Optimal Bidding Strategy for Microgrids in Joint Energy and Ancillary Service Markets Considering Flexible Ramping Products

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Complete List of Authors:	Wang, Jianxiao; Tsinghua University, Electrical Engineering Zhong, Haiwang; Tsinghua University, Electrical Engineering Tang, Wenyuan Rajagopal, Ram Xia, Qing; Tsinghua University, Electrical Engineering Kang, Chongqing; power system institute, Electrical Engineering Department, Tsinghua University

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Optimal Bidding Strategy for Microgrids in Joint Energy and Ancillary Service Markets Considering Flexible Ramping Products

Jianxiao Wang, *Student Member, IEEE*, Haiwang Zhong, *Member, IEEE*, Wenyuan Tang, *Member, IEEE*, Ram Rajagopal, *Member, IEEE*, Qing Xia, *Senior Member, IEEE*, Chongqing Kang, *Fellow, IEEE*

***Abstract*—Due to the volatile nature of wind and photovoltaic power, wind farms and solar stations are generally thought of as the consumers of ramping services. However, a microgrid (MG) is able to strategically integrate various distributed energy resources (DERs) to provide both energy and ancillary services (ASs) for the bulk power system. To evaluate the ramping capabilities of an MG in the joint energy and AS markets, an optimal bidding strategy is developed in this paper considering flexible ramping products (FRPs). By aggregating and coordinating various DERs, including wind turbines (WTs), photovoltaic systems (PVs), micro-turbines (MTs) and energy storage systems (ESSs), the MG is able to optimally allocate the capacities for energy, reserve, regulation and ramping. Taking advantage of the synergy among DERs, the MG can maximize its revenues from different markets. Moreover, the flexibility of the MG for the bulk power system can be fully exploited. To address the uncertainties introduced by renewable generation and market prices, a hybrid stochastic/robust optimization (RO) approach is adopted. Case studies based on a real-world MG with various DERs demonstrate the market behavior of the MG using the proposed bidding model.**

***Index Terms*—Ancillary service, flexible ramping product, microgrid, optimal bidding strategy, robust optimization.**

NOMENCLATURE

A. Indices and Sets

t	Time index
s	Price scenario index
Φ^B	Set of decision variables
Φ^U	Set of random variables
E	Superscript for energy
RES	Superscript for reserve service
$REGU$	Superscript for regulation-up service
$REGD$	Superscript for regulation-down service
$RAMPU$	Superscript for upward FRP service
$RAMPD$	Superscript for downward FRP service
WT	Superscript for wind turbines
PV	Superscript for photovoltaic systems
MT	Superscript for micro-turbines
ESS	Superscript for energy storage systems

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B. Parameters and Constants

$\hat{P}_t^{WT}$	Point forecast of historical wind power in the MG at time slot t
$\hat{P}_t^{PV}$	Point forecast of historical solar power in the MG at time slot t
Γ_t^{WT}	Robustness parameter of wind power
Γ_t^{PV}	Robustness parameter of solar power
$P_{\max}^{WT}$	Total wind power capacity in the MG
$P_{\max}^{PV}$	Total solar power capacity in the MG
N^{MT}	Number of MTs in the MG
N^{ESS}	Number of ESSs in the MG
γ_s	Weight of price scenario s
N^S	Number of price scenarios
$\lambda_{t,s}^{(\cdot)}$	Day-ahead market price at time slot t in scenario s
h	Time interval
$\beta^{(\cdot)}$	Expectation of real-time deployment ratio of ancillary services
c_i^{MT}	Operation cost per unit energy production of MT i
$P_{i,\max}^{MT}$	Maximal power of MT i
$P_{i,\max}^{MT,RAMPU}$	Maximal ramping-up capacity of MT i
$P_{i,\max}^{MT,RAMPD}$	Maximal ramping-down capacity of MT i
$P_{i,\alpha,\max}^{ESS}$	Maximal charging power of ESS i
$P_{i,\beta,\max}^{ESS}$	Maximal discharging power of ESS i
$\eta_{i,\alpha}^{ESS}$	Charging efficiency of ESS i
$\eta_{i,\beta}^{ESS}$	Discharging efficiency of ESS i
$SOC_{i,\min}^{ESS}$	Minimal state of charge of ESS i
$SOC_{i,\max}^{ESS}$	Maximal state of charge of ESS i
C_i^{ESS}	Capacity of ESS i
$E_{i,0}^{ESS}$	Initial stored energy of ESS i in scenario s
P_t^D	Load demand of the MG at time slot t

C. Variables

P_t^{AWT}	Random variable of available wind power at time slot t
P_t^{APV}	Random variable of available solar power at time slot t
ε_t^{WT}	Normalized error between actual and point forecast wind power

ε_t^{PV}	Normalized error between actual and point forecast solar power
$R_s^{(\cdot)}$	Revenue in scenario *s* from the day-ahead markets
C^{OP}	Operation costs of the MG
$P_t^{(\cdot)}$	Bidding capacity of the MG or DER for energy or ASs at time slot *t*
$\alpha_{i,t}^{ESS}$	Binary variable of ESS *i* at time slot *t* representing the status of charging
$\beta_{i,t}^{ESS}$	Binary variable of ESS *i* at time slot *t* representing the status of discharging
$E_{i,t}^{ESS}$	Stored energy of ESS *i* at time slot *t*

I. Introduction

A. Motivation

THE development of renewable energy has been drawing attention across the world in the past decade. California, for example, announced its ambitious goal of achieving a 50% renewable portfolio standard by 2030 [1]. While the use of renewable energy contributes to a more sustainable future, the variabilities and uncertainties of the renewable sources pose great challenges to the economic and reliable operations of the power system. With the increasing penetration of renewable energy, rapid ramping of generation resources may be insufficient to smooth out the huge fluctuations in renewable energy production [2]. Thus, it is critical to facilitate the accommodation of renewable generation while economically and reliably operating the power system.

