Optimal Scheduling Models And Algorithms Of Integrated Microgrids

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A thesis submitted to the Department of Industrial Engineering,
Cullen College of Engineering
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in Industrial Engineering

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University of Houston
December 2019

ABSTRACT

The microgrid is a distribution system that integrates the increasing number of renewable energy resources, storage systems and controllable loads to support a flexible and reliable renewable energy distribution. Currently, microgrids can be used for a broader range of applications in the rural area and disaster restoration efforts, and enable higher efficiency in managing uncontrollable renewable energy resources such as wind and solar. However, there are operational and technological problems using the microgrids that need to be resolved so that the entire electrical community will receive benefits of having clean and high-quality power with lower cost. We have identified three optimization problems in this dissertation: 1) a operational problem to find optimal electrical power price and quantity when microgrids should trade (sell/buy) surplus/lacking power with distribution system, 2) a technological problem to use the minimum cost to deal with operation uncertainties such as generators' output and operation mode change when the operator schedules a microgrid, and 3) a managerial problem to co-optimize the energy and ancillary service interaction between microgrids and power system. This work will provide insights into these problems and give some practical solutions.

First, we provide a solution of designing a competitive decentralized distribution system. In addition, we identify a clear definition of the role that microgrids can play in this electrical market so that the microgrid operators can achieve maximum benefits. Second, we provide a stability opportunity risk index to evaluate the effects of microgrid operator managing the scheduling uncertainties. Then, a co-optimization scheme is developed for microgrid operator to schedule ancillary service from external resources (distribution system) and internal resources (disputable units). Third, a transactive management scheme provides a decentralized solution by constructing a boundary between the responsibility of microgrid and distribution system. By having a bi-directional energy and ancillary service scheme between two entities, the efficiency of market operation is improved.

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Chapter 1 Introduction

1.1 Background and Motivation

The microgrid (MG) is proposed to facilitate the integration of distributed energy resources (DERs) into the electricity grid [1]. The emergence of distributed energy resources brings people's attention to renewable energy and associated problems such as economics [2], environmental challenges [3], and policy making [4]. An increasing number of distributed energy resources have been put into the electricity market. This increment is forecasted to accelerate over time [5]. The public and governments are enthusiastic to use sustainable and clean energy such as rooftop PVs, electric vehicles, and wind farms because of lower operation cost and less pollution. For example, Germany has implemented a plan to replace their nuclear power plants with renewable energy sources by 2022 [6]. However, the traditional control architectures of distributed energy resources represent two extremes: a centrally operated model of the entire system, or a scattered isolated control structure with little connection between entities. Neither are ideal solutions to reflect the current development of power system operations. To begin with, to monitor and regulate a large size of distributed energy resources through a centralized fashion requires costly complex infrastructure and platform, such as communication and information processing [7]. Meanwhile, controlling deregulated distributed energy resources in a totally spontaneous, decentralized fashion is also not optimal for DERs to maximize profit. Relatively small size of DERs make their direct individual participation in the distribution electricity market, although theoretically possible, highly impractical. Without coordination and market support, the efficiency of using renewable energy is very low. For instance, in an area near Dallas, TX, some wind farms are unable to square the excess energy generated at night with their storage and dispatch capabilities. As a result, they have to give away that electricity to customers without any profits [8]. One can claim that the microgrid is a compromise between centralized fashion and decentralized fashion. The microgrid is a small centralized power system with integration of distribution generators, power storage system and local customer, which provides a solution to improve the efficiency of the electrical operation. When the distribution system operator has little visibility to secondary and last mile low voltage (LV) grids in the current practice, the microgrid integration enhances the observability of operator in operation. If you study the entire distribution system, the microgrid is still a decentralized component which appears similar to other DERs. Whereas, we can easily identify MGs from individual DERs by features such as, two-way power flow [9], smart control strategies (demand response, load shifting) [10], and islanding capability [11], etc. It has already been proved that microgrids can benefit the entire power system through profitable and environmentally friendly services [12], higher power system resiliency [13], less transmission and distribution costs [14], fewer carbon emissions by the use of renewable power resources [15], and utilization of electrification in rural areas [12]. It is found that the microgrid is the most promising control and management model to utilize the distributed energy resources [16]. We can expect to use microgrids in a wide variety of electrical environments (Figure 1.1) [17].

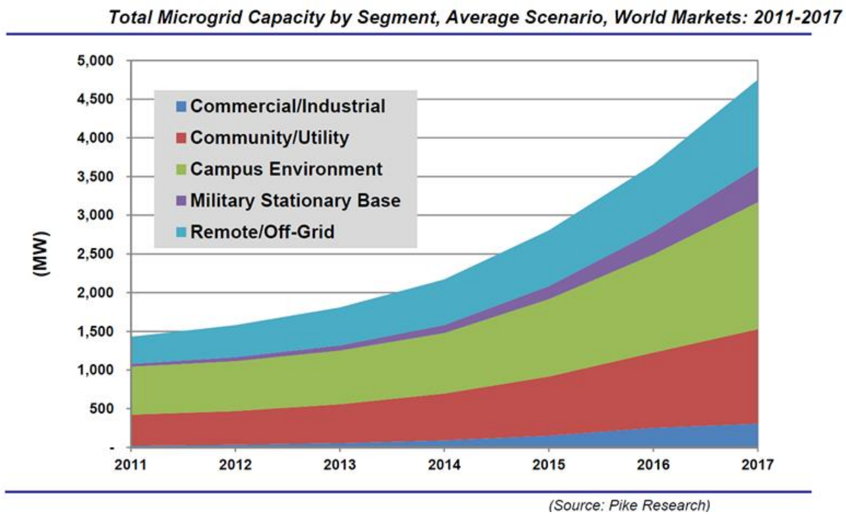

Figure 1. 1 Microgrid capacity from 2011 to 2017

The microgrid can be treated as a small, reliable power system [18]. However, it is different from the traditional power system or distribution power resource in a way that it can work in two operation mode [19]: grid-connected or islanding. When the MG is working in grid-connected mode, it can be treated as a portion of the entire power system. However, when the MG is working in islanding mode, it can be treated as an independent power system. To maximize the microgrid's benefits to electrification society, the microgrid relies on some cutting-edge technologies (Figure 1.2) such as data forecast [20], electric process control [21], reliability evaluation [18], smart meters [22], market design [23] and coordination strategy [24]. The microgrid operator (MGO) serves as the MG's administrator by monitoring the aforementioned advanced technologies and controlling all engineering activities (Figure 1.2). The main responsibility of the MGO is to optimally schedule the power transfer activities with minimum cost in uncertain environments [25]. For an optimal scheduling microgrid problem, several methods are proposed [25]–[27]. Because the microgrid needs to sell its surplus electric power to a distribution system, or buy power from a distribution system to fill a shortage, the interaction between the MG and distribution system as a part of scheduling activities also brings many researchers to work on coordination strategy [28], market design strategy [23] and optimal bidding strategy [29].

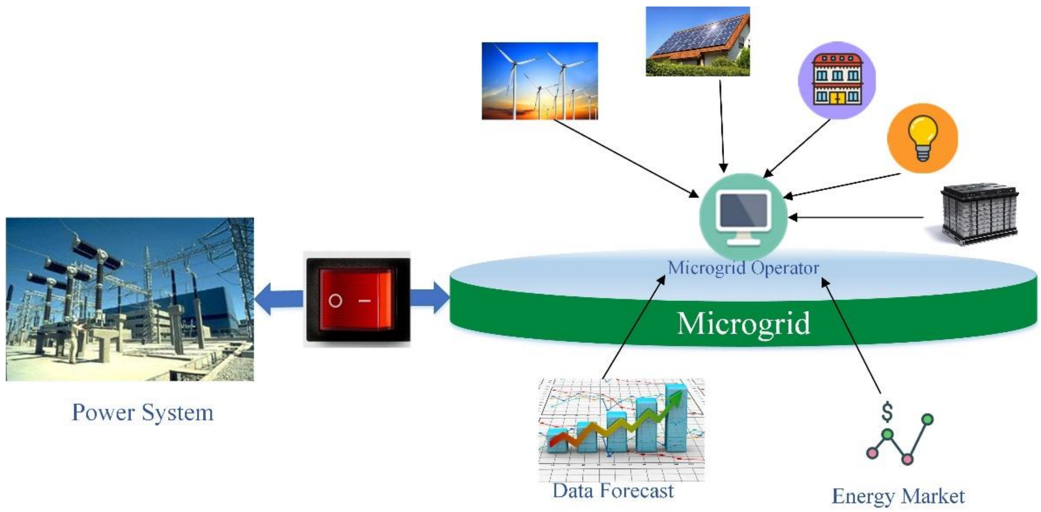

Figure 1. 2 Microgrid structure

In addition to the above traditional power scheduling management, the methods of dealing with uncertainties in scheduling problem also brings a lot of attention from researchers. In general, each generation units in power grid as well as power generation dispatch in day ahead market can be also participated into the other regulation markets for ancillary service generation. Ancillary services help balance the power grid. In existing independent system operators (ISOs) in U.S., there are two important ancillary services that market operators procure: regulation and reserves. The main intention of ancillary services is to provide the safe control margin to keep the operating variable of the system at the acceptable range, such as the voltage and frequency. Regulation and reserves work together to maintain this balance but have different roles: 1) the regulation is used to control small mismatches between load (the electricity being consumed) and generation (the electricity being produced), adjusting for small scale fluctuation on load profile. 2) The reserves help to recover system balance by making up for generation deficiencies if there is loss of a generation unit. As a result, ancillary services are also used to handle uncertainties in the power system to ensure quality of power being produced [30]. The quality of power can be measured through some indexes such as frequency stability [31], voltage stability [32], and capacity reserve [33]. Similarly, the microgrid operator should optimally schedule the power transfer without sacrificing the quality of power provided by the microgrid. In the literature, many researchers consider provided quality of power support from upstream grid and microgrid own generators by minimizing the power transferring operation cost together with preparing ancillary service cost in optimal scheduling problem to ensure a sound and stable operation [34]–[36].

This thesis is intended to address some of the above issues which have yet to be seriously researched: 1) the market strategy to schedule microgrid, 2) evaluation of MG quality of service and 3) co-optimization of energy and ancillary service. Microgrid can provide several main and ancillary services with beneficial features. The distribution system operators are motivated to trade these services via a competitive marketplace which is called “the distribution electricity market” in low voltage side. However, there are operational and technical problems with using the microgrids that need to be regulated in utility and distribution system sides, including lack of generalized regulatory and policy implications. For a specified microgrid, we can classify the power exchange into two categories: 1) power interaction between microgrid and the distribution system and 2) power exchange inside the microgrid among assorted suppliers and various customers. For power interaction between MGs and distribution systems, high penetration levels of distributed energy resources not only change the traditional power system operation technologically but also the market design [37]. A potential cause for concern for the distribution system operator is the extra market power that the microgrid could have brought to its market clearing process [38]. Specifically, some consequences of this extra market power are a decrease in the distribution system's revenue and an increase in its management costs, which lead microgrids and its DERs to become less appealing. An obvious reason is that the distributed energy resources have much lower operation cost than the traditional power generators. In the meantime, the scattered and vicinal distribution pattern may make the distribution system operator’s managerial antenna hard to reach. Finally, by aggregating some distributed energy resources and local customers, the microgrid is seeking to expand its influence in the market through trading electricity with the distribution system. There is a clear need for regulation policies concerning MGs and utilities to avoid conflicts of interest. To reach a market equilibrium between the two entities, we need to set up a market procedure and a trading policy to establish a bilateral contract. As for power interaction inside the MG, the microgrid operator needs to consider more uncertainty factors to provide high-quality service to the customers such as, change in demand, availability of power suppliers, and price deviation. To ensure a secure and stable scheduling, some preventive and corrective actions are needed to ensure stable and smooth operation of the entire microgrid [39].

We can summarize the above outside and inside microgrid concerns into three categories:

1) Market Strategy: the objective is to decide the optimal price and quantity for microgrid to trade electricity in a proper-design day-ahead distributed electricity market, find an optimal bidding strategy, and dealing with uncertainties;

2) Quality of Service: the objective is to determine the optimal reserve requirement under the specific quality of service and associated cost in optimal scheduling problem, overcome assorted uncertainties which may endanger the stability of the system;

3) Co-optimization: the objective is to co-optimize the energy and ancillary service resource allocation between microgrid and distribution system, improve the market operation efficiency.

In this thesis, some optimization models and their solution methods are presented to address the above issues in each research area.

1.2 Problem Description

The purpose of this thesis is to gain insight into some remaining issues in each research topic and propose some solution methods which can contribute to clear up the obstacles. To begin with, we want to identify and clarify the problem we want to solve in each topic before we provide the solutions. In the microgrid study area, the problems to be solved are details as follows:

1.2.1 Market Strategy

What is the optimal market structure of the distribution system? What role does the microgrid play in the distribution system? How do we maximize the mutual benefits of microgrid and distribution system? The distribution system can be defined as an entire setup of procedures, policies and interconnected flow of electricity from the source to the end user. Currently, a significant number microgrids pressure the distribution system to accommodate them through a fair and efficient market procedure so that their surplus or shortage power can be well scheduled. A good market design calls for an engineering approach [40]. Many tools, techniques, and processes have been developed over the last two decades for the management of bulk-power operations and wholesale energy markets based on market mechanism among the various entities. Lessons learned from the bulk-power experience can be applied to power distribution system among distributed resources, demand-side operations, microgrids, retail market operators. It must be noted that, distribution system operator (DSO) needs required adoption, extension, and necessary modification. Unfortunately, based on the existing designed market mechanisms in distribution system, there is no generalized framework, efficient and well-known strategies to handle the networked microgrids including pricing strategy, market clearing mechanism with bid/offer strategies. To adapt to the growth of microgrids and create a competitive distributed electricity market, a new business model with different operational philosophies is needed. The mechanisms for accommodating market-level transactions in the face of distribution electricity market participants are required based on operational and technical constraints of the distribution grid. The priority of these constrains established by the DSO based on operating guidelines, implicit economic values expressed in bids and offers from distribution market participants, and a combination of these. The new business model should be helpful in setting up trading procedures and evaluating real electricity market value and fully consider some MG features such as bi-directional power flow and sensitivity to price uncertainty. Currently, it is proven that the market-based DEM is the best solution to deal with high penetration levels of microgrids [41]. The market-based DEM with dynamic pricing is more flexible than the price-based DEM since it can guarantee the efficiency of a microgrid-integrated distribution system. Although existing literature assumes that MGs in DEM are price-takers [41]–[44], the microgrid is, in fact, a price-maker [45]. Current practice to analyze microgrid scheduling is based on unrealistic assumptions or oversimplified models, for example, unlimited bus [25], and fixed forecast price [46]. To find the optimal strategy for microgrids to influence the DEM, we need to study how to handle microgrid scheduling and distributed electricity market clearing at the same time. Corresponding solutions are provided separately to solve the issue using a coordinated strategy [47] and an optimal bidding strategy [29]. However, there is no clear and integrated method to solve all the issue simultaneously. Consequently, to prove MG can be a perfect fit for the DEM, we need to determine the best market structure for distribution system and the MG's role in this structure.

We embed some centralized MGs in a decentralized distribution system to find the optimal interaction scheme for both entities. The fundamental interaction elements are price and power quantity which can be presented as a set of price-power bid pairs. There is a conflict of interest between them; thus we use the Stackelberg Game method to describe this bidding process. The following step is to find the optimal bidding strategy.

As the bidding strategy is also influenced by some market uncertainty, we use the robust parameter.

1.2.2 Quality of Service

How much does it cost for a microgrid to meet a certain level of power quality requirement? How can microgrid handle uncertainties that threaten the quality of service? As mentioned at the beginning of this chapter, the microgrid is proposed to facilitate the integration of DERs. The primary motivation behind it is that it is hard for the system operator to regulate large-scale individual DERs [48]. Besides, the outputs of some distributed renewable energy resources are not stable [26]. Thus, the DER's quality of service cannot be easily controlled. It means that unregulated DERs may generate some low quality or unscheduled power to the grid and the customers, which may jeopardize the stability of the grid [49]. As the replacement of individual DERs, microgrids should give enough attention to power quality. Because the size and capacity of the microgrid is relatively larger than the individual DERs, the microgrid power output quality is much less of an issue for the entire distribution system [39]. However, power quality is important to the customers inside the microgrid. These customers are highly sensitive to the power quality because they have high expectations from MGs. Instead of choosing traditional distribution power resources, some customers trust microgrids because they have high reliability and resilience. For example, microgrids have a good reputation for their capability to deliver power during disasters or power outages by switching to islanding operation [50]. If the microgrid cannot deliver this capability, it will lose its unique selling proposition. Inevitably, increasing the quality of service means that the microgrid operator needs to spend more money on operation scheduling [51]. As a result, minimizing operating costs while maintaining a certain level of quality is a problem worth studying further.

To further analyze the factors associated with quality of service, we need to know the answers to the following challenges: Which quality of service indexes are important? Which components or events influence the quality of service? What kind of operation feature makes the microgrid special in dealing with quality of service? To contribute to these challenges, we need to understand the management process of the microgrid including different strategies in different operation modes, and uncertainties associated with microgrid operation. For a microgrid in grid-connected mode, the utility provides most of reserve for microgrid. In return, corresponding compensation should be paid to the utility [52]. For a microgrid in islanding mode, it should utilize its own resources through its load shedding and generation ramp up/down capability to handle the quality of service requirement [11] in case of contingencies. Current practice in handling the reserve requirement is not adequate to propose a unified framework to capture both operating mode conditions and uncertainties. The drawbacks of these methods include unsound operation mode assumptions (microgrids can only work in one operation mode with required reserve on that operating mode independent from the reserve requirement of another mode) [11], [53]–[55], which can lead to a unfair generation dispatch and capacity reserve shortage, an unrealistic payment method to quality of service providers [11], [55], [56]. As a result, there is a need for a microgrid control management strategy with regard to the two operation modes and some relevant uncertainty scenarios to ensure the stable operation of the microgrid.

1.2.3 Co-optimization of Microgrid and Power System

What is the optimal market structure of the distribution system when ancillary service is considered? What role does the microgrid play in the market with ancillary service? Higher penetration levels of microgrids (MGs) in the power distribution system post severe challenge the distribution system operator (DSO) to manage them because the visibility provided by microgrid operator (MGO) is limited. From the perspective of distribution system operator, the tendency of decentralization caused by the microgrid challenge traditional distribution system management structure. From other side, the microgrid operator as an independent operation entity has no responsibility to give out the decision making right. Besides, sharing scheduling decision with distribution system operator bring security risks to microgrid customers. The transactive management is proposed to facilitate the management structure upgrade in distribution system [57]. Under the framework of transactive management, some decision burden are lift from the distribution system operator's shoulder, for example, the power balance inside the microgrid. The main responsibility for distribution system operator is to management the energy/service interaction at the points of common coupling with microgrids. As a result, the transactive management provides a decentralized solution by constructing a boundary between the responsibility of MGO and DSO. However, this boundary and interaction scheme is not clear incorporating the ancillary service. An urgent problem to define the ancillary service flow direction between MGs and distribution system.

The ancillary service flow direction between microgrid and distribution system is debatable in vast literatures, even though the scope of such interaction is been narrowed down to the point of common coupling. Some research simplify the microgrid interaction scheme as electrical energy storage model, in which only ancillary service is allowed to transfer from microgrid to distribution system is allowed. This assumption is not true because there is internal balance for microgrid operator to maintain, so the microgrid is also need ancillary service as well to ensure the stable operation. On opposite, some literature assume that ancillary service is only allowed to transfer from distribution system to microgrid. The assumption is true only for specific problem setting, for example, the size of microgrid is much smaller than distribution system. So there is a need for a comprehensive model & management structure for transactive system involving microgrid and ancillary service.

1.3 Objective & Contributions

This thesis chooses two topics to address the first and second challenges. These two works provide solutions for these challenges. The proposed methods also demonstrate their feasibility and innovation while specifying and developing the ideas.

1.3.1 Market Strategy

For the first challenge, we will show the methods to design: a distribution electricity market with microgrids, a microgrid interaction scheme, MG bidding strategies with the distribution system, and a microgrid scheduling system. Depending on the regulatory provisions, and the extent of involvement of the utility as a participant in distribution electricity market activities, the distribution system operator may be an independent entity, or the distribution utility. In this work we assumed, a technical separation will have to exist between the utility-managed DSO functions and the marketing arm of the utility. In our proposed model, the utility-managed DSO structure represents an independent operator of the distribution system which is capable of incorporating networked microgrids as well as customer-side DER resources into the distribution system operation process. It can provide short-term price signals for prosumer operation decisions, while maintaining the reliability, safety, and integrity of the distribution system itself. Under above frameworks, the pricing and optimal cost allocation under the distribution electricity market is also presented. Using the locational marginal price (LMP) concept as reference for the basis for energy pricing, payment, and cost allocation in wholesale markets, we adopt the distribution LMP (DLMP) scheme which is proposed for application to distribution electricity market within the distribution system, among networked microgrids, end-users, and between distribution/MG/end-users and upstream utility. The proposed DLMPs in our framework is short term after the fact based on bids and offers mechanisms. The short-term DLMPs are used primarily for settlements among the market participants and the distribution market operator. Similar to wholesale markets, it is expected that DLMPs may take on a range of values (highly positive to zero or even negative) depending on the interplay between microgrids, prosumers, and consumer utility functions (expressed in bids and offers) and power distribution system operational constraints. As a result, we propose a bi-level programming model to describe the microgrid scheduling problem and the distribution system market clearing process in which MGs play as price-makers. We also define the biggest feature of the DEM as a market-based distribution system, in which all the market participants are encouraged to compete. A mathematical programming model with equilibrium constraints and several linearization techniques are suggested to improve computational performance of the proposed bi-level programming model. The MG bidding strategies are also proposed to remedy some impractical policies in the bi-level model. Considering price uncertainty as the primary concern in the market, we propose a robust optimization model to show the MGs' market reactions to price fluctuations. The key contribution of this work is to provide a coordinated pool strategy for the microgrid as a price maker to participate in the market-based distribution electricity market. Besides, proposing an optimal bidding strategy shows its capability to handle uncertainties. As a result, we can answer the following questions:

1) What is the optimal market structure for distribution system (market-based scheme)?

2) What role does the microgrid play (price maker)?

3) How can maximize the mutual benefits for both microgrid and distribution system (coordinated pool strategy)?

1.3.2 Quality of Service

The work relating to the second challenge of quality of service focuses on the factors (operation mode changes, renewable energy and load forecast error) which affect microgrid scheduling. The microgrid's operation mode decides the reserve service provider preferences. The forecast errors affect the power balance. In the grid-connected mode, the main reserve provider is the utility side. The microgrid needs to pay to the utility to purchase this service to meet the quality of service. However, during islanding operation, the microgrid needs to rely on its own reserve capability to maintain its quality of service since the connection with the utility is broken. Therefore, we propose a two-stage stochastic programming model consisting of a master problem of normal operation and a subproblem of microgrid risk management problem. Two types of uncertainties are considering in the model: 1) forecast error from renewable energy and load and 2) operation mode switch. The whole consideration of these uncertainties and power balance requirement constraints may impose the microgrid operator a highly expensive reserve and costly operation dispatch. To realize a trade-off between operational performance and risk mitigation, we force chance constraints on power balance with reserve capability using quality of service index, to provide less unserved electrical load consumption and to guarantee the secure operation of the microgrid. The main contribution of this work is providing a method for the microgrid operator to determine how much it cost would be to handle forecast error and operation mode uncertainties. This work would ensure a stable and sound operation of a microgrid with a smooth switch capability between grid-connected operation and islanding operation. This work increases awareness of the effect of contingencies on microgrid power quality.

1.3.3 Co-optimization of Microgrid and Power System

The work relating to the third challenge of co-optimization of microgrid and distribution system focuses on the ancillary service interaction scheme. Under the transactive management scheme, the microgrid operator gain more autonomy to make decision based on the market profile. The autonomy includes energy transfer decision and ancillary service decision. The microgrid internal balance is ensured by the microgrid operator itself, while the external balance of distribution system is ensured by the distribution system operator. In terms of interaction between, the co-optimization of energy and ancillary service decision is made on both entities. The purpose of this work is to find optimal co-optimization scheme and model the interaction scheme between two entities.

1.4 List of Outcomes

1.4.1 Journal Publications

- Yiwei Wu, Masoud Barati, and Gino Lim, A Pool Strategy of Microgrid in Power Distribution Electricity Market, Accepted, Early Access, *IEEE Transactions on Power Systems*, 2019.
- Yiwei Wu, J. Lim and J. Shi, "Stability-Constrained Microgrid Operation Scheduling Incorporating Frequency Control Reserve," Accepted, Early Access, *IEEE Transactions on Smart Grid*.
- Y. Wu, J. Shi G. J. Lim and L. Fan, "Optimal Management of Transactive Distribution Electricity Markets with Co-optimized Bidirectional Energy and Ancillary Service Exchanges with Microgrids", ready for submission, *IEEE Transactions on Smart Grid*

1.4.2 Conference Presentation

- Yiwei Wu, Masoud Barati, and Gino Lim, Optimal Market Based Pool Strategy of Microgrid, *IISE Annual Conference and Expo 2017*.

- Yiwei Wu, Masoud Barati, and Gino Lim, Quality of Service Constrained Microgrid Optimal Scheduling, *INFORMS Annual Conference 2018*.
- Yiwei Wu, and Gino Lim, and Jian Shi, A Co-optimization Scheme of Distributed Joint Market with Microgrids, *IISE Annual Conference and Expo 2019*.
- Yiwei Wu, Jian Shi, and Gino Lim, A Co-optimization Scheme of Distributed Joint Market with Microgrids, *INFORMS Annual Conference 2019*

1.5 Organization

This thesis is organized into four chapters as follows. In Chapter 2, we investigate existing research on the microgrid scheduling problem, market strategy, and quality of service. In Chapter 3, we propose a coordinated pool strategy for the microgrid in the distributed electricity market. Associated solution methods are developed to improve the efficiency of solving the bi-level model. A test is conducted on revised IEEE 33 bus distribution system test bed. In Chapter 4, a two-stage stochastic model is presented with normal operation in master problem and risk management in subproblem. In Chapter 5, a transactive management problem is studied. In Chapter 6, conclusions are drawn, some future study directions are provided.

Chapter 2 Literature Review

In this chapter, we do a thorough literature review for microgrid scheduling problem related to the research in this dissertation. Optimal scheduling, distribution system market designing, coordinated strategy, optimal bidding strategy, ancillary service are widely used in microgrid scheduling analysis. Relevant optimization theories including robust optimization, stochastic optimization, and bi-level programming optimization are summarized. Their application in microgrid scheduling is enthusiastically studied and reviewed in this chapter.

2.1 Market Strategy

Microgrid scheduling problem is developed based on unit commitment problem whose objective is to find the least cost to dispatch power resources while meeting customer, environment, system operating requirement. Microgrid scheduling problem can be treated as downsize of unit commitment problem [27]. However, it is different from traditional unit commitment problem in following aspects: 1) Microgrid's power resources including distributed energy resources which unit commitment problem usually does not have [58]. 2) the microgrid can work in either islanding operation or grid-connected operation which unit commitment has one working mode which can be treated as an islanding operation [25]. Based on these features, researchers developed several methods to show the benefits of optimally scheduling MGs. A resiliency-oriented microgrid scheduling scheme is proposed in [13] to shows that an effective scheduling can guarantee the economically optimal and robustness against uncertainties. A multi-period islanding constraints microgrid scheduling scheme is prosed in [25] to show that the feasibility to incorporate islanding scenarios into scheduling problem so that the reliability of microgrid can be improved. To capture the uncertainties associated with renewable energy resources, researchers try to use stochastic programming method [26], [59]–[65] , robust modeling method [48], [66]–[70], and stochastic dynamic programming method [71]–[73] to handle the uncertainties. We can classify the above literature into one general category whose study objectives focus on microgrid scheduling. To simplify the models, these microgrid scheduling studies assumed that the utility bus is unlimited [25]which can be used to absorb any surplus power or provide any unmet demand inside microgrid. This assumption is acceptable if the study objective is microgrid itself because the microgrid is relatively smaller than distribution system. However, if we extend the microgrid scheduling problem to the distribution system even the entire power system, the assumption is no longer valid [16].

The current studies are working on solving the compatibility between MG scheduling optimization and distribution system from two aspects: technology and marketing. The well-known technology method to solve interaction between small components and a large system is coordinated management [28], [46], [72]-[74]. The coordination management can one layer or multiple layers. In the one-layer coordinated management, centralized control operator coordinates its own power resources and customers. For example, microgrid centralized operator making decisions over all its DGs and demand has been proved to an efficient way to handle microgrid [74]. A coordinated management in distribution system is proposed in [75]considering the plug-in electric vehicles charging uncertainty. However, if the system becomes larger, one-layer coordination management is not enough to deal with it. As a result, a coordination management between different entities requires multi-layer coordination. For example, by incorporating some power resources and customers into its electricity boundary, microgrid has a certain level of autonomy. In the meantime, the distribution system operator or power system operator has some interest conflict with microgrid as the interaction price and quantity influence both parties' cost in the opposite way. So there is a clear need to solve this conflict. The decentralized coordination is a feasible method to deal with the interaction between microgrids and distribution system. Fathi and Bevrani [76] studied a coordinated method to manage multiple microgrids under demand uncertainty. To capture the uncertainties associated with DG outputs, a decentralized partially-observable Markov decision process is proposed to model networked MGs, so that the reliability of the system is improved [47]. A cooperative power dispatching algorithm is proposed to minimize interacted MGs' network operation cost [77]. The efficiency of the distributed network operation can be improved by implementing distribution network operator to control the coordinated scheme among entities [28]. It can be seen that decentralized coordination management is an efficient way to deal interaction between microgrids and distribution system through above literature. However, the current literature on decentralized coordinated management are implemented based on fixed pricing approach which does not guarantee optimality.

The well-design market strategy is also helpful in resolving interaction between MGs and distribution system. To realize an efficient market management, distribution system operator is needed to provide local resilience capability [78] and improve the efficiency to integrate DERs [79]. By setting an independent electricity trade platform in the distribution system, a universal market environment can be useful to perform several functionalities without creating extra market power [80]. A blueprint for DSO is proposed in [81], in which a DSO is asked to take responsibility for power balancing, wholesale market setting, and connecting ISO to demand side [82]. With a platform in hand, we still need associated market regulations [83], technology requirements[84], the rulemaking process [85], etc. Based on market form in distribution electricity market, we can classify DEM into price-based DEM and market-based DEM [41]. In the price-based scheduling method, a fixed price based on forecast supply and demand will apply to day-ahead scheduling process [86]. The fixed price strategy is convenient so that it has been used extensively in the scheduling problem [25], [26], [74], [87]. Another market form is market-based strategy [88].It has already been proved that allowing microgrids to participate into the market-based wholesale market can increase MGs' benefit (i.e. revenues-costs) [89]. We can further study the bidding strategy for microgrids in market-based distribution electricity market in reference source [44]. It has been proved that market based strategy is the best solution to solve high penetration of microgrids [41], since it can guarantee the efficiency of a microgrid-integrated distribution system. We can identify microgrid as a prosumer in the market-based DEM. As a result, microgrid at the endpoint of distribution system should be able to react to requests from the grid [90]. Besides, the MGs as small producers should be allowed to forecast their corresponding price quota curves [91], compete with other producers [92], and finally influence the market price [93]. So MG should plays as a price-maker in the market-based distribution electricity market which most of the literature fail to address.

The optimal bidding can be cast as the Stackelberg game in day-ahead wholesale electricity market where a producer plays the role of a leader, while competitors and consumers are the followers [94]. Ruiz and Conejo [95] propose a pool method to find producers' optimal offering strategy in the traditional power system by using a multiperiod network-constrained market clearing algorithm. Under this framework, bi-level programming is used to formulate the optimal offering strategy problem [96].A bi-level programming model can be converted into mathematical programming with equilibrium constraints (MPEC) [97], which is a highly non-convex optimization problem [98], [99]. Some methods have been studied to solve MPEC, for example, the Interior point penalty algorithm [100] and the Non-interior point algorithm [101]. However, these methods cannot guarantee a global optimal solution. A binary expansion solution approach proposed in [102] by converting MPEC into a mix-integer programming problem, which gives a global optimal solution.

