A Transactive Energy Framework for Coordinated Energy Management of Networked Microgrids With Distributionally Robust Optimization

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***Abstract*—Networked microgrids (MGs) are considered as an emerging grid design for the future distribution system (DS). The coordination of the networked MGs is critical in order to further enhance the operation efficiency and reliability of the system. In this paper, a transactive energy (TE) framework is proposed for the coordinated energy management of networked MGs in DS. Instead of direct coordination signals and fixed pricing schemes, the distribution network operator (DNO) organizes a transactive market with the MGs to coordinate the energy management in the operation. Further, a distributionally robust optimization (DRO)-based algorithm is developed to provide a robust solution of the detailed scheduling decisions in the proposed TE framework under uncertainty without being too conservative. Case studies with the proposed framework were conducted with the IEEE 33-bus system with three MGs and the IEEE 123-bus system with nine MGs. The results of the case studies show that the proposed TE-based framework can effectively coordinate the energy scheduling of the MGs. The operational cost of the DS is reduced significantly. Meanwhile, the proposed DRO-based algorithm provides a robust but not over-conservative solution for the operation decisions of the DNO and MGs in the proposed framework.**

***Index Terms*—Distributionally robust optimization (DRO), microgrids, networked microgrids, transactive control, transactive energy.**

NOMENCLATURE

A. Indices and Sets

g	Index of micro turbines (MTs) in the distribution system (DS)/microgrids (MGs).
i, j, k	Index of buses (nodes) in the DS/MGs.
m	Index of MGs in the DS.
t, τ	Index of time intervals.
v	Index of photovoltaic panels (PVs) in the DS/MGs.
w	Index of wind turbines (WTs) in the DS/MGs.
ω	Index of scenarios.
$\mathcal{E}_\mathcal{D}/\mathcal{E}_m$	Set of branches in the DS/MG m.
$\mathcal{G}_\mathcal{D}/\mathcal{G}_m$	Set of MTs in the DS/MG m.
$\mathcal{M}$	Set of MGs in the DS.
$\mathcal{N}_\mathcal{D}/\mathcal{N}_m$	Set of buses (nodes) in the DS/MG m.
$\mathcal{S}$	Ambiguity set of the distributionally robust optimization (DRO) model.
$\mathcal{T}$	Set of time intervals in scheduling horizon.
$\mathcal{V}_\mathcal{D}/\mathcal{V}_m$	Set of PVs in the DS/MG m.
$\mathcal{W}_\mathcal{D}/\mathcal{W}_m$	Set of WTs in the DS/MG m.
Ω	Set of scenarios.

B. Parameters

$a_g/b_g/c_g$	Second order/first order/constant coefficients of generation cost function of MT g.
p_g^+/p_g^-	Upper/lower limits of active power of MT g.
$p_{j,t,\omega}^L$	Active power demand of node j at time t in scenario ω.
$p_{v,t,\omega}^V$	Active power output of PV v at time t in scenario ω.
$p_{w,t,\omega}^W$	Active power output of WT w at time t in scenario ω.
q_g^+/q_g^-	Upper/lower limits of reactive power of MT g.
$q_{j,t,\omega}^L$	Reactive power demand of node j at time t in scenario ω.
$r_{i,j}$	Resistance of branch between node i and node j.
$s_{j,g}$	Grid connection indicator of MT g to node j.
$s_{j,m}$	Grid connection indicator of MG m to node j.
$s_{j,v}$	Grid connection indicator of PV v to node j.
$s_{j,w}$	Grid connection indicator of WT w to node j.
V_j^+/V_j^-	Upper/lower voltage limits of node j.
$x_{i,j}$	Reactance of branch between node i and node j.
α_t	Day-ahead spot price of electricity at time t.
$\beta_{t,\omega}$	Real-time regulating price of electricity at time t in scenario ω.
$\gamma_{t,\omega}$	Real-time electricity price of imbalance settlement at time t in scenario ω.
π_ω/ϖ_ω	Probability of scenario ω.
ϑ_1	Tolerant limit of norm-1 of the ambiguity set in the DRO model.
ϑ_∞	Tolerant limit of norm-infinity of the ambiguity set in the DRO model.

C. Variables

$J_{\mathcal{D},\omega}$	Operation cost of the DS in scenario ω.
$J_{m,\omega}$	Operation cost of MG m in scenario ω.

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$p_{g,t,\omega}$ Active power output of MT g at time t in scenario ω.

$p^F_{i,j,t,\omega}$ Active power flow from node i to node j at time t in scenario ω.

$p^M_{m,t,\omega}$ Active power exchange between MG m and DS at time t in scenario ω, positive value means injection from DS to MG, negative value means export from MG to DS.

$q_{g,t,\omega}$ Reactive power output of MT g at time t in scenario ω.

$q^F_{i,j,t,\omega}$ Reactive power flow from node i to node j at time t in scenario ω.

$q^M_{m,t,\omega}$ Reactive power exchange between MG m and DS at time t in scenario ω, positive value means injection from DS to MG, negative value means export from MG to DS.

p^H_t Scheduled active power exchange between DS and high voltage (HV) system at time t, positive value means injection from HV to DS, negative value means export from DS to HV.

$\Delta p^H_{t,\omega}$ Deviant active power exchange between DS and HV system at time t in scenario ω, positive value means higher consumption or lower export from DS, negative value means lower consumption or higher export from DS.

$V_{i,t,\omega}$ Voltage of node j at time t in scenario ω.

$\lambda_{t,\omega}$ Clearing price in transactive market at time t in scenario ω.

$\psi^\Delta_{t,\omega}$ Real-time imbalance settlement of DNO with HV system at time t in scenario ω.

D. Functions

Ψ_g Cost function of MT g.

I. Introduction

Microgrids (MGs) are integrated systems with connected loads and distributed energy resources (DERs) which can facilitate the implementation of many cherished functions of the smart grid, such as reliability and self-healing [1]. In recent years, networked MGs are considered as an emerging network design to further enhance the benefits of MGs [2]. The operation and reliability of the system can be improved by connecting multiple MGs to make a distribution system (DS) with networked MGs [3]–[6]. Thus, networked MGs will be an important network feature in the future distribution systems.

In a distribution system with multiple connected MGs, the coordination between the operations of the individual entities in the system becomes necessary. Some recent efforts have been made to study the coordinated energy management of networked MGs. The authors of [6] propose a control strategy for the coordinated operation of the networked MGs in a distribution system. The interest of the distribution network operator (DNO) and each MG in the system is considered with individual optimization models. The impact of the correlated wind generators on the energy management of the DS and networked MGs is investigated in [7]. A stochastic framework is proposed to model the uncertainties in load and wind generation in the study. In [8], the authors propose a transactive energy management method for the interconnected microgrid cluster. Four different management optimization models are proposed in the study with different requirements of the collective and individual interests of the MGs in the objective functions of the approach. In [9], an agent-based transactive energy management framework is proposed to handle the aggregation in the DS. An inter-microgrid auction based electricity market is organized to manage the excess supply or residual demand in the systems. The works in [8] and [9] both apply the TE concepts for the coordination of multiple MGs in the system. However, the bilevel framework in which the DNO is considered as an individual entity with its own interest in the coordinated operation is studied in this paper, while it is not included in the scope of [8] and [9]. The work in [10]–[12] focuses on the decentralized algorithms for the operation of networked MGs. In [10], an iterative bilevel stochastic programming algorithm is proposed based on penalties to guarantee the convergence of the solutions of each entities' operation decisions. Meanwhile, the alternating direction method of multipliers (ADMM) is used in [11], [12] to decentralize the energy management algorithms for the networked MGs in the DS.