The concept of the MG assumes a cluster of loads and DERs operating as a single controllable system [3]. Taking advantage of the synergy among various DERs, the renewable generators can cooperate with controllable energy resources to provide both energy and ancillary services (AS) for the bulk power system. For example, in a stand-alone mode, a wind farm must deviate from its maximum power output status and leave a margin to provide ramping services for the system. However, in an MG, the wind farm is able to leave the ramping margin by charging a Na/S battery without deviating from its maximum power. Hence, an MG can stably provide both energy and AS by integrating various DERs [4]. From the system point of view, MGs show the advantages of low investment costs, low pollutant emission and high operational flexibility. The flexibility of the MGs provided by the DERs can be aggregated for power system operations, thereby replacing high-cost centralized units and deferring the generation expansion. In addition, the MGs are located at the demand side, efficiently offering capacities to meet the local requirements. Compared with centralized thermal units, MGs can achieve localized energy balance without the loss accompanied with long-distance power transmission and difficulties caused by transmission congestions. Therefore, the concept of the MG provides new insights for exploiting the grid-friendly manner of DERs.

In most electricity markets across the world, ancillary services play a critical role in the reliable operation of power systems. In California, for example, the reserve and regulation services are co-optimized with the energy in the day-ahead market. To cope with the inadequacy of the system's ramping capacities, the flexible ramping product (FRP) has been introduced into the market recently to improve the dispatch flexibility and address the operational challenges [8] [9]. In existing studies, the bidding strategies of an MG with various DERs participating in the energy and reserve markets have been investigated [5]-[7]. These studies examined the abilities of an MG to provide capacities for energy and spinning reserve. However, few studies have focused on the combination of different types of ASs, especially the ramping services. With the integration of rapid ramping resources, e.g., micro-turbines (MTs) and energy storage systems (ESSs), an MG is a potential resource to provide flexibility for the power system. Therefore, it is imperative to evaluate the ramping capabilities of MGs in the market environment. This is the first work on the optimal bidding strategy for MGs participating in joint energy and AS markets considering FRPs.

B. Literature Review and Contributions

The optimal bidding strategies for MGs in the energy market have been widely investigated in the last decade. In [5], an optimal day-ahead price-based power scheduling problem is studied for a community-scale MG. The model aims at maximizing the expected benefits of the MG in the energy market while satisfying users' thermal comfort requirements. In [10], the day-ahead bidding strategy of a commercial virtual power plant (VPP) is addressed considering various DERs. To address the uncertainties in load consumptions and real-time prices, a three-stage stochastic optimization model is formulated for optimal energy scheduling. In [11], the optimal bidding strategy in the day-ahead energy market of an MG is proposed. The MG coordinates the energy consumption and production of its components and trades electricity in day-ahead and real-time markets. A hybrid stochastic/robust optimization method is adopted to address the uncertainties in renewable energy outputs and future prices. In [12], the concept of MG aggregators is introduced to involve small-scale MGs in the real-time balancing market bidding via a hierarchical market framework. At the upper level, the bidding strategy of the aggregator is optimized while the market is cleared at the lower level. In [13], the bidding problems of VPPs are investigated considering renewable distributed generators and inelastic demands. A stochastic bi-level optimization model is formulated to minimize the cost of the VPP in day-ahead and balancing markets.

An MG, as a controllable system, is able to provide both energy and AS for the power system by strategically coordinating various DERs. Thus, there have been extensive studies focused on the bidding strategies for MGs in joint energy and reserve markets. In [14], an arbitrage strategy for VPPs by participating in energy, spinning reserve and reactive power markets is presented. The security-constrained unit commitment (SCUC) model is established to maximize VPP's profits. In [15], the bidding problem by a VPP in a joint market of energy and spinning reserve service is addressed. The proposed bidding strategy is a non-equilibrium model based on the deterministic price-based unit commitment. In [16], a risk-averse optimal offering model for a VPP is proposed in the joint energy and reserve markets. Uncertainties in renewable generation and prices from day-ahead and balancing markets are considered. Reference [16] assesses how total and surplus profits of a VPP are affected by risk-aversion. In [7], a multi-objective joint energy and reserve market clearing model is presented in which the payment cost minimization and voltage stability maximization are considered.

To the best of our knowledge, few existing studies have focused on the combination of different types of ASs, especially the ramping services of an MG. By means of the synergy among various DERs, MGs can be thought of as potential ramping resources to cope with the inadequacy of the system's ramping capacities. Therefore, it is imperative to investigate the ramping capabilities of MGs in the market environment. In this paper, an optimal bidding model is established to evaluate the ramping capabilities of an MG in the joint energy and AS markets. By coordinating various DERs, including WTs, PVs, MTs and ESSs, the MG is able to maximize its revenues from the day-ahead markets. A hybrid stochastic/robust optimization method is adopted to address the uncertainties in renewable energy generation and market prices.

The major contributions of this paper are as follows.

1) FRPs are incorporated into the bidding model of an MG. The ramping capabilities of the MG can then be evaluated by optimizing the bidding model. By integrating various DERs, the ramping capabilities of the MG can be greatly improved.

2) The flexibility of an MG for the bulk power system is examined considering its participation in the joint energy, reserve, regulation and FRP markets.

3) A hybrid stochastic/robust optimization approach is adopted to address the uncertainties in renewable sources and market prices. The bidding problem with uncertain coefficients can be transformed into a mixed-integer linear programming (MILP) model that can be readily solved.

II. Problem Description

A. Co-optimization of Energy and Ancillary Service Markets

Without loss of generality, the co-optimization of energy and AS markets is implemented in this paper [17]. In the pool-based day-ahead markets, it is assumed that an MG can simultaneously bid in joint energy and AS markets. Considering its relatively small capacity, an MG is reasonably assumed to be a price-taker. As a controllable entity, the MG will strategically allocate available capacities in day-ahead markets to maximize the expected revenues. The MG bids energy and ASs, including spinning reserve service, regulation service and FRPs [8].