2.2 Quality of Service

In the microgrid scheduling problem, the microgrid operator determines the optimal dispatch of distribute energy resources, storage system and interaction with utility through PCC. Substantial researches have been published to study microgrid optimal scheduling and management from different aspects: the most popular model is grid-connected microgrid [26], [29], [44], [63], islanding model is addressed in [57], [103], [104], and combination of grid-connected model and islanding model can be found in [25], [105], [106].

Above literature regarding microgrid scheduling is developed based on the downsize unit commitment problem. However, they overlook the transient state of microgrid when it performs operation mode switch, especially the switch between grid-connected modes and islanding mode. This transient state is critical because the power exchange between microgrid and utility is forced to be zero [27]. Consequently, the frequency of microgrid will have rapid increment or decrement due to supply and demand imbalance [107]. This may also occur together with an inaccurate forecast, deviation of load, an intermittent output of renewable resources. Any accident happen will cause instability of microgrid [108], a decrease of quality of service [109], and low reliability[55], etc. To prevent such accidents from causing microgrid to a complete collapse, some preventive and protective actions are needed [39]. The most critical action is preparing/using power reserve which ancillary services provide [110].

The ancillary services can be classified into few categories: 1) capacity reserve which is needed on future schedule; 2) frequency regulation which is needed in real time. The capacity reserve is an essential issue for MG if it does not have storage system [62]. When MG is working in grid-connected mode as a small part of distribution system, the utility can be seen as unlimited bus have enough power capacity for MG [25]. However, considering MG may need to switch to islanded operation in case of contingencies happen in the upstream distribution system, maintain a certain level of reserve is still critical to ensure the stability of the system. A multi-period islanding method is proposed [25] to generate islanding cut from islanding operation subproblem to grid-connected operation master problem in order to have enough capacity preparation. Due to the uncertainties associated with renewable energy resources, the power mismatch in microgrid requires microgrid operator prepare capacity reserve to deal with power mismatch [11], [56], [111]. Above literature provide solution methods for capacity reserve, but they overlook the importance of preparing frequency regulation.

As for frequency regulation reserve, it is used to maintain the frequency stable which can be seen as system's health indicator [112]. It is assumed ideally that the power system should always keep the balance between aggregated power suppliers and aggregated load. As a result, the frequency should be stable at a specific frequency (50Hz/60Hz). However, in reality, this power balance cannot be reached all the time. The frequency regulation is used to maintain the stability of real power. The frequency regulation constraints are introduced into unit commitment in [34]. Similar methods are applied to downsize unit commitment such as islanding microgrid in [53], [54]. However, they are not considering the grid-connected microgrid operation reserve. To manage the frequency regulation reserve in a grid-connected microgrid, it's crucial to find who provide frequency reserve and who needs to pay for it. It's suggested that participants in the operation power system should pay compensation for frequency deviations and reserve capacity for frequency control to utility [52], [113]. In setting up this transaction, a power exchange for the frequency control market environment is needed [114]. A determining the optimal reserve capacity method is proposed for microgrid to participate in this market [42], [115]. However, there are two flaws in above works: 1) fail to consider primary reserve which is a response to large frequency deviation; 2) the power and reserve markets are not cleared simultaneously. The working mode switch requires the primary reserve. Besides, it's proved that clearing the ancillary market and power market in a specific order has been abandon [116].

In summary, there is a clear need to design a comprehensive scheme for microgrid scheduling problem by considering capacity reserve, frequency regulation in a co-optimization clearing market.

2.3 Co-optimization

The integration of microgrid is involved to have support from two aspects: first, the coordination with existing power system: the market design, operation procedure need to be changed based on microgrid's feature; second, the co-optimization of energy and ancillary service: the microgrid's role, type of service MG can provide. The research regarding coordination between microgrid and distribution can be found in vast literature. Multi-agent systems was used to manage multiple distributed energy resources including microgrids [117]–[119]. Except the multi-agent system method, the game theory based method is also very popular [120], [121]. The core idea behind the game theory based model is that the microgrid operator is more likely to be treated as independent entity which less rely on control & support of distribution system. In the distribution system, higher increasing penetration levels of distributed energy resources and MGs in distribution system bring challenge for distribution system operator (DSO) to manage the system [122]. Those DERs, especially hybrid resources and microgrid, which are able to operate independently occasionally without support or minor support of DS, require careful treatment from DSO. On the other side, the utility-managed DSO has the responsibility to maintain the distribution system reliability and efficiency [123]. With such market power and operation right, the DSO usually needs to have full situation awareness of entire market transactions and operations. However, the visibility that MGs can provide to DSO is very limited due to the control and management structure of MGO

[25]. A possible solution is to let DSO play a consultative role in the market operation, providing market information like price and congestion, helping market participants to match the demand and response, processing the transactions [124]. The distribution system constraints only include the location and physical capacity of connected DERs or MGs at the point of their connection, regardless of operation mode or internal scheduling decisions. One benefit of this solution is the decision burden on the DSO will be largely reduced through utilization of MGO. As a result, the overall decision efficiency is improved. This type of energy management structure is also known as transactive energy management [125]–[127]. However, under the transactive management framework, the co-optimization of energy and ancillary service has not been fully explored.

Current market designs show that the co-optimization of energy and ancillary service is a very important part of market procedure. For example, the Midcontinent Independent System Operator (MISO) has an ancillary service market mechanism to co-optimize the energy and ancillary service [128], [129]. The co-optimization can help power system to enhance operational flexibility [130]. The requirement for ancillary service is even higher when the power system has high penetration of renewable energy [131]. As a result, there is a clear need to have a co-optimization transactive market when the penetration level of microgrids is higher.

Chapter 3 A Pool Strategy of Microgrid in Power Distribution Electricity Market

3.1 Introduction

The microgrid concept is proposed to facilitate the integration of distributed energy resources into the electricity grid, which can reduce transmission grid losses and overcome limitations in distribution system [70]. By integrating distributed energy resources into microgrids with smart central controllers and smart sensors, MGs can provide highly reliable electrifications which can guide customers to lower their operation costs and utilize electricity more efficiently [132]. MGs can also benefit power system through profitable and environmentally friendly services [12], higher power system resiliency [13], less transmission and distribution costs [14], fewer carbon emissions by the use of renewable power resources [15], and utilization of electrification in rural areas [12]. With all of these benefits, microgrids can be expected to be used in a wide variety of electrical environments [133].

Microgrid can work in either Islanding or Grid-connected mode at the point of common coupling (PCC) [8]. To ensure a secure MG operation in a centralized manner [25], MG has three control levels: primary, secondary and tertiary. The primary and secondary controls are able to maintain the frequency/voltage of the MG. As the primary focus of this chapter, two goals of tertiary control are (1) to optimally manage the power flow between the MG and the utility grid [10], and (2) to minimize microgrid operation cost while providing high-quality service to various types of customers in uncertain environments. Although the benefits of optimally scheduling MGs have been reported in the literature [13], [25], [26], [70], [87], drawbacks of the existing approaches are that they are limited to MG scheduling, and do not address the interactions between microgrids and distribution system concerning power coordinated operation strategy and distribution electricity market price policy. With regard to power coordinated operation strategy, the distribution system was assumed as an infinite bus that can provide unlimited power supply/load to mitigate any power imbalance in MGs [25].However, this assumption has a crucial flaw because the distribution system operator, in fact, has the physical capacity limitation to do so. Furthermore, the distribution system operator does not have an incentive to provide power beyond the economically optimal level. As for the distribution electricity market pricing policy, due to the presence of price uncertainty and its consequences, the market price between microgrid and the distribution system is not known in advance. Consequently, the current practice of bidding/offering pricing strategies may not be optimal.

The coordinated strategy can be economically beneficial to both microgrids and the distribution system [74]. Such benefits of using a decentralized coordinated management (DCM) include higher profits [28], improved efficiency of DERs and reduced complexity of distribution network operation [47], and improved system reliability [76]. The current literature on DCM assumes fixed pricing strategy. However, the fixed pricing approach does not guarantee optimality because it is difficult to include the abnormal conditions such as overloading, islanding, component outages as well as load uncertainty and volatility of non-dispatchable generation units. These conditions can provide market power or non-beneficial outcomes for decentralized coordinated management participants. Hence, there is a clear need for an approach that considers both the coordinated management strategy and the distribution electricity market pricing policy.

A successful distributed electricity market requires a good pricing policy. Overall pricing schemes in the existing industrial DEMs can be found in [134]. Furthermore, a study has been reported to compare different distributed electricity market designs and pricing policies [135]. The pricing policies can be categorized as price-based and market-based management. The price-based management is an efficient way to handle the DEM by using fixed forecast price [25], [26], [87], [136]. However, this approach is not well suited when the microgrid penetration in the distribution network is high. Therefore, the market-based management was proposed as an alternative [41]. The market-based DEM with dynamic pricing is more flexible than the price-based DEM. However, the proposed market-based bidding strategy for MG does not guarantee optimality because the power interaction between MG and distribution system is determined by distribution system only. Furthermore, there is no explicit optimal bidding curve creation strategy which has the significant impact on distributed electricity market operation. Another bidding strategy for microgrid as price-taker in market-based wholesale market can be found in [44]. Nonetheless, the MG is not widely accepted by high voltage wholesale market directly because: 1) MG’s capacity is limited [137] and 2) the high voltage network is not designed for bi-directional power flow. The distribution system fits microgrid and other DERs with advanced distributed system operator and the distribution market operator (DMO), which is helpful in managing price information among market participants. In reality, the MGs and other DERs are two primary competing power suppliers in DEM, which constitute an oligopolistic distribution electricity market, leading to imperfect competition. An imperfect competitor is in fact a price-maker [45]. The price-maker's offering/bidding strategy has the ability to influence the market profile which is defined by aggregated behaviors of all market participants. Therefore, a new market-based mechanism is needed so that the MGs can impact the DEM's market price [45] whose offering/bidding strategy has the ability to influence the market profile defined by aggregated behaviors of all market participants. Therefore, a new market-based mechanism is needed so that the MGs can impact the DEM's market price. This chapter attempts to shed light on a realistic economical behavior of an MG in the distributed electricity market beyond the proposed market-based scheme [41]. Because an MG is a prosumer in the DS, a combined offer-and-bid pair can be submitted to the DEM. This necessitates a new strategy, in which an MG plays as a price-maker in the market-based distribution electricity market.

This problem can be cast as the Stackelberg game where a microgrid plays the role of a leader, while competitors and consumers are the followers [138]. Under this framework, bi-level programming is used to formulate the optimal offering strategy problem [139]. A bi-level programming model can be converted into mathematical programming with equilibrium constraints (MPEC) [97], which is a highly non-convex optimization problem [140]. To reduce computational burden for solving the MPEC model, a binary expansion solution approach proposed by [102] can be used to convert the MPEC model into a mix-integer programming (MIP) model, which gives a global optimal solution.

Therefore, this chapter proposes a new coordinated pool strategy, in which a microgrid plays as a price-maker in the market-based DEM. Considering MGs as strategic prosumers, a MIP model is developed to maximize the benefits for MGs from trading power in DEM through an optimal bidding/offering strategy. A modified bidding/offering policy is provided to overcome drawbacks of existing strategies.

The remainder of this Chapter is organized as follows. Section 3.2 presents the model outline and assumptions. Section 3.3 formulates the bi-level programming problem and solving algorithm. The model is tested under price uncertainty as well as MG contingencies such as islanding in Section 3.4. Relevant conclusions are discussed in Section 3.5.

3.2 Outline & Assumptions

The coordinated pool strategy we propose in this chapter has two levels as seen in Fig 3.1: a microgrid level and a distribution system level. In the MG level, the microgrid operator (MGO) is in charge of optimally scheduling MG-owned DGs and local consumers. In the DS level, the distribution system operator takes care of interactions between the DS and its participants. The distribution network operator (DNO) is responsible for power flow, and the distribution market operator is responsible for market regulation.

The pool bidding [95] and the coordinated management [28] are used together to solve the problem of high penetration levels of MGs in DS. The MGs are strategic players whose bids/offers are subject to market profile, which is decided by nonstrategic players such as the DS customers, DS-owned DGs, and high voltage utility nonstrategic players. The distribution electricity market uses a price signal such as Distribution Locational Marginal Price (DLMP) as feedback to MG's bids/offers. The DLMPs are widely used as price signals among market participants or between the market operator and the market agent [124].

The microgrid as a price-maker with an independent operator has autonomy to make its own scheduling and bidding/offering decisions in response to distribution system operation states and market price signals which leverage the MGs' transactive capabilities in the DEM [124]. As a result, it can help the distribution system operator reduce the decision burden and network complexity. At the same time, the power pool regulation at the distribution system level defines standards for processing and evaluating electricity price bids [141], which ensure the microgrids and distribution generators can freely participate in the distributed electricity market.

The key components to implement these regulations are DSO, DNO and DMO. The state of art distribution system operators can perform active managements including market regulations and demand response with greater flexibility and capability between supply and demand [142]. Such examples include Distributed System Platform Provider proceeding proposed by the New York Public Service Commission [79], the Multi-Microgrid in Chicago including the IIT Campus Microgrid (ICM) and the Bronzeville Community Microgrid (BCM) [143], and European Distribution System Operators advocated by the European Union [142]. Some distribution network operator's responsibilities like power balancing and network operation can also be taken by the DSO. It is too early to conclude that the DNO will be entirely replaced by the DSO [144] as the DNO's contributions in security and quality of supply and power flow management are significant [145]. In some distribution electricity markets such as Cornwall Local Energy Market [146] and TDI 2 [147], the DNO is successfully acting as the DSO to manage the distribution system. In our proposed framework, we adopted the concept of the transactive energy systems [124], which both DNO and DMO entities are defined under the unified DSO. The advanced DSO expands the conventional operational domain of the DNO and the DMO to enable a sound distribution system operation with high penetration levels of DERs. It also facilitates the MGs as prosumer to implement transactive exchanges.

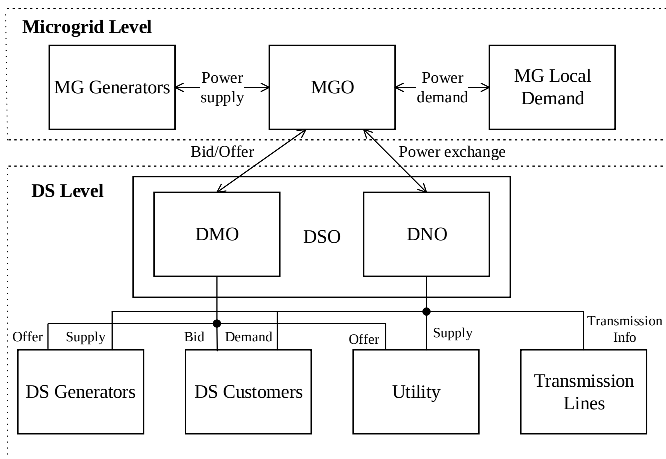

Figure 3. 1 Transactive distributed electricity market structure

Compared with previous DEM management strategies, our proposed strategy has the following advantages:

- Having MG as a strategic player enables a two-way power flow between MG and DS, which can smooth out or shift the peak hour load.
- The MGs' bidding/offering price based on DLMP reflects the exact market mechanism of the distribution electricity market. This approach helps the microgrid operator reduce its burden to determine the true market value of its power resources in trading in DEM.

- MGs as price-markers have direct influence on DEM price. However, influencing the price may create associated market risk due to price uncertainty, which MGs must take if it occurs.
- Efficiency of clearing the market can be improved by allowing competition among all the power source owners [41]. This can be done because the DMO can evaluate all the bids and offers ranging from the cheapest to the most expensive before transactions occur among all market participants.
- The separation of roles between a distribution network operator (technical functions: e.g. power flow) and a distribution market operator (market regulation) prevents the producers from abusing the market.

In this chapter, the distribution system network is modeled with AC Distribution load flow [148]. The DS-owned DGs and MGs are primary power suppliers of distribution electricity market. Two main consumers are MG community load and DS spot load. The DEM pool is cleared hourly, day-ahead within the *DistFlow* framework. The hourly DLMPs reflect adequately distributed MGs' influence to DEM. The 24 hourly DLMPs are obtained through dual variables associated with real power balance constraints. The MG scheduling model includes most of its features, i.e., unit linearized operation cost, generator capacity limits, and generator ramping up/down rates. The chapter assumes that DS-owned DGs offer with their marginal costs, and spot loads bid with forecast market prices. The MGs' bids/offers are based on actual DLMPs of DEM. We use linearized operation cost offering curves for all generators and linearized bidding curves for all customers.

3.3 Model & Solution Methodology

The following notation is used in developing the bi-level programming model:

Indices

t	Index for time periods, $t \in T$
b	Node subscript index in DS, $b \in B$
j	MG subscript index connected with DS, $j \in J$
k	Generation unit subscript index in MG j-th, $k \in K_j$
l	Consumer subscript index in DS $l \in L$
m	Utility node subscript index connected with DS, $m \in M$
n	Distributed generator (DG) subscript index in DS, $n \in N$

Parameters

δ_{it}^{G}	Marginal cost of generation unit i in MG in time t
δ_{nt}^{O}	Marginal cost of DG n in DS in time t
δ_{lt}^{L}	Marginal profit of consumer l in DS in time t
δ_{mt}^{U}	Marginal cost of utility m in time t
$P_{(.)\mathrm{t}}^{\max} / P_{(.)t}^{\min}$	Maximum/minimum real power output in time t
$Q_{(.)t}^{\max} / Q_{(.)t}^{\min}$	Maximum/minimum reactive power outputs in time t
$UR_{(.)} / DR_{(.)}$	Generator ramp up/down rates
D_{jt}^{P} / D_{jt}^{Q}	Real/reactive power consumption for MG *j-th* in time t
$K_{(.)}$	Incidence matrix
$\mathrm{O}_{(\cdot)}$	Large positive constant

Sets

T	Time period set $T = \{1,..,NT\}$, NT is number of time
B	DS node set $B = \{1,..,NB\}$, NB is number of node

$B^{(.)}$ Subset of B, means node with (.) component.)

K_j Generation unit set $K_j = \{1_j,..,NDG_j\}$ in MG *j-th*, NDG_j is number of units

J MG set $J = \{1,..,NM\}$, NM is number of MG

L Consumer set in DS $L = \{1,..,NL\}$, NL is number of load in DS

M Utility set in DS $M = \{1\}$

N DG in DS set $N = \{1,..,ND\}$, ND is number of DG units in DS

Variables

$P_{(.)t} / Q_{(.)\mathrm{t}}$ Real/reactive power output of the MG, DG, utility, consumer in time t

P_{bt}^{inj} / Q_{bt}^{inj} Real/reactive power injection at node b in time t

I_{kt} Binary variable associated with generator k state

c_{jt} Distribution locational marginal price for MG j in DS

α_{jt} Offering/Bidding price MG j submitted to DS in time t

P_{bt} Real power flow at node b in time t

Q_{bt} Reactive power flow at node b in time t

V_{bt} Voltage magnitude at node b in time t

β_{jt} MG j marginal operation cost in time t

ρ_{jt} MG j islanding state in time t.

3.3.1 Bi-level Programming Model

The optimal bidding problem is formulated as a bi-level programming model as follows:

$$\textbf{ULPM:} \ \min \sum_j \sum_t (\sum_k \delta_{kt}^G \cdot P_{kt} - \lambda_{b_j' t}^P \cdot P_{jt} + VOLL \cdot D_{jt}^P), \tag{3.1}$$

$$P_{kt}^{\min} I_{kt} \le P_{kt} \le P_{kt}^{\max} I_{kt}, \ \ \forall t, \forall k \in K_j, \forall j \in J, \tag{3.2}$$

$$Q_{kt}^{\min} I_{kt} \le Q_{kt} \le Q_{kt}^{\max} I_{kt}, \quad \forall t, \forall k \in K_j, \forall j \in J, \tag{3.3}$$

$$P_{kt} - P_{k(t-1)} \le RU_k, \quad \forall t, \forall k \in K_j, \forall j \in J, \tag{3.4}$$

$$P_{kt} - P_{ik(t-1)} \le RD_k, \quad \forall t, \forall k \in K_j, \forall j \in J, \tag{3.5}$$

$$\sum_k P_{kt} = D_{jt}^P + P_{jt}, \quad \forall t, \forall k \in K_j, \forall j \in J, \tag{3.6}$$

$$\text{and } \sum_k Q_{kt} = D_j^Q + Q_{jt}, \quad \forall t, k \in K_j, \forall j \in J; \tag{3.7}$$

LLPM:

$$\begin{aligned} P_{jt}, Q_{jt}, \lambda_{bt}^P \in & \arg\{\min \sum_t (\sum_n \delta_{nt}^O P_{nt} + \\ & \sum_j \alpha_{jt} P_{jt} + \sum_m \delta_{mt}^U P_{mt} - \sum_l \delta_{lt}^L P_{lt}) \end{aligned}, \tag{3.8}$$

$$P_{it}^{\min} \le P_{it} \le P_{it}^{\max} : \mu_{it}^{\mathrm{p}\min}, \mu_{it}^{\mathrm{p}\max}, \quad \forall t, \forall i \in J, L, M, N \ , \tag{3.9}$$

$$Q_{it}^{\min} \le Q_{it} \le Q_{it}^{\max} : \mu_{(.)t}^{\mathrm{q}\min}, \mu_{(.)t}^{\mathrm{q}\max}, \ \forall t, \forall i \in J, L, M, N \ , \tag{3.10}$$

$$P_{bt}^{inj} = K_n P_{nt} + K_j P_{jt} + K_m P_{mt} - K_l P_{lt}, \tag{3.11}$$

$$Q_{bt}^{inj} = K_n Q_{nt} + K_j Q_{jt} + K_m Q_{mt} - K_l Q_{lt} \ , \tag{3.12}$$

$$P_{(b+1)t} = P_{bt} - P_{bt}^{inj} : \lambda_{bt}^P, \ \forall b \in B, \forall t \ , \tag{3.13}$$

$$Q_{(b+1)t} = Q_{bt} - Q_{bt}^{inj} : \lambda_{bt}^Q, \ \forall b \in B, \forall t \ , \tag{3.14}$$

$$V_{(b+1)t} = V_{bt} - (r_b P_{bt} + x_{bt} Q_{bt}) / V_1^2 : \pi_{bt}, \ \forall b \in B, \forall t \ , \tag{3.15}$$

$$\text{and } V_{\min} \le V_{bt} \le V_{\max} : \pi_{bt}^{\min}, \pi_{bt}^{\max}, \ \forall b \in B, \forall t\} \ . \tag{3.16}$$

In the above model, the ULPM stands for upper level programming model, while LLPM stands for lower level programming model.

The objective function of the ULPM is to minimize power generation cost of microgrids, power exchange cost at point of common coupling and load shedding cost. The power exchange cost is negative when MGs are extracting power from the distribution system or positive when MGs are exporting power to the DS. Dispatchable generators in MG are subject to real power output capacity constraint (3.2), reactive power capacity output constraint (3.3), ramp up rate (3.4) and ramp down rate (3.5). Real power balance equations (3.6) and reactive power balance equations (3.7) together ensure that the power generated by DGs is used to supply the entire load and the power exchange at PCC. The DLMPs (λ_{bt}^{P}) are endogenously generated from the lower-level programming model (3.8) - (3.16) (LLPM), and the MG uses DLMPs as the base bidding/offering price $\lambda_{b_j't}^{P}$. The real power and reactive power exchange at PCC belong to the feasible set defined by the LLPM as in constraint (3.8).

The LLPM presents the distribution system market clearing problem with the objective to maximize the social welfare (3.8), which consists of four terms. The first three terms represent the total cost for the DS: operation cost from DS-owned DGs, power exchange with MG, and the cost of extracting power from utility power system. The last item is total benefits obtained by supplying power to customers. Constraint (3.9) and (3.10) guarantee that the DGs' outputs, MGs power exchange, utility extraction, and load requirement are within a capacity range. The constraints (3.11) - (3.15) are *DistFlow* equations that can be used to describe the complex power flows at each node for DS. Constraints (3.11) and (3.12) are real power injection and reactive power injection at each node. The possible equations to use are power balance equations, which can be written for real and reactive power for each bus. Constraints (3.13) and (3.14) are real and reactive power balance equations at each node, which guarantee the power balance. Constraint (3.15) is the node voltage equation. Voltage limits are defined in constraint (3.16). The justification of the linearized method for *DistFlow* can be found in [28].

Dual variables associated with each constraint are labeled next to the corresponding constraints: $\mu_{(.)t}^{\mathrm{p}\min}$, $\mu_{(.)t}^{\mathrm{p}\max}$, $\mu_{(.)t}^{\mathrm{q}\min}$, $\mu_{(.)t}^{\mathrm{q}\max}$, λ_{bt}^{P} , λ_{bt}^{Q} , π_{bt} , $\pi_{bt}^{\min}$ and $\pi_{bt}^{\max}$. It is noted that the LLPM is a linear programming model if the microgrids' bidding/offering price α_{jt} is treated as input parameters. Thus, the LLPM can be replaced with KKT optimality conditions to formulate as MPEC.

3.3.2 MPEC

The KKT optimality conditions for LLPM are constructed as follows:

$$\delta_{nt}^{O} - \mu_{nt}^{\mathrm{p}\min} + \mu_{nt}^{\mathrm{p}\max} - \lambda_{bt}^{P} = 0 \quad \forall b \in B^{n}, \forall t \ , \tag{3.17}$$

$$\delta_{mt}^{U} - \mu_{mt}^{\mathrm{p}\min} + \mu_{mt}^{\mathrm{p}\max} - \lambda_{bt}^{P} = 0 \quad \forall b \in B^{m}, \forall t \ , \tag{3.18}$$

$$\alpha_{jt} - \mu_{jt}^{\mathrm{p}\min} + \mu_{jt}^{\mathrm{p}\max} - \lambda_{bt}^{P} = 0 \quad \forall b \in B^{j}, \forall t \ , \tag{3.19}$$

$$-\delta_{lt}^{L} - \mu_{lt}^{\mathrm{p}\min} + \mu_{lt}^{\mathrm{p}\max} + \lambda_{bt}^{P} = 0 \quad \forall b \in B^{l}, \forall t \ , \tag{3.20}$$

$$-\mu_{it}^{\mathrm{q}\min} + \mu_{it}^{\mathrm{q}\max} - \lambda_{bt}^{Q} = 0 \quad \forall i \in J, L, M, N, \forall b \in J, L, M, N, \forall t \ , \tag{3.21}$$

$$\lambda_{bt}^{P} - \lambda_{(b+1)t}^{P} - r_{b}\pi_{b} / V_{1}^{2} = 0 \quad \forall b \in B, \forall t \ , \tag{3.22}$$

$$\lambda_{bt}^{Q} - \lambda_{(b+1)t}^{Q} - x_{b}\pi_{bt} / V_{1}^{2} = 0 \quad \forall b \in B, \forall t \ , \tag{3.23}$$

$$\pi_{bt} - \varepsilon_{(b+1)\mathrm{t}} - V_{bt}^{\min} + V_{it}^{\max} = 0 \quad \forall b \in B, \forall t \ , \tag{3.24}$$

$$0 \le \mu_{it}^{\mathrm{p}\min} \perp (P_{it} - P_{i}^{\min}) \ge 0, \forall t, \forall i \in J, L, M, N \ , \tag{3.25}$$

$$0 \le \mu_{it}^{\mathrm{p}\max} \perp (P_{i}^{\max} - P_{it}) \ge 0, \forall t, i \in J, L, M, N \ , \tag{3.26}$$

$$0 \le \mu_{it}^{\mathrm{q\,min}} \perp (Q_{it} - Q_i^{\min}) \ge 0, \forall t, \forall i \in J, L, M, N \quad , \tag{3.27}$$

$$0 \le \mu_{it}^{\mathrm{q\,max}} \perp (Q_i^{\max} - Q_{it}) \ge 0, \forall t, i \in J, L, M, N \quad , \tag{3.28}$$

$$0 \le \pi_{bt}^{\min} \perp (V_{bt} - V_b^{\min}) \ge 0, \ \forall b \in B, \forall t \quad , \tag{3.29}$$

$$0 \le \pi_{it}^{\max} \perp (V_i^{\max} - V_{it}) \ge 0, \ \forall b \in B, \forall t \quad , \tag{3.30}$$

$$(9) \ - \ (16) \ , \tag{3.31}$$

$$\text{and } \mu_{(.)t}^{\mathrm{p\,min}}, \mu_{(.)t}^{\mathrm{p\,max}}, \mu_{(.)t}^{\mathrm{q\,min}}, \mu_{(.)t}^{\mathrm{q\,max}}, \lambda_{bt}^{P}, \lambda_{bt}^{Q}, \pi_{bt}, \pi_{bt}^{\min}, \pi_{bt}^{\max} \ge 0. \tag{3.32}$$

The bi-level programming model is replaced with (3.1) - (3.8) and (3.17) - (3.32) as MPEC. The MPEC is a non-convex problem, thus the linearize technics are needed to solve the problem.

3.3.3 Equivalent Linear Formulation

The nonlinearity of MPEC comes from two parts: MGs' bidding/offering in upper-level objective function $c_{jt}P_{jt}$, and complementary slackness part in lower-level KKT equivalent constraints (3.25) - (3.30).

To linearize $\lambda_{b_j't}^{P} P_{jt}$, we applied strong duality method used in [95]. The corresponding linearized term of $\lambda_{b_j't}^{P} P_{jt}$ as follows:

$$\begin{aligned}
\Omega = \sum_{jt} \lambda_{b_j't}^{P} P_{jt} = &- \sum_{\substack{it \\ i \in N,M,L}} \mu_{ip}^{\mathrm{p\,max}} P_i^{\max} + \sum_{\substack{it \\ i \in N,M,L}} \mu_{itp}^{\min} P_i^{\min} \\
&- \sum_{\substack{it \\ i \in J,M,N,L}} \mu_{it}^{\mathrm{q\,max}} Q_i^{\max} + \sum_{\substack{it \\ i \in J,M,N,L}} \mu_{it}^{\mathrm{q\,min}} Q_i^{\min} - \sum_{bt} \pi_{bt}^{\max} V_{bt}^{\max} \ . \\
&+ \sum_{bt} \pi_{bt}^{\min} V_{bt}^{\min} - \sum_{nt} \delta_{nt}^{O} P_{nt} - \sum_{mt} \delta_{mt}^{U} P_{mt} + \sum_{lt} \delta_{lt}^{L} P_{lt}
\end{aligned} \tag{3.33}$$

The complementary slackness constraints (3.25) – (3.30) can be linearized as follow if we introduce a set of binary variables $\omega_{(.)t}$ $\tau_{(.)t}$ to linearize each part.

The linearize form of (3.25) -(3.30) as follows:

$$0 \le P_{it} - P_i^{\min} \le (1-\omega_{it}^{\mathrm{p}\min})\mathrm{O}_i, \ \forall t, \forall i \in J, L, M, N , \tag{3.34}$$

$$0 \le \mu_{it}^{\mathrm{p}\min} \le \omega_{it}^{\mathrm{p}\min}\mathrm{O}_i, \forall t, \forall i \in J, L, M, N \ , \tag{3.35}$$

$$0 \le P_i^{\max} - P_{it} \le (1-\omega_{it}^{\mathrm{p}\max})\mathrm{O}_i, \forall t, \forall i \in J, L, M, N \ , \tag{3.36}$$

$$0 \le \mu_{it}^{\mathrm{p}\max} \le \omega_{it}^{\mathrm{p}\max}\mathrm{O}_i, \forall t, \forall i \in J, L, M, N \ , \tag{3.37}$$

$$0 \le Q_{it} - Q_i^{\min} \le (1-\omega_{it}^{\mathrm{q}\min})\mathrm{O}_i, \forall t, \forall i \in J, L, M, N \ , \tag{3.38}$$

$$0 \le \mu_{it}^{\mathrm{q}\min} \le \omega_{it}^{\mathrm{q}\min}\mathrm{O}_i, \forall t, \forall i \in J, L, M, N \ , \tag{3.39}$$

$$0 \le Q_i^{\max} - Q_{it} \le (1-\omega_{it}^{\mathrm{q}\max})\mathrm{O}_i, \forall t, \forall i \in J, L, M, N \ , \tag{3.40}$$

$$0 \le \mu_{it}^{\mathrm{q}\max} \le \omega_{it}^{\mathrm{q}\max}\mathrm{O}_i, \forall t, \forall i \in J, L, M, N \ , \tag{3.41}$$

$$0 \le V_{bt} - V_b^{\min} \le (1-\tau_{bt}^{\min})\mathrm{O}_b, \forall t, \forall b \in B \ , \tag{3.42}$$

$$0 \le \pi_{bt}^{\min} \le \tau_{bt}^{\min}\mathrm{O}_b, \forall t, \forall b \in B \ , \tag{3.44}$$

$$0 \le V_{bt}^{\max} - V_{bt} \le (1-\tau_{it}^{\max})\mathrm{O}_b, \forall t, \forall b \in B \ , \tag{3.45}$$

$$\text{and} \ \ 0 \le \pi_{bt}^{\max} \le \tau_{bt}^{\max}\mathrm{O}_b, \forall t, \forall b \in B \ . \tag{3.46}$$

With a linearized form of MEPC, the bi-level programming is reformulated as a mix integer programming problem which can be solved by using some commercial software packages. The MIP formulation is as follows:

$$\min \sum_{itj} \delta_{it}^{G} P_{it} + \sum_{jt} VOLL \cdot D_{jt}^{P} + \Omega \ , \tag{3.47}$$

subject to: (3.2) - (3.8), (3.17) - (3.24), (3.31) - (3.32), (3.34) - (3.46).