The existing researches have provided valuable insights on the coordinated energy management of networked MGs. However, in the existing studies, the settlement for the power exchanges between the DS and MGs is determined by a rigid clearing scheme in which the clearing price for the power exchange between the DS and MGs is fixed. In this case, the flexibility of the MGs in the DS is not fully explored and the operation efficiency of the system is not optimized. In order to further enhance the efficiency of the operation, a transactive energy (TE) based energy management framework is proposed in this paper. Transactive energy is emerging as one of the most promising solutions for the decentralized coordination of different entities in the smart grid [13]. As defined by the GridWise Architecture Council (GWAC), TE is a set of economic and control mechanisms that allows the dynamic balance of supply and demand across the power system [14]. It uses value as a key operational parameter. Price signals are applied in TE to bridge all the components in the system, and the agreement between the control decisions of different components are determined through transactions. The TE concept is highly valued for its ability to fully utilize the response potential of various components in the system, perform stably and maintain the market efficiency. In the proposed framework, the DNO and each MG are considered as individual entities and maximize their own profits during the operation. A transacitive market is organized by the DNO to coordinate the energy management of the DS and MGs in the operation. Instead of fixed prices in the existing models, the power exchange between the DS and MGs in the operation is cleared with dynamic pricing in the transactive market. As such, the energy management of the DS and MGs can be coordinated and optimized according to the real-time operation condition, and the flexibility of the MGs is further explored compared with the fixed pricing schemes. In the TE framework, the clearing prices between the DS and MGs are determined according to the status of the system for every scheduling interval. It serves as a bridging signal between the DS and MGs. With the dynamic clearing prices, the MGs determine the scheduling decisions, and make agreements with the DNO on the power transaction between them. The transaction for the interval is settled with the clearing price of this interval. As a result, the flexibility of the system can be further exploited with the TE framework.

Further, the scenario based stochastic programming (SP) model is extensively-used in literature, which can optimize the expected value of the objective function for the system operation problem under uncertainty. However, the SP model does not provide robustness with its solution and it needs the exact probability distribution of the scenarios. On the other hand, robust optimization (RO) is used to give a robust solution by optimizing the objective function in the worst-case scenario. Nevertheless, it may be too conservative and perform badly in the usual cases [15]. In order to provide a robust solution without being over-conservative, a distributionally robust optimization (DRO) based algorithm is developed and used in this study to formulate and solve the optimization model of the proposed TE based energy management framework. DRO is an emerging technique in recent years to handle the robust optimization problem [16]. It provides an intermediate approach between the SP and RO. By applying the DRO based algorithm, two important advantages are provided by the proposed method. First, the exact probability distribution of the scenarios which may not be available in practice is not needed. Moreover, it offers robustness in the solution under uncertainty while avoiding over-conservative solutions. The main contributions of this paper are summarized as follows:

- A decentralized energy management framework based on transactive energy is proposed to coordinate the energy scheduling of the networked MGs in the distribution system.
- A bilevel quadratic optimization model is developed to determine the detailed energy scheduling decisions of the DNO and MGs in the transactive energy based framework.
- A DRO based algorithm is developed for the DNO to determine the energy scheduling decisions under uncertainty. To the best of the authors' knowledge, this is the first study on the DRO models for the energy management problem of networked MGs. In the existing literature, not any DRO based models have been proposed for the energy management problem of networked MGs which is formulated as a bilevel quadratic problem in this work. In this paper, a DRO model is developed for the transactive energy based scheduling problem of networked MGs, and the corresponding solving method is proposed. The proposed DRO based algorithm can provide a robust solution of the scheduling problem while preventing it from being too conservative like the solution by the generic robust optimization.

The rest of the paper is organized as follows. The transactive energy based energy management framework for networked MGs in the distribution system is introduced in Section II. In Section III, the detailed formulations of the DNO and MGs' optimization models are described. The DRO based algorithm is presented in Section IV. The case studies of the proposed coordinated energy management framework are presented and discussed in Section V, followed by the conclusions in Section VI.

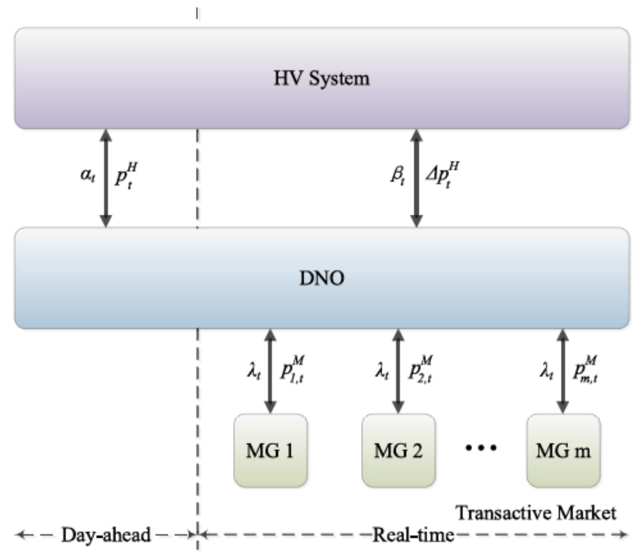

Fig. 1. Transactive Energy Management Framework for Networked Microgrids in Distribution System.

II. Transactive Energy Based Energy Management Framework for Networked MGs

In this study, we consider a common system architecture for a distribution system with networked MGs [6], [10], [12]. The distribution system is connected with the MGs, and at the same time connected to the up-stream high voltage (HV) system. Both the DS and MGs have loads and distributed generators (DGs), including dispatchable DGs and renewable energy source (RES)-based DGs. Either the DNO or each MG is considered as an individual entity in the system and determines its own operation decisions for the dispatchable units in the system. Each MG determines the output of the dispatchable units in the MG, and the deviant between the demand and generation will be compensated through the power exchange with the DS. At the same time, the DNO determines the output of the dispatchable units in the DS. Considering the power exchanges of all the MGs, the difference between the demand and generation in the DS is filled by the purchase/sales from/to the HV system. Because the operation of the DNO and each MG is correlated with each other, their operation need to be coordinated in order to achieve the efficient operation of the system. In this paper, a transactive energy based framework is designed for the coordination of the energy management of the DNO and MGs. The proposed framework is illustrated in Fig. 1.

