minimization of the transmission loss with the upstream grid is achieved simultaneously by maximization of power transaction in the community.

To reach this target, total transmitted power of individual microgrids with respect to the community need to be firstly distinguished. An auxiliary variable $p_C^{i,t}$ for i th individual microgrid is introduced as follows:

$$p_C^{i,t} = p_{M,b}^{i,t} + p_{M,s}^{i,t} + \sum_{j \in \{N_G - i\}} (p_{C,b}^{ij,t} + p_{C,s}^{ij,t}), \quad \forall t \in T \quad (6.40)$$

where $p_C^{i,t}$ is the summed transmitted power of microgrid i to all other microgrids in N_G and the main grid.

It can be recognized that $p_C^{i,t}$ is positive when the i th microgrid have the power surplus and negative when the microgrid have the power deficit. Based on these power flow directions, therefore, the corresponding elements in W can be excluded by the signs of $p_C^{i,t}$ in a further way as follows:

$$w_{ij} = M, \text{ if } p_C^{i,t} \times p_C^{j,t} \geq 0, \quad \forall i, j \in N_G \quad (6.41)$$

where M is a large positive number.

After elimination of all the irrelevant parameters, valid pairings of microgrids with different power flow directions can be always established with the pairing algorithm by using the modified coefficient matrix W in (6.28), (6.29) and (6.41).

$$\begin{cases} p_{C,b}^{xy,t} = p_C^{x,t}, p_{C,s}^{xy,t} = 0, p_{C,b}^{yx,t} = 0, p_{C,s}^{yx,t} = -p_C^{x,t}/(1-w_{xy}), \text{ if } p_C^{x,t} > 0, |p_C^{x,t}| < |(1-w_{xy})p_C^{y,t}| \\ p_{C,b}^{xy,t} = -(1-w_{xy})p_C^{y,t}, p_{C,s}^{xy,t} = 0, p_{C,b}^{yx,t} = 0, p_{C,s}^{yx,t} = p_C^{y,t}, \text{ if } p_C^{x,t} > 0, |p_C^{x,t}| > |(1-w_{xy})p_C^{y,t}| \\ p_{C,b}^{xy,t} = 0, p_{C,s}^{xy,t} = p_C^{x,t}, p_{C,b}^{yx,t} = -(1-w_{xy})p_C^{x,t}, p_{C,s}^{yx,t} = 0, \text{ if } p_C^{x,t} < 0, |(1-w_{xy})p_C^{x,t}| < |p_C^{y,t}| \\ p_{C,b}^{xy,t} = 0, p_{C,s}^{xy,t} = -p_C^{y,t}/(1-w_{xy}), p_{C,b}^{yx,t} = p_C^{y,t}, p_{C,s}^{yx,t} = 0, \text{ if } p_C^{x,t} < 0, |(1-w_{xy})p_C^{x,t}| > |p_C^{y,t}| \end{cases} \quad (6.42)$$

$$\begin{cases} p_C^{x,t} = 0, p_C^{y,t} = p_C^{y,t} + p_C^{x,t}/(1-w_{xy}), \text{ if } p_C^{x,t} > 0, |p_C^{x,t}| < |(1-w_{xy})p_C^{y,t}| \\ p_C^{y,t} = p_C^{x,t} + (1-w_{xy})p_C^{y,t}, p_C^{x,t} = 0, \text{ if } p_C^{x,t} > 0, |p_C^{x,t}| > |(1-w_{xy})p_C^{y,t}| \\ p_C^{x,t} = 0, p_C^{y,t} = p_C^{y,t} + (1-w_{xy})p_C^{x,t}, \text{ if } p_C^{x,t} < 0, |(1-w_{xy})p_C^{x,t}| < |p_C^{y,t}| \\ p_C^{y,t} = p_C^{x,t} + p_C^{y,t}/(1-w_{xy}), p_C^{x,t} = 0, \text{ if } p_C^{x,t} < 0, |(1-w_{xy})p_C^{x,t}| > |p_C^{y,t}| \end{cases} \quad (6.43)$$

Based on the optimized dispatch signals transmitted from individual microgrid-level EMSs, the community-level EMS can determine power exchanges among microgrids explicitly.