3.3.4 MG Bidding/Offering Strategy

The microgrid is prosumer such that (1) it can submit offers to the distribution market operator when it exports power to the DS or (2) it can submit bids to the distribution market operator when it extracts power from the DS. The bidding/offering prices for MGs in bi-level model always coincide with DLMPs. However, this bidding/offering strategy may result in a solution that is not practical for the following reasons: (i) a flat offer curve may result in multiple solutions and degeneracy [95]; (ii) some incentive(s) or even protective policy are necessary to maintain the profitability of MGs; (iii) no way to ensure the market clearing to have increasing offer curves or decreasing bid curves; and (iv) bidding/offering curves in practice are more complicated than the linearized or piecewise linearized curve adopted in our bi-level model.

To provide a remedy to the issues, we propose a direct and simple bidding/offering strategy for microgrids to find bidding/offering price (α'_{jt}) based on two pieces of price information: *MG corresponding marginal cost (* β_{jt} *)* and *DLMPs (* λ_{bt} *) in DS*. The marginal cost of an MG can be obtained at the intersection of the aggregated marginal cost curve of its DGs and the maximum capacity of its PCC. DLMPs are declared at the DS level through the DEM clearing mechanism. Hence, a modified bidding/offering strategy for MGs is proposed as follows:

i) the **Offering Strategy** is used for energy transfer from MG to DS:

1) If $P_{jt} = 0$, it indicates that either MG *j-th* is on islanding mode or bidding/offering prices are not accepted. If $\beta_{jt} < \lambda_{bt}^{P}$, then $\alpha'_{jt} = \lambda_{bt}^{P}$. If $\beta_{jt} > \lambda_{it}$, then $\alpha'_{jt} = \beta_{jt}$. This keeps MG *j-th* from being accepted at a higher price.

2) If $0 < P_{jt} \le P_j^{\max}$ and $\beta_{jt} < \lambda_{bt}^{P}$, it indicates that MG *j-th* is working on grid connected mode. The MG *j-th* is transferring power to DS where the market price is relatively higher. Then we set $\alpha'_{jt} = \lambda_{bt}^{P} - \varepsilon$ to make sure DS is willing to take more.

3) If $0 < P_{jt} \le P_j^{\max}$ and $\beta_{jt} > \lambda_{bt}^{P}$, it indicates that MG *j-th* is generating power with higher cost to supply DS loads at a lower price. Then we set $\alpha'_{jt} = \beta_{jt}$ to maintain MG's profitability in the market.

ii) the **Bidding Strategy** is used for energy transfer from DS to MG:

4) If $P_j^{\min} \le P_{jt} < 0$ and $\beta_{jt} < \lambda_{bt}^{P}$, it indicates that the MG *j-th* is extracting power from DS with higher cost even though it has a cheap power source available inside. Then we set $\alpha'_{jt} = \beta_{jt}$ to maintain the profitability of MG *j-th*.

5) If $P_j^{\min} \le P_{jt} < 0$ and $\beta_{jt} > \lambda_{bt}^{P}$, it indicates that MG *j-th* is extracting power from DS rather than generating power itself with higher cost. Then MG will bid with price $\alpha'_{jt} = \lambda_{bt}^{P} + \varepsilon$. The decreasing bid can encourage DS to export more power to MG *j-th*.

It is noted that ε is a very small positive constant, e.g., 10^{-5} .

3.3.5 Uncertainty Modeling

When MGs participate in DEM as price makers, uncertainties associated with their rivals (DS-owned DGs) and customers in DS highly affect the bidding/offering decisions that MGs make. The bidding/offering prices made by rivals and customers may fluctuate with load consumption changes. The probability distribution of a real-time market price is not precisely known and may vary with unpredictable system conditions in short term operation such as network, load and units availabilities [44]. Hence, a robust optimization method is more appropriate to handle these uncertainties. The offering price of DGs can be modeled as a summation of two terms $\delta_{nt}^{O} + \hat{\delta}_{nt}^{O}\xi_{nt}$, where δ_{nt}^{O} is a predicted offering price, ξ_{nt} is an unknown variable associated with price uncertainty, and $\hat{\delta}_{nt}^{O}$ is a scale parameter. In setting up a robust optimization model, the uncertainty set for ξ_{nt} is modeled as follows:

$$U_{nt} = \{\xi_{nt} : \xi_{nt} \in [-d_{nt}, d_{nt}]\}, \tag{3.48}$$

in above which parameter d_{nt} controls the level of uncertainty. If $d_{nt} = 0$, the price uncertainty is ignored. If $d_{nt} = 1$, it means that all price uncertainties are taken into account. Similarly, the customers' offering price (δ_{lt}^{L}) can be modeled as $\delta_{lt}^{L} + \hat{\delta}_{lt}^{L}\xi_{lt}$. The uncertainty set for ξ_{lt} is defined as

$$U_{lt} = \{\xi_{lt} : \xi_{lt} \in [-d_{lt}, d_{lt}]\}. \tag{3.49}$$

Consequently, the objective function that minimizes the worst-case scenario [149] can be stated as:

$$\begin{aligned}&\min(\sum_{jt}\alpha_{jt}P_{jt}+\sum_{mt}\delta_{mt}^{U}P_{mt}+\\&\max_{\xi_{nt}\in U_{nt}\xi_{lt}\in U_{lt}}(\sum_{nt}(\delta_{nt}^{O}+\hat{\delta}_{nt}^{O}\xi_{nt})P_{nt}-\sum_{lt}(\delta_{lt}^{L}+\hat{\delta}_{lt}^{L}\xi_{lt})P_{lt}))\end{aligned} \quad . \tag{3.50}$$

Proposition: In objective function (3.50),
$\max_{\xi_{nt}\in U_{nt}\xi_{lt}\in U_{lt}}(\sum_{nt}(\delta_{nt}^{O}+\hat{\delta}_{nt}^{O}\xi_{nt})P_{nt}-\sum_{lt}(\delta_{lt}^{L}+\hat{\delta}_{lt}^{L}\xi_{lt})P_{lt}))$ is equivalent to
$\sum_{nt}(\delta_{nt}^{O}+d_{nt}\hat{\delta}_{nt}^{O})P_{nt}-\sum_{lt}(\delta_{lt}^{L}-d_{lt}\hat{\delta}_{lt}^{L})P_{lt}$.

Proof:

$$\begin{aligned}&\max_{\xi_{nt}\in U_{nt}\xi_{lt}\in U_{lt}}(\sum_{nt}(\delta_{nt}^{O}+\hat{\delta}_{nt}^{O}\xi_{nt})P_{nt}-\sum_{lt}(\delta_{lt}^{L}+\hat{\delta}_{lt}^{L}\xi_{lt})P_{lt})\\&=\max_{\xi_{nt}\in U_{nt}}(\sum_{nt}(\delta_{nt}^{O}+\hat{\delta}_{nt}^{O}\xi_{it})P_{it})-\min_{\xi_{lt}\in U_{lt}}(\sum_{lt}(\delta_{lt}^{L}+\hat{\delta}_{lt}^{L}\xi_{lt})P_{lt})\,.\\&=\sum_{nt}(\delta_{nt}^{O}+d_{nt}\hat{\delta}_{nt}^{O})P_{nt}-\sum_{lt}(\delta_{lt}^{L}-d_{lt}\hat{\delta}_{lt}^{L})P_{lt}\end{aligned} \tag{3.51}$$

Therefore, the robust optimization model for the LLMP is:

$$\begin{aligned}&\min(\sum_{jt}\alpha_{jt}P_{jt}+\sum_{mt}\delta_{mt}^{U}P_{mt}\\&+\sum_{nt}(\delta_{nt}^{O}+d_{nt}\hat{\delta}_{nt}^{O})P_{nt}-\sum_{lt}(\delta_{lt}^{L}-d_{lt}\hat{\delta}_{lt}^{L})P_{lt})\end{aligned} \quad , \tag{3.52}$$

Subject to (10) - (17).

The objective function states that DS-owned DGs attempt to maximize their profits by offering the highest price possible. In the meantime, the customers wish to decrease its bidding price to lower the energy cost. Following the linearization process discussed in Section III (B&C), the robust-equivalent MIP model (53) is essentially the same as (47) by replacing δ_{nt}^{O} with $\delta_{nt}^{O}+d_{nt}\hat{\delta}_{nt}^{O}$ and δ_{lt}^{L} with $\delta_{lt}^{L}-d_{lt}\hat{\delta}_{lt}^{L}$ formulated as follows:

$$\min\sum_{itj}\delta_{it}^{G}P_{it}+\sum_{jt}VOLL\cdot D_{jt}^{P}+\Omega' \quad , \tag{3.53}$$

s.t. (2) - (8), (19), (20), (22)- (25), (32) - (33), (35) - (46),

$$\Omega'=\Omega(\delta_{nt}^{O}\rightarrow\delta_{nt}^{O}+d_{nt}\hat{\delta}_{nt}^{O},\delta_{lt}^{L}\rightarrow\delta_{lt}^{L}-d_{lt}\hat{\delta}_{lt}^{L})\,,$$

$$\delta_{nt}^{O} + d_{nt}\hat{\delta}_{nt}^{O} - \mu_{nt}^{\mathrm{p\,min}} + \mu_{nt}^{\mathrm{p\,max}} - \lambda_{bt}^{P} = 0 \quad \forall b \in B^{n}, \forall t \ , \tag{3.54}$$

$$\text{and } -\delta_{lt}^{L} + d_{lt}\hat{\delta}_{lt}^{L} - \mu_{lt}^{\mathrm{p\,min}} + \mu_{lt}^{\mathrm{p\,max}} + \lambda_{bt}^{P} = 0 \ \ \forall b \in B^{l}, \forall t \ . \tag{3.55}$$

3.4 Numerical Experiments

The model is tested on a modified IEEE 33-bus distribution system with three microgrids and five DGs in the system [150]. The model was solved using IBM CPLEX [151] on a computer laptop equipped with 2.80 GHz Intel CPU and 8GB of RAM. To express the all parameter of the system in per-unit, the power base of the test system is set at 10MVA. The voltage base of the system is set at 12.66kV at utility side. The other details of MGs can also be found in [150] including output capacity, price information, and load capacity. The following cases are used for experiments:

Case 0: Grid-connected MGs in a deterministic case (3.47),

Case 1: Grid-connected MGs in worst case scenarios (3.53),

Case 2: Islanded mode of MGs operation.

Case 0 and **Case 1:** The goal is to find the optimal bidding/offering strategy within a 24-hour time horizon. Fig 3.2 shows DLMP trend over time for both cases, in which the same DLMP is applied to all nodes in the network at a specific time. We find very little variation in DLMPs between nodes, reflecting a lack of binding line constraints on this small network. The trend shows different DLMPs between the deterministic model and the robust model during 1:00am-13:00pm and 20:00pm-midnight, which is referred to off-peak hours. During these specific time periods, the DLMP of the robust model is 10% higher than that of the deterministic model. There are two main reasons for this difference.

First, DS-owned DGs attempt to increase offer prices to secure maximum profits because they are not sure about the real-market price. Second, some DS-owned DGs (DG1, DG2 and DG5) are not fully dispatched during off-peak hours that MGs' bids/offers have limited influence on the market price. It also shows that DLMPs stay relatively low during the non-peak hours (less than 0.66 $/p.u.).

The DLMPs start increasing at 13:00pm until they reach the peak at 17:00pm, and gradually decline for the rest of the period. During this time period (peak-hours), the prices are considerably higher than non-peak hours. This is because the consumer requirements increase rapidly during this period, which is indicated in Table III [28]. We noticed that the DLMPs for both cases remain identical between 13:00pm and 20:00pm. After DS-owned DGs reach the maximum output capacity, the DS begins to import more power from MGs with extra generation capacity. This action helps DS to stabilize the DLMPs at the beginning and end of peak-hours. After both DGs and MGs reach the maximum capacity, the utility side is the only power supplier option that DS have, even at a relatively high price. The utility prices are the same for both cases, which provides another reason that the DLMPs are identical during peak hours.

We continue our discussions using Table 3.1., which shows the comparison between the two cases. The results in column "Entity" are associated with DS clearing market mechanism (DS) and MG operation (MG#). The sources of DS clearing market include MGs, DGs, loads, and utility. The sources of MG operation cost consist of (1) interaction with the DS and (2) power generation. The negative values in column "Cost" indicate profits. A positive value in column "Power Injection" indicates the total power transfer from a source to an entity, while a negative value indicates the opposite direction of the power transfer. The evidence of MGs' schedule adjustment can be found to show that MGs are helpful in dealing with DS price uncertainty during the peak hours. The power generation cost of MG1 and MG2 in the robust model ($10000 and $5300) is higher than in the deterministic model ($8900 and $4100). It is obvious that these extra powers are transferred to DS, as the difference power injection values show.

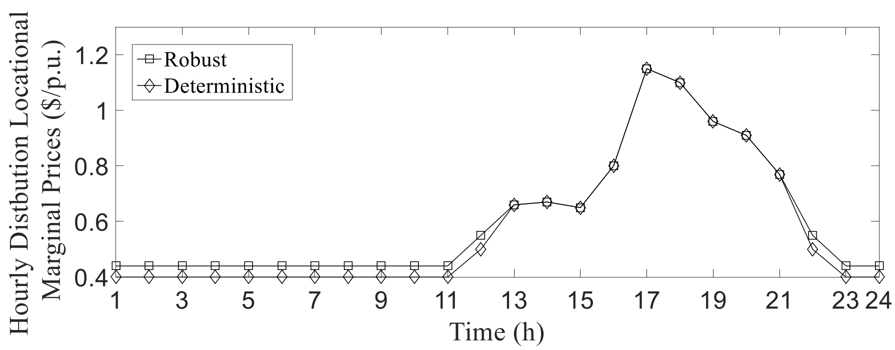

Figure 3. 2 DLMP of Case 1 and Case 2

Unlike other MGs, MG3's power generation cost ($6900 to $6400) decreases as well as power exportation (0.612p.u. to 0.514p.u.) in the robust model. There are two explanations. First, the location of MG3 is node 21, which is closer to the source node when compared with other MGs. The increasing exportation of power from MG3 will result in more power transmission loss in DS. Second, as input data (Table VI. [150]) shows, MG3 has a DG (DG3) which has the least operation cost (0.03 $/p.u.) among all DGs in MGs. This DG is fully dispatched for 24 hours in both cases. As a result, the MG3 is less price sensitive than the other two MGs, which makes it less influenced by price uncertainty.

The total profit of DS in the robust model ($5239) is less than that in the deterministic model($12802). The decrease of profit comes from two parts. First, DS extracts more power from MGs to compensate power shortage, which is caused by price uncertainty. Second, the customers decrease their bids to acquire power from DS, which leads to profit loss from supplying load

Table 3. 1 Result Comparison

Entity	**Sources**	**Case 0:**		**Case 1:**	
		Cost ($)	**Power Injection (p.u.)**	**Cost ($)**	**Power Injection (p.u.)**
DS	PCC(MG1)	-106	-0.15	1216.5	0.069
	PCC(MG2)	-3114.9	-0.803	-1641.2	-0.562
	PCC(MG3)	3818.7	0.621	3286.2	0.514
	DG	22200	5.831	22200	5.523
	Utility	1900	0.88	2300	0.96
	Loads	-37500	-6.379	-32600	-6.504
	Total	-12802	0	-5239	0
MG1	PCC	106	0.15	-1216.5	-0.069
	DG	8900	2.01	10000	2.229
	Total	9006	2.16	8783.5	2.16
MG2	PCC	3114.9	0.803	1641.2	0.562
	DG	4100	0.817	5300	1.058
	Total	7214.9	1.62	6941.2	1.62
MG3	PCC	-3818.7	-0.621	-3286.2	-0.514
	DG	6900	1.917	6400	1.81
	Total	3081.3	1.296	3286.2	1.296

Table 3.2. illustrates some examples of revised MGs bidding/offering strategy. For a specific MG *j-th* at time period t: The DLMP (λ_{bt}^{P}) and marginal cost (β_{jt}) and the power exchange between MG and DS (P_{jt}) are given. We can compare the original

bid/offers (α_{jt}) and the adjusted bid/offer (α'_{jt}). The MG1 at 10:00am extracts power from DS. $\beta_{1,10} < \lambda^{P}_{30,10}$, the bid with decreasing price is 0.44+ε. For MG2 at 21:00pm, $\beta_{2,21} > \lambda^{P}_{13,21}$, the fix offer is 0.5 to maintain its profit. For MG2 at 14:00pm, $\beta_{2,14} < \lambda^{P}_{13,14}$, the increasing offer is 0.66-ε. For MG3 at 3:00am, the $\beta_{3,3} < \lambda^{P}_{21,3}$, the fixed offer price is set at 0.5.

Table 3.3. is the results comparison between the original and the modified bidding/offering strategies for DS and MGs operation cost. The modified example assumes that the power interactions remain the same when the trading prices are modified. The MGs benefit from the policies to maintain the profitability. In the meantime, the obtained market clearing profit of DS decreases correspondingly. It can be seen that there is a \$470.08 total cost saving for MGs and a \$297.69 profit loss for DS. Therefore, we can expect that the proposed policy is practical and incentive, especially in the infancy of MG industry deployment.

Table 3. 2 Example of Modified MG Bidding/Offering Strategy

J	***t***	λ^{P}_{bt} **(\$/ p.u.)**	P_{jt} **(p.u.)**	α_{jt} **(\$/ p.u.)**	β_{jt} **(\$/ p.u.)**	α'_{jt} **(\$/p.u.)**
1	10	0.44	-0.024	0.44	0.5	0.44+ε
2	21	0.91	-0.047	0.91	0.5	0.5
2	14	0.66	0.026	0.66	0.5	0.66-ε
3	3	0.44	0.022	0.44	0.5	0.5

Table 3. 3 Comparisons of MG Bidding/Offering Strategy

Entity	**Operation Cost($)**	
	Original	**Modified**
MG1	8783.50	8765.80
MG2	6941.20	6796.45
MG3	3286.20	2978.57
Total MGs	19010.90	18540.82
DS	-5238.50	-4940.81

Case 2: This case studies the special occasion that MGs switch working mode from grid-connected to islanding in case of contingencies. We use $T-\tau$ islanding rules [25] to test the system. By introducing binary variable ρ_{jt} with constraints (3.56), (3.57) in upper level programming model, the ρ_{jt} can control the MG working modes switch. Then we add one more constraint (3.58) to control the total number of MG islanding hours as follows:

$$\rho_{jt} P_{it}^{\min} \le P_{it} \le \rho_{jt} P_{it}^{\max} \quad \forall t, \forall i \in J \ , \tag{3.56}$$

$$\rho_{jt} Q_{it}^{\min} \le Q_{it} \le \rho_{jt} Q_{it}^{\max} \quad \forall t, \forall i \in J \ , \tag{3.57}$$

$$\text{and} \sum_{t} \rho_{jt} = T - \tau \quad \forall i \in J \ . \tag{3.58}$$

The total number of islanding-hours (τ) from zero up to eight hours is tested based on the total operation time (24-hour (T) in the deterministic model). Figure 3.3 and Figure 3.4 show that the operation cost for MGs and clearing market profit for DS remain relatively stable as islanding hours increase. The larger number of islanding-hours results in decreasing interactions between MGs and DS. For MG with enough reserve, the more power generated through its own DGs to compensate the power lost during the islanding-hour. If not, the load shedding process is needed, which is likely to increase operation cost for MG. The DS, on the other side of islanding event, reacts to islanding events correspondingly. DS-owned DGs react to MGs' islanding action with an increasing or decreasing power output schedule. The solution results show that each MG has enough operating reserve to supply its local load without load shedding. Therefore, Figure 3.3 and Figure 3.4 illustrate that the MG's operation cost and DS's clearing market profit depend on their DGs' marginal cost in different number of hours islanding mode.

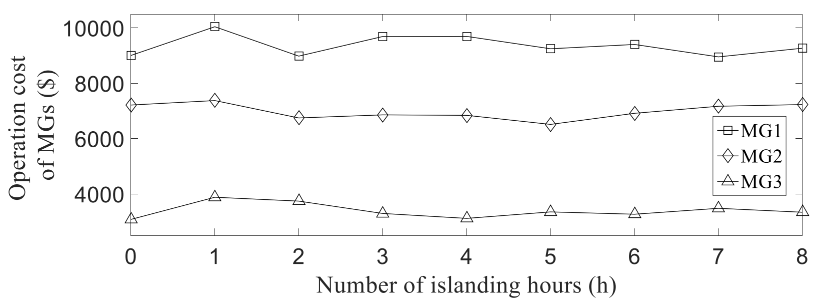

Figure 3. 3 Operation cost of MGs with increasing islanding time

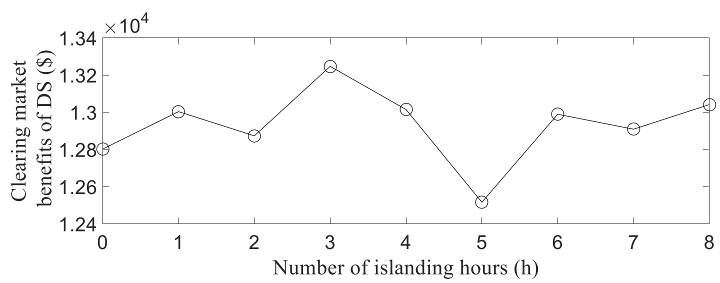

Figure 3. 4 DS clearing market benefits

In summary, the coordinated pool strategy provides an efficient way for MGs to participate into DEM with lower cost. A bidding/offering strategy enables MGs to successfully help DS to handle price uncertainty and islanding

3.5 Conclusion

A coordinated pool strategy for microgrid as price maker to participate in market-based distribution electricity market was proposed and formulated. We presented a reformulation of the original bi-level model as an equivalent linear mix-integer programming model, which is easier to solve. Three sets of experiments (models, strategies, and configurations) were performed to compare (1) deterministic model vs. robust optimization model, (2) original strategy vs. revised strategy, and (3) islanding mode vs. non-islanding mode. It was shown that having MGs in DS can help stabilize the DLMPs during the peak hours, and mitigate impact when an MG runs in an islanding mode. It is also shown that the proposed coordinated pool strategy performed well in dealing with the interactions between the DS and MGs. Furthermore, the market-based DEM created a fair and competitive environment for all market participants. Utilizing MGs as price makers with associated market risk enabled MGs to become competitive through a two-way power flow. One can extend our model to include ancillary service market

Chapter 4 Stability-Constrained Microgrid Operation Scheduling Incorporating Frequency Control Reserve

4.1 Introduction

Microgrids are becoming one of the most promising platforms to enable the large-scale adoption of renewable energy resources and dispatchable generators. By integrating distributed energy resources (DERs), active loads, and other smart elements into a localized self-contained network [152], microgrids represent a more flexible and secure operation paradigm that offers benefits such as higher power system resiliency [13], lower distribution cost [14], and improvement of rural electrification [12].

Microgrids are constantly exposed to uncertainties from components and operational environments [25]-[26]. The outputs of renewable generation in microgrids is a major source of uncertainties due to their highly volatile and stochastic nature. Another major type of uncertainties comes from the microgrid operation mode switching. A grid-connected microgrid can switch to island mode to maintain uninterrupted functioning when there is a disturbance in the upstream distribution network such as nature disasters [107] or cyber-attacks [153]. It can switch back to grid-connected mode and resynchronize with the utility grid (i.e. main grid) when the disturbance is cleared [107]. Such disturbances are often random events, which commonly cause deviations from the day-ahead islanding schedule, i.e., start time and its duration [154]. The power fluctuations resulted from these two sources of uncertainties introduce a significant risk in microgrid operation and may negatively impact the power balance within the microgrid. When a microgrid is connected to the main distribution network, this issue is less critical as the main grid can provide continuous support to help mitigate power mismatches in the microgrid. However, following the operation mode switching from grid-connected to islanded, the original power balance within a microgrid can be severely disturbed as the interaction between the microgrid and the main grid is forced to zero [155]. Given the limitation of size and capacity of synchronous generation in a microgrid, as well as the stressed stability margin [156][157], such large sudden power imbalances would lead to drastic frequency fluctuations, e.g., a frequency deviation at the rate of 10 Hz/second as reported in [158] , and even system-wide failures due to low system inertia. Therefore, the continuous balancing of resources and load within the microgrid needs to be tightly enforced to maintain the system frequency at its target value and ensure the stability of the microgrid during normal and abnormal operating conditions.

To facilitate the flexible integration of variable energy sources and stable microgrid operation [159], incorporating ancillary services to address frequency instability caused by uncertainties becomes a natural choice for microgrid operators [42]. Existing literature shows that market-based ancillary services can be exchanged on an hourly basis in the day-ahead market and provide a reliable, effective, and flexible way to maintain power balance between generation and demand, and limit system frequency excursions in real-time [15]-[18]. For the consideration of microgrid frequency stability, a certain amount of active power, commonly referred to as *frequency control reserve* (FCR), can be procured by the microgrid operator (MGO) [160] to respond immediately to potential system frequency deviations from the target value and provide the reserve capacity required to fulfill the operational requirement within a short period of time [161][36]. Under the assumption that a joint energy and ancillary services market [116] is available to the microgrid on the distribution system level, the MGO can (i) purchase fast-reacting FCR services as commodities from the main grid in grid-connected mode; (ii) prepare its own self-sustaining FCR provided by internal dispatchable units equipped with droop-based control for fast frequency regulation. Regardless of which approach the MGO takes, the operation uncertainties from supply/demand and microgrid operation mode switching, as well as the tradeoff between mitigating the risk of losing stability using ancillary services and the increased operation costs resulted from the reserve preparation needs to be analytically examined as a decision-making problem for MGO during scheduling.

Although microgrid operation scheduling has been extensively investigated in the literature, the research on microgrid scheduling incorporating both ancillary services and islanding has been limited. The primary drawback of current approaches is that the impact of operation mode switching is not adequately addressed in the scheduling process, which oversimplifies the scheduling problem to a scaled-down unit commitment problem. Such a scheme considers island mode [11], [53], [162], [163], and grid-connected mode [155], [164], without including the transition [42] in between. This is highly problematic for low-inertia systems such as microgrids as unexpected operation mode switching can be a major source for frequency deviations and ancillary services has to be adequately scheduled and readily deployable by the MGO when the islanding occurs. Notable literature such as [10] and [15] has attempted to systematically address the reserve provision for islanding events in microgrid scheduling in a joint market environment. A responsible party rule was provided in [15] which suggested that a microgrid can switch to island mode when the procured reserve band that can be purchased from the market cannot handle the frequency deviation. However, the provision of reserve before and after islanding are not considered. Another case in [10] shows that a microgrid is required to have enough reserve capacity to handle the power mismatch when it switches from grid-connected mode to island mode; nonetheless, the reserve providers are not clearly identified and the scheduling strategy for the duration of islanding is not discussed. A truly comprehensive scheduling scheme that incorporates the full process of the islanding event to assure the seamless transition between grid-connected mode and island mode is still yet to be developed.

Realizing the limitations of the previous research efforts, in this chapter, a novel two-stage microgrid scheduling strategy is proposed to facilitate the economic and stable operation of a microgrid that participates in the joint distribution market. To the best of our knowledge, this is a pioneering work on addressing the optimal scheduling of a microgrid with the full incorporation of market-oriented frequency control reserve scheduling and the transition between operation mode switching. While our goal for the proposed scheduling strategy is to produce the most cost-effective solution without violating any power balance constraints (i.e., frequency stability constraints), such a solution can be very difficult and costly to obtain in the face of uncertainties. Therefore, the authors argue that a certain degree of frequency stability constraint violation can be tolerated as long as the frequency deviation caused by such power mismatch is within a certain range at a cost, e.g., 59.3 Hz to 60.5 Hz, according to IEEE Std 1547.4 for a 60

Hz system [165]. This motivates us to formulate the microgrid operation scheduling problem in the form of chance-constrained programming (CCP) [166] where the frequency stability violation can be conveniently captured in the form of chance constraints that only need to be satisfied with a probability. However, the violation of such constraints will be susceptible to penalties when the system frequency exceeds the desired bounds, and load shedding or power curtailments are required to mitigate the power mismatch and maintain system stability. Through optimization, the proposed scheduling algorithm is seeking the complementary between frequency control reserve, as a service to ensure microgrid stability, and energy supply, which is cost-driven.

The detailed contributions of this chapter are described as follows:

1. A two-stage microgrid scheduling strategy is proposed based on CCP that allows the MGO to pursue its own economic interest of minimizing the operational cost of the microgrid while actively mitigating the risk of system instability within the scheduling horizon under uncertainty.

2. Islanding events along with the uncertainties associated with them are fully considered. The proposed scheduling strategy takes into account all states of microgrid operation including grid-connected, islanded, and the transition in between. Ancillary services providers and guidelines for reserve preparation are defined end-to-end to assure sufficient resources are allocated and ready for power imbalances.

3. A collaborative resource allocation strategy is formulated in the proposed scheduling framework to determine the proper amount of reserve from market purchase and internal preparation, respectively. This allows us to achieve another level of co-

optimization on top of the energy and reserve co-optimization that is originally offered in the joint market.

4. Policy studies are performed to evaluate the proposed microgrid scheduling strategy in terms of both operation economics and stability requirement.

The remainder of this chapter is organized as follows. Section II presents the proposed microgrid management strategy. Section III formulates the chance-constrained programming model and our proposed solution methodology. The model is tested under different operation scenarios and policy settings in Section IV. Conclusions are drawn in Section V.

4.2 Microgrid Management Strategy

4.2.1 Joint Market Environment

In a fully decentralized market environment, successful microgrid operation scheduling requires coordination with the electricity distribution market [31]. The participation of microgrids in a distribution level day-ahead electricity market by providing both energy and ancillary services such as reactive power/voltage control, active loss balancing and demand interruption was first discussed in [167] and [168]. The interfacing mechanisms of microgrids with ancillary services markets cleared by distribution system operator were systematically investigated and discussed in [169]. Algorithms to enable regulation and primary control service for individual and multiple microgrids have been reported [170] and [171]. Readers can find a collective review and discussion of the types and quantification of ancillary service provision by microgrid [172]. As a participant of a competitive market, literature [29], [44], [173], [174] have evaluated the optimal bidding strategy for microgrids in day-ahead and real-time joint energy and ancillary services markets to maximize the revenue and facilitate flexible integration of renewable DERs into the utility grid.

This chapter adopts the *power exchange for frequency control* (PXFC) market structure [114] as it provides a competitive and transparent market environment for participants to make individual decisions regarding the purchase quantities, purchase costs, as well as the risk for utilizing unreserved energy. The PXFC market consists of two submarkets: an energy market and a reserve market [15]. In the energy market, reference power is traded based on anticipated internal power generation and demand within the microgrid. In the reserve market, a bandwidth around the reference power is exchanged among market participants. This bandwidth, known as *frequency control band*, can be used as the reserved capacity of FCR to compensate for deviations from the expected reference power. By combining the reference power and the frequency control band, an *external reserve band* can be defined as

$$\Gamma_1 = \psi_1 \pm \theta_1, \tag{4.1}$$

where, ψ_1 denotes the reference power and θ_1 denotes the width of the frequency control band. It is clear that Γ_1 can be entirely purchased by the MGO from the joint market.