In the system model, the DS is connected with the HV system and the DNO needs to manage the power exchange between the DS and the HV system. In the day-ahead process, the DNO schedules the power exchange between the DS and HV system. The power exchange will be settled with the day-ahead spot price α_t. In the real-time operation, the power exchange between the DS and HV system may deviate from the scheduled power exchange in the day-ahead process due to the operation of the DNO and MGs under various sources of uncertainty such as RES and demand, etc. The deviant power exchange between the DS and HV system in the real-time operation will be settled according to the real-time price β_t in the balancing market. The imbalance settlement is determined according to the two-price balance settlement model which is implemented by power markets (such as NordPool) to encourage the consistency of the scheduled energy plan and the real-time operation [17]. During an up-regulating hour, the system needs upward regulation and the real-time price β_t is higher than the day-ahead spot price α_t. The purchase price for balance power equals to β_t while the sales price for balance power equals to α_t. On the contrary, the system needs downward regulation in a down-regulating hour, and the real-time price β_t is lower than the day-ahead spot price α_t. In this case, the purchase price for balance power equals to α_t while the sales price for balance power equals to β_t. With the purchase and sales prices for the balance power, the settlement for the deviant power exchange between the DNO and HV system in the real-time operation is calculated accordingly.

Meanwhile, the DNO needs to coordinate the MGs in the DS for the efficient operation. Instead of direct coordination signals and fixed pricing schemes, during the operation, the DNO organizes a transactive market with the MGs connected to the DS to coordinate the energy management of the MGs considering the real-time operational condition in the proposed framework. As shown in Fig. 1, the DNO determines and announces a clearing price λ_t for the power exchange of all the MGs in the DS of each time slot, and the MGs determine and feedback their operation decisions. Based on the price λ_t for the power exchange, each MG determines its operation decisions to minimize its own operation cost, and the power exchange between the MGs and DS is determined accordingly at the same time. The power exchange between the MGs and DS of each time slot will be cleared according to the clearing price λ_t and the power exchange between them at the slot. As such, the transaction between the DNO and MGs is committed with the clearing price λ_t and the power exchange in the proposed transactive market. As either the DNO or each MG is an individual entity and has its own interest, they will determine their operation decisions to maximize their own surplus. The optimization models for the operation of the DNO and MGs are presented in details in the following section.

III. Energy Scheduling Optimization Models of DNO and MGs

A. System Model of Distribution System and Microgrids

In the system model, both the DS and MGs have dispatchable DGs (which are micro turbines (MTs) in this study) and RES-based DGs (which are wind turbines (WTs) and photovoltaic panels (PVs) in this study), and the RES-based DGs are considered nondispatchable. Both the DNO and MGs need to determine the output of the MTs to minimize the operation cost. The generation cost of the MTs is formulated with a quadratic function of active power output [11] as follows.

$$\Psi_g\left(p_g\right) = a_g p_g^2 + b_g p_g + c_g \tag{1}$$

Following the work in [6], [10], [11], the linearized DistFlow model is used in this paper. The model has been widely applied and justified in the studies of DS and MGs, i.e., [18]–[20]. The linearized DistFlow model is known to approximate the exact AC power flow model well [21]. The linearized DistFlow equations are presented as follows.

$$p_{i,j}^F = \sum_{k\in\mathcal{N}:(j,k)\in\mathcal{E}} p_{j,k}^F - p_j, \qquad \forall i,j\in\mathcal{N},\ (i,j)\in\mathcal{E} \tag{2}$$

$$q_{i,j}^F = \sum_{k\in\mathcal{N}:(j,k)\in\mathcal{E}} q_{j,k}^F - q_j, \qquad \forall i,j\in\mathcal{N},\ (i,j)\in\mathcal{E} \tag{3}$$

$$V_j = V_i - \frac{r_{i,j}p_{i,j}^F + x_{i,j}q_{i,j}^F}{V_0}, \qquad \forall i,j\in\mathcal{N},\ (i,j)\in\mathcal{E} \tag{4}$$

$$p_j = p_j^G - p_j^L, \quad q_j = q_j^G - q_j^L, \quad \forall j\in\mathcal{N} \tag{5}$$

where p_j and q_j are the active and reactive power injection of node j in the system respectively, p_j^G and q_j^G are the generation at node j, p_j^L and q_j^L are the load at node j, V_0 is the voltage of the node at which the DS is connected to the HV system, $\mathcal{N}$ and $\mathcal{E}$ are the sets of the nodes and branches in the DS respectively.

B. Optimization Model of DNO

For the DNO, the energy scheduling aims to minimize the operation cost. Thus, the objective function of the energy scheduling problem of the DNO can be formulated as follows.

$$\begin{aligned}\min\ J_{\mathcal{D},\omega} = &\sum_{t\in\mathcal{T}}\alpha_t p_t^H + \sum_{t\in\mathcal{T}}\gamma_{t,\omega}\Delta p_{t,\omega}^H \\ &+ \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}_\mathcal{D}}\left(a_g p_{g,t,\omega}^2 + b_g p_{g,t,\omega} + c_g\right) \\ &- \sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}}\lambda_{t,\omega}p_{m,t,\omega}^{M*}\end{aligned} \tag{6}$$

The first term in the objective function of the DNO's optimization model is the cost for the scheduled power exchange between the DS and HV system. The second term is the cost for the deviant power exchange between the DS and HV system in the operation. γ_t is the price for the settlement calculation in the two-price balance model according to the system condition and the power exchange direction between the DS and HV system. The third term is the generation cost of the MTs in the DS. The fourth term is the settlement between the DS and MGs. In this study, the two-price model of the real-time balancing market is adopted [17], [22]. Thus, the price for the deviant power exchange $\Delta p_{t,\omega}^H$ between the DS and HV system in the operation can be determined as follows.

$$\gamma_{t,\omega} = \begin{cases}\alpha_t, & \text{if } (\Delta p_{t,\omega}^H < 0,\ \alpha_t \leqslant \beta_{t,\omega})\ or\ (\Delta p_{t,\omega}^H > 0,\ \alpha_t \geqslant \beta_{t,\omega}) \\ \beta_{t,\omega}, & \text{if } (\Delta p_{t,\omega}^H > 0,\ \alpha_t < \beta_{t,\omega})\ or\ (\Delta p_{t,\omega}^H < 0,\ \alpha_t > \beta_{t,\omega})\end{cases} \tag{7}$$

With the expression of price $\gamma_{t,\omega}$ above, the optimization model of the energy scheduling problem of the DNO can be reformulated as follows to facilitate an efficient solution with the off-the-shelf solvers.

$$\min\ J_{\mathcal{D},\omega} = \sum_{t\in\mathcal{T}} \alpha_t p_t^H + \sum_{t\in\mathcal{T}} \psi_{t,\omega}^{\Delta} + \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}_{\mathcal{D}}} \left(a_g p_{g,t,\omega}^2 + b_g p_{g,t,\omega} + c_g\right) - \sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}} \lambda_{t,\omega} p_{m,t,\omega}^{M*} \tag{8}$$

