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Optimal Management of Transactive Distribution Electricity Markets with Co-optimized Bidirectional Energy and Ancillary Service Exchanges

Yiwei Wu, *Student Member, IEEE*, Jian Shi, *Senior Member, IEEE*, Gino Lim, Lei Fan, *Senior Member, IEEE*, and Anahita Molavi, *Student Member, IEEE*

***Abstract*— This paper develops a novel co-optimized distribution system management algorithm for the distribution system operator to optimally manage the ever-increasing penetration of networked microgrids that are participating in the transactive distribution market as prosumers. For the first time, we evaluate how the incorporation of joint bidirectional energy and ancillary service exchanges could quantitatively increase the operation economy, flexibility, and reliability for both the microgrids and the distribution grid. We formulate the joint distribution system management problem using a bilevel programming approach, in which the upper level is a distribution system optimal management problem for the distribution system operator and the lower level is a microgrid optimal scheduling problem for each participating microgrid operator. Uncertainties from renewable energy generation and responsive loads within the distribution system are also incorporated in the problem formulation. The bilevel stochastic programming model is then reformulated as a single mixed-integer model to solve. The simulation-based case study supports that the proposed management scheme is capable of enhancing energy independency, system-wide efficiency, operational reliability, and economy of the distribution system in comparison with conventional transactive market management schemes.**

***Index Terms*—Transactive energy, Microgrids, Distribution system operator, Microgrid operator, Bilevel programming**

NOMENCLATURE

Parameters

$C_t^{ls/pc}$	Value of Load shedding/ power curtailment at time t
$D_t^{up/dw}$	Regulation up/down requirement at time t
$\boldsymbol{K}_{(.)}$	Incidence matrix
$\boldsymbol{P}_{(.)}$ / $\boldsymbol{R}_{(.)}$	Energy/regulation injection matrix
$P_n^{g,\min/\max}$	Min/max power output capacity of DG n
P_t^l	Load demand of microgrid j at time t
$P_j^{m,\min/\max}$	Min/max power output capacity of MG j
P_t^{re}	Forecasted Renewable energy output
$P_{\mathbf{m}}^{u,\min/\max}$	Min/max power output of utility
$P_k^{w,\mathbf{min}/\max}$	Min/max power output capacity of MG-owned DG k
$R_n^{g,up/dw,\min/\max}$	Min/max regulation up/down output capacity of DS-owned DG n
$R_k^{w,up/dw,\min/\max}$	Min/max regulation up/down output capacity of MG-owned DG k
$R_j^{\alpha,up/dw,\mathbf{min}/\max}$	Min/max regulation up/down transfer capacity from DS to MG
$R_j^{\beta,up/dw,\min/\max}$	Min/max regulation up/down transfer capacity from MG to DS
RD_n / RU_n	Ramp down/up rate of dispatchable generation unit n
SD_n / SU_n	Shut down/ startup cost of DS-owned DG n
T_n^{off} / T_n^{on}	Minimum off/on time of DS-owned DG n
T_k	Maximum full capacity running time for MG-owned DG k
$X_{nt}^{off/on}$	Off/on time of DS-owned DG n at time t
ΔP_{bts}^l / ΔP_{jts}^{re}	Load/renewable energy forecast deviations
W_t^0 / $L_{l,t}^0$	Mean value of forecasted renewable energy generation/load consumption
ξ_t^{w2} / $\xi_{l,t}^{l\ 2}$	Variance of forecasted renewable energy generation/load consumption
O	Large positive number

Sets

B	Bus set B ={1,…, NB}, NB is number of buses
J	MG set J ={1,…, NM}, NM is number of MGs
K_j	Generation unit set K_j = {1,…, NDG_j} in the j-*th* MG, NDG_j is the number of generation units
L	Consumer set in DS, L={1,…, NL}, NL is the number of loads 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,…,24}
S	Total number of scenarios

Variables

b_{nt}	Binary variable associated with dispatchable unit n at time t
$I_{jt}^{\alpha/\beta,up/dw}$	Binary variable associated with the regulation interaction between MG j and DS at time t
l_{bst}^{sh} / q_{bst}^{cu}	Load shedding/ power curtailment value at time t at node b in scenario s
p_{jt}^m / p_t^c	Power exchange at PCC at time t
p_{kt}^w	Power output of MG-owned DG k at time t
p_{nt}^g	Power output of DS-owned DG n at time t
p_{lt}^l	Controllable load l at time t
p_{mt}^u	Power output of utility m at time t
x_{nt} / y_{nt}	Startup/Shutdown indicator for DS-owned DG n at time t
$r_{nt}^{g,up/dw}$	Regulation up/down provided by DS-owned DG unit n at time t
$r_{jt}^{m,up/dw,\alpha}$	Regulation up/down transfer from DS to MG j at time t
$r_{jt}^{m,up/dw,\beta}$	Regulation up/down transferred from MG j to DS at time t
$r_{jt}^{c,up/dw,buy/sell}$	Regulation up/down buy/sell from MG j to DS at time t
$r_{kt}^{w,up/dw}$	Regulation up/down provided by DG k in MG at time t
$\tau_{(.)ts}$	Second stage decision variables associated with DG n or MG j in scenario s
σ_{kts}	Second stage decision variables associated with MG-owned DG k at time t in scenario s

υ_{jts}	Second stage decision variables associated with MG j at PCC at time t in scenario s
Δp_{jts}^{m}	Power deviation at PCC at time t in scenario s
$\omega_{k,t}$	Ancillary binary variables
$\mu_{kt}^{(.)\min/\max}, \pi_{kt}^{(.)}, \lambda_{bt}^{rup/dw}, \theta_{kts}^{rdw\max}$	Dual variables associated with second stage model constraints

I. Introduction

Microgrids are no longer a concept [1], but are 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 [2]–[5]. As the underlying technologies have become more advanced, microgrids equipped with advanced operation and control techniques can flexibly ramp up or down their demand [6]. 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 [7], all of which can be used as a grid resource to maximize the economic viability and help offset the investment [8] and maintenance cost that comes with the establishment of a microgrid [9]–[11].

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 its corresponding distribution system [12]. Such coordination includes the transactive interactions between the microgrid operators (MGOs), 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 [13]. 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 [14]–[16]. This clearly suggest 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 [17][18]. Furthermore, the transactive commodities should not be limited to energy. Energy derivatives, i.e., ancillary services, also need 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 decentralization, more self-management right and transactive opportunities 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. Effective operation of this model is crucial for fostering a healthy, transparent, competitive, and sustainable DSO-facilitated localized market [18][19].