The central EMS executes the pairing algorithm to find the microgrids in a pairing with minimal weighting coefficients, which are marked as $x, y \in N_G$. Correspondingly, the variables related to exchanged power of microgrid x, y need to be updated in the microgrid level. For all possible scenarios, the transmitted power between microgrid x and y are defined by the criteria in (6.42), and variables $p_C^{x,t}$ and $p_C^{y,t}$ indicating summed transmitted power of microgrid x and y respectively are updated in (6.43) as well.

At last, the weighting matrix W is updated as follows so that the successfully paired microgrids have been excluded:

$$w_{ij} = M \quad \forall w_{ij} \in r_i \ \& \ j \in N_G, \text{ if } p_C^{i,t} = 0 \quad \forall i \in \{x, y\} \quad (6.44)$$

After that, the first pairing of microgrids has been finished and the central EMS starts searching the next pairing for the rest of all microgrids in the community, until any of the total energy surplus of deficit among N_G becomes zero. The

```

1: for  $t \in T$ , do
2:   Lower-level EMS for individual microgrids:
3:   for microgrid  $i \in N_G$ , do
4:     1. Make local PV and load forecast and acquire the forecast electricity price in
        $T$ .
5:     2. Solve the local optimization problem  $\{M_i: \min (6.1), \text{ s.t. } (6.7)-(6.6)\}$ .
6:     3. All decision variables related to ESs, EVs and loads, including
        $p_{k,b}^{i,t}, p_{k,s}^{i,t}, u_M^{i,t}, \delta_k^{i,t}, \theta_k^{i,t}, \lambda_k^{i,t}, \mu_k^{i,t}, v_{k,s}^{i,t}, v_{k,e}^{i,t}, \alpha_{k,n}^{i,t}$  are determined; Binary variables
       related to main grid and other microgrids including  $u_M^{i,t}, u_C^{ij,t}$  are determined.
7:     4. The aggregated power  $p_C^{i,t}$  is calculated according to (6.40), while specific
        $p_{M,b}^{i,t}, p_{M,s}^{i,t}, p_{C,b}^{ij,t}, p_{C,s}^{ij,t}$  will be decided by the community-level EMS.
8:   end for
9:   Community-level EMS for microgrid community:
10:  1) The weighting coefficient matrix  $W$  is formulated according to (6.28), (6.29)
    and (6.41).
11:  while (6.45) is met, do
12:    2) The specific pairing  $\{x, y\}$  of microgrids with smallest weighting coefficients
    is determined by using Theorem 1.
13:    3) Power exchange variables  $p_{c,b}^{ij,t}$  and  $p_{c,s}^{ij,t}$  for  $i, j \in N_G$  are updated according
    to (6.42).
14:    4) The aggregated power  $p_C^{i,t}$  is updated by (6.43).
15:    5) The weighting coefficient matrix  $W$  is re-identified by using (6.44).
16:  end while
17:  6) All power flow variables including  $p_{M,b}^{i,t}, p_{M,s}^{i,t}, p_{C,b}^{ij,t}, p_{C,s}^{ij,t}$  for each individual
    microgrid  $i \in N_G$  at time  $t$  are determined.
18: end for

```

Figure 6.3: Algorithm of coordination strategy in two-level EMS.

stopping criterion can be expressed by the following equation:

$$\sum_{i \in N_G} \sum_{j \in \{N_G - i\}} p_{C,b}^{ij,t} \times \sum_{i \in N_G} \sum_{j \in \{N_G - i\}} p_{C,s}^{ij,t} = 0 \quad (6.45)$$

The overall procedure of the two-level EMS is described in Fig. 6.3. In the beginning of each time period, PV and load forecasts are made locally and the day-ahead electricity price is obtained. For each microgrid $i \in N_G$, dispatch decisions in the entire scheduling horizon are obtained by solving its own optimization problem in the local EMS individually, and $p_C^{i,t}$ is calculated by (6.40). Then in the central EMS, W is re-established based on (6.28), (6.29) and (6.41). Afterwards, the central EMS finds the microgrid pairing for current W . Procedures of the coordination strategy in the community-level EMS are iterated by (6.40)–(6.44) until the final criterion (6.45) is met.