Subject to

$$\psi_{t,\omega}^{\Delta} \geqslant \alpha_t \Delta p_{t,\omega}^H, \quad \forall t\in\mathcal{T} \tag{9}$$

$$\psi_{t,\omega}^{\Delta} \geqslant \beta_{t,\omega} \Delta p_{t,\omega}^H, \quad \forall t\in\mathcal{T} \tag{10}$$

$$p_{i,j,t,\omega}^F = \sum_{k\in\mathcal{N}_{\mathcal{D}}:(j,k)\in\mathcal{E}_{\mathcal{D}}} p_{j,k,t,\omega}^F + p_{j,t,\omega}^L + \sum_{m\in\mathcal{M}} s_{j,m} p_{m,t,\omega}^{M*} - \sum_{g\in\mathcal{G}_{\mathcal{D}}} s_{j,g} p_{g,t,\omega} - \sum_{w\in\mathcal{W}_{\mathcal{D}}} s_{j,w} p_{w,t,\omega}^W - \sum_{v\in\mathcal{V}_{\mathcal{D}}} s_{j,v} p_{v,t,\omega}^V, \quad \forall t\in\mathcal{T},\ \forall j\in\mathcal{N}_{\mathcal{D}}, (i,j)\in\mathcal{E}_{\mathcal{D}} \tag{11}$$

$$q_{i,j,t,\omega}^F = \sum_{k\in\mathcal{N}_{\mathcal{D}}:(j,k)\in\mathcal{E}_{\mathcal{D}}} q_{j,k,t,\omega}^F + q_{j,t,\omega}^L + \sum_{m\in\mathcal{M}} s_{j,m} q_{m,t,\omega}^{M*} - \sum_{g\in\mathcal{G}_{\mathcal{D}}} s_{j,g} q_{g,t,\omega}, \quad \forall t\in\mathcal{T},\ \forall j\in\mathcal{N}_{\mathcal{D}}, (i,j)\in\mathcal{E}_{\mathcal{D}} \tag{12}$$

$$V_{j,t,\omega} = V_{i,t,\omega} - \left(r_{i,j} p_{i,j,t,\omega}^F + x_{i,j} q_{i,j,t,\omega}^F\right)/V_0, \quad \forall t\in\mathcal{T}, \forall j\in\mathcal{N}_{\mathcal{D}}, (i,j)\in\mathcal{E}_{\mathcal{D}} \tag{13}$$

$$V_j^- \leqslant V_{j,t,\omega} \leqslant V_j^+, \quad \forall t\in\mathcal{T},\ \forall j\in\mathcal{N}_{\mathcal{D}} \tag{14}$$

$$p_g^- \leqslant p_{g,t,\omega} \leqslant p_g^+, \quad \forall t\in\mathcal{T},\ \forall g\in\mathcal{G}_{\mathcal{D}} \tag{15}$$

$$q_g^- \leqslant q_{g,t,\omega} \leqslant q_g^+, \quad \forall t\in\mathcal{T},\ \forall g\in\mathcal{G}_{\mathcal{D}} \tag{16}$$

Constraints (9) and (10) together with the second term of the objective function (8) reformulate the cost of the DNO for the deviant power exchange between the DS and HV system in the operation, which guarantees that $\psi_{t,\omega}^{\Delta}$ in the second term of (8) equals to $\gamma_{t,\omega}\Delta p_{t,\omega}^H$ in the original objective function (6). Constraints (11) to (14) are the power flow constraints from the DistFlow formulations. Constraints (15) and (16) are the capacity limits of the MTs. In the optimization of the DNO, p_t^H is the scheduled active power exchange of the distribution system with the HV system, which is the here-and-now decision. On the other hand, $\Delta p_{t,\omega}^H, p_{g,t,\omega}$ and $\lambda_{t,\omega}$ are the wait-and-see decisions. $\Delta p_{t,\omega}^H$ is the active power exchange deviation of the distribution system with the HV system in the real-time operation from the scheduled value p_t^H. In the operation, the DNO organizes the transactive market, and determines the dynamic price $\lambda_{t,\omega}$ to clear the power exchange with the MGs. $\{p_{m,t,\omega}^{M*}, q_{m,t,\omega}^{M*} : \forall m \in \mathcal{M}\}$ are the power exchange between the DS and MG m by the solutions of the MGs' energy scheduling optimization as follows.

$$\left(p_{m,t,\omega}^{M*}, q_{m,t,\omega}^{M*}\right) = \arg\min\ J_{m,\omega}\left(\lambda_{t,\omega}\right) \tag{17}$$

The optimization model of the MGs is presented in the following subsection.

C. Optimization Model of Microgrids

For each MG, the energy scheduling is to minimize its operation cost considering the clearing price $\lambda_{t,\omega}$ for the exchange between the DS and MGs which is announced by the DNO. The optimization model of the energy scheduling problem of MG $m\ (\forall m\in\mathcal{M})$ is presented as follows.

$$\min\ J_{m,\omega} = \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}_m} \left(a_g p_{g,t,\omega}^2 + b_g p_{g,t,\omega} + c_g\right) + \sum_{t\in\mathcal{T}} \lambda_{t,\omega} p_{m,t,\omega}^M \tag{18}$$

Subject to

$$p_{i,j,t,\omega}^F = \sum_{k\in\mathcal{N}_m:(j,k)\in\mathcal{E}_m} p_{j,k,t,\omega}^F + p_{j,t,\omega}^L - s_{j,m} p_{m,t,\omega}^M - \sum_{g\in\mathcal{G}_m} s_{j,g} p_{g,t,\omega} - \sum_{w\in\mathcal{W}_m} s_{j,w} p_{w,t,\omega}^W - \sum_{v\in\mathcal{V}_m} s_{j,v} p_{v,t,\omega}^V, \quad \forall t\in\mathcal{T},\ \forall j\in\mathcal{N}_m, (i,j)\in\mathcal{E}_m \tag{19}$$

$$q_{i,j,t,\omega}^F = \sum_{k\in\mathcal{N}_m:(j,k)\in\mathcal{E}_m} q_{j,k,t,\omega}^F + q_{j,t,\omega}^L - s_{j,m} q_{m,t,\omega}^M - \sum_{g\in\mathcal{G}_m} s_{j,g} q_{g,t,\omega}, \quad \forall t\in\mathcal{T},\ \forall j\in\mathcal{N}_m, (i,j)\in\mathcal{E}_m \tag{20}$$

$$V_{j,t,\omega} = V_{i,t,\omega} - \left(r_{i,j} p_{i,j,t,\omega}^F + x_{i,j} q_{i,j,t,\omega}^F\right)/V_0, \quad \forall t\in\mathcal{T}, \forall j\in\mathcal{N}_m, (i,j)\in\mathcal{E}_m \tag{21}$$

$$V_j^- \leqslant V_{j,t,\omega} \leqslant V_j^+, \quad \forall t\in\mathcal{T}, \forall j\in\mathcal{N}_m \tag{22}$$

$$p_g^- \leqslant p_{g,t,\omega} \leqslant p_g^+, \quad \forall t\in\mathcal{T}, \forall g\in\mathcal{G}_m \tag{23}$$

$$q_g^- \leqslant q_{g,t,\omega} \leqslant q_g^+, \quad \forall t\in\mathcal{T}, \forall g\in\mathcal{G}_m \tag{24}$$

The first term in the objective function (18) is the generation cost of the MTs in the MG, while the second term of (18) is the settlement with the DS. Constraints (19) to (22) are the power flow constraints from the DistFlow formulations. Constraints (23) and (24) are the capacity limits of the MTs.