FRPs are designed to relieve the system-wide ramping constraints, which are first introduced in California and MISO markets in the United States. The models and applications of FRPs have been investigated recently. In [18], the mathematical model of FRPs is formulated according to the California market. In [19], the security-constrained economic dispatch (SCED) model is presented to incorporate the ramping constraints. Numerical results demonstrate the effectiveness of the ramping constraints for reducing the instances of short-term scarcity conditions. In [20], a risk-constrained SCED scheme is proposed to optimize the dispatch and provision of FRPs. With the increasing demand for the ramping resources in the power system, the FRP market is expected to be fully operational in the near future [21].

The co-optimization of the energy and AS markets is implemented in most electricity markets operated by the independent system operators (ISOs) [22]. The bids of the MG in joint energy and AS markets must be determined before the closure of the day-ahead markets for the next day [11].

B. Uncertainty Modeling

In this paper, a hybrid stochastic/robust optimization approach is adopted to address the uncertainties in renewable generation and day-ahead market prices [11], [17]. The prices in the energy and AS markets are modeled via scenario-based stochastic programming. The uncertainties in wind and photovoltaic power are addressed using RO.

For market prices, an MG is concerned with the profiles of market prices to optimally allocate its available capacities in each market. The prices in different markets have strong correlations, which cannot be modeled with independent confidence intervals. For example, both prices of energy and spinning reserve are relatively high during peak hours because of high load demands. In addition, to allocate the capacities in different markets, the relative differences of prices are the major concern instead of the absolute values of market prices. Therefore, stochastic programming with multiple price scenarios is more appropriate than RO to model the uncertainty of market prices [11].

For renewable generations, the absolute capacities of wind and photovoltaic power have large impacts on the bidding strategy of an MG as well as the operation of the DERs in the MG. Moreover, because the intervals of wind and photovoltaic power can be obtained according to historical data, RO is an effective tool to address the uncertainties in renewable generation. Therefore, the robust mixed-integer linear programming (RMILP) in [23] is applied in this paper.

The available power of the WT and PV in the MG at time slot *t*, denoted by P_t^{AWT} and P_t^{APV}, are modeled as independent and bounded random variables. Under a confidence level σ, P_t^{AWT} takes values from the minimum power $\underline{P}_t^{AWT}$ to the maximum power $\overline{P}_t^{AWT}$, while P_t^{APV} takes values from $\underline{P}_t^{APV}$ to $\overline{P}_t^{APV}$. To obtain the confidence intervals of P_t^{AWT} and P_t^{APV}, the forecast errors are analyzed based on historical datasets.

For example, $\hat{P}_t^{WT}$ and P_t^{WT} are the point forecast and actual wind power at time slot *t*. Based on the historical data from the Wind Integration Datasets of the NREL [24], the probability distribution $f^{WT}\left(\hat{P}_t^{WT}/P_{\max}^{WT}\right)$ of wind power forecast errors ε_t^{WT} can be acquired, i.e.,

$$\varepsilon_t^{WT}=\frac{\hat{P}_t^{WT}\text{-}P_t^{WT}}{P_{\max}^{WT}},\ \varepsilon_t^{WT}\sim f^{WT}\left(\hat{P}_t^{WT}/P_{\max}^{WT}\right), \tag{1}$$

Then the upper and lower bounds of wind power forecast errors under the confidence level σ, $\varepsilon_{t,\max}^{WT}$ and $\varepsilon_{t,\min}^{WT}$, can be calculated as follows:

$$\varepsilon_{t,\min}^{WT} = \operatorname{Inf}\left\{ w\in[0,1] \left| \int_0^w f^{WT}(x)dx \ge \frac{1-\sigma}{2} \right. \right\}, \qquad (2)$$

$$\varepsilon_{t,\max}^{WT} = \operatorname{Inf}\left\{ w\in[0,1] \left| \int_0^w f^{WT}(x)dx \ge \frac{1+\sigma}{2} \right. \right\}, \qquad (3)$$

Fig. 1 shows the intervals of forecast errors with 95% confidence level under different levels of forecasted wind power.

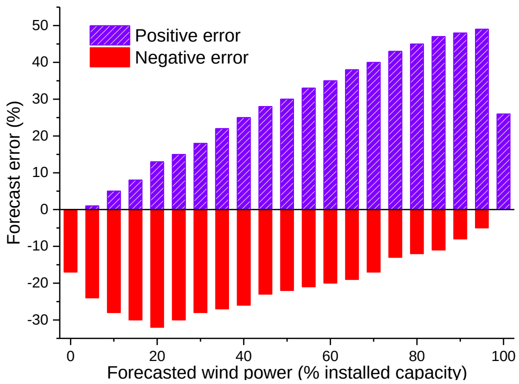

Fig. 1. The intervals of forecast errors with 95% confidence level under different levels of forecasted wind power.

According to the forecasted wind power, the minimum power $\underline{P}_t^{AWT}$ and the maximum power $\overline{P}_t^{AWT}$ can be calculated as follows:

$$\underline{P}_t^{AWT} = \hat{P}_t^{AWT} - P_{\max}^{WT} \cdot \varepsilon_{t,\max}^{WT}, \ \varepsilon_{t,\max}^{WT} > 0, \qquad (4)$$

$$\overline{P}_t^{AWT} = \hat{P}_t^{AWT} - P_{\max}^{WT} \cdot \varepsilon_{t,\min}^{WT}, \ \varepsilon_{t,\min}^{WT} < 0, \qquad (5)$$

Then the random variable for the available wind power at time slot t is bounded as follows:

$$P_t^{AWT} \in \left[\underline{P}_t^{AWT}, \overline{P}_t^{AWT} \right], \qquad (6)$$

The intervals for the available PV power can be obtained in a similar manner with wind power.

III. Optimal Bidding Model for Microgrids

By coordinating various DERs, the MG is able to provide flexibility for the bulk power system and participate in the joint energy and AS markets. In addition, FRPs are considered in the bidding strategy of the MG. As a price-taker, the MG strategically allocates the hourly capacities in the day-ahead markets.