However, the external reserve band Γ_1 by itself cannot guarantee the stable operation of the microgrid, as such reserve market will become unavailable to microgrid during the islanding operation. Therefore, the MGO needs to prepare its own operation reserve band to regain power balance and maintain system stability in island mode. Inverter-based dispatchable units can provide a fast response to frequency deviations in the form of *internal reserve band* Γ_2. Similar to the external reserve band, Γ_2 consists of an internal reference power ψ_2 and an internal frequency control bandwidth θ_2:

$$\Gamma_2 = \psi_2 \pm \theta_2 . \tag{4.2}$$

Considering the high operation cost associated with the dispatchable units, the MGO should be very careful in allocating the limited generation capacity of a microgrid for energy supply and internal reserve preparation. With Γ_1 and Γ_2 both contributing to the total energy and FCR provision in the form of a combined FCR band of Γ (i.e. $\Gamma=\Gamma_1+\Gamma_2$), a collaborative scheme is critical to schedule both Γ_1 and Γ_2 simultaneously to improve the scheduling efficiency and effectiveness. A two-stage scheduling process is proposed to achieve this goal in the proposed market environment. Considering the relatively small capacity of a microgrid, it is assumed that Γ_2 is not traded back to the main grid in this chapter.

4.2.2 Two-Stage Scheduling Strategy

The determination of the reserve band can be divided into two major stages: (i) *band preparation* and (ii) *band verification*. In the first stage, the MGO determines the amount of energy and FCR to prepare for the operation of the microgrid as well as the uncertainties that may occur in real-time through adjusting the combination of Γ_1 and Γ_2. The second stage is to test the total bandwidth requested in the first stage. A large number of scenarios need be tested to verify whether the bandwidth requested is sufficient to maintain the stable operation of the microgrid under various types and severities of operation uncertainties. The performance of these tests can then be submitted to a supervisory authority that oversees the microgrid operation to determine the penalty for power balance violation that may lead to load shedding (LS) or power curtailment (PC). The penalties are imposed to encourage the MGO to purchase a proper bandwidth in the first stage.

The connection between the first and second stage is the width of the reserve band. A wide bandwidth indicates a higher cost because more reserve will be scheduled to ensure stability, which is a typical decision preference of conservative decision makers, i.e., risk-averse in the context of decision analysis. Conversely, a narrow bandwidth means lower preparation cost, but it also increases the risk of system instability and the penalty cost resulted from load shedding and power curtailment, which is preferred by aggressive decision makers, i.e., risk-prone. To capture these differences in risk-behavior of the MGOs and provide a mathematical tool reflecting their risk level ($\varepsilon \in (0,1]$), the authors propose the concept of chance-constraints [175] that allows constraint violation up to the level of pre-specified ε, which is called the confidence level. Note that one can convert a set of constraint $Ax<=b$ to a chance constraint $\text{Prob}(Ax<=b)\geq 1-\varepsilon$. In this work, the confidence level ε is referred to as *stability opportunity risk* (*SOR*) to represent the MGO's risk preference. Hence, our proposed model incorporating the user-defined parameter SOR can be stated in the following form:

$$Prob\ (No\ LS\ or\ PC\ required) \geq 1\text{-SOR}\,, \tag{4.3}$$

where clearly indicates that SOR, as a risk measure, represents the level of the MGO's confidence in satisfying the stability constraint under uncertainty. Incorporating the concept of SOR, the proposed two-stage process is depicted in Fig. 1. Note that in the second stage, the MGO needs to iteratively adjust its SOR setting, if necessary, to ensure the feasibility of optimal solution under the prepared scenarios representing possible microgrid operation uncertainties.

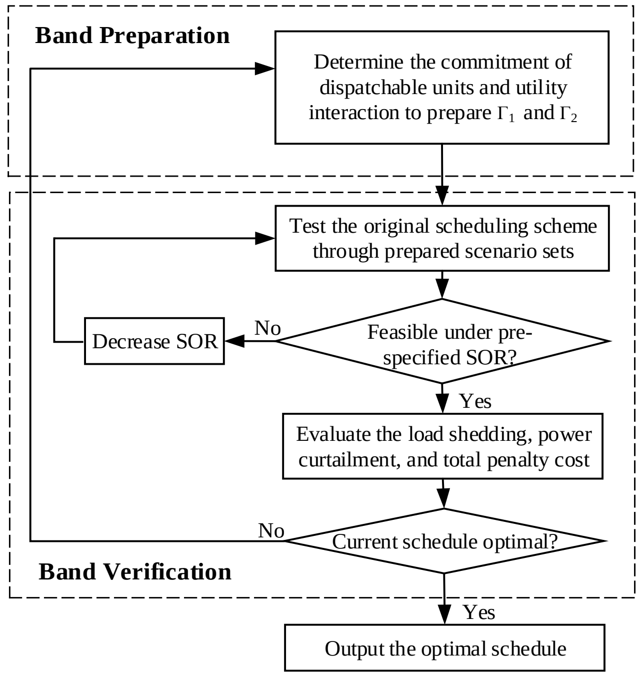

Figure 4. 1 Decision Flow Using SOR

4.2.3 Islanding Rules

As indicated in [15], the successful implementation of a PXFC market requires enforcement and penalty to assure participants do not misrepresent their load/generator characteristics (i.e., wrong width for the reserve band). This is especially true for microgrid operation around islanding events, since the type of reserve, the responsible parties of reserve provision, and the width of the reserve band all alter with the operation mode switching. For the purpose of microgrid scheduling, the following islanding rules are adopted:

Rule I: In grid-connected mode, the MGO purchases FCR from the main grid for frequency regulation.

***Comment*:** In grid-connected mode, only external reserve band Γ_1 is used because the frequency of the microgrid is dominantly determined by the main grid. The FCR purchased are primarily used to provide frequency regulation for uncertainty associated with DER and load variations.

Rule II: When the microgrid approaches the anticipated islanding start time, the MGO starts to lower the amount of market purchase and prepare internal FCR for the upcoming islanding event.

***Comment*:** During this time window, while the MGO still purchases a portion of Γ_1 from the main grid, it primarily relies on establishing Γ_2 to mitigate the large power mismatch caused by the upcoming islanding event.

Rule III: During the islanding event, the MGO fully relies on its own internal FCR for the frequency regulation.

***Comment*:** Once the microgrid fully enters into island mode and starts stable operation, the interactions between the main grid and the microgrid are paused. Only Γ_2 provided by dispatchable units within the microgrid can be used to mitigate frequency deviations.

Rule IV: When microgrid is approaching the anticipated islanding end time, the MGO starts to lower the amount of internal FCR for the upcoming reconnection to the main grid.

Comment**:** Similar to Rule II, during this time interval, the MGO needs to reduce Γ_2 as once reconnected to the main grid, the power mismatch will be primarily handled by Γ_1 to be purchased from the main grid.

Rule V: The penalty for the stability constraint violation in grid-connected mode is lower than that for island mode.

Comment**:** As a rule of thumb, grid-connected microgrid is allowed to take more risk as it has continuous support from the main grid. On the contrary, during island mode, the MGO has limited resources with no main grid backup. A higher penalty cost is thus used to discourage the MGO from taking risks.

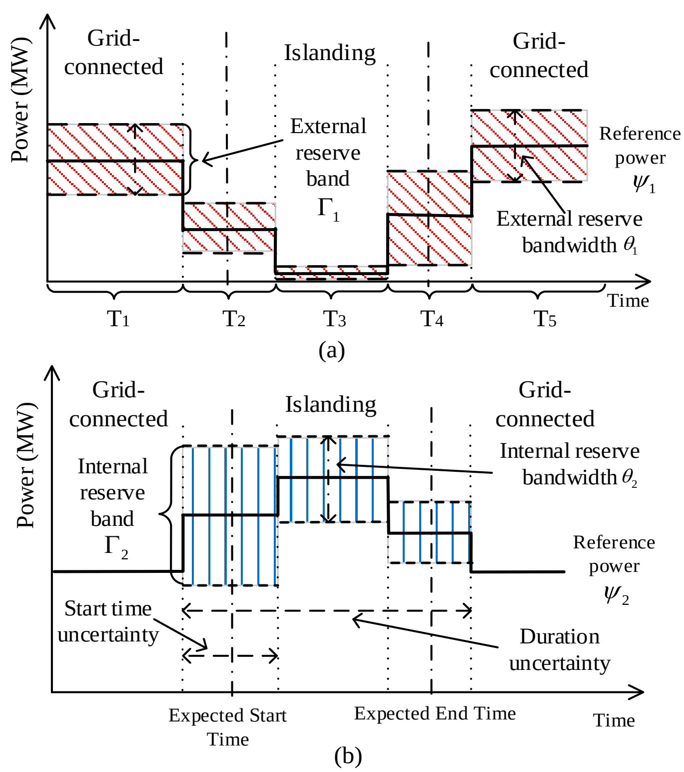

Figure 4. 2 External and Internal Reserve Band

A representative case describing the change of reserve provision incorporating the proposed islanding rules is shown in Fig. 2, which includes external reserve band (a) and internal reserve band (b). The whole islanding process can be divided into five phases denoted by time interval T_1 through T_5 in the figure. Prior to the operation mode switching, microgrid is in grid-connected mode during T_1. Due to uncertainties associated with the islanding start time, for the purpose of operation scheduling, the transition from grid-connected mode to island mode takes up-to a time duration of T_2 to complete. Then, the microgrid enters the stable islanding operation that lasts a duration of T_3. Once the microgrid is ready to be reconnected to the main grid, the transition back to grid-connected mode takes a period of time T_4 to complete considering the islanding duration uncertainty. The microgrid is fully back to grid-connected mode in T_5.

By comparing the bandwidth of Γ_1 and Γ_2 for different stages in (a) and (b), it can be observed that for this particular example, the bandwidth of Γ_1 in T_1 is consistent with the bandwidth of Γ_1 during T_5 and the bandwidth of Γ_2 during T_3. This is because according to Rule I and III, the reserve band mainly serves the need of frequency regulation for DERs during those time intervals. Rule II applies to period T_2, in which the bandwidth of Γ_1 is narrower than Γ_2 as microgrid is primarily responsible for the provision of FCR for the anticipated upcoming islanding event. Similarly, based on Rule IV the bandwidth of Γ_2 during T_4 is narrower than Γ_1 since now it is the responsibility of the main grid to provide sufficient bandwidth to handle the uncertainties associated with reconnection. Note that Γ_1 and Γ_2 are both scheduled during T_2 and T_4 due to the probabilistic nature of the proposed scheduling approach. For actual operation, once disconnected from the main grid, a microgrid loses its access to Γ_1 from the main grid immediately and this transition is instantaneous.

4.3 Model & Solution Methodology

The following notation is used in developing the two-stage chance-constrained model.

Indices

i	Traditional generation unit subscript index in MG
j	Renewable generation unit subscript index in MG
k	Load subscript index in MG
s	Scenario subscript index
t	Index for time periods

Parameters

c_i^g	Traditional generation unit i operation cost
c_i^r	Traditional generation unit i reserve cost
SD_i	Shut down cost of Traditional generation unit i
SU_i	Startup cost of Traditional generation unit i
ρ_t^c	Distribution system market power price at time t
ρ_t^r	Distribution system market reserve price at time t
$q^{c,\max}$	Maximum utility output capacity
$q^{c,\min}$	Minimum utility output capacity
$q_i^{g,\max}$	Maximum traditional generation unit i output capacity
$q_i^{g,\min}$	Minimum traditional generation unit i output capacity
$R_i^{up,\max}$	Maximum traditional generation unit i ramp up reserve capacity
$R_i^{dw,\max}$	Maximum traditional generation unit i ramp down reserve capacity
$R^{up,c,\max}$	Maximum utility ramp up reserve capacity
$R^{dw,c,\max}$	Maximum utility ramp down reserve capacity
α	Penalty cost associated with microgrid grid-connected mode
β	Penalty cost associated with microgrid islanding mode
$l_{k,t}$	Microgrid load
$q_{j,t}^w$	Renewable generation units output
$I_{s,t}$	Binary variable associated with islanding state

Set

D	Dispatchable generation unit set
L	Load set
M	Non-dispatchable generation unit set

Variables

$q_{i,t}^{g}$	Dispatchable generation units output
$b_{i,t}$	Binary variable associated with dispatchable units
$o_{i,t}$	Startup binary variable associated with dispatchable units
$v_{i,t}$	shut down binary variable associated with dispatchable units
$r_{i,t}^{up}$	Ramp up reserve output provided by dispatchable generation units
$r_{i,t}^{down}$	Ramp down reserve output provided by dispatchable generation units
q_{t}^{c}	Power exchange at PCC
$r_{t}^{up,c}$	Ramp up reserve provided by utility
$r_{t}^{dw,c}$	Ramp down reserve provided by utility

4.3.1 Two-Stage Chance-Constrained Programming Model

As previously discussed, the optimal scheduling problem described in Section II can be formulated as a two-stage chance-constrained programming model, in which the first-stage problem is formulated as follows

$$\min \sum_{i,t} (c_i^g q_{i,t}^g + x_{i,t} SU_i + y_{i,t} SD_i + c_i^r (R_{i,t}^{up}, R_{i,t}^{dw})) + \sum_t \left(\rho_t^c q_t^c + \rho^r (R_t^{up,c}, R_t^{dw,c}) \right). \quad (4.4)$$

The objective function (4.4) is to minimize the total operation cost of a microgrid which consists of dispatchable generation operation cost and interaction cost at the point of common coupling (PCC). More specifically, the generator operation cost is composed of power generation cost, startup cost, shutdown cost, and cost of the generation reserve preparation [176]. The interaction cost includes power interaction cost (negative if power is transferred from the microgrid to the utility) and ancillary services purchase cost. For simplicity, all the reserve cost functions c_i^r and ρ^r are defined as linear functions of variable $R_{i,t}^{up}, R_{i,t}^{dw}, R_t^{up,c}, R_t^{dw,c}$ as shown in (4.4) in this chapter.

As a general rule of thumb, all the dispatchable units within the microgrid are subject to power capacity constraints (4.5), minimum uptime (4.6) restrictions, and minimum downtime restrictions (4.7) as follows:

$$b_{i,t} q_i^{g,\min} \le q_{i,t}^g \le b_{i,t} q_i^{g,\max} \;\; \forall i \in D, \forall t, \tag{4.5}$$

$$(X_{i,t}^{on} - T_i^{on}) * (b_{i,t-1} - b_{i,t}) \ge 0 \;\; \forall i \in D, \forall t, \tag{4.6}$$

and $$(X_{i,t-1}^{off} - T_i^{off}) * (b_{i,t} - b_{i,t-1}) \ge 0 \;\; \forall i \in D, \forall t. \tag{4.7}$$

Under the assumption that all the dispatchable units can provide both ramp-up and ramp-down reserve, their reserve capacity limits can be described by (4.8) and (4.9):

$$0 \le R_{i,t}^{up,g} \le R_i^{up,\max} b_{i,t} \;\; \forall i \in D, \forall t \tag{4.8}$$

and $$0 \le R_{i,t}^{dw,g} \le R_i^{dw,\max} b_{i,t} \;\; \forall i \in D, \forall t\, . \tag{4.9}$$

The output capacity and ramp-up/down capability are limited by both physical characteristics and reserve capacities of the each dispatchable unit as shown in (4.10)-(4.13):

$$q_{i,t}^g + R_{i,t}^{up,g} \le q_i^{g,\max} \;\; \forall i \in D, \forall t\, , \tag{4.10}$$

$$q_{i,t}^g - R_{i,t}^{dw,g} \ge q_i^{g,\min} \;\; \forall i \in D, \forall t\, , \tag{4.11}$$

$$q_{i,t}^g - q_{i,t-1}^g + R_{i,t}^{up,g} \le (2 - b_{i,t-1} - b_{i,t}) q_{i,t}^{g,\min} + (1 + b_{i,t-1} - b_{i,t}) RU_i \quad \forall i \in D, \forall t\, , \tag{4.12}$$

and $$q_{i,t-1}^g - q_{i,t}^g - R_{i,t}^{dw,g} \le (2 - b_{i,t-1} - b_{i,t}) q_{i,t}^{g,\min} + (1 - b_{i,t-1} + b_{i,t}) RD_i \quad \forall i \in D, \forall t\, . \tag{4.13}$$

In a joint market environment, the interaction between the microgrid and the main grid includes power that flows both ways and external reserve that flows from main grid to the microgrid. The power interaction has upper/lower bounds as shown in (4.14) considering the physical limit of the PCC:

$$q^{c,\min} \le q_t^c \le q^{c,\max} \ \ \forall t \, . \tag{4.14}$$

The ramp-up external reserve and ramp-down external reserve capability offered by the main grid also have upper/lower limits as shown in (4.15) and (4.16):

$$0 \le R_t^{dw,c} \le R^{dw,c,\max} \ \ \forall t \tag{4.15}$$

$$\text{and } 0 \le R_t^{up,c} \le R^{up,c,\max} \ \ \forall t \, . \tag{4.16}$$

Combining the power exchange and external reserve procurement, the total interaction between the microgrid and the main grid needs to be within the physical limit imposed by the PCC at all time:

$$q_t^c + R_t^{up,c} \le q^{c,\max} \ \ \forall t \tag{4.17}$$

$$\text{and } q_t^c - R_t^{dw,c} \ge q^{c,\min} \ \ \forall t \, . \tag{4.18}$$

The power balance equation (4.19) ensures that the power generation from dispatchable and non-dispatchable units within the microgrid, together with the power exchange with the main grid, can supply the local demand of the microgrid:

$$\sum_i q_{i,t}^g + \sum_j q_{j,t}^w + q_t^c = \sum_k l_{k,t} \ \ \forall t \, . \tag{4.19}$$

The second stage model presents the determination of the risk penalty with the specification of different operation uncertainties scenarios as follows:

The objective function of the second stage problem is to minimize load shedding and power curtailment in both island mode and grid-connected mode as shown in (4.20):

$$\min \sum_{s,t} \begin{pmatrix} \alpha_t * (VOPC \cdot l_{s,t}^{sh} + VOLL \cdot q_{s,t}^{cu}) * I_{s,t}^{grid} \\ +\beta_t * (VOPC \cdot l_{s,t}^{sh} + VOLL \cdot q_{s,t}^{cu}) * I_{s,t}^{island} \end{pmatrix} . \tag{4.20}$$

Note that according to Rule V, the penalty coefficient α associated with island mode is higher than that of grid-connected mode *β*.

The chance constraints are used to demonstrate the effects of using external and internal reserve to handle frequency instability caused by power mismatch at two tails, see Fig. Particularly, if the total ramp-up reserve is insufficient to supply the load, load shedding will occur. Incorporated the previously defined concept of *SOR*, this chance constraint is shown in (4.21):

$$\text{Prob}(\sum_i q_{i,t}^{g} + \sum_j q_{j,t,s}^{w} + q_{s,t}^{c} + \sum_i r_{i,t,s}^{up,g} + r_{t,s}^{up,c} \geq \sum_k l_{k,t,s}) \geq 1 - SOR_1 \quad \forall t, \forall s. \quad (4.21)$$

If the total ramp-down reserve is insufficient to decrease the excessive generation, power curtailment will occur. Similarly, this chance constraint is shown in (4.22):

$$\text{Prob}(\sum_i q_{i,t}^{g} + \sum_j q_{j,t,s}^{w} + q_{s,t}^{c} - \sum_i r_{i,t,s}^{dw,g} - r_{t,s}^{dw,c} \leq \sum_k l_{k,t,s}) \geq 1 - SOR_2 \quad \forall t, \forall s. \quad (4.22)$$

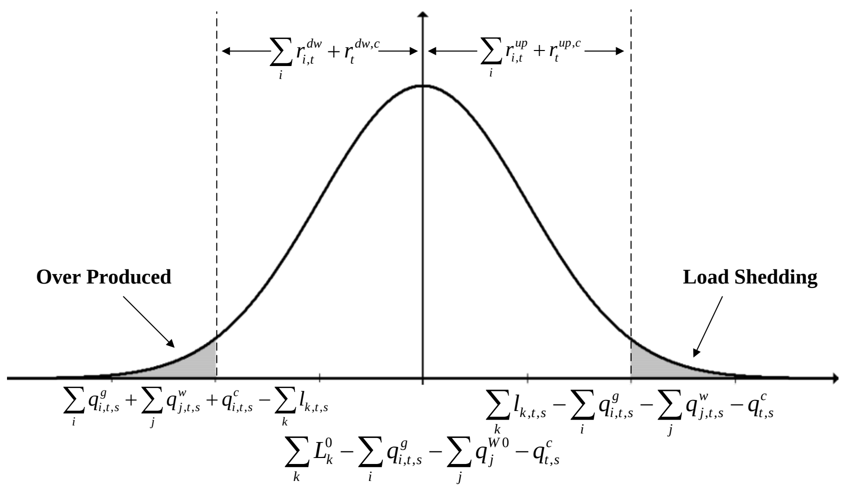

Figure 4. 3 Load Shedding and Power Curtailment

In this work, it is assumed that for the MGO's risk preference for load shedding (SOR_1) and generation curtailment (SOR_2) are equal. However, (4.21) and (4.22) are formulated in a generalized way to accommodate different risk preference settings easily when needed.

Following the possible load shedding and power curtailment operation, the power balance of the microgrid still needs to be strictly ensured as shown in (4.23). Constraint (4.24) ensures the validity of the load shedding and power curtailment operation:

$$\sum_i q_{i,t}^g + \sum_j q_{j,t,s}^w + q_{t,s}^c + \sum_i r_{i,t,s}^{up,g} + r_{t,s}^{up,c} - \sum_i r_{i,t,s}^{dw,g} - r_{t,s}^{dw,c} - q_{s,t}^{cu} = \sum_k l_{k,t,s} - l_{s,t}^{sh} \quad \forall t, \forall s \tag{4.23}$$

$$\text{and } l_{s,t}^{sh} \geq 0, q_{s,t}^{cu} \geq 0 \quad \forall t, \forall s\,. \tag{4.24}$$

A noticeable effect caused by operation mode switching is that the interaction with the main grid, including the access to external reserve, will disappear immediately after the microgrid switches to island mode. For this purpose, binary indicators $I_{s,t}^{grid}$ is introduced to indicate if the microgrid is in grid-connected mode (i.e. $I_{s,t}^{grid} = 1$) or island mode (i.e. $I_{s,t}^{grid} = 0$). It is evident the power interaction only exists when microgrid is working on grid-connected mode as depicted in (4.25):

$$0 \leq r_{t,s}^{up,c} \leq R_t^{up,c} I_{s,t}^{grid} \quad \forall t, \forall s \tag{4.25}$$

$$\text{and } 0 \leq r_{t,s}^{dw,c} \leq R_t^{dw,c} I_{s,t}^{grid} \quad \forall t, \forall s\,. \tag{4.26}$$

According to Rule I, when the microgrid is in grid-connected mode, no internal reserve is required. Introducing the complementary binary parameter $I_{s,t}^{island}$, this setting can be represented as:

$$0 \leq r_{i,t,s}^{up} \leq R_{i,t}^{up,g} I_{s,t}^{island} \tag{4.27}$$

$$\text{and } 0 \leq r_{i,t,s}^{dw} \leq R_{i,t}^{dw,g} I_{s,t}^{island}\,. \tag{4.28}$$

4.3.2 Scenario Generation

Two types of operational uncertainties are considered in this chapter: forecast error and operation mode switching. More specifically, normal distribution is adopted to describe the forecast errors of renewable energy output and hourly load consumption. The probability distribution of renewable energy output and hourly load forecast is given as:

$$q^{w}_{j,t,s} \sim N(W^{0}_{j,t}, {\sigma^{w}_{j,t}}^{2}) \ \ \forall j, \ \forall t, \tag{4.29}$$

$$\text{and } l_{k,t,s} \sim N(L^{0}_{k,t}, {\sigma^{l}_{k,t}}^{2}) \ \ \forall k, \ \forall t \tag{4.30}$$

The forecast error from renewable energy output and hourly load may have certain correlations for long-term microgrid planning. However, it is assumed that renewable energy output and load are independent from each other because such correlations are not significant for short-term operation (day-ahead) as studied in this chapter [177].

For indicator $I^{island}_{s,t}$ and $I^{grid}_{s,t}$ that represent the operation mode switching, a total of $N*T$ scenarios is considered in the scheduling process. Based on the proposed islanding rules, two types of information are required: start time μ and time duration υ. While the microgrid operator can make reasonable forecasts that the microgrid mode switching is expected to occur at time $\overline{\mu}$ for $\overline{\upsilon}$ hours, this forecast may not be accurate. If the probability distributions of μ and υ are independent of each other, a data set can be generate which contains start time and duration first, then convert it to binary indicators. Due to the lack of data in the occurrence and duration of disturbances that may lead to islanding, normal distribution is used to represent the islanding scenarios. The probability distribution functions of occurrence and duration are thus approximated as discrete scenarios so that it can be conveniently used in the proposed optimization model. More specifically, it is assumed that

$$\mu \sim N(\bar{u}, \sigma_{start}{}^2), \tag{4.31}$$

$$\text{and } \upsilon \sim N(\bar{\upsilon}, \sigma_{duration}{}^2) \tag{4.32}$$

The process of generating islanding scenarios is illustrated in Fig. 3. To begin with, a set of start time and duration data is generated based on probability distributions. Then, for each scenario, the sampling numbers are rounded to integers, so that a series of binary grid-connected indicators and islanding indicators can be generated to indicate the operation mode of a microgrid at a certain time slot within the scheduling horizon. These indicators are used later in the model as parameters.

Scenario #	Starting Time	Duration
1	11.583	1.962
2	12.936	3.216
3	8.781	2.303
4	11.938	2.383
⋮	⋮	⋮
N-1	12.424	3.657
N	11.753	1.809

Round to integer as 12 and 2.

Time Slot *t*		1		11	12	13	14		24
Grid-connected	$I_{4,t}^{grid}$	1	....	1	0	0	1	....	1
Islanding	$I_{4,t}^{island}$	0		0	1	1	0		0

Figure 4. 4 Generating Operation Mode Scenarios

The *Latin Hypercube Sampling* method is applied to generate *N* scenarios for stochastic variables. Each scenario has the same probability, thus the second stage objective function (4.20) can be replaced by:

$$\min \frac{1}{N} \sum_{N} \sum_{s,t} \begin{pmatrix} \alpha_t * (VOPC \cdot l_{s,t}^{sh} + VOLL \cdot q_{s,t}^{cu}) * I_{s,t}^{grid} \\ + \beta_t * (VOPC \cdot l_{s,t}^{sh} + VOLL \cdot q_{s,t}^{cu}) * I_{s,t}^{island} \end{pmatrix}. \tag{4.33}$$

4.3.3 Approximation

After scenario generation, the chance constraints are still difficult to solve since they are not convex. Hence, the chance constraints are approximated as mixed-integer constraints which are easier to solve, by introducing ancillary binary decision variable *z*. For a given sample size N: for each n, if $z_n = 0$, it means that the chance constraint is feasible in this scenario; if $z_n = 1$, the corresponding chance constraint is not feasible. The chance constraints are thus equivalent to limiting the number of z_n, where $1 \le n \le N$. Then, the chance constraints (4.21) and (4.22) can be approximated as follows:

$$\sum_i q_{i,t}^g + \sum_j q_{j,t,s}^w + q_{i,t}^c + \sum_i r_{i,t,s}^{up,g} + r_{t,s}^{up,c} - \sum_k l_{k,t,s} \ge z_n^{shed} \mathrm{O}\ \forall t, \forall s\,, \tag{4.34}$$

$$\sum_{n=1}^{N} z_n^{shed} \le N \cdot SOR_1\,, \tag{4.35}$$

$$\sum_i q_{i,t}^g + \sum_j q_{j,t,s}^w + q_{i,t}^c - \sum_i r_{i,t,s}^{dw,g} - r_{t,s}^{dw,c} - \sum_k l_{k,t,s} \le z_n^{curl} \mathrm{O}\ \forall t, \forall s\,, \tag{4.36}$$

$$\text{and } \sum_{n=1}^{N} z_n^{curl} \le N \cdot SOR_2\,. \tag{4.37}$$

The mixed-integer linear programming model can be derived by combining the first stage objective function (4.4) and second stage objective function (4.36) together:

$$\begin{aligned} &\min \sum_{i,t} (c_i^g q_{i,t}^g + x_{i,t} SU_i + y_{i,t} SD_i + c_i^r (R_{i,t}^{up}, R_{i,t}^{down})) \\ &+ \sum_t \rho^c q_t^c + \rho^r (R_t^{up,c}, R_t^{down,c}) + \frac{1}{N} \sum_{n=1}^{N} (\sum_{s,t} \begin{array}{l} \alpha_t * (VOPC \cdot l_{s,t}^{sh} + VOLL \cdot q_{s,t}^{cu}) * I_{s,t}^{grid} \\ + \beta_t * (VOPC \cdot l_{s,t}^{sh} + VOLL \cdot q_{s,t}^{cu}) * I_{s,t}^{island} \end{array}) \end{aligned} \tag{4.38}$$

$$s.t. \quad (4.5)-(4.19), (4.23)-(4.29), (4.35)-(4.38)\,. \tag{4.39}$$

The chance constraints (4.22) (4.23) cannot be used into solving the deterministic scheduling problem directly. There is a clear need that these constraints to be converted into deterministic formulations.

4.4 Numerical Experiments

The model derived in (4.39) and (4.40) is evaluated based on a microgrid with five dispatchable units, one solar generator, one wind generator, and one aggregate load. It is assumed that all dispatchable units are equipped with droop-control loops to provide fast ramp rates for frequency regulation. The detailed specifications of the microgrid and the utility grid it interacts with can be found in Table I-V in the Appendix. Additional market configurations considered in case studies can be found in Table VI-VIII including fixed penalty price, market-based penalty price, and market price.

The scheduling problem was solved using IBM CPLEX on a computer equipped with 2.80 GHz Intel CPU and 8GB of RAM. To evaluate the proposed scheduling strategy, the following two sets of policy studies are performed.

4.4.1 Operation Policy Study

In the first study, we conduct a set of experiments using different parameters including islanding scenarios, penalty price, reserve price, reserve capacity, and SOR to evaluate how the proposed scheduling approach performs under different operation settings. Four most representative cases are presented to illustrate our findings.

Policy I: Grid-connected microgrid operation without islanding

Policy II: Microgrid operation with operation mode switching

Policy III: Microgrid operation with operation mode switching under market-based penalty

Policy IV: Microgrid operation with operation mode switching and increased maximum allowable reserve band

Selected results are shown in Fig.4, which include the total operation cost (a), load shedding (b) and power curtailment (c) for the microgrid with regards to different SORs under different policies. Note that the same operation mode switching scenario is used in Policy II, III and IV for consistency whereas the islanding is expected to occur at 5:00 am with a duration of three hours. It is assumed that the deviations of the islanding start time μ and islanding duration υ can be modeled using the standard normal distribution with a mean value of 0 and a variance of 1 hour.