While the existing scheduling algorithms for transactive distribution markets [20]–[22] offer insights into the operation of such a transactive distribution system, two important challenges remain to be addressed [14], [23]–[25]. 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 [23], a coordinated distribution system energy management scheme was proposed considering only the energy exchange within the distribution grid with networked microgrids. In [26], a transactive mechanism is proposed for a 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 [10][27]. Therefore, a sound transactive market design calls for innovative and improved 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 transactive opportunities. However, some of the existing literature treated microgrids as DSO-owned energy storage resources for the provision of ancillary services in order to support the operation of the distribution system [28]–[30]. Under this management hierarchy, each microgrid acts as an involuntary provider of ancillary services [31]. 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 [32], the microgrid is modeled as a passive recipient 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 [25]. 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 paper, we propose a novel DSM algorithm that incorporates bi-directional energy and ancillary service flow in a transactive market environment. We formulate the optimal day-ahead scheduling problem as a bilevel programming model, in which the upper level represents the DSO schedule problem, and the lower level represents the MGOs' reactions to the DSO schedule. The proposed bilevel model is then reformulated into a mixed-integer linear programming (MILP) model through relaxing mathematical programming with equilibrium constraints (MPEC) [33]. The final MILP model gives a global optimal solution and reduces computational burden [34]. Note that while the microgrid is capable of supplying multiple categories of grid-supporting services, we focus on the *frequency regulation* as an example of a 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 response to maintain system stability, and therefore plays an important role in maintaining the stability and reliability of microgrids given their limited capacity and inertia.

The contributions of this paper can be summarized as follows:

1. This paper 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. To the best of our knowledge, this paper is the first of its kind.

2. This paper presents a novel stochastic bilevel programming model 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 existing transactive distribution system management schemes.

The remainder of this paper is organized as follows. Section II presents the outlines, key structures, and assumptions of the DSM strategy. Section III formulates a bilevel stochastic programming problem and the associated solution algorithm. The simulation-based case studies are carried out in Section IV with the conclusions drawn in Section V.

II. Outline and Assumptions

A. Joint Transactive Distribution Electricity Market

In this paper, we adopt and extend the fundamental distribution electricity market structure as described in [25] to support the transactive involvement of the microgrids and other market participants. We consider a day-ahead market in which both energy and regulation are traded on an hourly basis. The basic structure of this transactive distribution system involves two levels as shown in Figure 1: a distribution system level and a microgrid level. On the distribution system level, the DSO manages interactions between the distribution system and its participants, including grid operation (e.g., directing energy and ancillary service flows) and market operation (e.g., market regulation, facilitating transactive exchanges, and market clearing). Analogous to the independent system operators (ISOs) managing transmission networks, as an independent (nonprofit) grid operator, the DSO is responsible for managing DER variability, balancing between load and generation, as well as maintaining the efficient and reliable operation of the distribution grid. As the market operator, the DSO also has to provide competitive access to market resources and coordinate the market responsibility of different participants within the distribution network. Furthermore, the DSO is an aggregator in the upstream bulk power market (i.e., ISO market) which represents all the distribution system customers, DERs, and MGOs in its local distribution grid. It acts as the intermedium to optimize local distributed resources and integrate them into the upstream bulk power market in the form of a single aggregated bid to ISO.

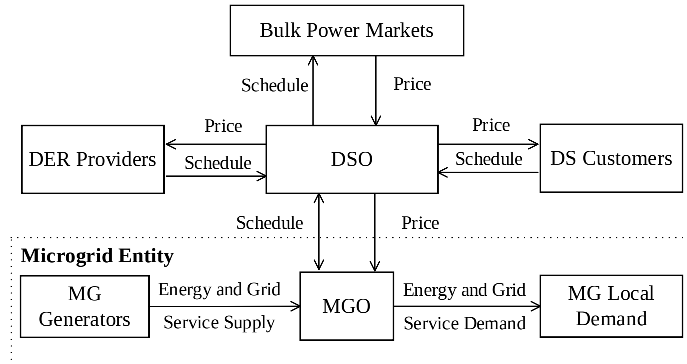

Fig. 1. A joint transactive distribution electricity market structure

On the microgrid level, the MGO has autonomy to optimally schedule the microgrid-owned assets and the transactive interactions in response to distribution system states and market price signals, all to address the energy needs of local loads. An MGO is a profit-driven entity that seeks to maximize its economic benefits. Based on this division of responsibility, the market equilibrium is then realized at the PCC between the DSO and each MGO. This hierarchy can be naturally modeled by a bilevel programming approach [35].

B. Bidirectional Energy and Ancillary Service Exchange

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 paper, 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 in real-time. This indicates that a total of five types of resources are traded under this framework. In addition to the bidirectional energy transactions, the regulation transactions of 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 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 as described in (1) and (2), respectively. 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. Specifically, when one unit of regulation up ΔR_{PCC} is exported (i.e., sold) from the MGO to the DSO, the capability of the microgrid to ramp up P_{MG} is reduced for the MGO as described in (1). 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 through ΔR_{PCC}, and thus this unit of "regulation up" has to be enforced by lowering one unit of the ramp down capability P_{DS} at this node as described in (2). Note here $L_{(.)}$ denotes the load, and P_{PCC} denotes the energy exchange at the PCC. This process is depicted in Fig. 2.

$$P_{MG} = L_{MG} + P_{PCC} + \Delta R_{PCC} \tag{1}$$

$$P_{PCC} + \Delta R_{PCC} + P_{DS} = L_{DS} \tag{2}$$

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.

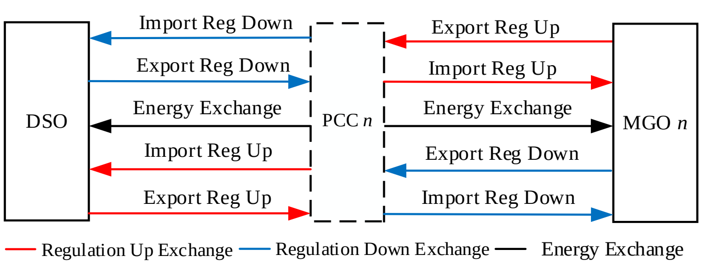

Fig. 2. Bidirectional energy and regulation exchange via the PCC

C. Assumptions

In this work, the following assumptions are adopted: each microgrid is modeled as an aggregated model without considering its internal network due to its limited geographical layout [36]. 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.

III. Model and Method

In this section, the proposed bilevel programming model is explained.