A. Objective

The objective of the optimal bidding strategy for an MG is to maximize the total revenue from the electricity energy, reserve, regulation and FRP market, shown as follows:

$$\max_{\Phi^B} \min_{\Phi^U} \sum_{s=1}^{N^S} \gamma_s \left(R_s^E + R_s^{RES} + R_s^{REG} + R_s^{FRP} - C^{OP} \right), \qquad (7)$$

where

$$R_s^E = \sum_{t=1}^{T} \lambda_{t,s}^E \Big[P_t^E + \beta^{RES} P_t^{RES} + \beta^{REG} \left(P_t^{REGU} - P_t^{REGD} \right) + \beta^{RAMP} \left(P_t^{RAMPU} - P_t^{RAMPD} \right) \Big] h, \qquad (8)$$

$$R_s^{RES} = \sum_{t=1}^{T} \lambda_{t,s}^{RES} P_t^{RES} h, \qquad (9)$$

$$R_s^{REG} = \sum_{t=1}^{T} \left(\lambda_{t,s}^{REGU} P_t^{REGU} + \lambda_{t,s}^{REGD} P_t^{REGD} \right) h, \qquad (10)$$

$$R_s^{FRP} = \sum_{t=1}^{T} \left(\lambda_{t,s}^{RAMPU} P_t^{RAMPU} + \lambda_{t,s}^{RAMPD} P_t^{RAMPD} \right) h, \qquad (11)$$

$$C^{OP} = \sum_{t=1}^{T} \sum_{i=1}^{N^{MT}} c_i^{MT} \Big[P_{i,t}^{MT,E} + \beta_i^{MT,RES} P_{i,t}^{MT,RES} + \beta_i^{MT,REG} \left(P_{i,t}^{MT,REGU} - P_{i,t}^{MT,REGD} \right) + \beta_i^{MT,RAMP} \left(P_{i,t}^{MT,RAMPU} - P_{i,t}^{MT,RAMPD} \right) \Big] h, \qquad (12)$$

To consider the influences of the real-time deployment of ASs, the ratios $\beta^{(\cdot)}$ are used to estimate the potential energy requirement in providing AS [17].

B. Constraints

1) The constraints of RGs

$$P_t^{WT,E} + P_t^{WT,RES} + P_t^{WT,REGU} + P_t^{WT,RAMPU} \le P_t^{AWT}, \ \forall t, \qquad (13)$$

$$P_t^{PV,E} + P_t^{PV,RES} + P_t^{PV,REGU} + P_t^{PV,RAMPU} \le P_t^{APV}, \ \forall t, \qquad (14)$$

$$P_t^{WT,E} - P_t^{WT,REGD} - P_t^{WT,RAMPD} \ge 0, \ \forall t, \qquad (15)$$

$$P_t^{PV,E} - P_t^{PV,REGD} - P_t^{PV,RAMPD} \ge 0, \ \forall t, \qquad (16)$$

2) The constraints of MTs

$$P_{i,t}^{MT,E} + P_{i,t}^{MT,RES} + P_{i,t}^{MT,REGU} + P_{i,t}^{MT,RAMPU} \le P_{i,\max}^{MT}, \ \forall i,t, \qquad (17)$$

$$P_{i,t}^{MT,E} - P_{i,t}^{MT,REGD} - P_{i,t}^{MT,RAMPD} \ge 0, \ \forall i,t, \qquad (18)$$

$$\left(P_{i,t+1}^{MT,E} + P_{i,t+1}^{MT,RES} + P_{i,t+1}^{MT,REGU} + P_{i,t+1}^{MT,RAMPU} \right) - \left(P_{i,t}^{MT,E} - P_{i,t}^{MT,REGD} - P_{i,t}^{MT,RAMPD} \right) \le P_{i,\max}^{MT,RAMPU}, \ \forall i,t, \qquad (19)$$

$$\left(P_{i,t}^{MT,E} + P_{i,t}^{MT,RES} + P_{i,t}^{MT,REGU} + P_{i,t}^{MT,RAMPU} \right) - \left(P_{i,t+1}^{MT,E} - P_{i,t+1}^{MT,REGD} - P_{i,t+1}^{MT,RAMPD} \right) \le P_{i,\max}^{MT,RAMPD}, \ \forall i,t, \qquad (20)$$

3) The constraints of ESSs

$$0 \le \alpha_{i,t}^{ESS} + \beta_{i,t}^{ESS} \le 1, \ \alpha_{i,t}^{ESS}, \beta_{i,t}^{ESS} \in \{0,1\}, \ \forall i,t, \qquad (21)$$

$$0 \le P_{i,t,\alpha}^{ESS} \le \alpha_{i,t}^{ESS} P_{i,\alpha,\max}^{ESS}, \ \forall i,t, \qquad (22)$$

$$0 \le P_{i,t,\beta}^{ESS} \le \beta_{i,t}^{ESS} P_{i,\beta,\max}^{ESS}, \ \forall i,t, \qquad (23)$$

$$P_{i,t}^{ESS,E} = P_{i,\beta,t}^{ESS} - P_{i,\alpha,t}^{ESS}, \ \forall i,t, \qquad (24)$$

$$P_{i,t}^{ESS,E} + P_{i,t}^{ESS,RES} + P_{i,t}^{ESS,REGU} + P_{i,t}^{ESS,RAMPU} \le P_{i,\beta,\max}^{ESS}, \ \forall i,t, \qquad (25)$$

$$P_{i,t}^{ESS,E} - P_{i,t}^{ESS,REGD} - P_{i,t}^{ESS,RAMPD} \ge -P_{i,\alpha,\max}^{ESS}, \ \forall i,t, \qquad (26)$$

$$P_{i,t}^{ESS,E} h^E + P_{i,t}^{ESS,RES} h^{RES} + P_{i,t}^{ESS,REGU} h^{REG} + P_{i,t}^{ESS,RAMPU} h^{RAMP} \le E_{i,t}^{ESS}, \ \forall i,t, \qquad (27)$$