D. Bilevel Optimization Model of DNO and Microgrids

As shown in the optimization models of the DNO and MGs presented above, the optimization problem of the MGs is actually nested in the DNO's optimization. Thus, the optimization of the DNO and MGs forms a bilevel optimization model. The bilevel optimization model for the energy management of the DNO and MGs is illustrated in Fig. 2. The clearing price λ_t is determined by the optimization of the DNO and serves as an

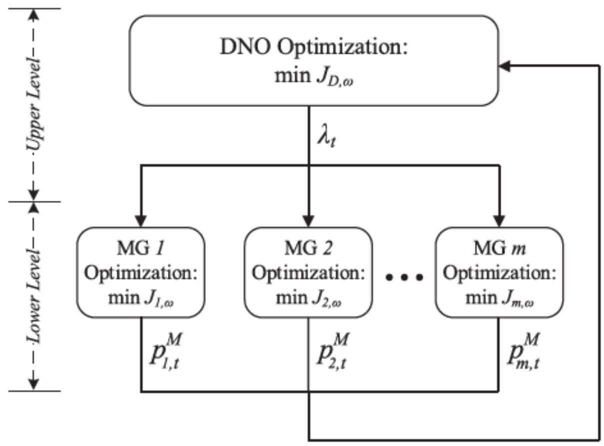

Fig. 2. Bilevel Optimization Model of DNO and Microgrids.

input of the MGs' optimization problem. Based on the λ_t determined by the DNO's optimization, the operation of the MGs are determined by the MGs' optimization, and the power exchange between the DNO and MGs are also determined accordingly. Meanwhile, the power exchange between the DNO and MGs in the DNO's optimization must match the solution of the MGs' optimization.

In order to solve the bilevel optimization, the Karush-Kuhn-Tucker (KKT) conditions of the MGs' optimization are used to convert the original bilevel optimization into a single level optimization problem. The optimization model of MG m ($\forall m \in \mathcal{M}$) is the minimization problem (18) subject to (19)-(24) which is a standard quadratic optimization problem. To simplify the presentation of the algorithm, we express the optimization model of MG m in a compact vector form as follows.

$$\min \; J_{m,\omega} = \frac{1}{2}\mathbf{x}^T_{m,\omega}\mathbf{H}_{m,\omega}\mathbf{x}_{m,\omega} + \mathbf{x}^T_{m,\omega}\mathbf{b}_{m,\omega} \tag{25}$$

Subject to

$$\mathbf{E}_{m,\omega}\mathbf{x}_{m,\omega} = \mathbf{c}_{m,\omega} \qquad (\boldsymbol{\xi}_{m,\omega}) \tag{26}$$

$$\mathbf{A}_{m,\omega}\mathbf{x}_{m,\omega} \leqslant \mathbf{d}_{m,\omega} \qquad (\boldsymbol{\mu}_{m,\omega}) \tag{27}$$

where $\boldsymbol{\xi}_{m,\omega}$ and $\boldsymbol{\mu}_{m,\omega}$ are the dual variables of the equality and inequality constraints respectively. The KKT conditions of the quadratic optimization (25) subject to (26) and (27) can be expressed as (26) and (27) together with the constraints (28)-(30) below.

$$\mathbf{H}_{m,\omega}\mathbf{x}_{m,\omega} + \mathbf{b}_{m,\omega} + \mathbf{E}^T_{m,\omega}\boldsymbol{\xi}_{m,\omega} + \mathbf{A}^T_{m,\omega}\boldsymbol{\mu}_{m,\omega} = \mathbf{0}, \quad \forall m \in \mathcal{M} \tag{28}$$

$$\boldsymbol{\mu}_{m,\omega} \geqslant \mathbf{0}, \quad \forall m \in \mathcal{M} \tag{29}$$

$$diag(\boldsymbol{\mu}_{m,\omega})(\mathbf{A}_{m,\omega}\mathbf{x}_{m,\omega} - \mathbf{d}_{m,\omega}) = \mathbf{0}, \quad \forall m \in \mathcal{M} \tag{30}$$

It can be easily proved that the optimization of the MGs is a convex quadratic programming problem. Thus, the KKT conditions expressed above guarantee the optimal solution of the MG's optimization problem. However, the complementary slackness condition (30) is nonlinear which makes the single-level optimization difficult to solve. In order to address this issue, the complementary slackness condition (30) is reformulated with an auxiliary binary variable vector $\mathbf{z}_{m,\omega}$ as follows.

$$\mathbf{d}_{m,\omega} - \mathbf{A}_{m,\omega}\mathbf{x}_{m,\omega} \leqslant L\mathbf{z}_{m,\omega}, \; \forall m \in \mathcal{M} \tag{31}$$

$$\boldsymbol{\mu}_{m,\omega} \leqslant L(\mathbf{1} - \mathbf{z}_{m,\omega}), \; \forall m \in \mathcal{M} \tag{32}$$

where L is a big enough scalar. With the process above, the original bilevel optimization model of the DNO and MGs is reformulated and solved by the minimization problem (8) subject to (9)-(16), (19)-(24), (28), (29), (31), (32).