A. 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 DGs, 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 follows:

$$\begin{aligned}
&\min \sum_t \sum_n (c_n^g(p_{nt}^g) + x_{nt}SU_n + y_{nt}SD_n + c_n^r(r_{nt}^{up}, r_{nt}^{down})) \\
&+\sum_t \sum_m \rho_t^c(p_{mt}^u) \\
&+\sum_t (\sum_j \rho_t^c(p_{jt}^m) + \sum_j \rho_t^{r,up}(r_{jt}^{m.up,\alpha}, r_{jt}^{m,up,\beta}) - \sum_j \rho_t^{r,dw}(r_{jt}^{m,dw,\alpha}, r_{jt}^{m,dw,\beta})) \\
&+\sum_s \sum_t \sum_b \frac{1}{S}(C_t^{ls}\cdot l_{bst}^{sh} + C_t^{pc}\cdot q_{bst}^{cu})
\end{aligned} \tag{3}$$

The first term of (3) represents the operation cost of DSO-owned DGs, including the cost of energy generation and the regulation provisions. The second term of (3) represents the cost of interactions between the DSO and the upstream system. In this paper, we assume that the DSO is a passive energy importer from the upstream system. The third term of (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 services 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 (3), c_n^g / c_n^r denote the cost function of the energy and regulation generation of DG unit n, respectively. ρ_t^c / ρ_t^r denote the market price function of energy and regulation at different time intervals t, respectively. For simplicity, all of the cost functions $c_i^{g/r}$ and $\rho_t^{c/r}$ are defined as linear functions.

The constraints of the upper level model are defined in (4)-(35). The power transfer is bidirectional and thus can be positive or negative (4). Four constraints are defined to represent the regulation interactions between the microgrid and the distribution system (5)-(10): The maximum capacity of each type of regulation is constrained by (5)-(8). For each type of regulation, import or export action is only allowed in one direction at one time interval as defined in (9) and (10). Note that exporting from distribution system to microgrid is denoted as α and importing from microgrid to distribution system is denote as β:

$$P_j^{m,\min} \le p_{jt}^m \le P_j^{m,\max}, \forall j \in J, \forall t \in T \tag{4}$$

$$0 \le r_{jt}^{m.up,\alpha} \le R_j^{\alpha,up,\max} I_{jt}^{\alpha,up}, \forall j \in J, \forall t \in T \tag{5}$$

$$0 \le r_{jt}^{m,up,\beta} \le R_j^{\beta,up,\max} I_{jt}^{\beta,up}, \forall j \in J, \forall t \in T \tag{6}$$

$$0 \le r_{jt}^{m,dw,\alpha} \le R_j^{\alpha,dw,\max} I_{jt}^{\alpha,dw}, \forall j \in J, \forall t \in T \quad (7)$$

$$0 \le r_{jt}^{m,dw,\beta} \le R_j^{\beta,dw,\max} I_j^{\beta,dw}, \forall j \in J, \forall t \in T \quad (8)$$

$$I_{jt}^{\alpha,up} + I_{jt}^{\beta,up} \le 1, \forall j \in J, \forall t \in T \quad (9)$$

$$I_{jt}^{\alpha,dw} + I_{jt}^{\beta,dw} \le 1, \forall j \in J, \forall t \in T \quad (10)$$

At the point of PCC, the net regulation that the DSO acquires from each microgrid is determined based on the interactions, which is measured by the imported quantity minus the exported quantity as described in (11) and (12):

$$r_{jt}^{m,up} = r_{jt}^{m,up,\beta} - r_{jt}^{m,up,\alpha}, \forall j \in J, \forall t \in T \quad (11)$$

$$r_{jt}^{m,dw} = r_{jt}^{m,dw,\beta} - r_{jt}^{m,dw,\alpha}, \forall j \in J, \forall t \in T \quad (12)$$

The energy and regulation transfer between the distribution system and the microgrids have to go through the PCC. Therefore, the physical limit of the power line at the PCC determines that the maximum power transfer between each microgrid and the distribution system cannot exceed a certain level as outlined in (13) and (14):

$$p_{jt}^{m} + r_{jt}^{m,up,\beta} + r_{jt}^{m,dw,\alpha} \le P_j^{\mathrm{m,max}}, \forall j \in J, \forall t \in T \quad (13)$$

$$p_{jt}^{m} - r_{jt}^{m,dw,\beta} - r_{jt}^{m,up,\alpha} \ge P_j^{\mathrm{m,min}}, \forall j \in J, \forall t \in T \quad (14)$$

Since all of the DGs in the distribution grid are assumed to be dispatchable units, the following mixed-integer model applies:

The real power output of each DG has an upper bound and a lower bound as described in (15):

$$b_{nt} P_n^{g,\min} \le p_{nt}^{g} \le b_{nt} P_n^{g,\max}, \forall n \in D, \forall t \in T \quad (15)$$

The minimum uptime and minimum downtime constraints for each DG are defined in (16) and (17), respectively:

$$(X_{nt}^{on} - T_n^{on})(b_{n(t-1)} - b_{nt}) \ge 0, \forall n \in D, \forall t \in T \quad (16)$$

$$(X_{n(t-1)}^{off} - T_n^{off})(b_{nt} - b_{n(t-1)}) \ge 0, \forall n \in D, \forall t \in T \quad (17)$$

The dispatchable units can also provide regulation up and regulation down to the distribution system within the limitation as described in (18) and (19), respectively:

$$0 \le r_{nt}^{g,up} \le R_n^{g,up,\max} b_{nt}, \forall n \in D, \forall t \in T \quad (18)$$

$$0 \le r_{nt}^{g,dw} \le R_n^{g,dw,\max} b_{nt}, \forall n \in D, \forall t \in T \quad (19)$$

The combined output of energy and regulation cannot exceed the power capacity of each DG as defined in (20) and (21):

$$p_{nt}^{g} + r_{nt}^{up,g} \le P_n^{g,\max} b_{nt}, \forall n \in D, \forall t \in T \quad (20)$$

$$p_{nt}^{g} - r_{nt}^{dw,g} \ge P_n^{g,\min} b_{nt}, \forall n \in D, \forall t \in T \quad (21)$$

The ramp up and ramp down capability of DG is constrained by (22) and (23), respectively:

$$p_{nt}^{g} - p_{n(t-1)}^{g} + r_{nt}^{g,up} \le (2 - b_{n(t-1)} - b_{nt}) P_{nt}^{g,\min} + (1 + b_{n(t-1)} - b_{nt}) RU_n \quad \forall n \in D, \forall t \in T \quad (22)$$

$$p_{n(t-1)}^{g} - p_{nt}^{g} - r_{nt}^{g,dw} \le (2 - b_{n(t-1)} - b_{nt}) P_{nt}^{g,\min} + (1 - b_{n(t-1)} + b_{nt}) RD_n \quad \forall n \in D, \forall t \in T \quad (23)$$