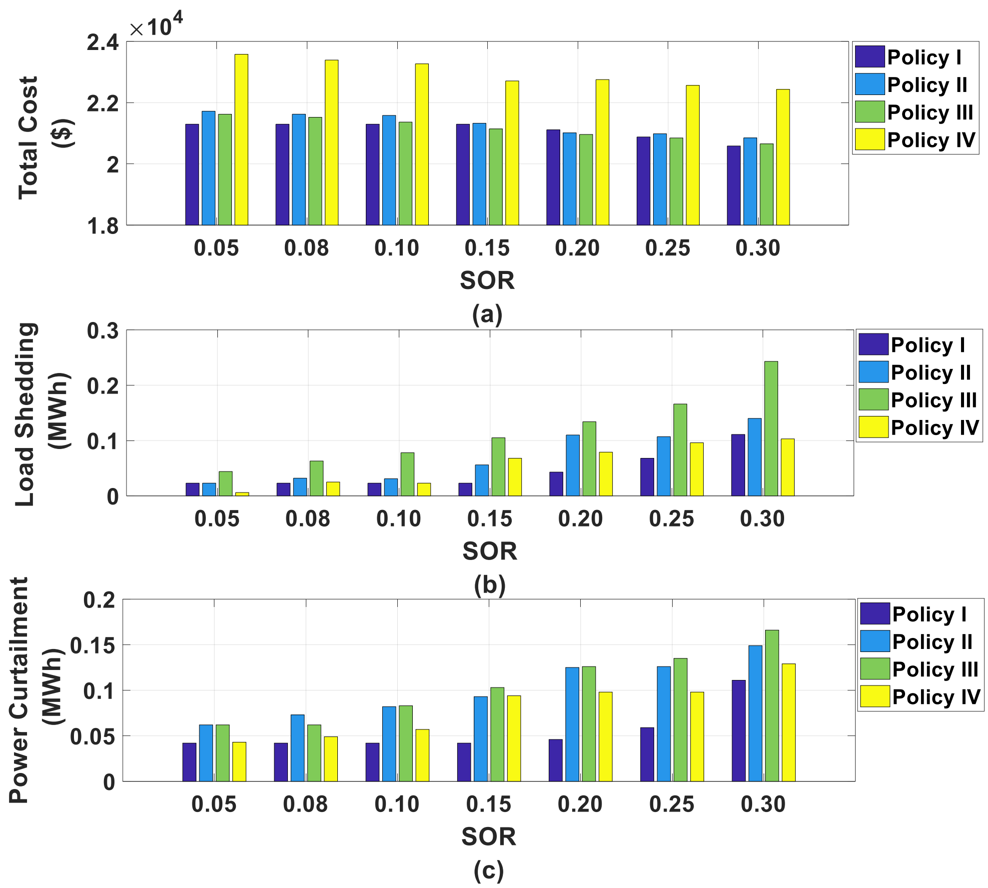

Figure 4. 5 Results of different operation policies under different SORs

A general trend shown in Fig.4 for all policies studied is that with an increased SOR, the operational cost decreases while the load shedding and power curtailment increase. This observation matches our trade-off analysis during the two-stage design in Section II. B. As a representative case, the external reserve band under two different levels of SOR is compared in Fig. 5 for Policy I. It can be clearly observed that when the SOR is lower, the reserve bandwidth is substantially wider which indicates that more reserve will be procured by the MGO to handle operation uncertainties since the MGO is more risk-averse. Conversely, for a risk-prone MGO that prefers a greater SOR in favor of reducing cost under uncertainty, less reserve will be procured.

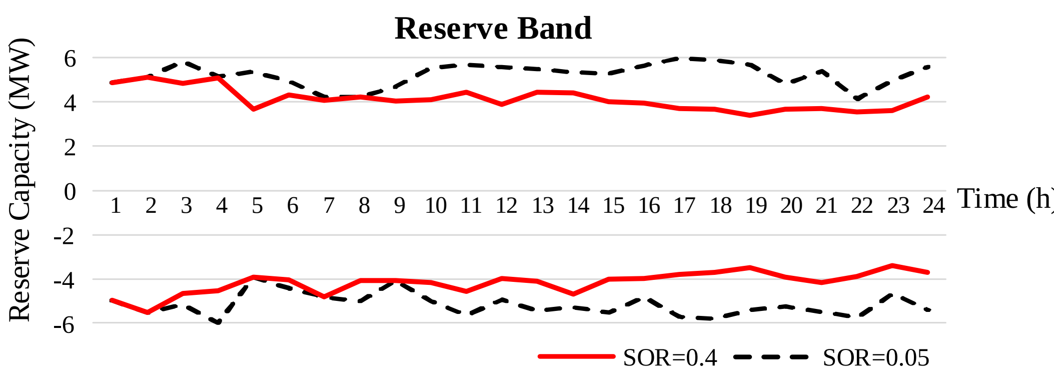

Figure 4. 6 Width of the External Reserve Band for Policy I under different SORs

To study the impact of islanding on the scheduling strategy under the same SOR, the simulation results from Policy I and Policy II are compared. In Policy I, there is no expected islanding for the scheduling period, while in policy II, an islanding event is considered. It can be observed that compared to Policy I, Policy II has a higher operation cost under the same SOR level, since expensive dispatchable units within the microgrid have to be deployed by the MGO to prepare the microgrid's internal reserve to handle the potential islanding.

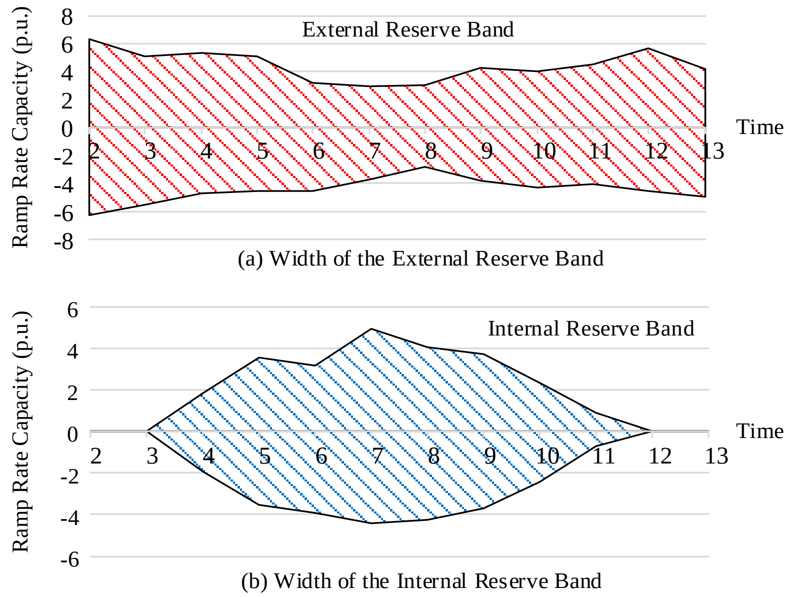

Figure 4. 7 Width of the External/Internal Reserve Band for Policy II

The external and internal reserve band derived from Policy II is shown in Fig. 6 when SOR=0.3. As the figure depicts, the external reserve band starts to shrink, and the internal reserve band starts to appear at 3:00 am due to the uncertainty associated with islanding start time. This observation matches islanding rule II as described in Section II.C. While the islanding is expected at 5:00 am, it will most likely occur any time within the time span between 3:00 am to 7:00 am based on the scenario generation process described in Section III.B. Between 5:00 am to 8:00 am, the bandwidth of the internal reserve is kept at a high level as according to islanding rule III, the MGO is now fully relying on it to handle operation uncertainties. Conversely, only limited external reverse bandwidth needs to be retained during this time period as the MGO may lose access to the utility grid during this period of time caused by islanding. Due to the uncertainty associated with the duration of the islanding, between 8:00 am to 11:00 am, the internal reserve band becomes narrower as the islanding end time is approaching, and the MGO starts to switch back to the external reserve. As shown in Fig. 6 (b), the internal reserve band completely disappears at 12:00 pm. It can also be observed that the external and internal reserve bands are not symmetrical in ramp-up and ramp-down capacity. For this experiment setting, the ramp-up reserve is always greater because the penalty associated with load shedding is commonly higher than power curtailment (see Table. IV in the Appendix). Another noticeable difference between Policy I and II is that, despite the increased operation cost, Policy II tends to result in higher load shedding and power curtailment. This suggests that although the internal reserve provided by dispatchable units helps mitigate the power mismatch during islanding, the microgrid still faces higher operational risk due to the loss of support from the utility grid.

Policy II can also be compared with Policy III where a market-based penalty price is adopted which has a similar trend as the fluctuation of market price (see Table. VII in the Appendix). It can be clearly observed that Policy III has significant higher load shedding and power curtailment with a slight decrease in total cost. This effect can be traced back to the penalty price during the expected islanding event. Since such event is expected to occur during non-peak hours during which the penalty prices are low, the MGO tends to take higher risk and accept penalty for cost-benefit consideration under this market configuration, which directly results in the high amount of power curtailment and load shedding. This motivates us to conduct more experiments to evaluate the positive and negative influence of prices, including penalty price and reserve price, on power curtailment and load shedding. It is found out that as a general trend, an increased penalty price can help reduce load shedding and power curtailment, but the effects are not significant. Similarly, results from the reserve price experiments show that a reduced reserve price has slightly positive effects on reducing load shedding and power curtailment, to a certain degree. This indicates that for a given SOR, while an increased penalty price/a reduced reserve price encourages the MGO to purchase more reserve, this effect is limited. On the contrary, if a reduced penalty price is available, the MGO is more inclined to procure less reserve and thus takes more risk of load shedding and power curtailment.

A noticeable case is presented in Policy IV in which the maximum allowable external reserve bandwidth is changed from 7 MW to 8 MW. The results shown in Fig.4 indicate that the operational cost rises drastically with considerably decreased load shedding and power curtailment. This matches our discussion in Section II.B that a wider bandwidth allows the MGO to purchase a higher amount of reserve to improve the microgrid operation at a cost. Compare Policy IV to Policy II and III, it can be observed that maximum allowable reserve bandwidth, rather than the costs of reserve and penalty, is the main factor that impacts the microgrid's stability performance in terms of load shedding and power curtailment.

4.4.2 Islanding Policy Study

In the previous study, it is concluded that islanding events have a large impact on the scheduling results. In this section, the previous study is further expanded, and a more in-depth analysis is performed that is focused on evaluating the effects of islanding events. The following different expected islanding start time are tested:

Policy I: Islanding is expected at start at 5:00 am,

Policy II: Islanding is expected at start at 10:00 am,

Policy III: Islanding is expected at start at 16:00 pm.

The expected start time indicate that the islanding event is expected to happen during non-peak hours (5am) for Policy I, peak hours (16:00pm) for Policy II, and in between (10:00am) for Policy III. The expected islanding duration for these three policies are set identical (three hours). The results are presented in Fig. 7 which include total cost (a), load shedding (b), and power curtailment (c). In terms of total cost, Policy III has the highest cost, while Policy I has the lowest cost, with Policy II in the middle. This indicates that islanding during peak hours will lead to a higher operational cost because of the increased marginal cost to use dispatchable units within the microgrid. The reserve preparation also negatively affects the microgrid's power capacity to supply loads. This is especially evident for islanding during peak hours when the dispatchable units are scarcer.

Fig. 7 also shows one interesting finding in (b) and (c): the load shedding and power curtailment for islanding events occurring during the peak hours are lower than that during non-peak hours. Intuitively, the higher marginal cost to prepare reserve during the peak hour will result in a higher load shedding and power curtailment. However, it can be further investigated that despite the higher marginal cost, the amount of reserve that can be acquired during peak hours is also higher because all the dispatchable units have already been turned on. As a result, the MGO can dispatch more capacity to provide reserve since the startup cost of those dispatchable units has already been covered before the anticipated islanding starts.

The policy studies conducted in this section confirm the effectiveness of the proposed microgrid scheduling which matches previous analysis in Section II. More policy studies can be performed under our framework such as the influence of energy storage system and renewable energy profile.

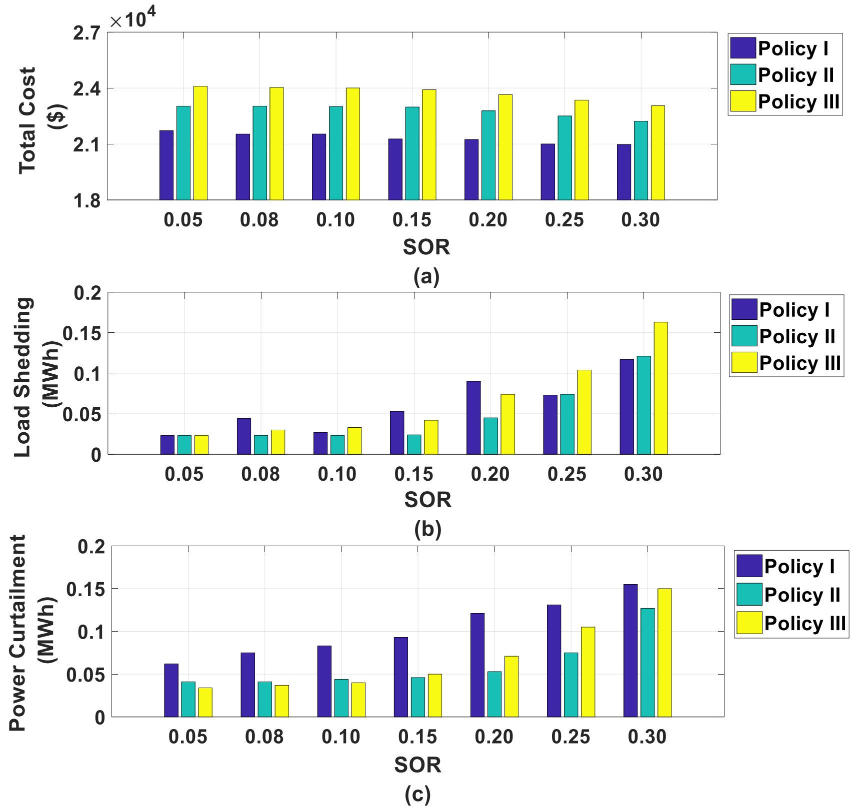

Figure 4. 8 Results of different islanding start time under different SORs

4.4 Conclusion

This chapter aims to bridge the current technological gaps within microgrid operation scheduling in a joint energy and ancillary services market environment with the consideration of operation uncertainties. Based on the existing concept of energy and ancillary services co-optimization, a novel two-stage microgrid scheduling approach is proposed based on CCP to allow the MGO to determine the optimal reserve preparation strategy to optimize the operational cost, increase the system efficiency while reducing the risk of system instability. Compared with previous works in the field, the proposed scheduling strategy offers a true end-to-end solution as it specifically covers all states of microgrid operation especially around operation mode switching and clearly identifies the responsible parties for reserve provision as well as the amount to prepare. This is critical for microgrid scheduling as it gives the MGO sufficient capability as well as internal/external resources to handle deviations caused by uncertainties associated with forecast error and operation mode switching in real-time at the lowest cost, and thus ensures efficient, economic and reliable microgrid operation. Simulation-based policy studies are conducted based on different aspects of microgrid operation including SOR levels, price setting, capacity setting, and expected islanding event to demonstrate the effectiveness of the proposed scheduling strategy in a joint market environment.

As an extension to our work, one can address the effects of two simplifications adopted in the proposed scheduling strategy through the derivation of detailed primary/secondary control strategy to enable the provision of frequency control reserve under our proposed scheduling framework. The effects of energy storage devices can also be systematically investigated. Energy storage devices such as batteries and super capacitors have insignificant direct cost for generation and start-up/shut-down compared with conventional dispatchable units, which makes them more flexible and efficient in storing and providing reserve capacities.

Chapter 5 Optimal Scheduling of Microgrids Participating in Co-optimized Transactive Distribution Electricity Markets

5.1 Introduction

Microgrids are no longer a concept [178], but rather an increasing common feature of the evolving electric grid in the face of rising electricity demands, increasing concerns over extreme natural disasters and vulnerability, and other widespread system security and reliability issues [152]. Microgrids represent a suite of smart technologies that feature distributed resources and generation [179], demand-side response and efficiency [43], energy cost reduction, and improved reliability and resiliency [13], all to facilitate the current revolution that the power and energy section is undergoing.

As the underlying technologies have become more advanced, microgrids equipped with advanced operation and control technics can flexibly ramp up or down their demand [86]. Experts see a future where microgrids provide a variety of grid services, such as frequency regulation, spinning/non-spinning reserves, capacity market, and black start [180], all of which can be used as a grid resource to maximize the economic viability of microgrid adoption and help offset the investment and maintenance cost that comes with the establishment of a microgrid [171], [181], [182]. As microgrids are tapped into the distribution system through the point of common coupling (PCC), it is obvious that the coordination between multiple networked microgrids and the distribution system need to be taken into consideration to simultaneously optimize the operation of a microgrid and the distribution system [183]. Such coordination include the transactive interactions between the microgrid operators (MGO), the distribution system operator (DSO), the bulk power systems, as well as other distributed energy resources (DERs), prosumers, and net consumers (i.e., loads) in the distribution system. A consensus has to be reached between all participants regarding the type of grid services that the microgrid is aiming to provide and the market mechanism and price policy of the distribution electricity market [16], [41], [47]. This clearly suggested that the DSO construct needs to expand its conventional operational role to facilitate the utilization of grid-edge resources and enable transactive exchanges that are economically beneficial to the MGOs, the DSO, and other participants in the distribution/retail market through an optimal coordination strategy [124]. Furthermore, the transactive commodities should not be limited to energy. Energy derivatives, e.g. ancillary services, also needs to be incorporated into this transactive paradigm as a small but vital part of the energy markets to balance the fluctuations in electricity generation and demand and maintain system stability.

Despite the apparent benefits, the management of such a multi-ownership market is also overwhelmingly difficult. On one hand, with the decentralization, more self-management right and market power are given to each participant to ensure consumer choice. On the other hand, the transactive DSO needs to carefully align the value streams for all market participants and coordinate their direct and indirect transactions of energy at a local level, while assuring the distribution system is operated safely, reliably, and economically. An effective operation of this model is crucial for fostering a healthy, transparent, competitive, and sustainable DSO-facilitated localized market.

While the existing scheduling algorithms for transactive distribution markets [184]–[186] offer insights into the operation of such a transactive distribution system, two important challenges remain [16], [187]–[189]. The first issue lies in the fact that the transactive schemes studied in the existing literature primarily focus on the energy exchange between participants. The transactive exchange of ancillary service in the distribution market, as an important grid-supporting function, has not been adequately explored. For instance, in [187], a coordinated distribution system energy management scheme was proposed considering only the energy exchange within the distribution grid with networked microgrids. In [190], a transactive mechanism is proposed for distribution system, in which the microgrid participates as a prosumer to evaluate its profit in the energy-only market. This limitation has greatly restrained the functionality, stability, and profitability of both the transactive market and decentralized distribution system. Thus, an increased amount of local operational flexibility at a reasonable cost is required to accommodate the variability and unpredictability of renewable generation and responsive loads as well as support stable operation. Given the limited capacity of the distribution system, distributed assets within the microgrids, such as DERs, responsive loads, electrical and thermal storages, and EV chargers, would provide valuable, local ancillary services through the adjustment of its power demand and output rather than a reliance on the centralized bulk power grid[191] [192]. Therefore, a sound transactive market design calls for innovative and improve joint distribution system management (DSM) schemes that include the transactive exchange of both energy and ancillary services simultaneously, especially when the microgrid penetration is high in the distribution network.

Another challenge of developing the scheduling algorithm for a transactive distribution system market lies in the regulatory provisions. While the *electric* boundary between the microgrid and the distribution system is clearly located at the PCC, the *management* boundary can be intertwined for the MGO and the DSO as two entities, especially with the incorporation of ancillary services. Despite its limited capacity, the transactive market mechanism enables the MGOs to join the competitive markets with ever-increasing barging space and operation *autonomy*. The ancillary services, primarily driven by opportunity cost, further provide microgrids more market power. However, some of the existing literature treated microgrids as <u>DSO-owned</u> energy storage resources for the provision of ancillary services in order to support the operation of the distribution system [170], [191], [193]. Under this management hierarchy, each microgrid acts as an involuntary provider of ancillary services. This assumption is highly problematic for a transactive market environment because each microgrid has its own self-interests, operational requirements, and economic incentives. Such a distributed intelligent autonomy cannot be simplified as an ESR. In [194], the microgrid is modeled as a <u>passive recipient</u> of ancillary services from the DSO, which suggests that the ancillary service can only flow unidirectionally from the distribution system to the microgrid. However, limiting the export capacity of the internally generated microgrid ancillary service can be an extravagant decision, as it holds the limited microgrid-owned distributed generator (DG) capacity as a standby that may or may not be consumed, thus lowering the system-wide energy efficiency. It is thus clear that the division of responsibility in such a transactive market has to be further explored with the incorporation of ancillary service and active engagement of microgrids as prosumers [189]. The DSM has to account for the conflict of interests between the exchanging of the limited capacity and the mutual benefits enabled by proactive collaborations among multiple MGOs and the DSO, as separate entities, transparently and competitively.

Based on the discussion set forth above, it is clear that the current DSM strategies have greatly limited the role that microgrids can play in the transactive distribution system market. To tackle this challenge, in this chapter, we propose a novel DSM algorithm that incorporates bi-directional energy and ancillary service flow in a transactive market environment. We formulate the optimal scheduling problem as a bilevel programming model, in which the upper level represents the DSO problem and lower level represents the MGOs' reactions to the DSO schedule. The proposed bilevel model is then converted into a mixed-integer programming (MIP) model through relaxing mathematical programming with equilibrium constraints (MPEC) [97]. The final MIP model gives a global optimal solution and reduces computational burden [102]. Note that while the microgrid is capable of supplying multiple categories of grid-supporting services, in this chapter, we focus on the *frequency regulation* as an example of market-based product of ancillary services. Frequency regulation, or simply put, *regulation*, has historically been a standard tradable product in the wholesale markets. The regulation service smooths out the instantaneous system frequency variations and provides quick responses to maintain system stability.

The contributions of this chapter are be summarized as follows:

1. This work explores the transactive DSM with the joint optimization of bidirectional energy and ancillary service exchange to expand the conventional operational domain of the DSO and fully enable and facilitate the grid-edge resources within the microgrids.

2. A novel stochastic bi-level programming model is presented to optimally manage the interactions among the DSO, the MGOs, and other participants under operational uncertainties. The proposed management strategy leverages the distributed market power and resource adequacy of each market participant while maintaining the reliable and efficient operation and integrity of the distribution grid.

3. The simulation results reveal the advantages of incorporating a joint-optimized scheduling algorithm with full microgrid autonomies, based on the comparisons with conventional approaches unidirectional interactions.

The remainder of this chapter is organized as follows. Section II presents the distribution system management strategy outline and assumptions. Section III formulated bi-level stochastic programming problem and solving algorithm. The model is test and compare with traditional transactive market design in Section IV. Relevant conclusions are discussed in Section V

5.2 Outline and Assumptions

5.2.1 Joint Market Environment

The transactive distribution system considered in this chapter involves two levels as shown in Figure 5.1: a distribution system level and a microgrid level. On the MG level, the MGO is in charge of optimally scheduling MG-owned assets. On the DS level, the DSO manages interactions between the DS and its participants including network operation (i.e., power and ancillary service flows) and market operation (i.e., market regulation).

Under this market structure, it is clear that the utility-managed DSO provides competitive access to markets and manages market responsibility of different participants on distribution networks. It also acts as the intermedium to provide reliable and secure DS operations by integrating the high penetration levels of DERs, hybrid resources, and MGs to the bulk power markets. On the other hand, the microgrid with the independent operator has autonomy to manage its own power management and transactive trading (i.e., purchasing and selling) of both power and ancillary services in response to distribution system operation states and market price signals which leverage the MGs' transactive capabilities in the distributed electricity market. As a result, it can help the distribution system operator reduce the decision burden and network complexity in a competitive market environment. However, the visibility that MGs can provide to DSO can be very limited due to the internal control and management structure of the microgrids. Therefore, the optimal power management of DSO has to take this factor into account, which prevents DSO from having full situation awareness of the entire market transactions and operations.

This limitation further suggests that in the envisioned transactive market environment, the construct of DSO plays a more consultative role in the market operation. Such a role includes providing market information such as price and congestion, helping market participants to match their demand and response, and processing the transactions. The distribution system constraints only include the location and physical capacity of connected DERs or MGs at the point of their connection, regardless of operation mode or internal scheduling decisions. One benefit of this solution is the decision burden on the DSO will be largely reduced through utilization of MGO. As a result, the overall decision efficiency is improved.

This transactive management structure motivates us to use Stackelberg game [195] to describe the interactions between the DSO and multiple MGOs. In this hierarchy, the DSO, as the leader, provides market information and exercises the rights to adjust, balance, and finalize the transactions among all transactive agents. The objective of the DSO is thus to minimize the market clearing cost for all the market participants. The MGOs, as followers, respond to the market price signals and actions of leader to make their individual scheduling decisions with the objective to minimize its operation cost. This hierarchy can be naturally modeled by a bi-level programming approach.

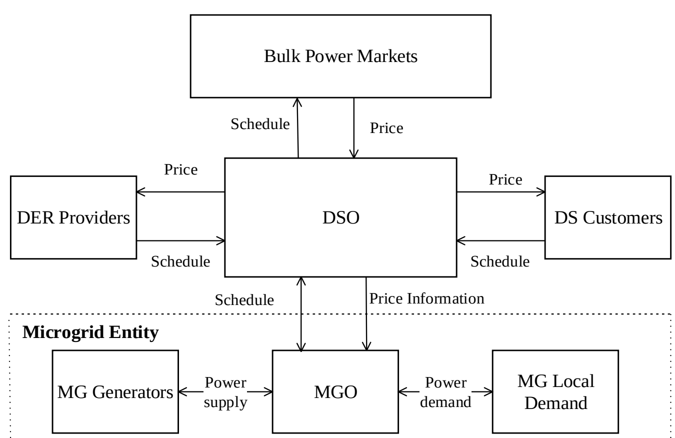

Figure 5. 1 Transactive Distribution System Management

5.2.2 Current Practice

The provision of ancillary service in one-directional fashion is suggested to be realistic in the DSO management. In [194],a co-optimization schemes for MG to use ancillary service from DS was presented. In [27], [42], [170], [191], [193], [194], the ancillary service is allowed to transfer from MG to support DS. The drawbacks of one-directional AS transfer approaches are: 1) cannot fully utilize the MG/DS reserve. No matter which direction that is allowed, one entity is assumed to be play only the supply role or demand role. However, since the MG is considered as prosumer in the distribution system, two-directional flow should be equipped with ancillary service transfer; 2) not fit the transactive energy management environment. In the transactive energy management scheme, the distribution system and MG are assumed to be separated entities. Such relationship is different with DS and DGs in a way that MGO and DSO have conflict of interest in sharing the limited capacity. One's contribution to other will result in a loss for itself. So there is need to consider bi-directional for both power and ancillary service which can provide a more flexible and efficient management scheme.

5.2.3 Our Approach

Compared with existing research efforts, we consider a market environment that incorporates the co-optimized bidirectional exchanges of energy and regulation between the DSO and the MGOs, simultaneously. Then, we propose a new transactive DSM scheme based on this extension for the DSO to strike the balance between decentralized market power and system-wide welfare, such as reliability and economy.

Due to the enabling of both bidirectional energy and ancillary service transfer, the microgrids can import and export both resources freely. For the ancillary service we focus on in this chapter, regulation falls into two categories of services, signified as regulation up or regulation down. Regulation up/down represents the ability to increase/decrease power output to balance supply and demand. This indicates that a total of five types of resources are traded under this framework. In addition to the bidirectional energy transactions, the transactions of regulation include four components: importing regulation up, importing regulation down, exporting regulation up, and exporting regulation down. We propose the following three rules to define the exchange of these resources based on their specific physical characteristics, while in accordance with the transactive energy management mechanism:

Rule 1: Energy is a homogeneous commodity in the electricity market, while the regulation services are non-homogeneous. This is evident due to the fact that the physical processes of generating regulation up and regulation down are different. As a result, the cost functions of regulation up/down are set differently for importing and exporting.

Rule 2: Under the proposed transactive management scheme, the MGOs and the DSO are independent operation entities with decoupled power balance constraints, therefore their only point of connection is established at the PCC. This indicates that the regulation up/down services can be treated as limited locational capability commodities. For example, when one unit of regulation up is exported (i.e., sold) from the MGO to the DSO, the capability of the microgrid to ramp up is reduced (1) for the MGO. However, from the DSO's perspective, when it imports (i.e., buys) one unit of "regulation up" service from the MGO. The physical "delivery" of this service has to be provided by the PCC, and thus this unit of "regulation up" has to be enforced by lowering one unit of the ramp down capability at this node (2). This process is depicted in Fig. 5.2. The microgrid internal power balance (5.1) and distribution system power balance (5.2) are described as:

$$P_{MG} = L_{MG} + P_{PCC} + \Delta R_{PCC} \tag{5.1}$$

$$\text{and } P_{PCC} + \Delta R_{PCC} + P_{DS} = L_{DS} \ , \tag{5.2}$$

where the reserve means different in different entities.

Rule 3: The exchange of energy and regulation share the line capacity of PCC. This rule is defined based on the fact that despite their differences, both energy and regulation have to be physically transferred in the form of active power.

All the transaction rules are used to demonstrate the changes have to be made when the bi-directional energy and ancillary service flow is introduced.

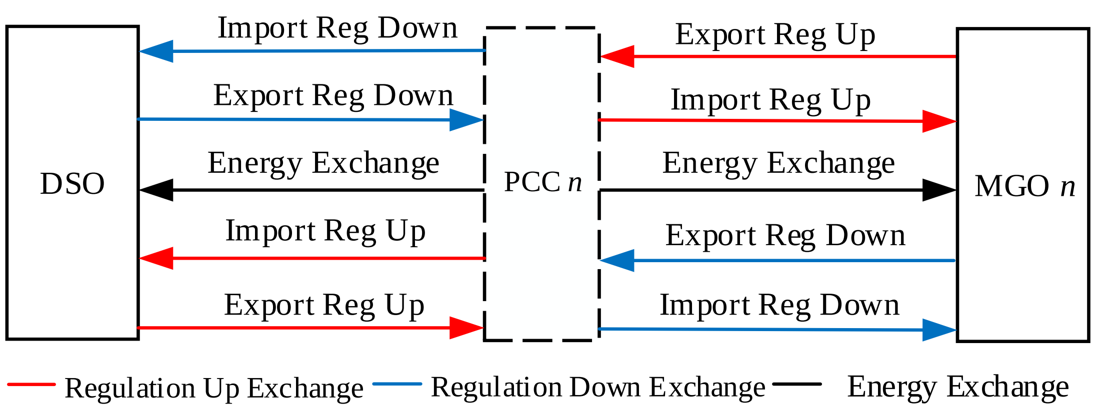

Figure 5. 2 Transactive Interaction between Microgrids and Distribution System

5.2.3 Assumptions

In this work, the following assumptions are adopted: each microgrids is modeled as an aggregated model without considering its internal network due to its limited geographical layout. The distribution system network is modeled with AC distribution load flow [148]. We consider two categories of DGs in the system: dispatchable DGs such as diesel/natural gas generators, and non-dispatchable units such as wind turbines and solar PV panels. We assume that the non-dispatchable units only exist in microgrids for effective energy management, while both the MGO and the DSO have dispatchable units which are equipped with fast-ramping capabilities that can provide both energy and regulation.

5.3 Model and Method

The problem is formulated as bi-level programming model, in which the upper level is the DSO management problem and the lower level is the microgrid scheduling problem.

The following notation is used in developing the two-stage stochastic model.