IV. Distributional Robust Optimization Model

In general, expected value is a good measurement of the performance for the optimization with stochastic variables. Therefore, the scenario based SP model is widely used for the optimization under uncertainty. The optimization of the energy scheduling problem presented in the previous section can be formulated through SP to minimize the expected value of the operation cost as follows.

$$\begin{aligned} \min \mathbb{E}_{\boldsymbol{\pi}}\left[J_{\mathcal{D}}\right] &= \sum_{\omega\in\Omega} \pi_\omega J_{\mathcal{D},\omega} \\ &= \sum_{t\in\mathcal{T}} \alpha_t p^H_t + \sum_{\omega\in\Omega} \pi_\omega \\ &\times \Bigg[\sum_{t\in\mathcal{T}} \psi^{\Delta}_{t,\omega} + \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}_{\mathcal{D}}} \\ &\qquad \left(a_g p^2_{g,t,\omega} + b_g p_{g,t,\omega} + c_g\right) \\ &\qquad - \sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}} \lambda_{t,\omega} p^M_{m,t,\omega}\Bigg] \end{aligned} \tag{33}$$

subject to (9)-(16), (19)-(24), (28), (29), (31) and (32), where π_ω is the probability of scenario ω. However, as discussed in Section I above, the SP model does not provide robustness in its solution and requires the exact distribution of the scenarios $\boldsymbol{\pi} = \{\pi_\omega, \forall \omega \in \Omega\}$, which may not be possible in many cases in practice. To this end, a DRO based model is developed for the scheduling problem with the proposed TE based framework under uncertainty to provide robustness in the solution while preventing it from being over-conservative. Instead of minimizing the expected operation cost or the operation cost in the worst-case scenario, the DRO approach minimizes the expected operation cost of the system with the worst-case probability distribution in the ambiguity set $\mathcal{S}$ of an estimated distribution $\boldsymbol{\varpi} = \{\varpi_\omega, \forall \omega \in \Omega\}$. The ambiguity set $\mathcal{S}$ can be defined by the norm-1 and norm-infinite tolerance [23] of the estimated distribution. It is expressed as follows.

$$\mathcal{S} = \left\{ \boldsymbol{\pi} \;\middle|\; \begin{array}{c} P(\omega \in \Omega) = 1 \\ \boldsymbol{\pi} \geqslant 0 \\ \|\boldsymbol{\pi} - \boldsymbol{\varpi}\|_1 \leqslant \vartheta_1 \\ \|\boldsymbol{\pi} - \boldsymbol{\varpi}\|_\infty \leqslant \vartheta_\infty \end{array} \right\} \tag{34}$$

where ϑ_1 and ϑ_∞ are the norm-1 and norm-infinite tolerance limits respectively. Thus, the optimization model with DRO is

Algorithm 1: Minimax Optimization Via Relaxation.

0. Denote the energy management decisions by vector $\mathbf{x}$, and denote the clearing prices by vector $\boldsymbol{\lambda}$. Denote $\mathbb{E}[J_{\mathcal{D}}]$ by K.
1. Pick a random distribution $\boldsymbol{\pi} \in \mathcal{S}$ and set $\mathcal{R}_\pi = \{\boldsymbol{\pi}\}$.
2. Solve $(\mathbf{x}^*, \boldsymbol{\lambda}^*) = \arg\min\{\max_{\boldsymbol{\pi}\in\mathcal{R}_\pi} K\}$ and $K^* = \max_{\boldsymbol{\pi}\in\mathcal{R}_\pi} K(\mathbf{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{\pi})$.
3. Solve $\boldsymbol{\pi}^* = \arg\max_{\boldsymbol{\pi}\in\mathcal{S}} K(\mathbf{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{\pi})$.
4. If $|K(\mathbf{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{\pi}^*) - K^*| \leqslant \epsilon$ then return $(\mathbf{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{\pi}^*)$ as the solution, else append $\boldsymbol{\pi}^*$ to $\mathcal{R}_\pi$ and go to Step 2.

formulated as follows.

$$\begin{aligned}\min_{\boldsymbol{\pi}\in\mathcal{S}}\max \mathbb{E}[J_{\mathcal{D}}] &= \min_{\boldsymbol{\pi}\in\mathcal{S}}\max \left[\sum_{\omega\in\Omega} \pi_\omega J_{\mathcal{D},\omega}\right] \\ &= \min_{\boldsymbol{\pi}\in\mathcal{S}}\max \Bigg\{\sum_{t\in\mathcal{T}} \alpha_t p_t^H + \sum_{\omega\in\Omega} \pi_\omega \Bigg[\sum_{t\in\mathcal{T}} \psi_{t,\omega}^{\Delta} \\ &\quad + \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}_{\mathcal{D}}} \left(a_g p_{g,t,\omega}^2 + b_g p_{g,t,\omega} + c_g\right) \\ &\quad - \sum_{t\in\mathcal{T}}\sum_{m\in\mathcal{M}} \lambda_{t,\omega} p_{m,t,\omega}^M \Bigg]\Bigg\} \end{aligned} \tag{35}$$

subject to (9)-(16), (19)-(24), (28), (29), (31), (32) and (34). The DRO model above is a mixed integer quadratic minimax optimization model. The integer variables are the binary auxiliary variables $\mathbf{z}_{m,\omega}$ in constraints (31) and (32). In this study, an iterative algorithm based on the relaxation approach for the minimax optimization [24] is developed and used to solve the DRO problem. The steps of the algorithm are described in Algorithm 1.

The outputs of Algorithm 1 give the energy scheduling decision of the DNO by $\mathbf{x}^*$ and the optimal clearing prices in the transactive market by $\boldsymbol{\lambda}^*$ at the same time. With the clearing prices in the transactive market, each MG carries out its own optimization and determines the operation in each scenario.

V. Case Study

In order to illustrate the performance of the proposed method for the energy management of networked MGs, case studies were carried out on the modified IEEE 33-bus system with three individual MGs and the modified IEEE 123-bus system with nine individual MGs. The results of the case studies are presented and discussed in this section.

A. Case Study Descriptions

The first scenario of the case studies was conducted on the modified IEEE 33-bus system with three MGs [10], [12]. The single line diagram of the system is shown in Fig. 3. The load at the buses in the MGs and the RES based distributed generation in the system are summarized in Table I and Table II respectively. The resistance and reactance of all the branches in the MGs are set to be 0.06 and 0.1 p.u., and the base power is set to be

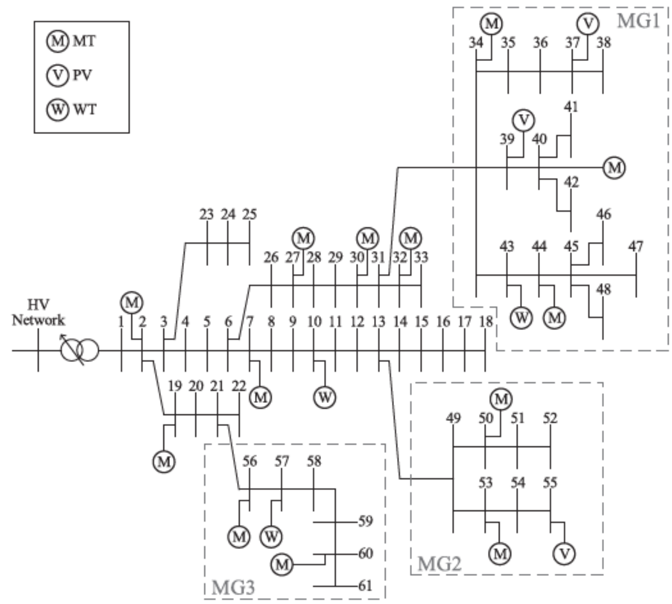

Fig. 3. IEEE 33-Bus System with Three Microgrids.