The distribution system is connected to the upstream bulk power system. The capacity of this connection is subject to a bound (24):

$$P_m^{u,\min} \le p_{mt}^{u} \le P_m^{u,\max}, \forall t \in T, \forall m \in M \quad (24)$$

The net consumers (i.e., loads) in the distribution system are assumed controllable and can vary within a range of the expected value as (25):

$$P_{lt}^{l,\min} \le p_{lt}^{l} \le P_{lt}^{l,\max}, \forall l \in L, \forall t \in T \quad (25)$$

In this work, we adopt *DistFlow* equations as described in [37] that can be used to describe the distribution power flows at each node for the distribution system. Equation (26) illustrates the power injections at each node, and Equation (27) represents the power balance equations at each node:

$$\boldsymbol{P}_{bt}^{inj} = \boldsymbol{K}_n \boldsymbol{P}_{nt} + \boldsymbol{K}_j \boldsymbol{P}_{jt} + \boldsymbol{K}_u \boldsymbol{P}_{mt} - \boldsymbol{K}_l \boldsymbol{P}_{lt}, \forall b \in B, \forall t \in T \quad (26)$$

$$\boldsymbol{P}_{(b+1)t} = \boldsymbol{P}_{bt} - \boldsymbol{P}_{bt}^{inj}, \forall b \in B, \forall t \in T \quad (27)$$

The real power flow equations (26) and (27) can be extended to model the similar “flow” of the regulation exchanges as demonstrated by (28)-(31). Similarly, there are node injection equations for regulation up (28) and regulation down (29). The regulation balance at each node is enforced by (30) and (31):

$$\boldsymbol{R}_{bt}^{up,inj} = \boldsymbol{K}_n \boldsymbol{R}_{nt} + \boldsymbol{K}_j \boldsymbol{R}_{jt} - \boldsymbol{K}_l \boldsymbol{R}_{lt}^{up}, \forall b \in B, \forall t \in T \quad (28)$$

$$\boldsymbol{P}_{(b+1)t}^{up} = \boldsymbol{R}_{bt}^{up} - \boldsymbol{R}_{bt}^{up,inj}, \forall b \in B, \forall t \in T \quad (29)$$

$$\boldsymbol{R}_{bt}^{\mathrm{dw},inj} = \boldsymbol{K}_n \boldsymbol{R}_{nt} + \boldsymbol{K}_j \boldsymbol{R}_{jt} - \boldsymbol{K}_l \boldsymbol{R}_{lt}^{dw}, \forall b \in B, \forall t \in T \quad (30)$$

$$\boldsymbol{R}_{(b+1)t}^{\mathrm{dw}} = \boldsymbol{R}_{bt}^{\mathrm{dw}} - \boldsymbol{R}_{bt}^{\mathrm{dw},inj}, \forall b \in B, \forall t \in T \quad (31)$$

Note that the power loss resulted from the power flow is not considered in this model due to its limited impact on the market participants’ behaviors. Moreover, as both the energy and regulation are transmitted within the distribution network in the form of active power, the reactive power flow and the associated voltage constraints are not considered to reduce computational burden for solving the model.

The regulation requirements at each node should be larger than zero, while subject to an upper bound in the form of a regulation band as defined in (32) and (33):

$$0 \le r_{lt}^{dw} \le R_{lt}^{dw,\max}, \forall l \in L, \forall t \in T \quad (32)$$

$$0 \le r_{lt}^{up} \le R_{lt}^{up,\max}, \forall l \in L, \forall t \in T \quad (33)$$

As depicted in Fig. 2, the delivery process at the PCC can be described in (34)-(37), according to Rule 2 proposed in II.B:

$$r_{jt}^{m,up,\alpha} = r_{jt}^{\mathrm{c,dw,buy}}, \forall j \in J, \forall t \in T \quad (34)$$

$$r_{jt}^{m,dw,\alpha} = r_{jt}^{\mathrm{c,up,buy}}, \forall j \in J, \forall t \in T \quad (35)$$

$$r_{jt}^{m,up,\beta} = r_{jt}^{\mathrm{c,dw,sell}}, \forall j \in J, \forall t \in T \quad (36)$$

$$r_{jt}^{m,dw,\beta} = r_{jt}^{\mathrm{c,up,sell}}, \forall j \in J, \forall t \in T \quad (37)$$

Within the distribution system, two categories of uncertainties are considered. The first category of uncertainties is associated with the load in the distribution electricity market. It is evident that their operational uncertainty needs to be directly handled by the DSO. The second category of uncertainties comes from the renewable sources within the microgrids. This requires the MGOs to procure a sufficient amount of regulation from their internal resources or the transactive market. However, the DSO, being 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:

$$\sum_n \tau_{nts}^{g,up} + \sum_j (\tau_{jts}^{m,up,\beta} - \tau_{jts}^{m,\mathbf{up},\alpha}) - (\sum_n \tau_{nts}^{g,\mathrm{dw}} + \sum_j (\tau_{jts}^{m,\mathrm{dw},\beta} - \tau_{jts}^{m,\mathrm{dw},\alpha})) - q_{bst}^{cu} = \Delta P_{bts}^{l} - l_{bst}^{sh} + \sum_j \Delta p_{jts}^{m}, \forall t \in T, \forall s, \forall b \in B \quad (38)$$

The regulation provision from the DGs can be adjusted in each scenario. The ready-to-use regulation is subject to the upper bound as determined in (18) and (19):

$$0 \le \tau_{nts}^{g,up} \le r_{nt}^{g,up}, \forall n \in D, \forall t \in T \quad (39)$$

$$0 \le \tau_{nts}^{g,\text{dw}} \le r_{nt}^{g,dw} \quad ,\forall n \in D, \forall t \in T \tag{40}$$

It is noted that decision variables related to microgrid operation, including the energy transfer p_{jt}^{m} and the ancillary service interaction $r_{jt}^{m,up,\alpha}$, $r_{jt}^{m,up,\beta}$, $r_{jt}^{m,dw,\alpha}$, and $r_{jt}^{m,dw,\beta}$ in the DSO management problem will be transferred to the lower level to be solved with the microgrid scheduling problem as these decisions have to be made collectively by both the DSO and the MGO.