It should be remarked the optimization in the local EMS of each individual microgrid is a mixed-integer linear problem, which can be solved in parallel at fast speed by a bunch of mature solvers. In the meantime, it is also important to note that the central EMS has no iterative interaction with individual microgrids, since the aggregated variable $p_C^{i,t}$ is collected only once from the corresponding i th local EMS. For the whole two-level EMS, therefore, the computational speed will be significantly improved compared with the traditional hierarchical EMS. The verification will be provided in Chapter 6.5.

6.5 Performance Evaluation

In this section, the mathematical model of the two-level EMS is demonstrated in MATLAB and the optimization problem is solved using CPLEX [132]. While the local EMS in each individual microgrid solves the optimization problem by its own interest, the main objective of the community-level EMS is to coordinate the energy exchange, so that the total power flow to the upstream grid is minimized. The central EMS in the microgrid community resolves the optimization problem

Table 6.1: Microgrid Characteristics

Microgrid	house 1	house 2	apartment	PV station
ES				
Capacity(kWh)	8	8	12	12
Max&Min P (kW)	-4/4	-4/4	-4/4	-4/4
Initial SOC(%)	20.9	33.1	33	31
SOC range(%)	17.0-84.1	17.5-83.5	16.9-82.1	18.7-89.0
Efficiency	95%	95%	95%	95%
EV				
Capacity (kWh)	16	16	N.A.	N.A.
Max&Min P (kW)	-1.44/3.6	-1.44/3.6		
Initial SOC(%)	52.63	33.1		
Operation periods (h)	0-4,8,8, 19,09-24	0-7,6,5,18,93-24		
SOC range(%) (%)	15.8-83.7	19.9-81.6		
Min depart SOC(%)	51.45	61.58		
Efficiency	95%	95%		
PV				
Capacity (kWp)	2	2	16	16
Unified location				
(l^x, l^y)	(0.12, 0.13)	(0.16, 0.79)	(0.83, 0.11)	(0.09, 0.26)

Table 6.2: Parameters of dispatchable loads

Appliance	Power(kW)	Operating periods	Operation duration(h)	type
Washing machine	0.7	0-19,23-24	1	1
Cleaner	0.6	0-4,6,24	4	1
Air conditioner	1.2	0-7,18-24	3	1
Lighting	0.15	6-7,18-23.5	5	1
Oven	1.16	11-13	0.5	1
Toaster	1.2	7-9	0.25	2
Dish washer	1	0-4,9-11,14-17,20-24	1	2

by using the coordination strategy with the proposed pairing algorithm. The simulation is conducted for a 24h scheduling horizon, and the sampling time resolution for the community-level controller is half an hour.

(a)

(b)

Figure 6.4: Non-dispatchable load of (a) house 1 and house 2; and (b) apartment and PV station.

Figure 6.5: Unified PV power in 4 microgrids.

Figure 6.6: Electricity price of microgrids.

6.5.1 Case 1: 4-microgrid Community

In the first case, a microgrid community with 4 microgrids is considered including two individual houses, an apartment building involving 10 homes and a small PV station. The specifications of 4 microgrids are detailed in Table 6.1. For each home in individual houses and the apartment building, type 1 and type 2 loads are listed in Table 6.2 with predefined operation time ranges. The non-dispatchable load profiles of 4 microgrids are shown in Figure. 6.4. The unified half-hourly PV forecast data per kWp on rated capacity is depicted in Fig. 6.5. The electricity purchasing and selling price of the microgrid community are adopted from Energy Market Company of Singapore (EMCSG) [103], as depicted in Fig. 6.6. The transaction price in the microgrid community are set as the average of these two prices. All the loss factors in the microgrid community ($\varepsilon_{ij} \forall i, j \in N_g$) are set to be 0.05.

6.5.1.1 Results of Individual Microgrids

The hourly energy scheduling for two houses is presented in Fig. 6.7a and Fig. 6.7b. It can be observed that two houses can cover most of electricity demand themselves by PV in the daytime. Dispatchable loads are scheduled within off-peak hours due to the relatively low electricity price. The ES and EV are charged until the

required energy levels are reached at hours with low electricity prices (e.g., at hour 2 and 23). However, the ES can effectively respond the high price signals in the daytime whereas the EV does not involve since it is already departed. Particularly, when the electricity price increases at hour 7, the EV in house 2 starts to charge to reduce the electricity consumption of the upstream grid.