Indices

b	The node subscript index in the distribution system (DS), $b \in B$
j	Microgrid (MG) subscript index connected with DS, $j \in J$
l	Consumer subscript index in DS, $l \in L$
m	Utility node subscript index connected with DS, $m \in M$
n	Distributed generator (DG) subscript index in DS, $n \in N$
k	DG subscript index in microgrid j, $k \in K_j$
s	Scenario subscript index
t	Index for time periods, $t \in T$

Parameters

$C^{ls/pc}$	Value of Load shedding/ power curtailment
$K_{(.)}$	Incidence matrix
$P_n^{g,\min/\max}$	Max/min DG in DS power output capacity
$P_j^{\mathrm{m,max}}$	Max/min MG in DS power output capacity
P_t^{re}	Forecasted Renewable energy output
$P_{\mathrm{m}}^{u,\max}$	Max/min utility real power output capacity
$P_k^{\mathrm{w,min/max}}$	Max/min DG in MG power output capacity
$R_n^{g,up/dw,\min/\max}$	Max/min DG in DS reserve output capacity
$R_k^{\mathrm{w,up/dw,min/max}}$	Max/min DG in MG reserve output capacity
$R_j^{\alpha,up/dw,\min/\max}$	Max/min from DS to MG reserve transfer capacity
$R_j^{\beta,up/dw,\min/\max}$	Max/min from MG to DS reserve transfer capacity
S	Total number of scenarios

SD_i / SU_i	Shut down/ startup cost of dispatchable generation unit *i*
T_i^{off} / T_i^{on}	Minimum off/on time of dispatchable generation unit *i*
T_k	Maximum full capacity running time for DG in MG
$X_{i,t}^{off/on}$	Off/on time of dispatchable generation unit *i* at time *t*
$\Delta P_{bts}^{l} / \Delta P_{jts}^{re}$	Load/renewable energy forecast deviations

Sets

J	MG set $J = \{1,..,NM\}$, NM is number of MG
K_j	Generation unit set $K_j = \{1_j,..,NDG_j\}$ in *j-th* MG, NDG_j is number of generation units
L	Consumer set in DS $L = \{1,..,NL\}$, NL is number of load in DS
M	Utility set in DS M={1}
N	DG in DS set $N = \{1,..,ND\}$, ND is number of distributed generation units in DS
T	Time period set $T = \{1,..,NT\}$, NT is number of time

Variables

$b_{n,t}$	Binary variable associated with dispatchable unit *i* at time *t*
$l_{b,s,t}^{sh}$ / $q_{b,s,t}^{cu}$	Load shedding/ power curtailment value at time *t* in scenario *s*
$p_{j,t}^{m}$	Power exchange at PCC at time *t*
$p_{n,t}^{g}$	Dispatchable generation units output *n* at time *t*
p_{lt}^{l}	Controllable load *l* at time *t*
$p_{m,t}^{u}$	Utility power output *m* at time *t*
$x_{i,t}$ / $y_{i,t}$	Startup/Shutdown indicator for DG unit *i* at time *t* in the DS
$r_{n,t}^{g,up/dw}$	Ramp down/up reserve provided by DG unit *n* at time *t*
$r_{j,t}^{m.up/dw,\alpha}$	Regulation up/down transfer from DS to MG *j* at time *t*
$r_{j,t}^{m,up/dw,\beta}$	Regulation up/down transferred from MG *j* to DS at time *t*
$r_{j,t}^{c,up/dw,buy/sell}$	Regulation up/down buy/sell for MG *j* to DS at time *t*
$r_{k,t}^{w,up}$	Ramp down/up provided by DG *k* in MG at time *t* in scenario *s*

τ	Second stage decision variables associated with DG n and MG j
σ	Second stage decision variables associated with DG in Microgrid
υ	Second stage decision variables associated with MG at PCC
Δp_{jts}^{m}	Power deviation at the point of common coupling

5.3.1 DSO Management Problem

In the upper level of the problem formulation, the DSO is in charge of market clearing and management of the distribution system. There are four market participants in the system: microgrids, individual distributed energy resources, the upstream system, and customers (loads). Specifically, the DGs are dispatchable units that can provide both energy and regulation, and the upstream system can only provide energy. The objective function of DSO management model is then to minimize the market clearing cost for all of the aforementioned market participants as:

$$\begin{aligned}
&\min \sum_{t}\sum_{n}(c_n^g(p_{nt}^g) + x_{n,t}SU_n + y_{n,t}SD_n + c_n^r(r_{nt}^{up}, r_{nt}^{down})) \\
&+\sum_{t}\sum_{m}\rho_t^c(p_{mt}^u) \\
&+\sum_{t}(\sum_{j}\rho_t^c(p_{jt}^c) + \sum_{j}\rho_t^{r,up}(r_{jt}^{m.up,\alpha}, r_{jt}^{m,up,\beta}) - \sum_{j}\rho_t^{r,dw}(r_{jt}^{m,dw,\alpha}, r_{jt}^{m,dw,\beta})) \cdot \\
&+\sum_{s}\sum_{t}\sum_{b}\frac{1}{S}(C_t^{ls}\cdot LS_{bst} + C_t^{pc}\cdot PC_{bst})
\end{aligned} \tag{5.3}$$

The first term of (5.3) represents the operation cost of DSO-owned DGs, including the cost of energy generation, the regulation provisions. The second term of (5.3) represents the cost of energy interactions with the upstream system. The third term of (5.3) captures the cost of interactions between microgrids and the DSO, including the interaction cost of energy, regulation up, and regulation down. Since energy and regulation are both bidirectional, the DSO can import or export energy/ancillary service from and to microgrids, respectively. Therefore, the operation cost of interacting with microgrids can be positive or negative. The management effects are evaluated through the combined average penalty cost of load shedding and power curtailment in the fourth term of (3) over all scenarios. Note that in (5.3), c_i^g / c_i^r denote the cost function of the energy and regulation generation of DG unit *i*, respectively. ρ_t^c / ρ_t^r denote the market price function of energy and regulation at different time slot *t*, respectively. For simplicity, all the cost functions $c_i^{g/r}$ and $\rho_t^{c/r}$ are defined as linear functions in this chapter.

The power transfer is bidirectional and thus can be positive or negative (5.4). Four constraints are defined to represent the regulation interactions between the microgrid and the distribution system (5.5)-(5.10): exporting from distribution system to microgrid (denote as α) and importing from microgrid to distribution system (denote as β). For each type of regulation, import or export action is only allowed in one direction at one time slot (5.9) (5.10):

$$P_j^{\mathrm{m,min}} \le p_{jt}^m \le P_j^{\mathrm{m,max}} \ , \forall j \in J, \forall t \in T \ , \tag{5.4}$$

$$0 \le r_{jt}^{m.\alpha,up} \le R_j^{\alpha,up,\max} \ , \forall j \in J, \forall t \in T \ , \tag{5.5}$$

$$0 \le r_{jt}^{m,\beta,up} \le R_j^{\beta,up,\max} \ , \forall j \in J, \forall t \in T \ , \tag{5.6}$$

$$0 \le r_{jt}^{m,\alpha,dw} \le R_j^{\alpha,dw,\max} \ , \forall j \in J, \forall t \in T \ , \tag{5.7}$$

$$0 \le r_{jt}^{m,\beta,dw} \le R_j^{\beta,dw,\max} \ , \forall j \in J, \forall t \in T \ , \tag{5.8}$$

$$I_{jt}^{\alpha,dw} + I_j^{\beta,dw} \le 1 \, , \forall j \in J, \forall t \in T \ , \tag{5.9}$$

$$\text{and}\, I_{jt}^{\alpha,up} + I_{jt}^{\beta,up} \le 1\,, \forall j \in J, \forall t \in T \quad . \tag{5.10}$$

At the point of PCC, the net ancillary service which DSO can acquire from each microgrid can be calculated based on interaction quantity difference, which is purchase quantity minus the sell quantity (5.11) (5.12):

$$r_{jt}^{m,up} = r_{jt}^{m,up,\beta} - r_{jt}^{m.up,\alpha} \;\; \forall j \in J, \forall t \in T \tag{5.11}$$

$$\text{and } \; r_{jt}^{m,dw} = r_{jt}^{m,dw,\beta} - r_{jt}^{m,dw,\alpha} \;\; \forall j \in J, \forall t \in T \quad . \tag{5.12}$$

The power transfer and ancillary transfer between DG and MGs are both realized through the PCC. The physical limit of power transmission line at PCC determine the maximum power transfer between MG and DS cannot exceed certain level. The ancillary service flow direction worth careful examination here: if the default power flow direct the from MG to DS, the regulation up reserve transfer from MG to DS is positive, regulation down reserve from MG to DS is negative, vice versa:

$$p_{jt}^{m} + r_{jt}^{m,up,\beta} + r_{jt}^{m,dw,\alpha} \le P_{j}^{\mathrm{m,max}} \;\; \forall j \in J, \forall t \in T \tag{5.13}$$

$$\text{and } \; p_{jt}^{m} - r_{jt}^{m,dw,\beta} - r_{jt}^{m.up,\alpha} \ge P_{j}^{\mathrm{m,min}} \;\; \forall j \in J, \forall t \in T \quad . \tag{5.14}$$

There are some DGs in the distribution system as well as microgrids. Since all of them are assumed to be dispatchable units, the mix-integer model constraints are applied to represent their features:

The real power output of DG has upper bound and lower bound (5.15) as:

$$b_{nt} P_{n}^{g,\max} \le p_{nt}^{g} \le b_{nt} P_{n}^{g,\min} \;\; \forall n \in D, \forall t \in T \quad . \tag{5.15}$$

There are minimum uptime (5.16) restrictions, and minimum downtime restrictions (5.17) for each DG as:

$$(X_{nt}^{on} - T_n^{on}) * (b_{n(t-1)} - b_{nt}) \geq 0 \ \forall n \in D, \forall t \in T \tag{5.16}$$

and $$(X_{n(t-1)}^{off} - T_n^{off}) * (b_{nt} - b_{n(t-1)}) \geq 0 \ \forall n \in D, \forall t \in T \ . \tag{5.17}$$

The dispatchable DG units can also provide regulation up (5.18) and regulation down (5.19) ancillary service to DS as:

$$0 \leq r_{nt}^{g,up} \leq R_n^{g,up,\max} b_{nt} \ \ \forall n \in D, \forall t \in T \tag{5.18}$$

and $$0 \leq r_{nt}^{g,dw} \leq R_n^{g,dw,\max} b_{nt} \ \ \forall n \in D, \forall t \in T \ . \tag{5.19}$$

The output of real power and regulation ancillary service combined cannot exceed the physical capacity of each DG (5.20) (5.21):

$$p_{nt}^{g} + r_{nt}^{up,g} \leq P_n^{g,\max} \ \ \forall n \in D, \forall t \in T \tag{5.20}$$

and $$p_{nt}^{g} - r_{nt}^{dw,g} \geq P_n^{g,\min} \ \ \forall n \in D, \forall t \in T \ . \tag{5.21}$$

The ramp up (5.22) and ramp down (5.23) capability of DG is determined by both power ramp up/down and ancillary services usage:

$$p_{nt}^{g} p_{nt}^{g} - p_{n(t-1)}^{g} + r_{nt}^{g,up} \leq (2 - b_{n(t-1)} - b_{nt}) P_{nt}^{g,\min} + (1 + b_{n(t-1)} - b_{nt}) RU_n \ \ \forall n \in D, \forall t \in T, \tag{5.22}$$

and $$p_{n(t-1)}^{g} - p_{nt}^{g} - r_{nt}^{g,dw} \leq (2 - b_{n(t-1)} - b_{nt}) P_{nt}^{g,\min} + (1 - b_{n(t-1)} + b_{nt}) RD_n \ \ \ \forall n \in D, \forall t \in T. \tag{5.23}$$

The distribution system is connected with upstream high-voltage system (5.24):

$$P_m^{u,\min} \leq p_{mt}^{u} \leq P_m^{u,\max} \ \ \forall t \in T, \forall m \in M \ \ . \tag{5.24}$$

The loads in the distribution system are assumed controllable and can vary within a range of 5% of the expected value as defined in:

$$P_l^{l,\min} \le p_{lt}^l \le P_l^{l,\max} \quad \forall l \in L, \forall t \in T \quad . \tag{5.25}$$

In this work, we are adopt *DistFlow* equations that can be used to describe the complex power flows at each node for DS. In this work, we only consider the real power flow. Equation (5.26) illustrate the power injection at each node, Equation (5.27) is the real power balance equations at each node:

$$P_{bt}^{inj} = K_n(P_{nt}) + K_j(P_{jt}) + K_u P_t^u - K_l P_{lt} \quad \forall b \in B, \forall t \in T \tag{5.26}$$

and $$P_{(b+1)t} = P_{bt} - P_{bt}^{inj} \quad \forall b \in B, \forall t \in T \quad . \tag{5.27}$$

In this work, we extend the real power flow equations (5.26) (5.27) to reserve flow equations (5.28)-(5.31) as the ramp up/down reserves are essentially the same as real power. Similarly, there are node injection equations for ramp up (5.28) and ramp down (5.29) and reserve balance equations at each node (5.30) (5.31). It is noted that the ramp down reserve direction is the opposite of default power flow direction. Two negatives make a positive, as a result, the ramp down equations look as same as ramp up reserve equations:

$$R_{bt}^{up,inj} = K_n(R_{nt}) + K_j(R_{jt}) - K_l R_{lt}^{up} \quad \forall b \in B, \forall t \in T \quad , \tag{5.28}$$

$$R_{(b+1)t}^{up} = R_{bt}^{up} - R_{bt}^{up,inj} \quad \forall b \in B, \forall t \in T \quad , \tag{5.29}$$

$$R_{bt}^{dw,inj} = K_n(R_{nt}) + K_j(R_{jt}) - K_l R_{lt}^{dw} \quad \forall b \in B, \forall t \in T \quad , \tag{5.30}$$

and $$R_{(b+1)t}^{dw} = R_{bt}^{dw} - R_{bt}^{dw,inj} \quad , \forall b \in B, \forall t \in T \quad . \tag{5.31}$$

Reserve requirement at each node is determined by DS based on system requirements:

$$0 \le R_{lt}^{dw} \le R_{lt}^{dw,\max}, \forall l \in L, \forall t \in T \quad , \tag{5.32}$$

and $$0 \le R_{lt}^{up} \le R_{lt}^{up,\max}, \forall l \in L, \forall t \in T \quad . \tag{5.33}$$

All the interaction between MG and DS is realized through PCC. The microgrid and distribution system are two relative independent entities. As a result, the regulation up and regulation down at PCC is different than traditional DGs and DS. When a microgrid is transfer regulation up ancillary service to DS, it means that certain level of MG ramp up capacity is token from MG itself. As a result, the capability to ramp up balance MG's power balance is weaken, which strengthen the ramp down capability for microgrid itself. In perspective of microgrid, the action of transfer ancillary service to DS fit the definition of selling service, while same transfer for DS is purchase service from MG. So in this case, the counterpart of notation α/β for distribution system is buy/sell for microgrids:

$$r_{jt}^{m,up,\alpha} = r_{jt}^{\mathrm{c,dw,buy}} \ , \forall j \in J, \forall t \in T \ , \tag{5.34}$$

$$r_{jt}^{m,dw,\alpha} = r_{jt}^{\mathrm{c,up,buy}} \ , \forall j \in J, \forall t \in T \ , \tag{5.35}$$

$$r_{jt}^{m,up,\beta} = r_{jt}^{\mathrm{c,dw,sell}} \ , \forall j \in J, \forall t \in T \ , \tag{5.36}$$

$$\text{and } r_{jt}^{m,dw,\beta} = r_{jt}^{\mathrm{c,up,sell}} \ , \forall j \in J, \forall t \in T \ . \tag{5.37}$$

Within the distribution system, two categories of the uncertainties are considered. The first category of uncertainties is associated with the net consumers in the distribution electricity market. It is evident that their operational uncertainty is directly handled by the DSO. In the meanwhile, the second category of uncertainties come from the renewable sources within the microgrids. This requires the MGOs to procure sufficient amount of regulation service from their internal resources or the transactive market. However, the DSO, as the market operator, needs to ensure the reliability of the overall distribution system, including the microgrids. Therefore, any deviations at the PCCs need to be settled by the DSO. If not, load shedding or power curtailment will be penalized as follows:

$$\sum_n \tau_{nts}^{g,up} + \sum_j (\tau_{jts}^{m,up,\beta} - \tau_{jts}^{m,\mathrm{up},\alpha}) - (\sum_n \tau_{nts}^{g,\mathrm{dw}} + \sum_j (\tau_{jts}^{m,\mathrm{dw},\beta} - \tau_{jts}^{m,\mathrm{dw},\alpha}))$$
$$-q_{bst}^{cu} = \Delta P_{bts}^{l} - l_{bst}^{sh} + \sum_j \Delta p_{jts}^{m} \quad ,\forall t \in T, \forall s, \forall b \in B \quad . \tag{5.38}$$

The reserve used from DGs in DS can be adjusted in each scenario. The ready to use reserve can reach the quantity upper bound determined in the first stage:

$$0 \le \tau_{n,t,s}^{g,up} \le r_{n,t}^{g,up} \quad \forall n \in D, \forall t \in T \tag{5.39}$$

and $0 \le \tau_{n,t,s}^{\mathrm{dw},g} \le r_{n,t}^{g,dw} \quad \forall n \in D, \forall t \in T$. (5.40)

5.3.2 Microgrid Scheduling Problem

The lower level problem is a microgrid scheduling problem. Under management of the DSO, each MGO needs to schedule its internal generation sources and loads. The scheduling problem for microgrid *j* is described as follows:

The objective function of the lower level programming model is to minimize the operation cost which includes: 1) the operation cost of the microgrid's internal DGs to produce energy and regulation as described in the first term of (5.41); 2) the interaction cost between the microgrid and the distribution system resulted from the bidirectional exchange of energy (i.e., the second term of (5.41)) and regulation (i.e., the third term of (5.41)):

$$\min \sum_t \sum_k (c_k^w(p_{kt}^w) + c_k^r(r_{kt}^{up,w}, r_{kt}^{dw,w})) + \sum_t \rho_t^c(p_t^c)$$
$$+ \sum_t (\rho_t^{r,\mathrm{buy}}(r_t^{\mathrm{up,c,buy}}, r_t^{dw,c,buy}) - \rho_t^{r,sell}(r_{it}^{\mathrm{up,c,sell}}, r_t^{dw,c,sell})) \quad . \tag{5.41}$$

The DGs in the microgrid are assumed to be small size dispatchable generators and non-dispatchable renewable generators. For those dispatchable DG, the startup/shutdown cost is not considered. So, we use linear model to represent those DGs:

$$P_k^{\mathrm{w,min}} + r_{k,t}^{\mathrm{w,dw}} \le p_{k,t}^{w} \le P_k^{\mathrm{w,max}} - r_{k,t}^{w,up} \quad \forall k \in K, \forall t \ , \tag{5.42}$$

$$R_k^{\mathrm{w,up,min}} \le r_{k,t}^{w,up} \le R_k^{\mathrm{w,up,max}} \quad \forall k \in K, \forall t \ , \tag{5.43}$$

and $$R_k^{\mathrm{w,dw,min}} \le r_{k,t}^{\mathrm{w,dw}} \le R_k^{\mathrm{w,dw,max}} \quad \forall k \in K, \forall t \ . \tag{5.44}$$

The limited energy capacity of the DGs in each microgrid is enforced by (5.45)-(5.47), which indicates that the DG k cannot run at their full capacity beyond the time duration of T_k.:

$$\sum_{t}^{t+T} p_{kt}^{w} \le T_k p_k^{\mathrm{w,max}} \ , \forall k \in K, \forall t \in T \ , \tag{5.45}$$

$$\sum_{t}^{t+T} r_{kt}^{\mathrm{up},w} \le T_k R_k^{u,\max} \ , \forall k \in K, \forall t \in T \ , \tag{5.46}$$

and $$\sum_{t}^{t+T} r_{kt}^{\mathrm{dw},w} \le T_k R_k^{\mathrm{dw,max}} \ , \forall k \in K, \forall t \in T \ . \tag{5.47}$$

The MGO needs to maintain the internal power balance in each microgrid. The power generated through dispatchable units and renewable units is equal to load and PCC interaction:

$$\sum_{k} p_{k,t}^{w} + P_t^{re} = P_t^{l} + p_t^{c} \quad \forall t \in T \ . \tag{5.48}$$

The prepared reserve inside the microgrid ensure so that MGO is able to handle uncertainty associated with renewable unit output. The source of reserve can be acquired from itself or from the distribution system interaction:

$$\sum_k r_{kt}^{\mathrm{w,up}} + r_t^{\mathrm{c,up,buy}} - r_t^{\mathrm{c,up,sell}} \geq D_t^{up} \quad ,\forall t \in T \ , \tag{5.49}$$

and $$\sum_k r_{kt}^{\mathrm{w,dw}} + r_t^{\mathrm{c,dw,buy}} - r_t^{\mathrm{c,dw,sell}} \geq D_t^{dw} \quad ,\forall t \in T \ . \tag{5.50}$$

When the original scheduling plan is tested through generated scenarios which account for stochastic output of non-dispatchable units or load, the prepared reserve in mg will be used to handle the uncertainty. In the microgrid layer, there is no power curtailment and load shedding need to be considered, as the out of sample power deviation will be transferred by PCC which will be handled in the DSO layer:

$$\Delta P_{jts}^{re} + \sum_k \sigma_{kts}^{w\mathrm{up}} + \upsilon_{jts}^{\mathrm{c,up,buy}} - \upsilon_{jts}^{\mathrm{c,up,sell}} - (\sum_k \sigma_{kts}^{w,\mathrm{dw}} + \upsilon_{jt}^{\mathrm{c,dw,buy}} - \upsilon_{jt}^{\mathrm{c,dw,sell}}) = \Delta p_{jts}^{m} \quad ,\forall j \in J, \forall t \in T, \forall s$$

. (5.51)

The microgrid relies on its DGs (5.47) (5.48) and transactive reserve (5.50)-(5.54) to adjust the power balance:

$$0 \leq \sigma_{k,t,s}^{up,\mathrm{w}} \leq r_{k,t}^{up,\mathrm{w}} \quad \forall k \in K, \forall t \ , \tag{5.50}$$

$$0 \leq \sigma_{k,t,s}^{\mathrm{dw,w}} \leq r_{k,t}^{dw,\mathrm{w}} \quad \forall k \in K, \forall t \ , \tag{5.51}$$

$$0 \leq \tau_{k,t,sk}^{m,up,\beta} \leq r_{k,t}^{\mathrm{up},m,\beta} \ \ \forall i \in K, \forall t \ , \tag{5.52}$$

$$0 \leq \tau_{k,t,s}^{\mathrm{m,dw},\beta} \leq r_{k,t}^{\mathrm{dw},m,\beta} \ \ \forall i \in K, \forall t \ , \tag{5.53}$$

$$0 \leq \tau_{i,t,s}^{\mathrm{up},m,\alpha} \leq r_{i,t}^{\mathrm{up},m,\alpha} \ \ \forall i \in K, \forall t \ , \tag{5.54}$$

and $$0 \leq \tau_{k,t,s}^{\mathrm{dw},m,\alpha} \leq r_{k,t}^{\mathrm{dw},m,\alpha} \ \ \forall k \in K, \forall t \ . \tag{5.55}$$

5.3.3 Solution

The KKT optimality conditions for LLPM are constructed as follows:

$$c_k^{w} - \mu_{kt}^{\mathrm{p\,min}} + \mu_{kt}^{\mathrm{p\,max}} - \lambda_t^{P} + \sum_{\mathrm{t}}^{t+T} \pi_{kt}^{p} - \lambda_{ts}^{se} = 0 \ \forall k \in K, \forall t, \forall s \ , \tag{5.56}$$

$$c_k^{\mathrm{rup}} - \mu_{kt}^{\mathrm{r\,up\,min}} + \mu_{kt}^{\mathrm{r\,up\,max}} - \mu_{kt}^{\mathrm{p\,max}} - \lambda_t^{rup} + \sum_{\mathrm{t}}^{t+T} \pi_{kt}^{rup} - \theta_{kts}^{rup\,\mathrm{max}} = 0 \ \forall k \in K, \forall t, \forall s \ , \tag{5.57}$$

$$c_k^{rdw} - \mu_{kt}^{\mathrm{rdw\,min}} + \mu_{kt}^{\mathrm{rdw\,max}} + \mu_{kt}^{\mathrm{p\,min}} - \lambda_t^{rdw} + \sum_{\mathrm{t}}^{t+T} \pi_{kt}^{rdw} - \theta_{kts}^{rdw\,\mathrm{max}} = 0 \ \forall k \in K, \forall t, \forall s \ , \tag{5.58}$$

$$\rho^{\Delta} - \lambda_{ts}^{se} = 0 \ \forall i \in G, \forall t \ , \tag{5.59}$$

$$0 \le p_{k,t}^{w} - P_k^{\mathrm{w,min}} + r_{k,t}^{\mathrm{dw},w} \perp \mu_{kt}^{\mathrm{p\,min}} \ge 0 \, \forall k \in K, \forall t, \forall s \ , \tag{5.60}$$

$$0 \le P_k^{\mathrm{w,max}} - r_{k,t}^{\mathrm{up},w} - p_{k,t}^{w} \perp \mu_{kt}^{\mathrm{p\,max}} \ge 0 \ \ \forall k \in K, \forall t \ , \tag{5.61}$$

$$0 \le r_{k,t}^{\mathrm{up},w} - R_k^{\mathrm{up,min}} \perp \mu_{kt}^{\mathrm{r\,up\,min}} \ \ \forall k \in K, \forall t \ , \tag{5.62}$$

$$0 \le R_k^{\mathrm{up,max}} - r_{k,t}^{\mathrm{up},w} \perp \mu_{kt}^{\mathrm{rup\,max}} \ \ \forall k \in K, \forall t \ , \tag{5.63}$$

$$0 \le r_{k,t}^{\mathrm{dw},w} - R_k^{\mathrm{dw,min}} \perp \mu_{kt}^{\mathrm{rdw\,min}} \ \ \forall k \in K, \forall t \ , \tag{5.64}$$

$$0 \le R_k^{\mathrm{dw,max}} - r_{kt}^{\mathrm{dw},w} \perp \mu_{kt}^{\mathrm{rdw\,max}} \ \forall k \in K, \forall t \ , \tag{5.65}$$

$$0 \le T * p_k^{\mathrm{w,max}} - \sum_{t}^{t+T} p_{k,t}^{w} \perp \pi_{kt}^{p} \ \ \forall k \in K, \forall t \ , \tag{5.66}$$

$$0 \le T * R_k^{u,\mathrm{max}} - \sum_{t}^{t+T} r_{k,t}^{\mathrm{up},w} \perp \pi_{kt}^{rup} \ \ \forall k \in K, \forall t \ , \tag{5.67}$$

$$0 \le R_{k,t}^{\mathrm{up},w} + r_{k,t}^{\mathrm{up,c,buy}} - r_{k,t}^{\mathrm{up,c,sell}} - D_{k,t}^{up} \perp \lambda_{bt}^{rup} \ge 0 \ \ \forall k \in K, \forall t \ , \tag{5.68}$$

$$0 \le R_{k,t}^{\mathrm{dw},w} + r_{k,t}^{\mathrm{dw,c,buy}} - r_{k,t}^{\mathrm{dw,c,sell}} - D_{k,t}^{dw} \perp \lambda_{bt}^{rdw} \ge 0 \, \forall k \in K, \forall t \ , \tag{5.69}$$

$$0 \le r_{kt}^{\mathrm{up},w} - \sigma_{k,t,s}^{\mathrm{up},w} \perp \theta_{kts}^{rup\,\mathrm{max}} \ge 0 \ \forall k \in K, \forall t \ , \tag{5.70}$$

$$0 \le r_{kt}^{\mathrm{dw},w} - \sigma_{kt}^{\mathrm{dw},w} \perp \theta_{kts}^{rdw\,\mathrm{max}} \ge 0 \ \forall k \in K, \forall t \ , \tag{5.71}$$

where The KKT optimality conditions contain stationarity (5.56)-(5.59), complementary slackness, primal feasibility, and dual feasibility (5.60)-(5.71).

The complementary slackness constraints can be linearized if we introduce a set of binary variables to linearize each part.

5.4 Numerical Experiments

5.4.1 Policy Study

In this section, the performance of the proposed DSM approach is illustrated on a modified IEEE 33-bus distribution system with three microgrids and five DGs in the system as shown in Fig. 5.3. The model was solved using IBM CPLEX on a laptop with 2.80 GHz Intel CPU and 8GB of RAM. To express all parameters of the system in per-unit the power base of the test system is set at 10MVA. The voltage base of the system is set at 12.66kV at the utility side.

The microgrid is aggregated with both dispatchable and non-dispatchable units in it. The other details of distribution system and MGs can also be found in appendix.

We compare the performances of the following four policies which represent four different types of transactive energy exchange schemes:

Policy I: Only energy is involved in the interactions between microgrids and the distribution system.

Policy II: Ancillary service is allowed to be transferred from the distribution system to microgrids.

Policy III: Ancillary service is allowed to be transferred from microgrids to the distribution system.

Policy IV: The proposed transactive approach with bi-directional energy and ancillary service flow between the distribution system and microgrids.

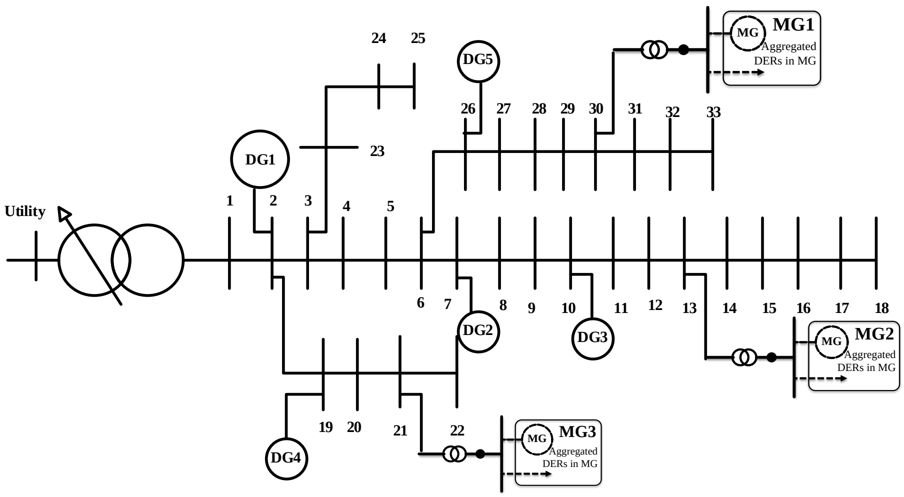

Figure 5. 3 Modified IEEE 33 Bus Test System

It is evident that with the removal of ancillary service interaction constraints (5.5) - (5.10), Policy I represents the conventional management of a transactive energy market. On the other hand, Policy II and Policy III considers unidirectional ancillary service flow, which indicate that only one constraint is considered. The same scenarios and system parameters are considered for all four policy studies. The results for the four policies can be found in Table 5.1 through Table 5.4.

Table 5.1 shows the details of the regulation transactions within the distribution system under study, including the quantities transferred and the cost for the DSO under each policy. Note that a negative cost would be interpreted as a profit for the DSO. When we compare the total costs for the DSO, the last row of Table I clearly shows that Policy IV leads to the highest DSO profit compared to the other policies. In fact, the DSO is able to make a profit while taking care of uncertainties associated with the loads and the participating microgrids in addition to maintaining the system-wide power balance. This clearly suggests that the overall social welfare can be enhanced by incorporating the proposed joint optimization of bidirectional energy and ancillary service transactions.

The second-best policy profit-wise is Policy II. It can be observed that compared with Policy IV, the regulation exported from the DGs is increased from 0.715 p.u. to 0.800 p.u. in Policy II. This indicates that due to the limitation of unidirectional regulation exchange (i.e., regulation can only flow into the microgrids), the microgrids have to completely rely on the DGs for their regulation provision. However, with the enabling of bidirectional regulation exchanges, the MGOs are actively exporting their internal regulation resources to the distribution system market in Policy IV. They are therefore less relying on the DGs, but more on each other to meet their regulation demand. This is in accordance with our expectation that the system-wide resource utilization would improve with the joint optimization of bidirectional energy and ancillary service flow. This is also in accordance with the vision that microgrids, as distributed intelligent autonomies, will play an ever-increasingly dominant role in future transactive distribution systems.

Table 5.2 shows the load shedding, power curtailment, and the associated penalty cost of each policy. It can be observed that Policy I, among all policies, demonstrates the worst performance in handling operational uncertainties. In the other three policies, the load shedding and power curtailment are zero. This indicates that the energy-only transactive market operation can be insufficient in the face of operation uncertainties. The transactive regulation exchange between the DSO and the microgrids, either unidirectional or bidirectional, better prepares each market participant and enhances the distribution system's overall capacity to handle uncertainties.

Table 5. 1 Ancillary Services Interaction Results for DS

	Policy I	**Policy II**	**Policy III**	**Policy IV**
Regulation Transfer from MG to DS (p.u.)	0	0	0.152	1.405
The associated Cost for the DSO ($)	0	0	81.80	836.80
Regulation Transfer from DS to MG (p.u.)	0	-0.798	0	-2.119
The associated Cost for the DSO ($)	0	-615.20	0	-1530.61
Regulation provided by DGs (p.u.)	0. 644	0.800	0.495	0.715
The associated Cost for the DSO ($)	238.02	304.18	181.60	271.68
Total Regulation Cost for the DSO ($)	238.02	-311.02	263.40	-422.12

Table 5. 2 Uncertainty Handling Results

	Policy I	**Policy II**	**Policy III**	**Policy IV**
Load Shedding (p.u.)	0.003	0	0	0
Power Curtailment (p.u.)	0	0	0	0
Associated Penalty Cost ($)	6.74	0	0	0

Table 5.3 lists the total cost of distribution system for four policies. shows the energy transactions within the distribution system. It can be observed that Policy IV would leads the lowest operation cost ($2991.09) for the DSO compared to Policy I-III. Meanwhile, facilitated by the bidirectional regulation exchange, the MGOs are capable of exporting the largest amount of energy (1.200 p.u.) to the distribution system. This added capacity greatly empowers the distribution system by enabling the DSO to reduce the energy purchased from the bulk power system from 1.952 p.u. in Policy I to 1.146 p.u. in Policy IV. This reduction indicates that the proposed DSM strategy, facilitated by the transactive bidirectional ancillary service exchange, allows for the DSO to become less dependent on its upstream grid. Instead, more energy demands can be satisfied through the transactive exchanges locally, which significantly increases the distribution system's flexibility, resiliency, and energy efficiency. The proposed management strategy is also financially favorable as it minimizes the total operation cost of the DSO.