B. MGO 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. This cost includes: 1) the operation cost of the microgrid's internal DGs to produce energy and regulation as described in the first term of (41) and 2) the interaction cost between the microgrid and the distribution system, resulting from the bidirectional exchange of energy (i.e., the second term of (41)) and regulation (i.e., the third term of (41)). Note that similar to (3), in (41), c_k^w / c_k^r denote the cost function of energy and regulation generation of DG unit *k*, respectively, and are assumed linear; $\rho_t^c / \rho_t^{r,(.)}$ denote the bidding/offering function of energy and regulation for microgrid *j* to interact with the distribution system, which are also assumed to be linear.

$$\begin{aligned} &\min \sum_t \sum_k (c_k^w(p_{kt}^w) + c_k^r(r_{kt}^{up,w}, r_{kt}^{dw,w})) + \sum_t \rho_t^c(p_t^c) \\ &+ \sum_t (\rho_t^{r,\text{buy}}(r_t^{\text{up,c,buy}}, r_t^{dw,c,buy}) - \rho_t^{r,sell}(r_i^{\text{up,c,sell}}, r_t^{dw,c,sell})) \end{aligned} \tag{41}$$

Note that while it is possible for different MGs/MGOs to have different cost functions, we considered a uniform cost function for all MGOs as described in (41). However, our model gives the flexibility for MGs to choose appropriate and different parameter values for the cost function based on their own specifications. Hence, the actual cost functions can be different from each other.

The generation resources contained in the microgrid include small size dispatchable DGs and non-dispatchable renewable resources. Considering the enhanced controllability and flexibility of such DGs, the startup/shutdown costs are not considered. We use the following linear model to represent those DGs:

$$P_k^{\text{w,min}} + r_{kt}^{\text{w,dw}} \le p_{kt}^w \le P_k^{\text{w,max}} - r_{kt}^{w,up} \ ,\forall k \in K, \forall t \in T \tag{42}$$

$$R_k^{\text{w,up,min}} \le r_{kt}^{w,up} \le R_k^{\text{w,up,max}} \ ,\forall k \in K, \forall t \in T \tag{43}$$

$$R_k^{\text{w,dw,min}} \le r_{kt}^{\text{w,dw}} \le R_k^{\text{w,dw,max}} \ ,\forall k \in K, \forall t \in T \tag{44}$$

The limited energy capacity of the DGs in each microgrid is enforced by (45)-(47), which indicates that the DG *k* cannot run at their full capacity beyond the time duration of T_k:

$$\sum_t^{t+T} p_{kt}^w \le T_k P_k^{\text{w,max}} \ ,\forall k \in K, \forall t \in T \tag{45}$$

$$\sum_t^{t+T} r_{kt}^{\text{up},w} \le T_k R_k^{up,\max} \ ,\forall k \in K, \forall t \in T \tag{46}$$

$$\sum_t^{t+T} r_{kt}^{\text{dw},w} \le T_k R_k^{\text{dw,max}} \ ,\forall k \in K, \forall t \in T \tag{47}$$

The MGO needs to maintain its internal power balance. This suggests that the combined power generation of the dispatchable units and renewable units should be equal to the total amount of microgrid load plus the PCC interaction as described in (48):

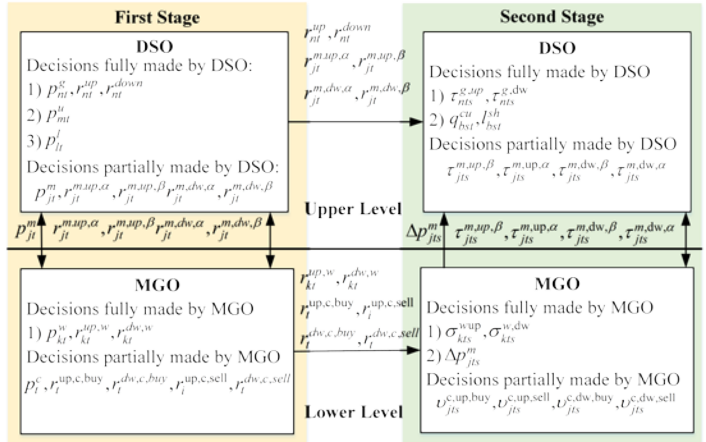

Fig. 3. The proposed bilevel model

$$\sum_k p_{k,t}^w + P_t^{re} = P_t^l + p_t^c \ ,\forall t \in T \tag{48}$$

A certain amount of regulation is prepared within the microgrid to assure that the MGO has sufficient resources readily deployable in order to handle the potential operational uncertainty associated with renewable unit outputs. This regulation can be acquired either by internal production or from the distribution system interaction as described in (49) and (50) for regulation up and regulation down, respectively:

$$\sum_k r_{kt}^{\text{w,up}} + r_t^{\text{c,up,buy}} - r_t^{\text{c,up,sell}} \ge D_t^{up} \ ,\forall t \in T \tag{49}$$

$$\sum_k r_{kt}^{\text{w,dw}} + r_t^{\text{c,dw,buy}} - r_t^{\text{c,dw,sell}} \ge D_t^{dw} \ ,\forall t \in T \tag{50}$$

As mentioned earlier, the DSO is in charge of the system-wide reliability. This suggests that when the original microgrid scheduling scheme is tested through the generated scenarios, no power curtailment or load shedding needs to be performed by the MGO. The out of sample power deviations will be transferred to PCC to be handled in the DSO layer as defined in (51):

$$\begin{aligned} &\Delta P_{jts}^{re} + \sum_k \sigma_{kts}^{w\,\text{up}} + \upsilon_{jts}^{\text{c,up,buy}} - \upsilon_{jts}^{\text{c,up,sell}} - (\sum_k \sigma_{kts}^{w,\text{dw}} + \upsilon_{jts}^{\text{c,dw,buy}} - \upsilon_{jts}^{\text{c,dw,sell}}) \\ &= \Delta p_{jts}^m \ ,\forall j \in J, \forall t \in T, \forall s \end{aligned} \tag{51}$$

The microgrid relies on its DGs (43)-(44) and transactive regulation exchange (52)-(56) to adjust its power balance:

$$0 \le \sigma_{kts}^{\text{w,up}} \le r_{kt}^{\text{w,up}} \ ,\forall k \in K, \forall t \in T, \forall s \tag{52}$$

$$0 \le \sigma_{kts}^{\text{w,dw}} \le r_{kt}^{\text{w,dw}} \ ,\forall k \in K, \forall t \in T, \forall s \tag{53}$$

$$0 \le \upsilon_{jts}^{\text{c,up,buy}} \le r_t^{\text{c,up,buy}} \ ,\forall j \in J, \forall t \in T, \forall s \tag{54}$$

$$0 \le \upsilon_{jts}^{\text{c,up,sell}} \le r_t^{\text{c,up,sell}} \ ,\forall j \in J, \forall t \in T, \forall s \tag{55}$$

$$0 \le \upsilon_{jt}^{\text{c,dw,buy}} \le r_t^{\text{c,dw,buy}} \ ,\forall j \in J, \forall t \in T, \forall s \tag{56}$$

$$0 \le \upsilon_{jt}^{\text{c,dw,sell}} \le r_t^{\text{c,dw,sell}} \ ,\forall j \in J, \forall t \in T, \forall s \tag{57}$$

MGO then transfers the un-handled part of the uncertainty back to the DSO in the form of PCC deviations Δp_{jts}^m.