For further illustration, the detailed scheduling of appliances in house 1 is presented in Fig. 6.8. It can be observed that most power consumption is distributed among the time intervals when electricity prices are at lowest even though the scheduling flexibility is provided over the entire time horizon. The scheduling for type 2 loads is made such that part of power consumption is moved to hours with higher prices to meet users' demands. For both types of dispatchable loads, the times with the lowest prices are selected by the local EMS given that user preferences are allowed.

The scheduling for the apartment building follows the similar patterns, which is illustrated in Fig. 6.7c. Similarly, the load consumption is distributed among the time intervals when the electricity price is low. Both types of dispatchable loads are scheduled within off-peak hours due to relatively low electricity price even though the type 1 loads has the full flexibility during the whole day. However, different from the scenario of houses, since the PV output cannot fully cover its need, it is necessary for the apartment to buy a part of additional power from other microgrids with surplus or even from the upstream grid.

The scheduling of the PV station is shown in Fig. 6.7d. Since there is barely small non-dispatchable load in this microgrid, the net power is exporting from the PV station to other microgrids. On the other hand, as no power can be provided by PV at night, the power consumption must be supplied by the local energy storage, the upstream grid and other microgrids together.

(a)

(b)

(c)

(d)

Figure 6.7: Energy scheduling in (a) house 1; (b) house 2; (c) apartment; and (d) PV station.

Figure 6.8: Detailed scheduling of dispatchable loads in house 1.

Table 6.3: Energy flow results in 24 hours

Time (h)	Energy flow (kWh)					
	1-2	1-3	1-4	2-3	2-4	3-4
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0
7	0	0	0	0	0	0
8	0	0	0	0	0	0
9	0	0	0	0	-1.0798	-3.3395
10	0	0	0	0	0	-8.8526
11	0	0.1501	0	0	0	-10.4804
12	0	0.3298	0	0	0	-9.0236
13	0	0.2102	0	0	0	-8.8724
14	0	0.5107	0	0	0	-7.2907
15	0	0.3018	0	0	0	-9.1386
16	0	0	-0.5124	0	-0.9727	-3.9986
17	0	0	-0.6501	0	0	0
18	0	0	0	0	0	0
19	0	0	0	0	0	0
20	0	0	0	0	0	0
21	0	0	0	0	0	0
22	0	0	0	0	0	0
23	0	0	0	0	0	0
24	0	0	0	0	0	0

Table 6.4: Operation cost of each microgrid community with 4 microgrids

Cost (\$)	house 1	house 2	apartment	PV station	total
original	5.981	6.068	72.233	-10.558	73.724
grid-side	5.496	5.036	56.028	-1.068	65.493
community	-0.075	0.560	12.513	-11.753	1.245
total	5.421	5.596	68.542	-12.821	66.737
improvement	9.361%	7.619%	5.109%	21.544%	9.474%

6.5.1.2 Results of Microgrid community

The energy flow within the microgrid community is detailed in Table 6.3, in which four microgrids are abbreviated from 1 to 4, respectively. It is shown that house 1 (microgrid 1) has the higher priority to export its surplus to the apartment building (microgrid 3) due to a smaller weighting coefficient, even when both two houses have excessive power from the PV at daytime. Similarly, when the PV output in house 1 cannot meet all the local loads at hour 17, the higher priority has granted it to acquire additional power from the PV station (microgrid 4) than the other two microgrids.

With the implementation of the proposed method, the total operational cost has been not only decreased for each individual microgrid, but for the entire microgrid community, as shown in Table 6.4. Compared with the direct transaction with the upstream grid, the operational cost of each microgrid has been reduced from 5.109% to 21.544% at most. On the other hand, by using the coordination strategy, the transaction with the upstream grid has been decreased by \$8.231 even with \$1.245 of the transmission loss in the microgrid community. In total, the operational cost of the community has been decreased by 9.474%. Therefore, individual microgrids can benefit from the proposed two-level EMS by reducing local operational costs, which would potentially attract external microgrids for active participation into the community.