TABLE I
LOAD INFORMATION OF MGS

MG No.	Bus No.	Total Active Load (MW)	Total Reactive Load (MVAr)
MG1	34,35,36,37,38,39,40,41, 42,43,44,45,46,47,48	2.10	1.20
MG2	49,50,51,52,53,54,55	1.05	0.70
MG3	56,57,58,59,60,61	0.72	0.48

TABLE II
INFORMATION OF RES BASED DGS IN SYSTEM

Bus No.	10	37	39	43	55	57
DER Type	WT	PV	PV	WT	PV	WT
Maximum Active Power Output (kW)	400	200	100	400	300	400

TABLE III
KEY PARAMETERS IN CASE STUDIES

Parameter	Value
MT Cost Function Coefficient (a_g)	$3.0 \times 10^{-4}\,\$/(\mathrm{kWh})^2$
MT Cost Function Coefficient (b_g)	$0.3\,\$/\mathrm{kWh}$
MT Cost Function Coefficient (c_g)	$0\,\$$
MT Active Power Output Limit (p_g^+)	600 kW
MT Reactive Power Output Limit (q_g^+)	200 kVar
Voltage Limits (V_j^+, V_j^-)	1.1, 0.9 $p.u.$

100 MVA. The key parameters in the case studies are listed in Table III.

In order to further illustrate the performance of the proposed transactive energy management framework, a second scenario was also conducted on the modified IEEE 123-bus system connected with nine MGs [25]. The diagram of the test system is shown in Fig. 4. The total load of the system is 3.49 MW. The MTs and WTs in the system have the same parameters with

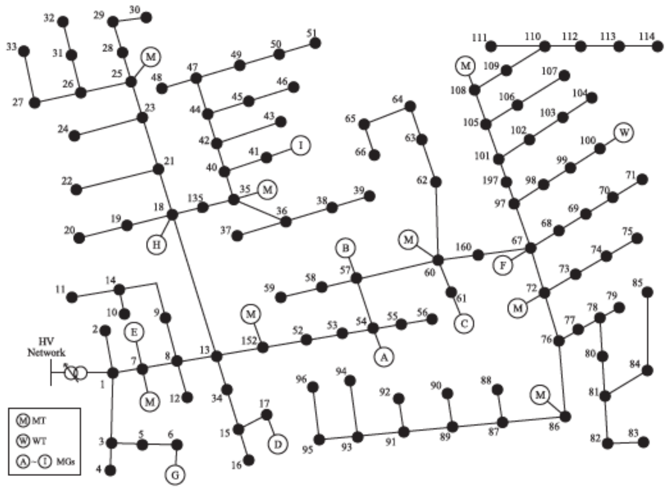

Fig. 4. IEEE 123-Bus Test System with Nine Microgrids.

the previous case in the modified IEEE 33-bus system. Nine MGs, denoted by MG A to I, are connected to the modified IEEE 123-bus test system, in which MG A to C have the same configuration with MG1 in the previous case, MG D to F have the same configuration with MG2 in the previous case, and MG G to I have the same configuration with MG3 in the previous case.

The optimization problems in the case studies were solved on a laptop with Intel Core i5 CPU (2.30GHz) and 8GB RAM. The running time of the optimization for each case of the DS is less than 10 minutes. The operation of the energy management is scheduled on an hourly basis. The running time of the proposed algorithm can meet the time requirement of the scheduling problem.

B. Simulation on Modified IEEE 33-Bus System

The results of the case study with the modified IEEE 33-bus system with three MGs show that the proposed TE based framework is able to coordinate the MGs in the DS as expected. The power exchange between the DS and MGs in each time slot is identical with the DNO's optimization and the optimization of the MGs with the announced clearing prices by the DNO in the transactive market. More importantly, the proposed TE based framework will result in higher operation efficiency than the fixed pricing schemes, in which the power exchange between the DNO and MGs is settled with a fixed price λ. Fig. 5 shows the operation cost of the DS with both the proposed TE based framework and the fixed pricing schemes. It is shown that the operation cost of the DS is significantly reduced by the proposed TE based framework compared with the fixed pricing schemes with any price.

The detailed numbers of the operation costs of all the entities in the system are listed in Table IV. They are the expected costs of the entities in the planning horizon of 24 hours. The operation costs of the MGs show various trends with the change of the prices in the fixed pricing schemes. When the price is very low, the MGs will import a large amount of electricity from the DS,

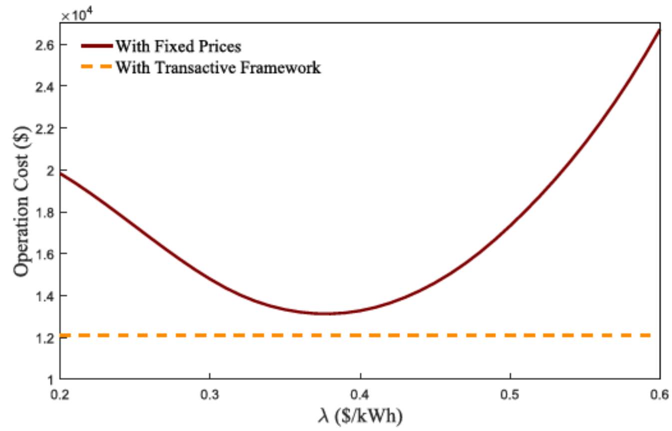

Fig. 5. Operation Cost of DS with Tranascitve Framework and Fixed Prices for IEEE 33-Bus Test System with Three MGs.

TABLE IV
OPERATION COST WITH DIFFERENT PRICING SCHEMES

Unit: $	DNO	MG1	MG2	MG3
Transactive Framework	12098	10074	5156	2896
$\lambda = 0.30\$/\mathrm{kWh}$	14782	8270	4318	2487
$\lambda = 0.35\$/\mathrm{kWh}$	13325	9498	4938	2802
$\lambda = 0.40\$/\mathrm{kWh}$	13271	10426	5357	2916
$\lambda = 0.45\$/\mathrm{kWh}$	14607	11054	5577	2831
$\lambda = 0.50\$/\mathrm{kWh}$	17326	11383	5597	2545
$\lambda = 0.55\$/\mathrm{kWh}$	21282	11411	5416	2060
$\lambda = 0.60\$/\mathrm{kWh}$	26716	11139	5036	1374

even in the peak hours. On the contrary, when the price is very high, the MGs will start to export electricity to the DS when it is in the off-peak hours. Both of the cases will damage the profit of the DS, and such pricing strategies will not be accepted by the DNO. Thus the DNO will choose an intermediate price when its own operation cost is the lowest, which is about $0.4\$/\mathrm{kWh}$ in the case study. In this case, the operation costs of all the MGs are slightly higher than or roughly the same as the case with the proposed TE based framework. Thus, the proposed TE based coordination approach reduces the operation cost of the DS by better scheduling decisions and deploying the flexibility of the distributed energy resources more efficiently instead of damaging the profit of the MGs.