The structure of the proposed bilevel model is illustrated in Fig. 3. The first/second stage of the DSO management are described by (3)-(37) and (38)-(40); while the first/second stage of the MGO management are described by (41)-(50) and (51)-(57).

C. Solution

As the lower level programming model (LLPM) is a linear programming model, it can be replaced with Karush-Kuhn-Tucker (KKT) optimality conditions as follows:

$$\begin{aligned} & c_k^w - \mu_{kt}^{\mathbf{p}\min} + \mu_{kt}^{\mathrm{p}\max} \\ & -\lambda_t^P + \sum_{\mathbf{t}}^{t+T} \pi_{kt}^p - \lambda_{ts}^{se} = 0, \forall k \in K, \forall t \in T, \forall s \end{aligned} \tag{58}$$

$$\begin{aligned} & c_k^{r\mathbf{up}} - \mu_{kt}^{\mathbf{r}\,\mathrm{up}\min} + \mu_{kt}^{\mathbf{r}\,\mathrm{up}\max} - \mu_{kt}^{\mathrm{p}\max} - \lambda_t^{rup} \\ & + \sum_{\mathbf{t}}^{t+T} \pi_{kt}^{rup} - \theta_{kts}^{rup\max} = 0, \forall k \in K, \forall t \in T, \forall s \end{aligned} \tag{59}$$

$$\begin{aligned} & c_k^{rdw} - \mu_{kt}^{\mathbf{rdw}\min} + \mu_{kt}^{\mathbf{rdw}\max} + \mu_{kt}^{\mathbf{p}\min} \\ & -\lambda_t^{rdw} + \sum_{\mathbf{t}}^{t+T} \pi_{kt}^{rdw} - \theta_{kts}^{rdw\max} = 0, \forall k \in K, \forall t \in T, \forall s \end{aligned} \tag{60}$$

$$\rho^{\Delta} - \lambda_{ts}^{se} = 0, \forall i \in G, \forall t \in T \tag{61}$$

$$0 \le p_{k,t}^w - P_k^{\mathrm{w,min}} + r_{k,t}^{w,\mathrm{dw}} \perp \mu_{kt}^{\mathrm{p}\min} \ge 0, \forall k \in K, \forall t \in T \tag{62}$$

$$0 \le P_k^{\mathrm{w,max}} - r_{k,t}^{w,\mathrm{up}} - p_{k,t}^w \perp \mu_{kt}^{\mathrm{p}\max} \ge 0, \forall k \in K, \forall t \in T \tag{63}$$

$$0 \le r_{k,t}^{w,\mathrm{up}} - R_k^{\mathrm{up,min}} \perp \mu_{kt}^{\mathbf{r}\,\mathrm{up}\min}, \forall k \in K, \forall t \in T \tag{64}$$

$$0 \le R_k^{\mathrm{up,max}} - r_{k,t}^{w,\mathrm{up}} \perp \mu_{kt}^{\mathrm{rup}\max}, \forall k \in K, \forall t \in T \tag{65}$$

$$0 \le r_{k,t}^{w,\mathrm{dw}} - R_k^{\mathrm{dw,min}} \perp \mu_{kt}^{\mathbf{rdw}\min}, \forall k \in K, \forall t \in T \tag{66}$$

$$0 \le R_k^{\mathrm{dw,max}} - r_{kt}^{w,\mathrm{dw}} \perp \mu_{kt}^{\mathrm{rdw}\max}, \forall k \in K, \forall t \in T \tag{67}$$

$$0 \le T_k * p_k^{\mathrm{w,max}} - \sum_t^{t+T} p_{kt}^w \perp \pi_{kt}^p, \forall k \in K, \forall t \in T \tag{68}$$

$$0 \le T_k * R_k^{u,\max} - \sum_t^{t+T} r_{kt}^{w,\mathrm{up}} \perp \pi_{kt}^{r,up}, \forall k \in K, \forall t \in T \tag{69}$$

$$0 \le R_{kt}^{\mathrm{up},w} + r_{kt}^{\mathrm{up,c,buy}} - r_{kt}^{\mathrm{up,c,sell}} - D_{kt}^{up} \perp \lambda_{bt}^{rup} \ge 0, \forall k \in K, \forall t \tag{70}$$

$$0 \le R_{kt}^{\mathrm{dw},w} + r_{kt}^{\mathrm{dw,c,buy}} - r_{kt}^{\mathrm{dw,c,sell}} - D_{kt}^{dw} \perp \lambda_{bt}^{rdw} \ge 0, \forall k \in K, \forall t \tag{71}$$

$$0 \le r_{kt}^{w,\mathrm{up}} - \sigma_{kts}^{\mathrm{up},w} \perp \theta_{kts}^{rup\max} \ge 0, \forall k \in K, \forall t \in T \tag{72}$$

$$0 \le r_{kt}^{w,\mathrm{dw}} - \sigma_{kt}^{w,\mathrm{dw}} \perp \theta_{kts}^{rdw\max} \ge 0, \forall k \in K, \forall t \in T \tag{73}$$

The KKT optimality conditions contain stationarity (58)-(61), complementary slackness, primal feasibility, and dual feasibility (62)-(73).

Now the proposed model is converted to a mathematical programming with equilibrium constraints (MPEC) problem, which is nonlinear due the existence of complementary slackness part (62)-(73). Hence, a set of binary variables are introduced to linearize each of the complementary slackness constraints [34]. An example is presented below to show the linearization of (62) by introducing binary variable $\omega_{k,t}$ and a large positive number O:

$$0 \le p_{k,t}^w - P_k^{\mathrm{w,min}} + r_{k,t}^{w,\mathrm{dw}} \le (1-\omega_{k,t})O, \ \forall k \in K, \forall t \in T \tag{74}$$

$$0 \le \mu_{kt}^{\mathrm{p}\min} \le \omega_{k,t} O, \forall k \in K, \forall t \in T \tag{75}$$

In this way, the original nonlinear constraint (62) can be replaced with (74) and (75). Other complementary constraints can be replaced in a similar way and not included here for brevity. The finalized MILP model is presented as follows:

$$\begin{gathered} \textit{Objective function}\text{: (3)} \\ \textit{s.t.}\ \text{(4)-(40), (58)-(61), linearized (62)-(73)} \end{gathered} \tag{76}$$