$$E_{i,t}^{ESS} - P_{i,t}^{ESS,E} h^E + P_{i,t}^{ESS,REGD} h^{REG} + P_{i,t}^{ESS,RAMPD} h^{RAMP} \le SOC_{i,\max}^{ESS} C_i^{ESS}, \ \forall i,t, \qquad (28)$$

$$E_{i,t}^{ESS} = E_{i,t-1}^{ESS} + \left(P_{i,\alpha,t}^{ESS} \eta_{i,\alpha}^{ESS} - P_{i,\beta,t}^{ESS} / \eta_{i,\beta}^{ESS} \right) h, \ \forall i,t, \qquad (29)$$

$$SOC_{i,\min}^{ESS} \le E_{i,t}^{ESS} / C_i^{ESS} \le SOC_{i,\max}^{ESS}, \ \forall i,t, \qquad (30)$$

$$E_{i,0}^{ESS} = E_{i,T}^{ESS}, \ \forall i, \qquad (31)$$

where $\alpha_{i,t}^{ESS}$ and $\beta_{i,t}^{ESS}$ are binary variables representing the working condition of the ESS i at time slot t. $\alpha_{i,t}^{ESS}=1, \beta_{i,t}^{ESS}=0$ indicates the ESS is charging; $\alpha_{i,t}^{ESS}=0, \beta_{i,t}^{ESS}=1$ indicates the ESS is discharging; $\alpha_{i,t}^{ESS}=0, \beta_{i,t}^{ESS}=0$ indicates the ESS is standing by. The power limits of ESSs are shown in (22) and (23). Constraints (27) and (28) indicate that an ESS must be able to maintain the fully deployed output level for h^{E} (typically 1 h) energy, h^{RES} (typically 1 h) spinning reserve, h^{REG} (typically 15 min) regulation up/down and h^{RAMP} (typically 15 min) ramping up/down [22]. Constraint (29) represents the relationship between stored energy and charging/discharging power. In (30), the ESS is bounded by the minimum and maximum of the state of charge (SOC). In (31), the initial and final stored energy should be equal.

4) The constraints of the MG

$$P_t^{E} = P_t^{WT,E} + P_t^{PV,E} + \sum_{i=1}^{N^{MT}} P_{i,t}^{MT,E} + \sum_{i=1}^{N^{ESS}} P_{i,t}^{ESS,E} - P_t^{D},\ \forall t, \quad (32)$$

$$P_t^{m} = P_t^{WT,m} + P_t^{PV,m} + \sum_{i=1}^{N^{MT}} P_{i,t}^{MT,m} + \sum_{i=1}^{N^{ESS}} P_{i,t}^{ESS,m},\ \forall t \quad (33)$$
$$\forall m \in \{RES, REGU, REGD, RAMPU, RAMPD\},$$

The MG's capacity for energy and AS is supported by the DERs operated by the MG aggregator, as shown in (32)-(33). Therefore, the objective (7) and the constraints (8)-(33) form the proposed bidding model. The solution algorithm is elaborated in Section IV.

IV. Reformulation via Robust Optimization Approach

Because of its flexibility, controllability and moderate computational cost, the RO approach provides applicable solutions to the general stochastic optimization problems. In the optimal bidding model, the set of random variables Φ^{U} includes the available wind and photovoltaic power P_t^{AWT} and P_t^{APV}. This problem can be formulated as an RMILP by introducing dual and auxiliary variables as follows:

$$\max_{\Phi^{B} \cup \Phi^{D}} \sum_{s=1}^{N^{S}} \gamma_s \left(R_s^{E} + R_s^{RES} + R_s^{REG} + R_s^{FRP} - C^{OP} \right), \quad (34)$$

subject to

$$\text{Constraints (15) - (33)},$$

$$P_t^{WT,E} + P_t^{WT,RES} + P_t^{WT,REGU} + P_t^{WT,RAMPU} + \Gamma_t^{WT} z_t^{WT} + q_t^{WT} \le \frac{1}{2}\left(\underline{P}_t^{AWT} + \overline{P}_t^{AWT} \right),\ \forall t, \quad (35)$$

$$P_t^{PV,E} + P_t^{PV,RES} + P_t^{PV,REGU} + P_t^{PV,RAMPU} + \Gamma_t^{PV} z_t^{PV} + q_t^{PV} \le \frac{1}{2}\left(\underline{P}_t^{APV} + \overline{P}_t^{APV} \right),\ \forall t, \quad (36)$$

$$z_t^{WT} + q_t^{WT} \ge \frac{1}{2}\left(\overline{P}_t^{AWT} - \underline{P}_t^{AWT} \right) y_t^{WT},\ \forall t, \quad (37)$$

$$z_t^{PV} + q_t^{PV} \ge \frac{1}{2}\left(\overline{P}_t^{APV} - \underline{P}_t^{APV} \right) y_t^{PV},\ \forall t, \quad (38)$$

$$y_t^{WT}, y_t^{PV} \ge 1,\ \forall t, \quad (39)$$

$$z_t^{WT}, z_t^{PV}, q_t^{WT}, q_t^{PV} \ge 0,\ \forall t, \quad (40)$$

where $z_t^{WT}, z_t^{PV}, q_t^{WT}, q_t^{PV}$ are the dual variables of the original problems and y_t^{WT}, y_t^{PV} are the auxiliary variables that help linearize the problem. Γ_t^{WT} and Γ_t^{PV} are the robustness parameters, which take on values in the interval $[0, |J_t^{WT}|]$ and $[0, |J_t^{PV}|]$, where J_t^{WT} and J_t^{PV} are sets including all random variables in constraints (13) and (14) at time slot t. Note that there is just one random variable in each constraint, so $|J_t^{WT}| = |J_t^{PV}| = 1$. The details of the RO approach can be found in reference [23].

The RMILP seeks to maximize the MG's revenues from each market under the worst case caused by the uncertainties in renewable generations. The hourly parameters Γ_t^{WT} and Γ_t^{PV} adjust the robustness degree of constraints (13) and (14) against the uncertainties in the wind and photovoltaic power. The larger the robustness parameters are, the more conservative the RMILP problem becomes. The influences of selecting different robustness parameters are investigated in Section V.