Figure 6.9: Unified location of a regional microgrid community with 50 individual microgrids.

6.5.2 Case 2: 50-microgrid community

In order to validate the proposed EMS can handle the scenario with a large amount of microgrids, we further investigate a regional microgrid community including 50 microgrids, with 40 houses, 5 apartment buildings and 5 PV stations. The characteristics of individual microgrids are the same with those in Case 1. The normalized coordinate mapping of individual microgrids ($l_i^x, l_i^y \forall i \in N_G$) is presented graphically in Fig. 6.9, showing the geographical locations that four types of microgrids are averagely spread in the area. It is assumed that all microgrids are connected with the PCC to the upstream grid and no direction connection exists between any two microgrids. Hence, the weighting coefficient matrix W is generated by using the geographical Euclidean distances according to Fig. 6.9.

The operational cost results in this case are presented in Table 6.5. It is

Table 6.5: Average operation cost of microgrid community with 50 microgrids

Cost (\$)	house 1	house 2	apartment	PV station	total
original	6.083	6.035	71.979	-10.487	548.361
grid-side	5.503	5.040	55.770	-1.059	490.268
community	0.208	0.560	12.306	-10.996	8.036
total	5.711	5.600	68.076	-12.055	498.304
improvement	6.111%	7.201%	5.422%	14.958%	9.129%

observed that the operational cost of the entire microgrid community in 24 hours has been reduced from \$548.361 to \$490.268, while the transmission loss in the microgrid community is \$8.036. In total, the electricity expense has been improved by 9.129%. In addition, the proposed EMS also benefits all types of individual microgrids with average cost improvements ranging from 5.422% to 14.958%. As a result, the implementation of the proposed EMS may implicitly decrease the electricity price from the upstream grid in turn, since the stress to power congestion at peak hours in the distribution level would be alleviated.

6.5.3 Comparison with Existing Methods

Three existing approaches in the literature have been compared using the same case studies to further evaluate the performance and advantages of the proposed two-level EMS with the pairing algorithm. Firstly, the single-level centralized structure in [77] is adopted as the centralized EMS benchmark, in which all the microgrids are combined just as one big microgrid. A mathematical model similar in Chapter 6.3.2 is formulated for the combined microgrid and solved. Secondly, for the two-level EMS benchmark, the mechanism proposed in [138] without stochastic processes is utilized in the community level. An iterative algorithm is used to eliminate power exchange imbalances among microgrids by using Lagrangian relaxation. Finally, the purely decentralized framework by merely using the microgrid-level EMS is added for comparison, in which each microgrid makes power transactions directly with the upstream grid rather than

Table 6.6: Comparative results for 4 microgrids

Algorithm	Operational cost (\$)	Computation time (s)
proposed	66.73	1.17
[77]	66.60	36.16
[138]	66.67	22.49
direct transaction	73.72	1.01

Table 6.7: Comparative results for 50 microgrids

Algorithm	Operational cost (\$)	Computation time (s)
proposed	498.30	15.06
[77]	497.22	2053.48
[138]	497.96	1378.13
direct transaction	617.41	12.82

others in the community.

Comparative results with existing methods in Case 1 and 2 are presented in Table 6.6 and Table 6.7, respectively. It is seen in Table 6.6 that the proposed EMS has achieved the optimized operational cost slightly higher by just 0.2% to the best result with [77], whereas the computation time is nearly 19 times faster than the second best result with [138]. It should be noted that the operational cost in [77] is the minimum since all the information from individual microgrids has been fully collected and gathered into the centralized EMS, which may nevertheless put forward serious privacy concerns. Similar privacy problems exist in [138] that information of dispatch signals needs to be exchanged among interlinked microgrids and with the central EMS. On the contrary, private information is well preserved in our proposed EMS, since no communication among local EMSs of individual microgrids or with the central EMS of the microgrid community is required by any means. Communications between the central EMS and local EMSs only involve total energy exchanges of individual microgrids that do not expose any detailed decision making inside microgrids.