D. Uncertainty Modeling

Two major sources of uncertainties in this paper are renewable energy generations and load consumptions in the distribution system. For the purpose of scheduling, the forecasted values will be used. Then we use normal distribution to describe the forecasting errors. The probability distributions of the renewable energy output and hourly load forecast are defined in (77) and (78), respectively:

$$P_t^{re} \sim N(W_t^0, \xi_t^{w2}) \ \forall t \in T \tag{77}$$

$$p_{lt}^l \sim N(L_{l,t}^0, \xi_{l,t}^{l\ 2}) \ \forall l \in L, \ \forall t \in T \tag{78}$$

In (77) and (78), the mean values of the normal distribution is the forecasted hourly load consumption and renewable energy generation, and the standard deviation is set to be 10% of the expected hourly values, respectively. It is noted that the load consumption uncertainty is considered in (25) and (38) on the upper level and in (48) and (51) on and lower level, while the renewable energy output forecast is only considered in (51) on the lower level.

IV. Numerical Experiments

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. 4. The model was solved using IBM CPLEX [39] 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 detailed specifications of the test system, including the models and parameters of the DGs and the microgrids can be found in dataset contained in [40]. 50 scenarios are generated using the Latin Hypercube Sampling method to represent the uncertainties associated with the renewable energy generations and load consumptions [38].

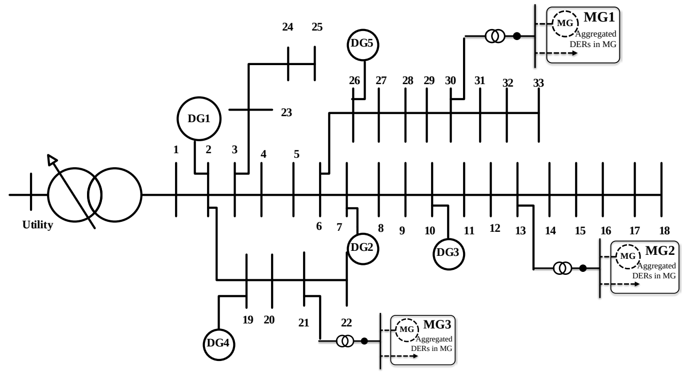

Fig. 4. The modified IEEE 33-bus distribution system

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 bidirectional interactions between microgrids and the distribution system.

Policy II: Bidirectional energy exchanges with unidirectional regulation exchange from the distribution system to microgrids.

Policy III: Bidirectional energy exchanges with unidirectional regulation exchange from microgrids to the distribution system.

Policy IV: The proposed transactive approach based on model (76) that incorporates bi-directional energy and regulation flow between the distribution system and microgrids.

Specifically, Policy I represents the conventional management of a transactive energy market where no ancillary service (i.e., regulation) is exchanged as adopted in [22] and [23]. Due to the lack of regulation exchanges, the DSO and MGOs have to prepare their own regulation resources to handle their own operational uncertainties in this policy. Policy II considers unidirectional ancillary service flow from distribution system to the microgrid as discussed in [31]. Policy III considers the transactive paradigm in which microgrids can only exports regulation and supports the distribution system as proposed in [32]. Note that the same scenarios and parameters are considered for all four policy studies to ensure a fair comparison.

The running time for each policy is reported as follows. Policy I, II, and III took about 2-3 seconds each to complete on average. By contrast, Policy IV took roughly 70 seconds to complete. This is due to the fact that more binary variables are incorporated in the proposed model to capture the bi-directional interactions of regulation up/down.

The results for the four policies can be found in Table I through Table III. Table I 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 as an independent operator, the goal of the DSO is to minimize the market clearing cost for all of market participant. Therefore, a lower cost for the DSO indicates better social welfare and resource utilization for the distribution system. For example, the total regulation cost for the DSO is $263.4 under Policy III. This is because the DSO can only passively purchase regulation from the DGs in the distribution system and the microgrids to maintain the frequency requirement due to the restriction of the unidirectional regulation flow. This cost is collectively paid by the distribution system customers. By contract, the regulation cost for the DSO is $-311.02 (i.e., a profit of $311.02) under Policy II. As the microgrids are eligible to purchase regulation from the DSO under this policy, it is clear that the DSO can facilitate the regulation exchanges between the MGOs and the distribution market, which results in enhanced system welfare. The profit for the DSO can be used for maintaining the DSO's normal operation, as well as distribution system maintenance and capacity expansions. The DSO can also return part of its profit back to the distribution system customers and DGs.

TABLE I. REGULATION INTERACTIONS WITHIN THE DISTRIBUTION SYSTEM

		Policy I	Policy II	Policy III	Policy IV
MG to DS	Regulation Transfer (p.u.)	0	0	0.152	1.405
	Cost for the DSO ($)	0	0	81.80	836.80
DS to MG	Regulation Transfer (p.u.)	0	0.798	0	2.119
	Cost for the DSO ($)	0	-615.20	0	-1530.61
DGs to DS	Regulation Provided (p.u.)	0.644	0.800	0.495	0.715
	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**

Furthermore, when we compare the total costs for the DSO under all policies, the last row of Table I clearly shows that Policy IV leads to the lowest DSO cost compared to the other policies. In fact, the DSO is able to make a profit of $422.12 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 system economics can be enhanced by incorporating the proposed bidirectional joint optimization of energy and regulation.

It can also be observed that with the enabling of bidirectional regulation exchanges, the MGOs are actively exporting and importing their internal regulation resources to the distribution system market in Policy IV (1.405 p.u. of exporting and 2.119 p.u. of importing, respectively). They are therefore relying 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 will play an ever-increasingly dominant role in transactive distribution systems.