V. Case Studies

The test environment is a ThinkPad T440p operating at 2.40 GHz with 8 cores. The program is developed using MATLAB R2015a. The optimization solver is CPLEX 12.4 [26].

A. Basic Data

Historical data of the Electric Reliability Council of Texas (ERCOT) day-ahead market prices [27] from July 1, 2016, to September 30, 2016, are used to generate 20 typical scenarios to address the uncertainties in day-ahead market prices. These price scenarios are generated by K-means clustering. The average hourly prices in the energy and AS markets are shown in Fig. 2. The wind and solar power are the real-world data from a wind farm and a photovoltaic station in a province in China. According to Section II, under 95% confidence level, the forecasted wind and photovoltaic power and the confidence intervals are shown in Fig. 3. The parameters of the other DERs in the MG are shown in TABLE I.

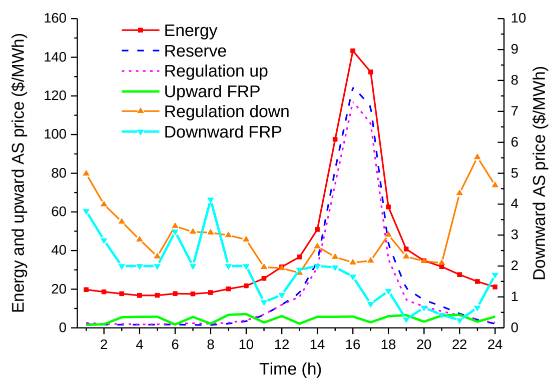

Fig. 2. Average day-ahead hourly prices in the energy and AS markets.

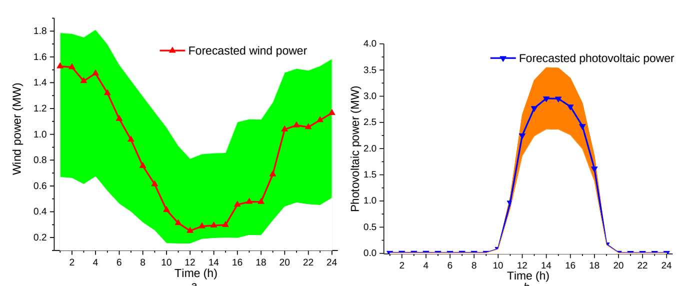

Fig. 3. The forecasted renewable power and the confidence intervals.

To evaluate the ramping capabilities and the benefits of the MG in joint energy and AS markets, three cases are considered:

Case 1: i) S1, where the MG bids in the joint energy and AS markets considering FRPs with $\Gamma_t^{WT}=\Gamma_t^{PV}=1$; ii) S2, where the MG bids in the joint energy and AS markets without FRPs with $\Gamma_t^{WT}=\Gamma_t^{PV}=1$; iii) S3, where the MG only bids in the energy market with $\Gamma_t^{WT}=\Gamma_t^{PV}=1$.

Case 2: i) S1; ii) S4, where the MG bids in the joint energy and AS markets considering FRPs with $\Gamma_t^{WT}=\Gamma_t^{PV}=0.6$; iii) S5, where the MG bids in the joint energy and AS markets considering FRPs with $\Gamma_t^{WT}=\Gamma_t^{PV}=0.2$.

Case 3: i) S1; ii) S6, where the MG bids in the joint energy and AS markets considering FRPs with $\Gamma_t^{WT}=\Gamma_t^{PV}=1$, while the FRP prices are 1.2 times of those in S1; iii) S7, where the MG bids in the joint energy and AS markets considering FRPs with $\Gamma_t^{WT}=\Gamma_t^{PV}=1$, while the FRP prices are 0.8 times of those in S1.

TABLE I
PARAMETERS OF THE DERS IN THE MG

DER	c_i^{MT}($/MWh)	$P_{i,\max}^{MT}$(MW)	$P_{i,\max}^{MT,RAMPU}$ (MW/h)	$P_{i,\max}^{MT,RAMPD}$ (MW/h)
MT-1	13	3	2	2
MT-2	10	4	2	2
MT-3	18	2	2	2
ESS-1	$\eta_{i,\alpha}^{ESS}$	$\eta_{i,\beta}^{ESS}$	$SOC_{i,\min}^{ESS}$	$SOC_{i,\max}^{ESS}$
	0.95	0.95	0.1	0.9
	C_i^{ESS}(MWh)	$E_{i,0}^{ESS}$(MWh)	$P_{i,\alpha,\max}^{ESS}$(MW)	$P_{i,\beta,\max}^{ESS}$(MW)
	12	6	2	2
ESS-2	$\eta_{i,\alpha}^{ESS}$	$\eta_{i,\beta}^{ESS}$	$SOC_{i,\min}^{ESS}$	$SOC_{i,\max}^{ESS}$
	0.95	0.95	0.1	0.9
	C_i^{ESS}(MWh)	$E_{i,0}^{ESS}$(MWh)	$P_{i,\alpha,\max}^{ESS}$(MW)	$P_{i,\beta,\max}^{ESS}$(MW)
	20	10	2.5	2.5

B. Base Case Results

In S1, the MG bids in joint energy and AS markets considering FRPs. The optimal bidding strategies of the MG are shown in Fig. 4.

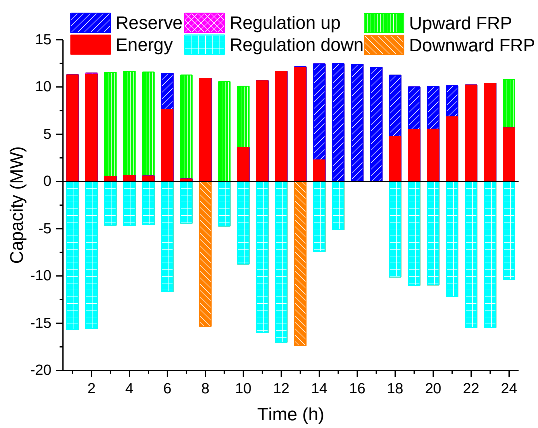

Fig. 4. Optimal bidding strategies of the MG in the base case.