Additionally, a case with a fixed pricing curve rather than a fixed pricing level is also simulated and compared to further demonstrate the performance of the proposed framework. It is assumed that the fixed pricing curve is the same as the day-ahead spot prices as shown in Fig. 6. The expected operation cost of the DS is about \$15600 in this case compared with the cost of about \$12100 with the proposed TE based framework. Although the price is fluctuated and aligned with the day-ahead spot prices in this case, the pricing is still rigid and the flexibility of the system is not fully exploited with the fixed pricing schemes. As a result, the operational cost of the DS is obviously higher than the case with the proposed TE based framework.

In order to provide a robust solution without being over-conservative, the DRO based algorithm is developed and used in

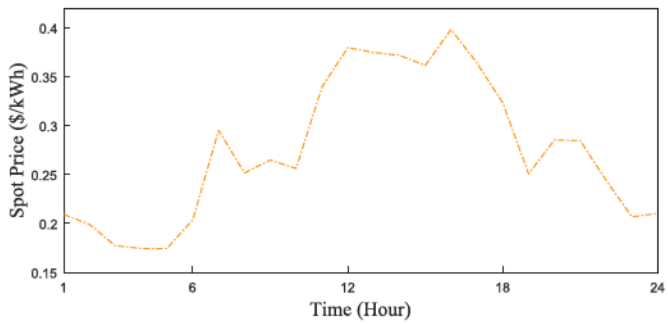

Fig. 6. Day-ahead Spot Price Curve.

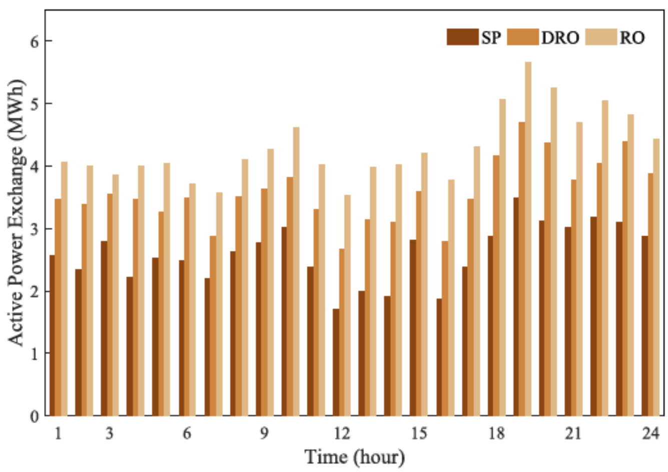

Fig. 7. Scheduled Active Power Exchange between DS and HV System.

TABLE V
OPERATION COST WITH DIFFERENT ALGORITHMS

Unit: $	SP	DRO	RO
Expected Operation Cost	11834.48	12098.31	14261.82
Worst-Case Operation Cost	16003.40	14820.02	14307.15

the proposed framework. The result with the DRO based algorithm is compared with the outputs using the SP and RO models. The scheduled active power exchange between the DS and HV system in the day-ahead process with different algorithms are shown in Fig. 7. In order to hedge the risk, the solution with the RO model schedules the highest amount of electricity in the day-ahead process to the prevent possible power shortage in the operation which may result in high imbalance costs in the worst case. On the other hand, the solution with the SP model schedules the least electricity in the day-ahead process in order to achieve a lowest expected cost. However, the solution with the DRO based algorithm offers an intermediate solution.

The expected operation cost of the DNO and the results in the worst-case scenario with different algorithms are listed in Table V. It is shown that the solution with the SP model has the lowest expected operation cost of the DNO. However, it provides no robustness with the solution in the worst case. The DNO's operation cost with SP is obviously higher than both the cases using the DRO and RO models. The solution with

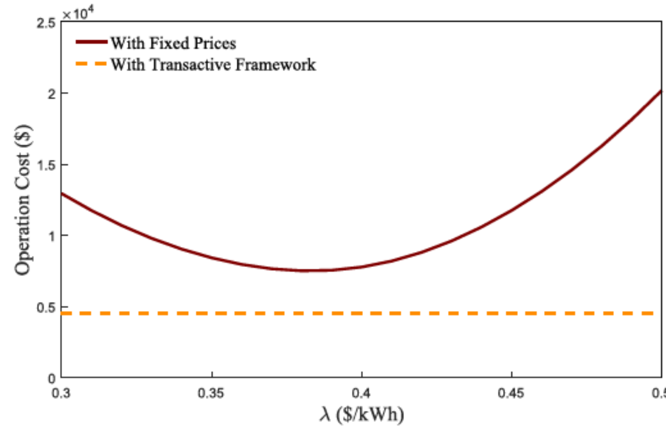

Fig. 8. Operation Cost of DS with Tranascitve Framework and Fixed Prices for IEEE 123-Bus Test System with Nine MGs.

the RO model is very robust in the worst-case scenario. It has the lowest operation cost among the three algorithms. However, the solution is so conservative that the expected operation cost using RO is significantly higher than the other two algorithms. With the proposed DRO based algorithm, the expected operation cost of the DNO increases marginally compared with the result with the SP model. Meanwhile, the DNO's operation cost in the worst-case scenario is just slightly higher than the case using RO and obviously lower than the case using SP. Thus, the DRO based algorithm can provide a robust solution for the proposed TE based coordinated energy management framework under uncertainty while it prevents the solution from being over-conservative which is the case with the RO model.

C. Simulation on Modified IEEE 123-Bus System

The results of the case with the modified IEEE 123-bus test system with nine MGs share the same trend with the previous case with the modified IEEE 33-bus system with three MGs. Fig. 8 shows the operation cost of the DS with both the proposed TE based framework and the fixed pricing schemes in this case.

Similar to the results of the previous case, the operation cost of the DS is greatly reduced by the proposed TE based framework with respect to the fixed pricing schemes at any price point. The expected operation cost of the DS with the proposed TE based framework is about $4550 while it is higher than $7000 for all the cases with the fixed pricing schemes. The proposed TE based energy management framework can effectively improve the operation efficiency of the DS in the case study.

VI. CONCLUSION

In this paper, a transactive energy based energy management framework is proposed for the coordinated operation of networked MGs in distribution systems. Instead of direct coordination signals and fixed pricing schemes, the DNO organizes a transactive energy market and determines the dynamic prices in the proposed framework to settle the power exchange between the DS and MGs in the real-time operation. Either the DNO or each MG is considered as an individual entity and maximizes its own profit in the proposed framework. A bilevel optimization model is developed to achieve the convergence between the operation decisions of the DNO and MGs. A DRO based algorithm is developed and used to provide a robust solution of the optimization problems while preventing the solution from being over-conservative. The case study results of the proposed framework show that the transactive energy based energy management approach significantly improves the operation efficiency of the system. The operation cost of the DS is greatly reduced compared with the fixed pricing schemes. Further, the DRO based algorithm is able to provide a robust solution compared with the stochastic programming model. Meanwhile, it avoids the over-conservative solutions like the case with the robust optimization model.

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