TABLE II. 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
Total Penalty Cost for DSO ($)	6.74	0	0	0

Table II 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 uncertainty. 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 uncertainty. 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 III. ENERGY INTERACTIONS WITHIN THE DISTRIBUTION SYSTEM

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

Table III shows the overall transactions within the distribution system. It can be observed that Policy IV leads to the lowest overall operation cost ($2991.1) 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 (1.2 p.u.) to the distribution system compared to the other policies. This added capacity greatly empowers the distribution system by enabling the DSO to reduce the energy purchased from the bulk power system from 1.907 p.u. in Policy I to 1.146 p.u. in Policy IV. It is thus evident 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

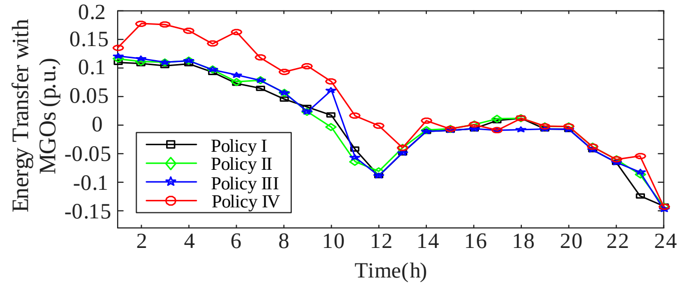

Fig. 5. Hourly energy transfer with MGOs

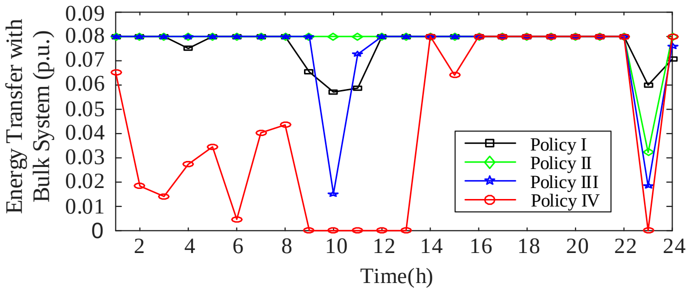

Fig. 6. Hourly energy exchange with upstream bulk power system

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.

In addition, the hourly energy exchanges between the DSO and the MGOs and the upstream bulk power system in the day-ahead 24 hours' market are provided in Figs. 5 and 6, respectively. The default energy transfer direction is from the microgrid/bulk power system to the distribution system which is noted as positive value. Fig. 5 clearly illustrates that under Policy IV, the MGOs are actively participating in the energy exchange in the distribution market in a more aggressive manner throughout the day, especially during the non-peak hours in which more energy is injected into the distribution system from microgrids. Meanwhile, Fig. 6 depicts that under Policy I-III, the DSO is constantly and consistently importing energy from the upstream bulk power system. By contrast, Policy IV allows the DSO to not entirely rely on the bulk power system for most part of the day. In fact, the DSO is not importing any energy between 9AM and 1PM as shown in the figure, suggesting complete energy independency during these hours. The DSO is only importing energy from the upstream system during the peak hours when the local energy consumptions are high.

While the proposed approach offers indisputable advantages over the existing transactive market mechanisms, it is worth mentioning that it also requires continuous, complex, and seamless interactions among market participants. As shown in Figs. 5 and 6, such interactions lack significant patterns and thus can be challenging for the market participants who seek to maximize their own self-interests.

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.

V. Conclusion

Transactive management provides a decentralized solution for the DSO to handle the ever-increasing proliferation of microgrids within the distribution system. In this paper, 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 bilevel 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 the 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 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 paper 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.

Some of the simplifications adopted in this work can be explored as future work. For instance, one can explore the role of energy storage devices in further enhancing the microgrid/MGO's autonomy and competitiveness in the proposed transactive distribution electricity markets. The bidding strategies for the MGOs in the proposed transitive market can be another interesting topic to pursue as future work.

References

[1] R. H. Lasseter and P. Piagi, "Microgrid: A Conceptual Solution," *2004 IEEE 35th Annual Power Electronics Specialists Conference*, Aachen, Germany, 2004, pp. 4285-4290

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

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

[4] 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.

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

[6] 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.

[7] 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.

[8] A. Molavi, J. Shi, Y. Wu, and G. J. Lim, "Enabling smart ports through the integration of microgrids : A two-stage stochastic programming approach," *Appl. Energy*, vol. 258, no. June 2019, p. 114022, 2020.

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

[10] 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.

[11] S. Karagiannopoulos, S. Member, J. Gallmann, and M. Gonz, "Active Distribution Grids offering Ancillary Services in Islanded and Grid-connected Mode," *IEEE Trans. on Smart Grid*, vol. 11, no. 1, pp. 623-633, Jan. 2020.

[12] 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.

[13] M. N. Faqiry, A. K. Zarabie, F. Nassery, H. Wu, and S. Das, “A day-ahead market energy auction for distribution system operation,” in *2017 IEEE International Conference on Electro Information Technology (EIT)*, 2017, pp. 182–187.

[14] 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.

[15] Y. Wang, Z. Huang, M. Shahidehpour, L. L. Lai, Z. Wang and Q. Zhu, "Reconfigurable Distribution Network for Managing Transactive Energy in a Multi-Microgrid System," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1286-1295, March 2020

[16] S. Parhizi, A. Khodaei, and M. Shahidehpour, “Market-based vs. Price-based Microgrid Optimal Scheduling,” *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 615-623, March 2018.

[17] 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.

[18] Z. Liu, L. Wang, S. Member, and L. Ma, “A Transactive Energy Framework for Coordinated Energy Management of Networked Microgrids With Distributionally Robust Optimization,” *IEEE Trans. on Power Systems*, vol. 35, no. 1, pp. 395-404, Jan. 2020.

[19] J. Wang and X. Lu, “Sustainable and Resilient Distribution Systems With Networked Microgrids,” *Proceedings of the IEEE*, vol. 108, no. 2, pp. 238-241, Feb. 2020.

[20] 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.

[21] 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.

[22] Z. Wang, S. Member, B. Chen, J. Wang, S. Member, 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.

[23] Z. Wang *et al.*, “Coordinated Energy Management of Networked Microgrids in Distribution Systems,” *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 45–53, 2015.

[24] 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.

[25] Y. Wu, M. Barati, and G. J. Lim, “A Pool Strategy of Microgrid in Power Distribution Electricity Market,” *IEEE Trans. Power Syst.*, vol. 35, no. 1, pp. 3-12, Jan. 2020.

[26] 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. 10, no. 6, pp. 6029-6040, Nov. 2019.

[27] 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.

[28] 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.

[29] 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.

[30] 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.

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

[32] Y. Wu, G. J. Lim, and J. Shi, “Stability-Constrained Microgrid Operation Scheduling Incorporating Frequency Control Reserve,” *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1007-1017, March 2020.

[33] 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.

[34] 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.

[35] 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.

[36] 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.

[37] 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.

[38] A. Khayatian, M. Barati, and G.J. Lim, “Integrated Microgrid Expansion Planning in Electricity Market with Uncertainty,” *IEEE Trans. Power Syst.*, 33(4), pp 3634-3643, July 2018.

[39] IBM CPLEX, Available at: https://www.ibm.com/analytics/cplex-optimizer. [accessed 2019].

[40] “Data Set for Manuscript “Optimal Management of Transactive Distribution Electricity Markets with Co-optimized Bidirectional Energy and Ancillary Service Exchanges” [Online]. Available: http://e2map.egr.uh.edu/sites/e2map/files/files/publications/data%20table.pdf