The MG strategically allocates the available capacity in each hour to maximize the revenues from the joint energy and AS markets. Because of the opportunity costs of the ancillary services, the MG will optimally allocate the capacity according to the difference of market prices. As shown in Fig. 2, when the prices of spinning reserve are high and the opportunity costs are relatively low, the capacity is provided for reserve instead of bidding in the energy market. Similar conclusions can be drawn from the regulation-up service and the upward FRP. In addition, by means of shedding renewable generation and decreasing the output of DERs, the MG can provide regulation-down service and downward FRPs. When the prices of the downward FRP are higher than those of the regulation-down service, the MG will bid the capacity for ramping-down service.

The optimal bidding strategies of the DERs in the energy market are shown in Fig. 5. Because the operational costs of wind and photovoltaic power are zero, the capacity of WT and PV is fully used in the energy market to maximize the energy revenues. The operational cost of M-2 is relatively low; thus, all the available capacity is provided for energy. However, the costs of the other two MTs are higher, thereby driving MT-1 and MT-3 to bid the available capacity for ancillary services during some periods. In the process of arbitrage, the ESSs will charge during the valley hours and discharge during the peak hours. In addition, because the ESSs can flexibly adjust the consumption or production, the ESSs will strategically bid for energy and ancillary services. The energy capacity of the MG is equal to the difference between the capacity offered by the DERs and the load demands.

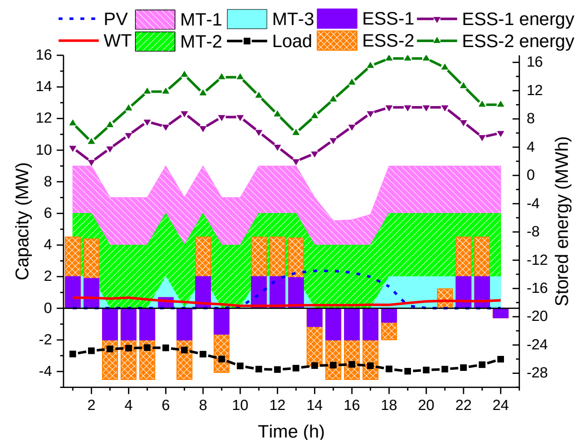

Fig. 5. Optimal bidding strategies of the DERs in the energy market.

The expected revenues of the DERs in different markets are shown in TABLE II. By strategically allocating the capacity of the DERs in different markets, the MG can obtain the optimal expected revenues with 20.32% energy, 64.08% reserve, 9.01% regulation and 6.59% FRPs. As one can observe, it is beneficial for the MG to participate in the joint energy and AS markets, in which FRPs are also important fractions.

TABLE II
THE EXPECTED REVENUES OF THE DERS IN DIFFERENT MARKETS

Revenue	Energy ($)	Reserve ($)	Regulation ($)	FRP ($)	Day-ahead market ($)
WT	274.60	0	26.91	1.66	303.17
PV	1187.59	0	22.12	4.25	1213.96
MT-1	1473.05	419.02	121.97	12.06	2026.10
MT-2	2803.10	0	125.33	12.06	2940.49
MT-3	345.91	711.07	80.39	85.00	1222.37
ESS-1	-544.82	1612.98	131.42	168.40	1367.98
ESS-2	-695.45	2038.77	163.97	208.65	1715.94

MG	1516.79	4781.84	672.11	492.08	7462.82

C. *Comparison Results in Case 1*

TABLE III shows the expected revenues from each market in Case 1.

TABLE III
THE EXPECTED REVENUES FROM EACH MARKET IN CASE 1

Revenue	Energy ($)	Reserve ($)	Regulation ($)	FRP ($)	Day-ahead market ($)
S1	1516.79	4781.84	672.11	492.08	7462.82
S2	1400.23	5024.56	831.83	0	7256.62
S3	5588.77	0	0	0	5588.77

Comparing the results in S1 and those in S2, one can observe that the MG can increase its revenues by 2.84% if providing ramping capacities. Hence, it is beneficial for the MG to bid in FRPs. Comparing the results in S1 and those in S3, one can observe that the MG can increase its revenues by 33.53% if participating in joint energy and AS markets.

Therefore, by participating in joint energy and AS markets considering FRPs, the MG can further increase its day-ahead revenues, and meanwhile provide ramping capacities for the bulk power system, which fully exploits the grid-friendly potentials of the MG.

D. *Comparison Results in Case 2*

The total FRPs provided by the MG in Case 2 are compared in TABLE IV.

TABLE IV
THE TOTAL FRPS PROVIDED BY THE MG IN CASE 2

	S1	S4	S5
Upward FRP (MW)	66.15	66.34	66.52
Downward FRP (MW)	32.69	33.29	33.83

From the comparison results, the total FRPs provided by the MG increase with the decrease of the conservatism degree. A smaller conservatism degree indicates a larger amount of available renewable generation is expected, thereby leading to an increase in the ramping capacities of the MG. The expected revenues from each market in Case 2 are shown in TABLE V.

TABLE V
THE EXPECTED REVENUES FROM EACH MARKET IN CASE 2

Revenue	Energy ($)	Reserve ($)	Regulation ($)	FRP ($)	Day-ahead market ($)
S1	1516.79	4781.84	672.11	492.08	7462.82
S4	1673.40	4900.84	685.42	494.91	7754.57
S5	1869.43	4979.47	699.40	497.61	8045.91

With the decrease of the conservatism degree, the revenues from each market will increase. As the simulation results show, with the synergy of the DERs in the MG, the renewable generation can cooperate with the MTs and ESSs and be fully accommodated without curtailment. Therefore, as a controllable aggregator, the MG is able to provide more ASs.