Table 5.4 shows the cost of each MGOs and DSO in four different policies. It can be observed from the table that even through the Policy IV has the least cost among four policies regarding the DSO cost, a relative higher cost for MGs operation comparing with

Policy I and III. MGOs in Policy II is similar to Policy IV. It can be explained that when the ancillary service transfer direction from DS to MG is activated, DSO can easily find the cheapest energy/AS sell to MG. For some MGO which has less economic power and AS produce capability, MGs need to take corresponding higher operation cost.

Table 5. 3 Total Cost of DSO

	Policy I	**Policy II**	**Policy III**	**Policy IV**
Net Energy Transfer from MG to DS (p.u.)	0.291	0.388	0.397	1.200
The associated Energy Interaction Cost for the DSO ($)	-99.97	-34.61	-79.02	33.18
Energy Transfer from DG to DS (p.u.)	4.690	4.548	4.629	4.543
The associated Energy Interaction Cost for the DSO ($)	2259.23	2187.48	2228.26	2186.20
Entergy Transfer from Bulk Power System to DS (p.u.)	1.907	1.952	1.862	1.146
The Associated Energy Interaction Cost for the DSO ($)	1257.61	1277.76	1227.92	895.19
Penalty Cost ($)	6.74	0	0	0
Total Regulation Cost($)	238.02	-311.02	263.40	-422.12
Total Cost ($)	3668.35	3119.60	3640.56	**2991.09**

Table 5. 4 MGO and DSO Cost

	Policy I	**Policy II**	**Policy III**	**Policy IV**
MG1	169.84	160.85	162.10	175.13
MG2	154.50	184.07	156.94	167.18
MG3	83.67	100.87	93.95	115.97
DSO	368.12	317.28	359.99	317.16

5.4.2 Summary

In summary, the simulation results provided in this section clearly illustrate the advantages of the proposed approach as illustrated in Section II. It is demonstrated that the proposed management scheme is capable of increasing the microgrids' participation in the distribution market as prosumers. This effectively enhances the energy independency, system-wide efficiency and reliability, operational flexibility, as well as the economy of the distribution system by fully utilizing the microgrids' potential.

5.5 Conclusion

Transactive management provides a decentralized solution for the DSO to handle the ever-increasing proliferation of microgrids within the distribution system. In this chapter, we propose a novel optimal DSM strategy that allows the DSO to jointly co-optimize the transactive bidirectional exchange of both energy and ancillary services in a market environment. A stochastic bi-level programming approach is adopted to assist both the DSO, as a regulatory entity, and the MGOs, as proactive consumers, to strike a balance between their operation economics and their system-wide reliability, flexibility, and energy independency on a distribution system consisting of networked microgrids.

The simulation results of the four policy studies indicate that the proposed approach is superior in various ways compared to the existing transactive management schemes. Our work is one of the pioneering efforts to that explores the methodology for building a comprehensive, fully self-sustaining, and transactive-based decentralized distribution system. We envision that the research effort presented in this chapter will facilitate the transformation of the traditional role of the DSO and promote a healthy and sustainable localized market in a more decentralized electrical power industry landscape.

Chapter 6 Conclusions and Future Work

This thesis studied the microgrid optimal scheduling model and algorithm from two aspects: 1) asset management, which focus on individual microgrid scheduling problem (Chapter 4) and 2) operation planning, which expand the individual microgrid scheduling to distribution layer operation (Chapter 3 and Chapter 5). In the context of asset management, the proposed method can help microgrid owner to reduce the total scheduling cost while handling different types of operational uncertainties such as renewable energy output and islanding event. In terms of operation planning, the pool strategy (Chapter 3) helped microgrid improve market competitiveness, and transactive management scheme (Chapter 5) totally changed the traditional market transaction rules and procedures by introducing the bidirectional energy and ancillary service flow, which help the distribution system utilize the microgrids to support system operation.

Some further study can be explored based this work are: 1) using data-driven or machine learning methods to model microgrid scheduling problem and 2) integrate the microgrid scheduling to real-time electricity market. The data-driven approach is a popular method which can improve the uncertainty modelling using more realistic data instead of using precise probability distribution (stochastic method) or unprecise bound (robust method). It can be expected that the data-driven approach can be used to model more types of operational uncertainties based on different data resources or limited data. In the context of real-time market, since this study solved the scheduling on the day-ahead basis which proved the operation flexibility and adequacy of microgrid scheduling, it is possible that microgrid can play a more important role in the real-time market which requires more quick response. One can expend the day-ahead scheduling to real-time scheduling using rolling horizon method which iteratively solves the essential same problem in a short time horizon and interval. An interesting study point will be how to honor the day-ahead scheduling results in the real-time market.

References

[1] P. Basak, S. Chowdhury, S. Halder Nee Dey, and S. P. Chowdhury, “A literature review on integration of distributed energy resources in the perspective of control, protection and stability of microgrid,” *Renew. Sustain. Energy Rev.*, vol. 16, no. 8, pp. 5545–5556, 2012.

[2] Y. Zoka, A. Sugimoto, N. Yorino, K. Kawahara, and J. Kubokawa, “An economic evaluation for an autonomous independent network of distributed energy resources,” *Electr. Power Syst. Res.*, vol. 77, no. 7, pp. 831–838, 2007.

[3] M. F. Akorede, H. Hizam, and E. Pouresmaeil, “Distributed energy resources and benefits to the environment,” *Renew. Sustain. Energy Rev.*, vol. 14, no. 2, pp. 724–734, 2010.

[4] K. Alanne and A. Saari, “Distributed energy generation and sustainable development,” *Renew. Sustain. Energy Rev.*, vol. 10, no. 6, pp. 539–558, 2006.

[5] Department of Energy, “Action Plan Addressing The Electricity Distribution System.” [Online]. Available: https://energy.gov/sites/prod/files/2013/05/f0/GTT12_Dist-ActionPlan.pdf.

[6] S. Evans, “Germany: Nuclear power plants to close by 2022,” *BBC News*. [Online]. Available: http://www.bbc.com/news/world-europe-13592208.

[7] T. J. Hammons, “Integrating renewable energy sources into European grids,” *Int. J. Electr. Power Energy Syst.*, vol. 30, no. 8, pp. 462–475, 2008.

[8] C. Krauss and D. Cardwell, “A Texas Utility Offers a Nighttime Special: Free

Electricity," *The New York Times*. Nov. 8, 2015. [Online]. Available: https://www.nytimes.com/2015/11/09/business/energy-environment/a-texas-utility-offers-a-nighttime-special-free-electricity.html

[9] E. Dall'Anese, H. Zhu, and G. B. Giannakis, "Distributed optimal power flow for smart microgrids," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1464–1475, 2013.

[10] M. Mazidi, A. Zakariazadeh, S. Jadid, and P. Siano, "Integrated scheduling of renewable generation and demand response programs in a microgrid," *Energy Convers. Manag.*, vol. 86, pp. 1118–1127, 2014.

[11] S. Zhang, J. Yang, X. Wu, and R. Zhu, "Dynamic power provisioning for cost minimization in islanding micro-grid with renewable energy," *2014 IEEE PES Innov. Smart Grid Technol. Conf. ISGT 2014*, pp. 0–4, 2014.

[12] M. Shahidehpour and S. Pullins, "Microgrids, modernization, and rural electrification ," *IEEE Electrif. Mag.*, vol. 3, no. 1, pp. 2–6, 2015.

[13] A. Khodaei, "Resiliency-oriented microgrid optimal scheduling," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1584–1591, 2014.

[14] A. Khodaei and M. Shahidehpour, "Microgrid-based co-optimization of generation and transmission planning in power systems," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1582–1590, 2013.

[15] B. Starfield, H. Lotfi, A. Khodaei, and S. Bahramirad, "State of the Art in Reserach on Microgrids: A Review," *IEEE Access*, vol. 3, no. 1, pp. 890–925, 2015.

[16] H. S. V. S. Kumar Nunna and S. Doolla, “Multiagent-based distributedenergy-resource management for intelligent microgrids,” *IEEE Trans. Ind. Electron.*, vol. 60, no. 4, pp. 1678–1687, 2013.

[17] C. Wheelock, “Peter Asmus Senior Analyst EXECUTIVE SUMMARY: Microgrids Section 1 EXECUTIVE SUMMARY,” pp. 2011–2017, 2012.

[18] S. Wang, Z. Li, L. Wu, M. Shahidehpour, and Z. Li, “New metrics for assessing the reliability and economics of microgrids in distribution system,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2852–2861, 2013.

[19] F. Katiraei and M. R. Iravani, “Power management strategies for a microgrid with multiple distributed generation units,” *IEEE Trans. Power Syst.*, vol. 21, no. 4, pp. 1821–1831, 2006.

[20] N. Amjady, F. Keynia, and H. Zareipour, “Short-term load forecast of microgrids by a new bilevel prediction strategy,” *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 286–294, 2010.

[21] A. L. Dimeas and N. D. Hatziargyriou, “Operation of a multiagent system for microgrid control,” *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1447–1455, 2005.

[22] M. Tasdighi, H. Ghasemi, and A. Rahimi-Kian, “Residential Microgrid Scheduling Based on Smart Meters Data and Temperature Dependent Thermal Load Modeling,” *IEEE Trans. Smart Grid*, vol. Early Acce, no. 1, pp. 1–9, 2013.

[23] M. H. Cintuglu, H. Martin, and O. A. Mohammed, “Real-time implementation of multiagent-based game theory reverse auction model for microgrid market

operation," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 1064–1072, 2015.

[24] X. Liu, P. Wang, and P. C. Loh, "A hybrid AC/DC microgrid and its coordination control," *IEEE Trans. Smart Grid*, vol. 2, no. 2, pp. 278–286, 2011.

[25] A. Khodaei, "Microgrid Optimal Scheduling With Multi-Period Islanding Constraints," *IEEE Trans. Power Syst.*, vol. 29, no. 3, pp. 1383–1392, 2013.

[26] W. Su, J. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1876–1883, 2014.

[27] G. Liu, M. Starke, B. Xiao, X. Zhang, and K. Tomsovic, "Microgrid optimal scheduling with chance-constrained islanding capability," *Electr. Power Syst. Res.*, vol. 145, pp. 197–206, 2017.

[28] Z. Wang, B. Chen, J. Wang, M. M. Begovic, and C. Chen, "Coordinated energy management of networked microgrids in distribution systems," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 45–53, 2015.

[29] D. T. Nguyen and L. B. Le, "Optimal bidding strategy for microgrids considering renewable energy and building thermal dynamics," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1608–1620, 2014.

[30] G. Joos, B. T. Ooi, D. McGillis, F. D. Galiana, and R. Marceau, "The potential of distributed generation to provide ancillary\nservices," *2000 Power Eng. Soc. Summer Meet. (Cat. No.00CH37134)*, vol. 3, no. d, pp. 1762–1767, 2000.

[31] Y. G. Rebours, D. S. Kirschen, M. Trotignon, and S. Rossignol, "A survey of

frequency and voltage control ancillary services - Part I: Technical features," *IEEE Trans. Power Syst.*, vol. 22, no. 1, pp. 350–357, 2007.

[32] A. G. Madureira and J. A. Peças Lopes, "Ancillary services market framework for voltage control in distribution networks with microgrids," *Electr. Power Syst. Res.*, vol. 86, pp. 1–7, 2012.

[33] R. Billinton and R. Karki, "Capacity reserve assessment using system well-being analysis," *IEEE Trans. Power Syst.*, vol. 14, no. 2, pp. 433–438, 1999.

[34] J. F. Restrepo and F. D. Galiana, "Unit commitment with primary frequency regulation constraints," *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 1836–1842, 2005.

[35] Y. Fu, M. Shahidehpour, and Z. Li, "Security-constrained unit commitment with ac constraints," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1538–1550, 2005.

[36] K. W. Cheung, P. Shamsollahi, D. Sun, J. Milligan, and M. Potishnak, "Energy and ancillary service dispatch for the interim ISO New England electricity market," *IEEE Trans. Power Syst.*, vol. 15, no. 3, pp. 968–974, 2000.

[37] M. J. N. Van Werven and M. J. J. Scheepers, "The changing role of distribution system operators in liberalised and decentralising electricity markets," *2005 Int. Conf. Futur. Power Syst.*, pp. 1–6, 2005.

[38] A. Sinha, A. K. Basu, R. N. Lahiri, S. Chowdhury, S. P. Chowdhury, and P. A. Crossley, "Setting of market clearing price (MCP) in Microgrid power scenario," *IEEE Power Energy Soc. 2008 Gen. Meet. Convers. Deliv. Electr. Energy 21st*

Century, PES, pp. 1–8, 2008.

[39] D. S. Kirschen and G. Strbac, *Fundamentals of Power System Economics*. Chichester, U.K: Wiley; 1 edition (May 21, 2004).

[40] A. E. Roth, “The Economist as Engineer: Game Theory, Experimentation, and Computation as Tools for Design Economics,” *Econometrica*, vol. 70, no. 4, pp. 1341–1378, 2002.

[41] S. Parhizi, A. Khodaei, and M. Shahidehpour, “Market-based vs. Price-based Microgrid Optimal Scheduling,” *IEEE Trans. Smart Grid*, vol. 3053, no. c, pp. 1–1, 2016.

[42] S. Y. Lee, Y. G. Jin, and Y. T. Yoon, “Determining the Optimal Reserve Capacity in a Microgrid with Islanded Operation,” *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1369–1376, 2016.

[43] D. T. Nguyen and L. B. Le, “Risk-constrained profit maximization for microgrid aggregators with demand response,” *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 135–146, 2015.

[44] G. Liu, S. Member, Y. Xu, and K. Tomsovic, “Bidding Strategy for Microgrid in Day-Ahead Market Based on Hybrid Stochastic / Robust,” vol. 7, no. 1, pp. 227–237, 2016.

[45] P. A. Samuelson and W. D. Nordhaus, “Economics.” 2000.

[46] A. Khodaei, S. Bahramirad, and M. Shahidehpour, “Microgrid Planning Under Uncertainty,” *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2417–2425, 2014.

[47] J. Wu and X. Guan, “Coordinated Multi-Microgrids Optimal Control Algorithm for Smart Distribution Management System,” *Smart Grid, IEEE Trans.*, vol. 4, no. 4, pp. 2174–2181, 2013.

[48] A. Khodaei, S. Bahramirad, and M. Shahidehpour, “Microgrid Planning Under Uncertainty,” *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2417–2425, 2015.

[49] A. K. Srivastava, R. Zamora, and D. Bowman, “Impact of distributed generation with storage on electric grid stability,” *2011 IEEE Power Energy Soc. Gen. Meet.*, pp. 1–5, 2011.

[50] C. Abbey D. Cornforth, N. Hatziargyriou, K. Hirose, A. Kwasinski, E. Kyriakides, G. Platt, L. Reyes, and S. Suryanarayanan, “Powering through the storm: Microgrids operation for more efficient disaster recovery,” *IEEE Power Energy Mag.*, vol. 12, no. 3, pp. 67–76, 2014.

[51] D. Erickson, “Microgrids : A Regulatory Perspective California Public Utilities Commission.”

[52] Y. G. Rebours, D. S. Kirschen, M. Trotignon, and S. Rossignol, “A survey of frequency and voltage control ancillary services - Part II: Economic features,” *IEEE Trans. Power Syst.*, vol. 22, no. 1, pp. 358–366, 2007.

[53] N. Rezaei and M. Kalantar, “Stochastic frequency-security constrained energy and reserve management of an inverter interfaced islanded microgrid considering demand response programs,” *Int. J. Electr. Power Energy Syst.*, vol. 69, pp. 273–286, 2015.

[54] N. Rezaei and M. Kalantar, “Hierarchical energy and frequency security pricing in a smart microgrid: An equilibrium-inspired epsilon constraint based multi-objective decision making approach,” *Energy Convers. Manag.*, vol. 98, pp. 533–543, 2015.

[55] R. Doherty and M. O'Malley, “A new approach to quantify reserve demand in systems with significant installed wind capacity,” *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 587–595, 2005.

[56] X. Yan, D. Abbes, and B. Francois, “Uncertainty analysis for day ahead power reserve quantification in an urban microgrid including PV generators,” *Renew. Energy*, vol. 106, pp. 288–297, 2017.

[57] T. Logenthiran, D. Srinivasan, and A. M. Khambadkone, “Multi-agent system for energy resource scheduling of integrated microgrids in a distributed system,” *Electr. Power Syst. Res.*, vol. 81, no. 1, pp. 138–148, 2011.

[58] S. J. Ahn and S. Il Moon, “Economic scheduling of distributed generators in a microgrid considering various constraints,” *2009 IEEE Power Energy Soc. Gen. Meet. PES ’09*, pp. 1–6, 2009.

[59] I. Prodan and E. Zio, “An optimization-based control approach for reliable microgrid energy management under uncertainties,” *2013 IEEE Integr. Stoch. Energy Power Syst. Work. ISEPS 2013 - Proc.*, pp. 4–7, 2013.

[60] M. Zachar and P. Daoutidis, “Microgrid/Macrogrid Energy Exchange: A Novel Market Structure and Stochastic Scheduling,” *IEEE Trans. Smart Grid*, vol. 8, no. 1, pp. 178–189, 2017.

[61] S. Lee, Y. Jin, G. Jang, and Y. Yoon, “Optimal bidding of a microgrid based on probabilistic analysis of island operation,” *Energies*, vol. 9, no. 10, pp. 1–14, 2016.

[62] A. Zakariazadeh, S. Jadid, and P. Siano, “Smart microgrid energy and reserve scheduling with demand response using stochastic optimization,” *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 523–533, 2014.

[63] G. Cardoso, M. Stadler, A. Siddiqui, C. Marnay, N. Deforest, A. Barbosa-Póvoa, and P. Ferrão, “Microgrid reliability modeling and battery scheduling using stochastic linear programming,” *Electr. Power Syst. Res.*, vol. 103, pp. 61–69, 2013.

[64] Z. Xu, X. Guan, Q. Jia, J. Wu, D. Wang, and S. Chen, “Performance Analysis and Comparison on Energy Storage Devices for Smart Building,” *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2136–2147, 2012.

[65] S. Kennedy and M. M. Marden, “Reliability of islanded microgrids with stochastic generation and prioritized load,” *2009 IEEE Bucharest PowerTech Innov. Ideas Towar. Electr. Grid Futur.*, pp. 2–8, 2009.

[66] Y. A. R. I. Mohamed and A. A. Radwan, “Hierarchical control system for robust microgrid operation and seamless mode transfer in active distribution systems,” *IEEE Trans. Smart Grid*, vol. 2, no. 2, pp. 352–362, 2011.

[67] Q. Wang, J. P. Watson, and Y. Guan, “Two-stage robust optimization for N-k contingency-constrained unit commitment,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2366–2375, 2013.

[68] E. Kuznetsova, C. Ruiz, Y.-F. Li, and E. Zio, “Analysis of robust optimization for decentralized microgrid energy management under uncertainty,” *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 815–832, 2015.

[69] E. Kuznetsova, Y. F. Li, C. Ruiz, and E. Zio, “An integrated framework of agent-based modelling and robust optimization for microgrid energy management,” *Appl. Energy*, vol. 129, pp. 70–88, 2014.

[70] Y. Zhang, N. and Gatsis, and G. B. Giannakis, “Robust energy management for microgrids with high penetration renewables,” *Energy Policy*, vol. 33, no. 6, pp. 787–798, 2005.

[71] T. Logenthiran and D. Srinivasan, “Short term generation scheduling of a microgrid,” *IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON*, pp. 1–6, 2009.

[72] L. M. Costa and G. Kariniotakis, “A Stochastic Dynamic Programming Model for Optimal Use of Local Energy Resources in a Market Environment,” *2007 IEEE Lausanne Power Tech*, pp. 449–454, 2007.

[73] I. C. Paschalidis, B. Li, and M. C. Caramanis, “Demand-side management for regulation service provisioning through internal pricing,” *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1531–1539, 2012.

[74] A. G. Tsikalakis and N. D. Hatziargyriou, “Centralized control for optimizing microgrids operation,” *IEEE Trans. Energy Convers.*, vol. 23, no. 1, pp. 241–248, 2008.

[75] W. Su, J. Wang, K. Zhang, and A. Q. Huang, “Model predictive control-based

power dispatch for distribution system considering plug-in electric vehicle uncertainty," *Electr. Power Syst. Res.*, vol. 106, pp. 29–35, 2014.

[76] M. Fathi and H. Bevrani, "Adaptive energy consumption scheduling for connected microgrids under demand uncertainty," *IEEE Trans. Power Deliv.*, vol. 28, no. 3, pp. 1576–1583, 2013.

[77] M. Fathi and H. Bevrani, "Statistical cooperative power dispatching in interconnected microgrids," *IEEE Trans. Sustain. Energy*, vol. 4, no. 3, pp. 586–593, 2013.

[78] L. Kristov and P. De Martini, "21 st Century Electric Distribution System Operations," no. May, pp. 1–11, 2014.

[79] New York State Public Service Commission, "Developing the REV Market in New York: DPS Staff Straw Proposal on Track One Issues," 2014.

[80] P. De Martini, "MORE THAN SMART: A Framework to Make the Distribution Grid More Open, Efficient and Resilient," *Greentech Leadersh. Gr.*

[81] L. Kristov, C. Independent, and S. Operator, "21 st Century Electric Distribution System Operations," no. May, pp. 1–11, 2014.

[82] F. Rahimi and S. Mokhtari, "From ISO to DSO," *Public Utilities Fortnightly*. pp. 42–50, 2014.

[83] J. Lazar, "Performance-Based Regulation for EU Distribution System Operators," no. May, pp. 1052–1069, 2014.

[84] A. Malot, "The transformation from DNO to DSO," 2014. [Online]. Available:

http://blog.schneider-electric.com/utilities/2014/11/27/transformation-dno-dso/.

[85] J. Lazar, “Electricity Regulation in the US: A Guide,” p. 228, 2016.

[86] C. Zhang, Y. Xu, Z. Y. Dong, and K. P. Wong, “Robust Coordination of Distributed Generation and Price-Based Demand Response in Microgrids,” *IEEE Trans. Smart Grid*, vol. 3053, no. c, pp. 1–1, 2017.

[87] Z. Wu, W. Gu, R. Wang, X. Yuan, and W. Liu, “Economic optimal schedule of CHP microgrid system using chance constrained programming and particle swarm optimization,” *IEEE Power Energy Soc. Gen. Meet.*, pp. 1–11, 2011.

[88] S. Parhizi and A. Khodaei, “Market-based microgrid optimal scheduling,” *2015 IEEE Int. Conf. Smart Grid Commun. SmartGridComm 2015*, pp. 55–60, 2016.

[89] R. Palma-behnke, S. Member, J. L. C. a, and L. S. Vargas, “Model With Integration of Distributed Generation and Load Curtailment Options,” *Power*, vol. 20, no. 4, pp. 1718–1727, 2005.

[90] H. Vogt, H. Weiss, P. Spiess, and A. P. Karduck, “Market-based prosumer participation in the smart grid,” *4th IEEE Int. Conf. Digit. Ecosyst. Technol. - Conf. Proc. IEEE-DEST 2010, DEST 2010*, pp. 592–597, 2010.

[91] S. De La Torre, J. M. Arroyo, A. J. Conejo, and J. Contreras, “Price maker self-scheduling in a pool-based electricity market: A mixed-integer LP approach,” *IEEE Trans. Power Syst.*, vol. 17, no. 4, pp. 1037–1042, 2002.

[92] PWC, “A strategic entry plan for the microgrid business,” 2016. [Online] https://www.strategyand.pwc.com/gx/en/reports/powering-up-the-neighborhood-

grid.pdf

[93] N. A. Ruhi, N. Chen, K. Dvijotham, and A. Wierman, "Opportunities for Price Manipulation by Aggregators in Electricity Markets," *ACM SIGMETRICS Perform. Eval. Rev.*, vol. 44, no. 2, pp. 49–51, 2016.

[94] A. K. David and Fushuan Wen, "Strategic bidding in competitive electricity markets: a literature survey," *2000 Power Eng. Soc. Summer Meet. (Cat. No.00CH37134)*, vol. 4, pp. 2168–2173, 2000.

[95] C. Ruiz and A. J. Conejo, "Pool strategy of a producer with endogenous formation of locational marginal prices," *IEEE Trans. Power Syst.*, vol. 24, no. 4, pp. 1855–1866, 2009.

[96] M. Fampa, L. A. Barroso, D. Candal, and L. Simonetti, "Bilevel optimization applied to strategic pricing in competitive electricity markets," *Comput. Optim. Appl.*, vol. 39, no. 2, pp. 121–142, 2008.

[97] B. F. Hobbs, C. B. Metzler, and J. S. Pang, "Strategic gaming analysis for electric power systems: An MPEC approach," *IEEE Trans. Power Syst.*, vol. 15, no. 2, pp. 638–645, 2000.

[98] B. Colson, P. Marcotte, and G. Savard, "An overview of bilevel optimization," *Ann. Oper. Res.*, vol. 153, no. 1, pp. 235–256, 2007.

[99] B. Colson, P. Marcotte, and G. Savard, "Bilevel programming: A survey," *4or*, vol. 3, no. 2, pp. 87–107, 2005.

[100] A. V. Demiguel and F. J. Nogales, "On the relationship between bilevel

decomposition algorithms and direct interior-point methods," pp. 1–20.

[101] M. De Luján Latorre and S. Granville, "The Stackelberg equilibrium applied to AC power systems - A non-interior point algorithm," *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 611–618, 2003.

[102] M. V. Pereira, S. Granville, M. H. C. Fampa, R. Dix, and L. A. Barroso, "Strategic bidding under uncertainty: A binary expansion approach," *IEEE Trans. Power Syst.*, vol. 20, no. 1, pp. 180–188, 2005.

[103] T. Logenthiran, D. Srinivasan, A. M. Khambadkone, and T. S. Raj, "Optimal sizing of an islanded microgrid using Evolutionary Strategy," *2010 IEEE 11th Int. Conf. Probabilistic Methods Appl. to Power Syst. PMAPS 2010*, pp. 12–17, 2010.

[104] M. Marzband, A. Sumper, J. L. Domínguez-García, and R. Gumara-Ferret, "Experimental validation of a real time energy management system for microgrids in islanded mode using a local day-ahead electricity market and MINLP," *Energy Convers. Manag.*, vol. 76, pp. 314–322, 2013.

[105] Q. Jiang, M. Xue, and G. Geng, "Energy management of microgrid in grid-connected and stand-alone modes," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3380–3389, 2013.

[106] A. Khodaei, "Provisional Microgrids," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1107–1115, 2015.

[107] L. Che, M. Khodayar, and M. Shahidehpour, "Only connect: Microgrids for distribution system restoration," *IEEE Power Energy Mag.*, vol. 12, no. 1, pp. 70–

81, 2014.

[108] A. Seon-Ju, N. Soon-Ryul, C. Joon-Ho, and M. Seung-Il, “Power Scheduling of Distributed Generators for Economic and Stable Operation of a Microgrid,” *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 398–405, 2013.

[109] X. Wu, J. Yang, H. Xi, and S. Zhang, “QoS-constrained energy management in smart microgrid,” *IEEE Int. Conf. Control Autom. ICCA*, pp. 1327–1332, 2014.

[110] PJM, “Ancillary Services,” no. July, 2015.

[111] V. Mohan, J. G. Singh, and W. Ongsakul, “An efficient two stage stochastic optimal energy and reserve management in a microgrid,” *Appl. Energy*, vol. 160, pp. 28–38, 2015.

[112] NERC, “Balancing and Frequency Control,” 2011.

[113] M. D. Galus, S. Koch, and G. Andersson, “Provision of load frequency control by PHEVs, controllable loads, and a cogeneration unit,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4568–4582, 2011.

[114] P. Dash, “Power exchange for frequency control (PXFC),” *IEEE PES Winter Meet. 1999*, pp. 809–819 vol.2, 1999.

[115] S. Y. Lee, Y. G. Jin, S. K. Kim, and Y. T. Yoon, “Operation planning of reserve in microgrid considering market participation and energy storage system,” *J. Electr. Eng. Technol.*, vol. 9, no. 3, pp. 1089–1095, 2014.

[116] S. S. Oren, “Auction design for ancillary reserve products,” *Power Eng. Soc. Summer Meet. 2002 IEEE*, vol. 3, pp. 1238–1239, 2002.

[117] H. S. V. S. K. Nunna and S. Doolla, “Demand Response in Smart Distribution System With Multiple Microgrids,” *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1641–1649, 2012.

[118] M. Pipattanasomporn, H. Feroze, and S. Rahman, “Multi-Agent Systems in a Distributed Smart Grid : Design and Implementation,” *2009 IEEE/PES Power Syst. Conf. Expo.*, pp. 1–8, 2009.

[119] X. Zhou, Y. Gu, Y. Ma, L. Cui, and S. Liu, “Hybrid Operation Control Method for Micro-grid Based on MAS,” *2010 IEEE Int. Conf. Prog. Informatics Comput.*, vol. 1, no. 50877053, pp. 72–75, 2010.

[120] S. J. Kazempour, S. Member, A. J. Conejo, and C. Ruiz, “Generation Investment Equilibria With Strategic Producers — Part I : Formulation,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2613–2622, 2013.

[121] J. Wang, M. Shahidehpour, Z. Li, and A. Botterud, “Strategic Generation Capacity Expansion Planning With Incomplete Information,” vol. 24, no. 2, pp. 1002–1010, 2009.

[122] D. Apostolopoulou, S. Bahramirad, and A. Khodaei, “The Interface of Power: Moving Toward Distribution System Operators,” *IEEE Power Energy Mag.*, vol. 14, no. june 2016, pp. 46–51.

[123] W. Liu, Q. Wu, F. Wen, J. Østergaard, and S. Member, “Day-Ahead Congestion Management in Distribution Systems Through Household Demand Response and Distribution Congestion Prices,” vol. 5, no. 6, pp. 2739–2747, 2014.

[124] F. Rahimi, A. Ipakchi, and F. Fletcher, “The Changing Electrical Landscape: End-to-End Power System Operation Under the Transactive Energy Paradigm,” *IEEE Power Energy Mag.*, vol. 14, no. 3, pp. 52–62, 2016.

[125] J. Lian, H. Ren, Y. Sun, D. J. Hammerstrom, and S. Member, “Performance Evaluation for Transactive Energy Systems Using Double-Auction Market,” *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4128–4137, 2019.

[126] J. Li, C. Zhang, Z. Xu, J. Wang, J. Zhao, and Y. Zhang, “Distributed Transactive Energy Trading Framework in Distribution Networks,” *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 7215–7227, 2018.

[127] F. Lezama, J. Soares, P. Hernandez-leal, M. Kaisers, T. Pinto, and Z. Vale, “Local Energy Markets : Paving the Path Toward Fully Transactive Energy Systems,” *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4081–4088, 2019.

[128] Y. Chen, P. Gribik, and J. Gardner, “Transmission Constraints Into Energy and Ancillary Service Co-Optimization,” *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 537–549, 2014.

[129] Y. Chen, M. Keyser, M. H. Tackett, and X. Ma, “Incorporating Short-Term Stored Energy Resource Into Midwest ISO Energy and Ancillary Service Market,” *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 829–838, 2011.

[130] Q. Wang and B. Hodge, “Enhancing Power System Operational Flexibility With Flexible Ramping Products : A Review,” *IEEE Trans. Ind. Informatics*, vol. 13, no. 4, pp. 1652–1664, 2017.

[131] T. Ding, Z. Wu, J. Lv, and S. Member, “Robust Co-Optimization to Energy and Ancillary Service Joint Dispatch Considering Wind Power Uncertainties in Real-Time Electricity Markets,” *IEEE Trans. Sustain. Energy*, vol. 7, no. 4, pp. 1547–1557, 2016.

[132] M. Shahidehpour, “Role of smart microgrid in a perfect power system,” *IEEE PES Gen. Meet. PES 2010*, p. 60616, 2010.