Shortcomings of existing methods on computational burden has been mag-

nified with the increasing number of microgrids in the community, as shown in Table 6.7. It takes just 15 seconds for the proposed EMS to the optimized result with a degradation of 0.21%, whereas it takes nearly half an hour for the centralized method in [77] and 23 minutes for the decentralized method in [138]. Such the discrepancy on computational efficiency would become more noticeable with size expansion of the microgrid community. With this respect, therefore, our proposed EMS has outstanding advantages in terms of the trade-off between computation efficiency and solution quality.

6.6 Summary

In this paper, a coordinated two-level EMS model for multiple small-scale microgrids in a regional community is proposed, accounting for minimization of the community-level operational cost and maximization of individual microgrid-level benefits simultaneously. The local EMSs inside microgrids aim to minimize the individual operational cost, while the central EMS determines specific power transactions inside the microgrid community by using the pairing algorithm to further reduce individual operational costs and transmission losses. The proposed EMS has been applied into two case studies with different scales of microgrid community. By comparing with existing approaches, simulation results have demonstrated the significant advantages of the proposed EMS on modeling generality, computational complexity and privacy security, that the optimization time has been reduced significantly by the non-iterative algorithm, and privacy issues have been eliminated by minimal information exchange.

Chapter 7

Conclusions and Future Works

The summary and overall conclusion of the thesis are presented in this chapter. The thesis begins with reviews on current development of microgrids and energy management systems with regards to various scales of microgrids. The performance of the proposed control methods has been verified through case studies. The research results have demonstrated that the proposed EMS is effective for different applications in microgrids. Furthermore, future works about improving EMS for microgrids are also presented.

7.1 Conclusion

This thesis developed a novel infrastructure of the energy management system (EMS) of microgrids to assess and optimize the operation involving RESs and ESs. The issues of economy-reliability conflict, cost evaluation, hierarchical control in microgrids have been formulated and addressed.

The growing interest on RES have evolved traditional power systems to be more sustainable and environmentally friendly, however its indeterminacy have introduced stability and reliability issues in power systems. On the other hand, ESs have greatly catalyzed the evolution of energy management in power system. Large-scale ESs have been integrated into systems to mitigate supply/demand variation and fluctuations brought by RES.

The proposed OPF algorithms have been thoroughly discussed to handle uncertainties of RESs and dynamic characteristics of ESs respectively. A DC OPF algorithm considering worst-case scenarios is firstly presented in Chapter 3. It accounts for uncertainties brought by loads and renewable energy sources (RES), while in the meantime the highest system reliability level can be achieved. By assigning selected values with largest probabilities to random variables, the probabilistic OPF formulation is converted into a set of deterministic OPF problems in which the additional auxiliary constraints are implemented to represent the uncertain influences. In Chapter 4, an OPF model considering ES with adaptive operation costs are proposed to optimize power generation and storage scheduling in multiple time periods. The operation cost coefficients of ES are auto-adjusted according to SOC and TOU cost of generators, specifying the dynamic characteristics of ESs. The effectiveness of the proposed OPF algorithms is applied into IEEE 14-bus and an IEEE 57-bus benchmarks. Simulation results have validated the robustness of the proposed method that the optimal scheduling of ESs is not only price-sensitive but also responsive to the sudden load change.

Hybrid ES that combines different types of ESs inherits advantages for each individual to provide an effective and reliable solution. It further urges different dispatch decisions to be made given various operation targets and ES characteristics. Hence, in the face of various devices in the hybrid ES, different time resolutions are required for the comprehensive design of EMS: the long-term time horizon represents operational economy and the short-term time horizon reflects system security. In this context, A novel two-layer EMS for microgrid including the hybrid ES is developed in Chapter 5. Power dispatch is scheduled to minimize the operational cost in the upper layer, and forecast uncertainties and power fluctuations by RES are minimized in the lower layer. The degradation cost models of battery and supercapacitor are developed to accurately reflect the explicit degradation process, bridging the long-term capital cost and the short-term operational cost for real-time economic dispatch. Simulation studies successfully demonstrate that different types of ESs including batteries and supercapacitors can be implemented in different layers for multiple decision-making objectives. Scenarios incorporating different pricing schemes, prediction horizon lengths and forecast accuracies have proved effectiveness of the proposed two-layer EMS structure.