[133] W. Bower, I. Llc, J. Reilly, and R. Associates, “The Advanced Microgrid Integration and Interoperability,” *Sandia Rep.*, no. March, pp. 1–56, 2014.

[134] C. Edmunds, S. Galloway, and S. Gill, “Distributed electricity markets and distribution locational marginal prices: A review,” in *2017 52nd International Universities Power Engineering Conference (UPEC)*, 2017, pp. 1–6.

[135] E. Mengelkamp, P. Staudt, J. Garttner, and C. Weinhardt, “Trading on local energy markets: A comparison of market designs and bidding strategies,” *Int. Conf. Eur. Energy Mark. EEM*, 2017.

[136] M. Che, L.; Khodayar, M.; Shahidehpour, “Only Connect,” *IEEE Power Energy Mag.*, no. february, pp. 70–81, 2014.

[137] Z. Liang, T. Chen, H. Pourbabak, and W. Su, “Robust distributed energy resources management for microgrids in a retail electricity market,” *2017 North Am. Power Symp. NAPS 2017*, 2017.

[138] A. G. Bakirtzis, N. P. Ziogos, A. C. Tellidou, and G. A. Bakirtzis, “Electricity producer offering strategies in day-ahead energy market with step-wise offers,”

IEEE Trans. Power Syst., vol. 22, no. 4, pp. 1804–1818, 2007.

[139] A. Baillo, M. Ventosa, M. Rivier, and A. Ramos, “Optimal offering strategies for generation companies operating in electricity spot markets,” *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 745–753, 2004.

[140] Z.-Q. Luo, J.-S. Pang, and D. Ralph, *Mathematical programs with equilibrium constraints*. Cambridge University Press, 1996.

[141] T. Ackermann, G. Andersson, and L. Söder, “Electricity market regulations and their impact on distributed generation,” *Electr. Util. Deregul. Restruct. Power Technol. 2000. Proceedings. DRPT 2000. Int. Conf.*, no. April, pp. 608–613, 2000.

[142] P. Mallet, P. O. Granstrom, P. Hallberg, G. Lorenz, and P. Mandatova, “Power to the People!: European Perspectives on the Future of Electric Distribution,” *IEEE Power Energy Mag.*, vol. 12, no. 2, pp. 51–64, 2014.

[143] M. Shahidehpour, Z. Li, S. Bahramirad, Z. Li, and W. Tian, “Networked Microgrids: Exploring the Possibilities of the IIT-Bronzeville Grid,” *IEEE Power Energy Mag.*, vol. 15, no. 4, pp. 63–71, 2017.

[144] A. Malot, “The transformation from DNO to DSO.” 2014.

[145] J. A. P. Lopes, N. Hatziargyriou, J. Mutale, P. Djapic, and N. Jenkins, “Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities,” *Electr. Power Syst. Res.*, vol. 77, no. 9, pp. 1189–1203, 2007.

[146] Centrica, “Cornwall Local Energy Market.” 2017. [Online] https://www.centrica.com/innovation/cornwall-local-energy-market

[147] National Grid, "Transmission and Distribution Interface 2.0 (TDI)," *Bid Doc. to Ofgem*, vol. 0, 2017.

[148] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *Power Deliv. IEEE Trans.*, vol. 4, no. 2, pp. 1401–1407, 1989.

[149] D. Bertsimas and M. Sim, "The Price of Robustness," *Oper. Res.*, vol. 52, no. 1, pp. 35–53, 2004.

[150] Y. Wu, Masoud Barati, and Gino Lim, "Data set for Manuscript ' A Pool Strategy of Microgrid in Power Distribution Electricity Market .'"

[151] "IBM - ILOG is now part of IBM." [Online]. Available: https://www-01.ibm.com/software/info/ilog/. [Accessed: 04-Dec-2017].

[152] N. Hatziargyriou, H. Asano, R. Iravani, and C. Marnay, "Microgrids," *IEEE Power Energy Mag.*, vol. 5, no. 4, pp. 78–94, 2007.

[153] L. Che and M. Shahidehpour, "Adaptive Formation of Microgrids with Mobile Emergency Resources for Critical Service Restoration in Extreme Conditions," *IEEE Trans. Power Syst.*, vol. PP, no. c, p. 1, 2018.

[154] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "Stochastic Energy Management of Microgrids during Unscheduled Islanding Period," *IEEE Trans. Ind. Informatics*, vol. 13, no. 3, pp. 1079–1087, 2017.

[155] G. Liu, M. Starke, B. Xiao, X. Zhang, and K. Tomsovic, "Microgrid optimal scheduling with chance-constrained islanding capability," *Electr. Power Syst. Res.*,

vol. 145, pp. 197–206, 2017.

[156] D. E. Olivares, A. Mehrizi-Sani, A H. Etemadi, C A. Cañizares, R. Iravani, M. Kazerani, A H. Hajimiragha, O. Gomis-Bellmunt, M. Saeedifard, R. Palma-Behnke, G A. Jiménez-Estévez, "Trends in Microgrid Control," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1905–1919, 2014.

[157] R. Firestone and C. Marnay, "Energy manager design for microgrids," Report, no. 150, 2005.

[158] Q. Zhou, Z. Li, Q. Wu, and M. Shahidehpour, "Two-Stage Load Shedding for Secondary Control in Hierarchical Operation of Islanded Microgrids," *IEEE Trans. Smart Grid*, vol. 3053, no. c, pp. 1–8, 2018.

[159] Z. Li and M. Shahidehpour, "Security-constrained unit commitment for simultaneous clearing of energy and ancillary services markets," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 1079–1088, 2005.

[160] P. a Ruiz, C. R. Philbrick, E. Zak, K. W. Cheung, and P. W. Sauer, "Uncertainty Management in the Unit Commitment Problem," *Power Syst. IEEE Trans.*, vol. 24, no. 2, pp. 642–651, 2009.

[161] M. Q. Wang and H. B. Gooi, "Spinning reserve estimation in microgrids," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1164–1174, 2011.

[162] Z. Shi, H. Liang, S. Huang, and V. Dinavahi, "Distributionally Robust Chance-Constrained Energy Management for Islanded Microgrids," *IEEE Trans. Smart Grid*, vol. 3053, no. c, pp. 1–11, 2018.

[163] D. E. Olivares, C. A. Canizares, and M. Kazerani, “A centralized energy management system for isolated microgrids,” *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1864–1875, 2014.

[164] Y. Li, T. Zhao, P. Wang, H. Gooi. L.Wu, Y. Liu, J. Ye, “Optimal operation of multimicrogrids via cooperative energy and reserve scheduling,” *IEEE Trans. Ind. Informatics*, vol. 14, no. 8, pp. 3459–3468, 2018.

[165] IEEE Std 1547.4, *IEEE Guide for Design , Operation , and Integration of Distributed Resource Island Systems with Electric Power Systems IEEE Standards Coordinating Committee 21 Sponsored by the*, no. July. 2011.

[166] Q. Wang, Y. Guan, and J. Wang, “A chance-constrained two-stage stochastic program for unit commitment with uncertain wind power output,” *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 206–215, 2012.

[167] J. T. Saraiva and M. H. Gomes, “Provision of some ancillary services by microgrid agents,” *2010 7th Int. Conf. Eur. Energy Mark. EEM 2010*, pp. 1–8, 2010.

[168] I. Goroohi Sardou, M. E. Khodayar, K. Khaledian, M. Soleimani-Damaneh, and M. T. Ameli, “Energy and Reserve Market Clearing with Microgrid Aggregators,” *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2703–2712, 2016.

[169] A. Majzoobi and A. Khodaei, “Application of microgrids in providing ancillary services to the utility grid,” *Energy*, vol. 123, pp. 555–563, 2017.

[170] C. A. Baone, N. Acharya, and H. L. N. Wiegman, “Optimal day-ahead scheduling for microgrid participation in frequency regulation markets,” *2016 IEEE Power*

Energy Soc. Innov. Smart Grid Technol. Conf. ISGT 2016, pp. 1–5, 2016.

[171] C. Yuen, A. Oudalov, and A. Timbus, “The provision of frequency control reserves from multiple microgrids,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 1, pp. 173–183, 2011.

[172] S. Qin, “Quantification of Ancillary Service Provision by Microgrid,” no. November, 2015.

[173] J. Wang, H. Zhong, Q. Xia, Z. Ma, Z. Wang, and X. Wu, “Robust Bidding Strategy for Microgrids in Joint Energy , Reserve and Regulation Markets,” no. 51537005.

[174] J. Wang H. Zhong, W. Tang, R. Rajagopal. Q. Xia, C. Kang, and Y. Wang, “Optimal bidding strategy for microgrids in joint energy and ancillary service markets considering flexible ramping products q,” *Appl. Energy*, vol. 205, pp. 294–303, 2017.

[175] G. J. Lim, M. Rungta, M. R. Baharnemati, G. J. Lim, M. Rungta, and M. R. Baharnemati, “Reliability analysis of evacuation routes under capacity uncertainty of road links Reliability analysis of evacuation routes under capacity uncertainty of road links,” vol. 8830, 2015.

[176] T. Li and M. Shahidehpour, “Price-based unit commitment: a case of Lagrangian relaxation versus mixed integer programming,” *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 2015–2025, 2005.

[177] Z. Wu, P. Zeng, X. P. Zhang, and Q. Zhou, “A Solution to the Chance-Constrained

Two-Stage Stochastic Program for Unit Commitment with Wind Energy Integration," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4185–4196, 2016.

[178] R. H. Lasseter and P. Piagi, "Microgrid: A Conceptual Solution," no. June, 2004.

[179] L. Che X. Zhang, M. Shahidehpour, A. Alabdulwahab, A. Abusorrah, "Optimal Interconnection Planning of Community Microgrids With Renewable Energy Sources," *IEEE Trans. Smart Grid*, vol. 8, no. 3, pp. 1054–1063, 2017.

[180] S. Abbasi, M. Barati, and G. J. Lim, "A Parallel Sectionalized Restoration Scheme for Resilient Smart Grid Systems," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1660–1670, 2019.

[181] A. Iovine, G. Damm, and P. Alou, "Nonlinear Control for DC Microgrids Enabling Efficient Renewable Power Integration and Ancillary Services for AC Grids," vol. 34, no. 6, pp. 5136–5146, 2019.

[182] S. Karagiannopoulos, S. Member, J. Gallmann, and M. Gonz, "Active Distribution Grids offering Ancillary Services in Islanded and Grid-connected Mode," pp. 1–11.

[183] G. E. Asimakopoulou, A. L. Dimeas, and N. D. Hatziargyriou, "Leader-follower strategies for energy management of multi-microgrids," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1909–1916, 2013.

[184] J. Wu and X. Guan, "Coordinated Multi-Microgrids Optimal Control Algorithm for Smart Distribution," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2174–2181, 2013.

[185] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, “Role of Outage Management Strategy in Reliability Performance of Multi-Microgrid Distribution Systems,” *IEEE Trans. Power Syst.*, vol. 8950, no. c, pp. 1–10, 2017.

[186] Z. Wang, B. Chen, J. Wang, and J. Kim, “Decentralized Energy Management System for Networked Microgrids in Grid-Connected and Islanded Modes,” *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 1097–1105, 2016.

[187] Z. Wang B. Chen, J. Wang, M. Begovic. C. Chen, “Coordinated Energy Management of Networked Microgrids in Distribution Systems,” *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 45–53, 2015.

[188] Y. K. Renani, M. Ehsan, and M. Shahidehpour, “Optimal Transactive Market Operations With Distribution System Operators,” *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6692–6701, 2018.

[189] Y. Wu, M. Barati, and G. J. Lim, “Transactions on Power Systems A Pool Strategy of Microgrid in Power Distribution Electricity Market,” *IEEE Trans. Power Syst.*, vol. PP, no. c, p. 1, 2019.

[190] A. K. Zarabie, S. Das, and M. N. Faqiry, “Fairness-Regularized DLMP-Based Bilevel Transactive Energy Mechanism in Distribution Systems,” *IEEE Trans. Smart Grid*, vol. PP, no. c, p. 1, 2019.

[191] C. Yuen, A. Oudalov, and A. Timbus, “The Provision of Frequency Control Reserves From Multiple Microgrids,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 1, pp. 173–183, 2011.

[192] Y. Huo and G. Gruosso, “Hardware-in-the-Loop Framework for Validation of Ancillary Service in Microgrids : Feasibility , Problems and Improvement,” *IEEE Access*, vol. 7, pp. 58104–58112, 2019.

[193] A. La Bella, M. Farina, C. Sandroni, and R. Scattolini, “Design of Aggregators for the Day-Ahead Management of Microgrids Providing Active and Reactive Power Services,” *IEEE Trans. Control Syst. Technol.*, vol. PP, pp. 1–9, 2019.

[194] Y. Wu, G. J. Lim, and J. Shi, “Stability-Constrained Microgrid Operation Scheduling Incorporating Frequency Control Reserve,” in *IEEE Transactions on Smart Grid*, 2019.

[195] N. Liu, X. Yu, C. Wang, and J. Wang, “Energy Sharing Management for Microgrids With PV Prosumers : A Stackelberg Game Approach,” *IEEE Trans. Ind. Informatics*, vol. 13, no. 3, pp. 1088–1098, 2017.

Appendix

A. Data of IEEE 33-node Distribution System (Chapter 3)

In the Chapter 2, IEEE 33-node distribution system is used for Numerical Experiments. Fig. 1 demonstrates the network of modified IEEE 33-node distribution system with three Microgrids and three distributed generators. The branch-feeder data are shown in Table I. The Table II shows the base load point data. The hourly load coefficients can be found in Table III. Table IV provides the distributed generators data in distribution system. Table V demonstrates the Microgrid information in distribution system. Table VI is data of distributed generators information for each Microgrid inside.

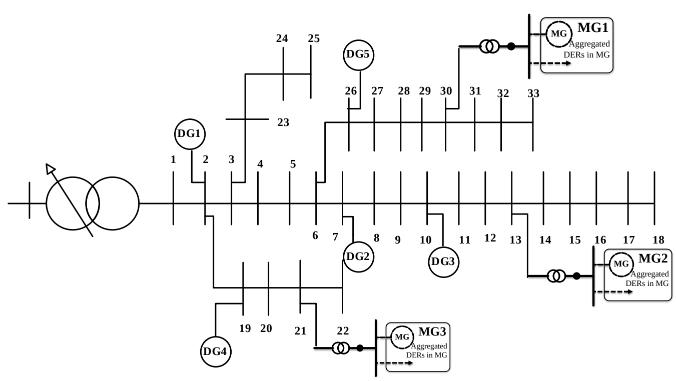

Figure. 1. Modified IEEE 33-node distribution system

TABLE I. BRANCH-FEEDER DATA

Line No.	**From Node**	**To Node**	**r(ohm)**	**x(ohm)**
1	1	2	0.0922	0.047
2	2	3	0.493	0.2511
3	3	4	0.366	0.1864
4	4	5	0.3811	0.1941
5	5	6	0.819	0.707
6	6	7	0.1872	0.6188
7	7	8	0.7114	0.2351
8	8	9	1.03	0.74
9	9	10	1.044	0.74
10	10	11	0.1966	0.066
11	11	12	0.3744	0.1238
12	12	13	1.468	1.155
13	13	14	0.5416	0.7129
14	14	15	0.591	0.526
15	15	16	0.7463	0.545
16	16	17	1.289	1.721
17	17	18	0.732	0.574
18	2	19	0.164	0.1565
19	19	20	1.5042	1.3554
20	20	21	0.4095	0.4784
21	21	22	0.7089	0.9373
22	3	23	0.4512	0.3083

23	23	24	0.898	0.7091
24	24	25	0.896	0.7011
25	6	26	0.203	0.1034
26	26	27	0.2842	0.1447
27	27	28	1.059	0.9337
28	28	29	0.8042	0.7006
29	29	30	0.5075	0.2585
30	30	31	0.9744	0.963
31	31	32	0.3105	0.3619
32	32	33	0.341	0.5302

TABLE II. BASE LOAD DATA

Node No.	**P (kw)**	**Q (kvar)**
2	100	60
3	90	40
4	120	80
5	60	30
6	60	20
7	200	100
8	200	100
9	60	20
10	60	20
11	45	30
12	60	35
13	60	35
14	120	80
15	60	10
16	60	20
17	60	20

18	90	40
19	90	40
20	90	40
21	90	40
22	90	40
23	90	50
24	420	200
25	420	200
26	60	25
27	60	25
28	60	20
29	120	70
30	200	600
31	150	70
32	210	100
33	60	40

TABLE III. HOURLY LOAD COEFFICIENTS

Time	**Coefficient**
1	0.5409
2	0.5291
3	0.5248
4	0.5595
5	0.5446
6	0.5458
7	0.6270
8	0.6772
9	0.6933

10	0.7299
11	0.7485
12	0.7515
13	0.8625
14	0.9461
15	0.9517
16	0.9721
17	0.9994
18	1.0000
19	0.9641
20	0.9610
21	0.8674
22	0.8073
23	0.6084
24	0.5855

TABLE IV. DISTRIBUTED GENERATOR DATA IN DS

DG No.	**Location (Node No.)**	**Max Active Output (p.u.)**	**Max Reactive Output (p.u.)**	**Cost Coefficient ($/p.u.)**
1	2	0.06	0.04	0.04
2	7	0.06	0.04	0.04
3	10	0.08	0.06	0.03
4	19	0.06	0.04	0.04

5	26	0.04	0.03	0.05

TABLE V. MICROGRID DATA AT PCCS

MG NO.	Location (Node No.)	Max/Min Active Power at PCC (p.u.)	Max/Min Reactive Power at PCC (p.u.)
1	30	±0.04	±0.05
2	13	±0.07	±0.05
3	21	±0.05	±0.05

TABLE VI. DISTRIBUTED GENERATOR DATA IN MGS

MG No.	DG No.	Max Active Output (p.u.)	Max Reactive Output (p.u.)	Cost Coefficient ($/p.u.)	Active Loads (p.u.)	Reactive Loads (p.u.)
1	1	0.06	0.04	0.04	0.12	0.072
	2	0.04	0.03	0.05		
	3	0.04	0.03	0.05		
2	1	0.04	0.03	0.05	0.09	0.06
	2	0.04	0.03	0.05		
	3	0.04	0.03	0.05		
3	1	0.06	0.04	0.03	0.072	0.048
	2	0.04	0.03	0.05		

B. Data of Microgrid Scheduling System (Chapter 4)

Table. I demonstrates the dispatchable units' power output information inside the Microgrid. Table II shows the reserve output information of dispatchable units. The Table III shows the load expected output standard variance data. The renewable energy (wind and solar) expected output and standard variance per hour can be found in Table IV. Table V provides the main grid interaction data with microgrid. Table VI and Table VII present the different penalty price data sets (Fixed and Market based). Table VIII demonstrates the market price information used for power interaction between microgrid and main grid

TALBE I DISPATCHABLE UNIT OUTPUT

Unit No.	**Cost ($/MWh)**	**Min (MW)**	**Max (MW)**	**Min up/down time (h)**	**Start up cost ($)**	**Shut down Cost ($)**
1	21.6	4	15	4	35	10
2	33.8	2.5	12	3	25	10
3	45.4	2	10	2	20	8
4	52.8	1.5	8	2	15	6
5	66.3	0.8	5	2	10	6

TABLE II DISPATCHABLE UNIT RESERVE OUTPUT

Unit No.	**Ramp up (MW/h)**	**Ramp down (MW/h)**	**Max UP/DOWN Reserve Max(MW)**	**Min UP/DOWN Reserve (MW)**	**ramp up/down reserve cost**
1	4	4.5	3	0	15.2
2	3	3.5	2	0	23.6

3	3	3.5	1.5	0	25.8
4	2	2.5	1	0	17.6
5	1.5	2	0.8	0	26.7

TABLE III HOURLY LOAD DATA

Hour	Expected Load (MWh)	Standard deviation (MWh)
1	26.19	1.5
2	25.95	1.5
3	25.41	1.5
4	27.09	1.5
5	26.37	1.5
6	26.43	1.5
7	30.36	2
8	32.79	2
9	33.57	2
10	35.34	2
11	36.24	2
12	36.39	2
13	41.76	3
14	45.81	3
15	46.08	3
16	47.07	3
17	48.39	3.5
18	48.42	3.5
19	46.68	3.5

20	46.53	3
21	42	3
22	39.09	2
23	29.46	1.5
24	28.35	1.5

TABLE IV RENEWABLE ENERGY DATA

Hour	**Wind**		**Solar**	
	Expected Output (MWh)	**Standard Deviation (MWh)**	**Expected Output (MWh)**	**Standard Deviation (MWh)**
1	15.86	2.5	0	0
2	15.11	2.5	0	0
3	12.36	2	0	0
4	10.23	2	0	0
5	8.85	1	0	0
6	6.48	1	0	0
7	5.92	1	0	0
8	6.02	0.6	2.45	0.1
9	4.13	0.6	6	0.3
10	2.16	0.3	9.1	0.6

11	1.89	0.3	11.25	1
12	2.61	0.3	12.8	1
13	3.39	0.3	13.15	1.3
14	3.70	0.3	13.35	1.3
15	3.50	0.3	11.65	1
16	3.52	0.3	9.95	0.7
17	3.58	0.5	7.85	0.5
18	3.94	0.5	4.9	0.3
19	3.83	0.5	2.05	0.1
20	4.30	0.6	0.05	0
21	5.14	0.6	0	0
22	6.97	1	0	0
23	10.99	1.5	0	0
24	14.88	2	0	0

TABLE V MAIN GRID DATA

Min Output (MW)	**Max Output (MW)**	**Max Ramp Up Reserve (MW)**	**Max Ramp Down Reserve (MW)**	**Min Ramp Up Reserve (MW)**	**Min Ramp Down Reserve (MW)**
-18	18	6	6	0	0

TABLE VI FIXED PENALTY PRICE

Penalty Type	Load Shedding		Power Curtailment	
Operation Mode	Grid-connected	Islanding	Grid-connected	Islanding
Penalty ($/MWh)	80	120	40	60

TABLE VI. MARKET-BASED PENALTY PRICE

	Load Shedding		Power Curtailment	
Time (hour)	Grid-connected	Islanding	Grid-connected	Islanding
1	40	60	32	48
2	40	60	32	48
3	40	60	32	48
4	40	60	32	48
5	40	60	32	48
6	40	60	32	48
7	40	60	32	48
8	40	60	32	48
9	40	60	32	48
10	40	60	32	48
11	96	144	80	120
12	96	144	80	120
13	96	144	80	120
14	96	144	80	120
15	96	144	80	120
16	160	240	120	180
17	160	240	120	180
18	160	240	120	180
19	160	240	120	180
20	160	240	120	180
21	160	240	120	180
22	160	240	120	180
23	96	144	80	120

24	96	144	80	120

TABLE VII. MARKET PRICE

Hour	Power Interaction Cost ($/MWh)	Ramp Up Reserve Cost ($/MW)	Ramp Down Reserve Cost ($/MW)
1	13.53	10.23	10.23
2	9.87	10.46	10.46
3	12.16	11.01	11.01
4	13.82	11.06	11.06
5	16.66	11.84	11.84
6	16.92	12.16	12.16
7	15.57	13.12	13.12
8	20.55	14.88	14.88
9	19.66	14.88	14.88
10	24.38	16.64	16.64
11	33.35	16.32	16.32
12	62.06	20.64	20.64
13	59.21	24.32	24.32
14	59.91	24.96	24.96
15	58.90	26.72	26.72
16	71.81	28.64	28.64
17	103.91	30.47	30.47
18	99.25	35.71	35.71
19	86.45	36.32	36.32
20	81.48	32.56	32.56

21	69.64	30.8	30.8
22	63.86	25.92	25.92
23	53.48	24.56	24.56
24	51.01	22.96	22.96

C. Data of IEEE 33-node Transactive Distribution System (Chapter 5)

The line data are shown in Table I. The Table II shows the basic load data. The hourly load coefficients can be found in Table III. Table IV provides the distributed generators data in distribution system. Table V demonstrates the Microgrid information in distribution system. Table VI-Table XI are data of distributed generators information for each Microgrid. Table XII and Table XIII are price information that used for interactions between Microgrids and Distribution System.

TABLE I. LINE DATA

Line No.	**From Node**	**To Node**	**r(ohm)**	**x(ohm)**
1	1	2	0.0922	0.047
2	2	3	0.493	0.2511
3	3	4	0.366	0.1864
4	4	5	0.3811	0.1941
5	5	6	0.819	0.707
6	6	7	0.1872	0.6188
7	7	8	0.7114	0.2351
8	8	9	1.03	0.74
9	9	10	1.044	0.74
10	10	11	0.1966	0.066
11	11	12	0.3744	0.1238
12	12	13	1.468	1.155
13	13	14	0.5416	0.7129
14	14	15	0.591	0.526

15	15	16	0.7463	0.545
16	16	17	1.289	1.721
17	17	18	0.732	0.574
18	2	19	0.164	0.1565
19	19	20	1.5042	1.3554
20	20	21	0.4095	0.4784
21	21	22	0.7089	0.9373
22	3	23	0.4512	0.3083
23	23	24	0.898	0.7091
24	24	25	0.896	0.7011
25	6	26	0.203	0.1034
26	26	27	0.2842	0.1447
27	27	28	1.059	0.9337
28	28	29	0.8042	0.7006
29	29	30	0.5075	0.2585
30	30	31	0.9744	0.963
31	31	32	0.3105	0.3619
32	32	33	0.341	0.5302

TABLE II. LOAD DATA

Node No.	**P (kw)**	**Q (kvar)**
2	100	60
3	90	40
4	120	80
5	60	30
6	60	20

7	200	100
8	200	100
9	60	20
10	60	20
11	45	30
12	60	35
13	60	35
14	120	80
15	60	10
16	60	20
17	60	20
18	90	40
19	90	40
20	90	40
21	90	40
22	90	40
23	90	50
24	420	200
25	420	200
26	60	25
27	60	25
28	60	20
29	120	70
30	200	600
31	150	70
32	210	100
33	60	40

TABLE III. HOURLY LOAD COEFFICIENTS

Time	Coefficient
1	0.5409
2	0.5291
3	0.5248
4	0.5595
5	0.5446
6	0.5458
7	0.6270
8	0.6772
9	0.6933
10	0.7299
11	0.7485
12	0.7515
13	0.8625
14	0.9461
15	0.9517
16	0.9721
17	0.9994
18	1.0000
19	0.9641
20	0.9610
21	0.8674
22	0.8073
23	0.6084
24	0.5855

TABLE IV. DISTRIBUTED GENERATOR IN DS

DG No.	Location	Maximum Active Output (p.u.)	Minimum Active Output (p.u.)	Minimum up time (h)	Minimum down time (h)
1	2	0.06	0	8	3
2	7	0.06	0	8	3
3	10	0.08	0	10	4
4	19	0.06	0	8	3
5	26	0.04	0	6	2

TABLE V. DISTRIBUTED GENERATOR IN DS

DG No.	Ramp up rate (p.u./h)	Ramp up rate (p.u./h)	Ramp down rate (p.u./h)	Maximum reserve output (p.u.)	Minimum reserve output (p.u.)
1	0.01	0.01	0.012	0.004	0
2	0.01	0.01	0.012	0.004	0
3	0.015	0.015	0.02	0.005	0
4	0.01	0.01	0.012	0.004	0
5	0.08	0.08	0.01	0.003	0

TABLE VI. COST OF DISTRIBUTED GENERATOR IN DS

DG No.	Startup cost ($)	Shut down cost ($)	Operation cost ($)	Reserve up cost ($)	Reserve down cost ($)
1	0.08	0.03	0.05	0.04	0.04
2	0.08	0.03	0.05	0.04	0.04

3	0.1	0.03	0.04	0.03	0.03
4	0.08	0.03	0.05	0.04	0.04
5	0.07	0.04	0.06	0.05	0.05

TABLE VII. DISPATCHABLE DISTRIBUTED GENERATORS IN MG 1

DG #	Maximum Power (p.u.)	Maximum Reserve (p.u.)	Operation cost ($)	Reserve cost ($)	Maximum full capacity running time (h)
1	0.06	0.006	0.06	0.05	8
2	0.04	0.004	0.07	0.06	6
3	0.04	0.004	0.07	0.06	6

TABLE VIII. DISPATCHABLE DISTRIBUTED GENERATORS IN MG 2

DG #	Maximum Power (p.u.)	Maximum Reserve (p.u.)	Operation cost ($)	Reserve cost ($)	Maximum full capacity running time (h)
1	0.04	0.004	0.07	0.06	6
2	0.04	0.004	0.07	0.06	6
3	0.04	0.004	0.07	0.06	6

TABLE IX. DISPATCHABLE DISTRIBUTED GENERATORS IN MG 3

DG #	Maximum Power (p.u.)	Maximum Reserve (p.u.)	Operation cost ($)	Reserve cost ($)	Maximum full capacity running time (h)
1	0.06	0.006	0.06	0.05	8
2	0.04	0.004	0.07	0.06	6

TABLE X. MICROGRID OUTPUT

MG NO.	Location	Max/Min Active Output (p.u.)	Max/Min Reserve (p.u.)
1	30	±0.1	±0.04
2	13	±0.1	±0.04
3	21	±0.1	±0.04

TABLE XI. RENEWABLE ENERGY PROFILE IN MGS

Time	MG 1	MG 2	MG 3
1	0.0048	0.0000	0.0033
2	0.0045	0.0000	0.0032
3	0.0037	0.0000	0.0026
4	0.0031	0.0000	0.0021
5	0.0027	0.0000	0.0019
6	0.0019	0.0000	0.0014
7	0.0018	0.0000	0.0012
8	0.0018	0.0010	0.0020
9	0.0012	0.0024	0.0025
10	0.0006	0.0036	0.0030
11	0.0006	0.0045	0.0035
12	0.0008	0.0051	0.0041
13	0.0010	0.0053	0.0044
14	0.0011	0.0053	0.0045
15	0.0010	0.0047	0.0040
16	0.0011	0.0040	0.0035
17	0.0011	0.0031	0.0030
18	0.0012	0.0020	0.0022

19	0.0011	0.0008	0.0014
20	0.0013	0.0000	0.0009
21	0.0015	0.0000	0.0011
22	0.0021	0.0000	0.0015
23	0.0033	0.0000	0.0023
24	0.0045	0.0000	0.0031

TABLE XI. ENERGY MARKET PRICE

Hour	**Market Price ($/p.u.)**
1	0.0350
2	0.0310
3	0.0335
4	0.0354
5	0.0385
6	0.0388
7	0.0373
8	0.0428
9	0.0458
10	0.0511
11	0.0611
12	0.0790
13	0.0758

14	0.0766
15	0.0754
16	0.0898
17	0.1255
18	0.1203
19	0.1061
20	0.1005
21	0.0874
22	0.0810
23	0.0694
24	0.0667

TABLE XII. REGULATION MARKET PRICE

Time	Regulation Up MG to DS Market Price ($/p.u.)	Regulation Up DS to MG Market Price ($/p.u.)	Regulation Down DS to MG Market Price ($/p.u.)	Regulation Down MG to DS Market Price ($/p.u.))
1	0.0336	0.0336	0.0288	0.0288
2	0.0406	0.0406	0.0348	0.0348
3	0.0434	0.0434	0.0372	0.0372
4	0.0462	0.0462	0.0396	0.0396
5	0.0476	0.0476	0.0408	0.0408
6	0.049	0.049	0.042	0.042
7	0.04676	0.04676	0.04008	0.04008
8	0.0532	0.0532	0.0456	0.0456
9	0.0546	0.0546	0.0468	0.0468

10	0.056	0.056	0.048	0.048
11	0.063	0.063	0.054	0.054
12	0.0826	0.0826	0.0708	0.0708
13	0.07975	0.07975	0.068352	0.068352
14	0.08069	0.08069	0.069168	0.069168
15	0.07932	0.07932	0.067992	0.067992
16	0.09672	0.09672	0.082896	0.082896
17	0.12355	0.12355	0.1059	0.1059
18	0.11967	0.11967	0.102576	0.102576
19	0.11642	0.11642	0.099792	0.099792
20	0.10973	0.10973	0.094056	0.094056
21	0.09379	0.09379	0.0804	0.0804
22	0.086	0.086	0.073716	0.073716
23	0.07202	0.07202	0.06174	0.06174
24	0.0687	0.0687	0.058884	0.058884