Microgrid community, clustering several microgrids in adjacent feeders, can provide additional benefit to individual members through resource sharing while minimizing dependency effect and operate as an autonomous entity to enhance power system reliability under extreme conditions. The EMS for single microgrids is further extended to microgrid community scenarios in which a generalized two-stage EMS model for the interconnected residential community with multiple microgrids is proposed in Chapter 6. Minimization problems of total operational cost and impacts of the microgrid community on the upstream distribution grid are both investigated. The distributed EMS is integrated in the microgrid level. Based on the detailed model of individual microgrid with ESs, EVs, RES and controllable loads, the distributed EMS solves the optimization problem in each

individual microgrid to determine the optimal energy dispatch based on the interest of microgrid owners. In the upper stage, the community-level central EMS is implemented to explicitly determine the power exchange between microgrids and with the upstream distribution grid. A non-iterative pairing algorithm is proposed so that the energy exchange with the distribution grid is minimized that microgrid owners can adjust the scheduling freely to determine their participation levels. Private confidential information such as specific scheduling inside microgrids is well kept, as public information for communication only involves energy exchange values of each microgrid.

To summarize, the proposed EMS for microgrids has covered different conditions with regards to various topologies of individual microgrids and microgrid communities. Achievements of the integrated architecture for microgrids coupled with RESs and ESs can be realized with the implementation of proposed algorithms.

7.2 Recommendations for Further Research

In this thesis, a comprehensive methodology about effective planning and efficient operation in the context of microgrids has been proposed, that the novel EMS involving RESs and ESs are presented to assess the performance and optimize the operation in microgrids. Due to its applicability and versatility, the design of EMS for more advanced microgrids requires extensive research stability, reliability and power quality issues. Considering assumptions and limitations of the modeling and control methods in this thesis, further investigation can be conducted in several potential areas, which are described as follows.

a. Analysis of Reliability Expenditures

The proposed OPF for microgrids in the thesis has obtained the highest reliability by imposing additional auxiliary constraints. The robust degree and EENS in

the optimized result have been both improved, whereas the generation cost of the proposed methods is slightly higher than with the traditional OPF. Such the increase is mainly due to the reserved transmission capability as additional elements to counteract uncertainties.

Nevertheless, there might be a possibility of load curtailment or loss of generation capacity in some infeasible scenarios when physical power system constraints are violated, leading to greater economy and reliability losses of the overall system. In view of the above issues, it is reasonable to anticipate that the improvement on existing methodologies in future studies could be committed by imposing reliability indices as part of operational cost. Multi-objective optimization would be a feasible approach in combination with current methods while more literature and references need to be scrutinized.

b. Stochastic Hierarchical EMS with Hybrid ES in Microgrids

In current research, a two-layer EMS for individual microgrid with the hybrid ES considering degradation cost models has been proposed, in which power dispatch is scheduled to minimize the operational cost in the upper layer and power fluctuations caused by RES forecast errors are minimized in the lower layer.

Although indeterminacy issues have been well dealt with by different functionalities of hybrid ESs in the proposed model, the distinct limitation still exists that uncertainties occurring in both supply and demand sides are hardly taken into account in real-time operation. According to this respect, one of the future works would focus on the multi-stage stochastic formulation, in which trade-offs between computational capability and robustness of optimization problems should be taken care of.

c. Development of Resilience-based EMS for Microgrids

There are currently various energy management objectives involved with protec-

tion and regulation capabilities which have vast potentials to be further developed, such as post-contingency recovery, microgrid partitioning, etc. Research focus has expanded those factors in microgrids to provide additional resilience as local resources and black start reserves. Penetration of DERs and development on decentralized control algorithms have further improved resilience by exploiting their capabilities for fast and efficient restoration in microgrids. Specifically, the capability to anticipate risks, limit contingency/fault impact and maintain services upon survival are becoming crucial in more advanced and evolution techniques in terms of more distributed environment.

The future research should focus on the combination of reliable and resilient EMS for microgrids in which stability boundaries could be appropriately defined by analytic approaches. The interesting topic worth to be further investigated is to improve post-disaster recovery for multiple energy systems, specifically by using existing distributed generations to restore critical loads in microgrids, in which reconfiguration model for load restoration by sectionalizing microgrids would be a good topic for future studies.

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