E. *Comparison Results in Case 3*

The FRPs provided by the MG in Case 3 are compared in Fig. 6. From the comparison results, when the ramping capacities of the bulk power system are insufficient, leading to higher FRP prices, the MG is able to provide more ramping capacities to support the bulk power system while maximizing its individual revenues. The expected revenues from each market in Case 3 are shown in TABLE VI.

From the results in S1 and S6, by increasing the FRP prices by 20%, the total revenues of the MG from the day-ahead market will increase, and the FRP revenues increase by 49.43%. With more available capacities provided for FRPs, the revenues from other AS are reduced in S6. From the results in S1 and S7, by reducing the FRP prices by 20%, the total revenues will decrease, the FRP revenues decrease by 32.60% while more capacities can be provided for other AS.

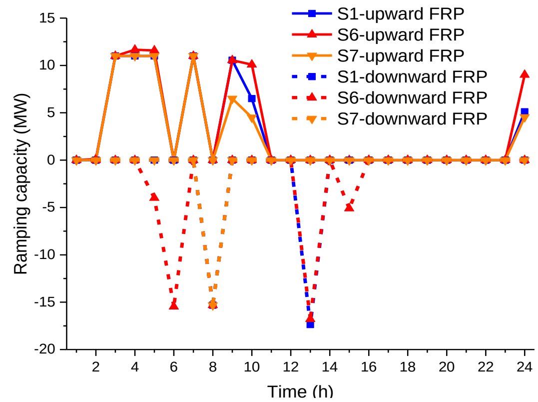

Fig. 6. The FRPs provided by the MG in Case 3.

TABLE VI
THE EXPECTED REVENUES FROM EACH MARKET IN CASE 3

Revenue	Energy ($)	Reserve ($)	Regulation ($)	FRP ($)	Day-ahead market ($)
S1	1516.79	4781.84	672.11	492.08	7462.82
S6	1507.76	4743.33	588.67	735.33	7575.09
S7	1454.74	4870.49	716.80	331.68	7373.71

F. *Sensitivity Analysis*

The base case S1 is simulated with different robustness parameters to investigate the influence of the degree of conservatism on the bidding strategies. The revenues of the MG with different robustness parameters are shown in Fig. 7.

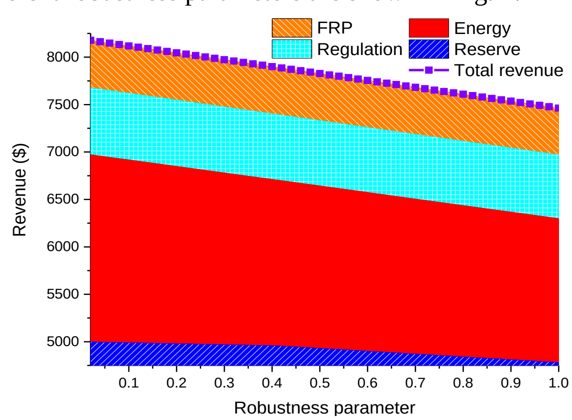

Fig. 7. The revenues of the MG with different robustness parameters.

Because the operational costs of the WT and PV are zero, the MG will optimally allocate the available capacity of the WT and PV in the energy market. Therefore, with the increase of the conservatism degree, the revenues from each market are gradually reduced because of the decreasing expectations of the renewable generation. As one can observe, the FRP revenues can increase by 1.43% from $\Gamma_t^{WT} = \Gamma_t^{PV} = 1$ to $\Gamma_t^{WT} = \Gamma_t^{PV} = 0$.

Then the base case S1 is simulated with different ramping prices to investigate the ramping capabilities of the MG. With the prices of energy, reserve and regulation services unchanged, the bidding curves of upward and downward FRPs provided by the MG at 10:00 are shown in Fig. 8.

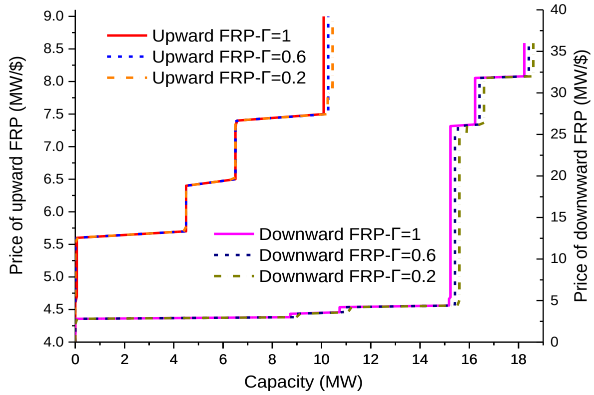

Fig. 8. The bidding curves of upward and downward FRPs provided by the MG at 10:00.

From the bidding curves of FRPs, when the prices go up, the FRPs provided by the MG will increase, which maximize the revenues from day-ahead markets. The ramping capabilities of the MG at 10:00 can be observed from the curves, shown in TABLE VII.

TABLE VII
THE RAMPING CAPABILITIES OF THE MG AT 10:00

	Γ=1	Γ=0.6	Γ=0.2
Upward FRP (MW)	10.09	10.27	10.45
Downward FRP (MW)	18.24	18.42	18.60

Under different degrees of conservatism, the bidding curves of the MG for FRPs have the same shape. However, with the decrease of the degree of conservatism, the ramping capabilities of the MG will increase because more renewable generations are expected.

VI. CONCLUSION

In this paper, flexible ramping products are incorporated in an optimal bidding framework for MGs. The bidding model aims at maximizing the expected revenues from different markets while aggregating and coordinating various DERs, including WTs, PVs, MTs and ESSs. Therefore, the MG is able to strategically allocate the capacities for energy, reserve, regulation and ramping. A hybrid stochastic/robust optimization approach is adopted to address the uncertainties in renewable energy and day-ahead market prices. The bidding problem with uncertain coefficients can be transformed into a mixed-integer linear programming model that can be readily solved. Case studies based on an MG with various DERs demonstrate the market behavior of the MG using the proposed bidding model. Based on the proposed model and scheme, on one hand, the bidding strategies of MGs can be optimized to maximize the day-ahead market revenues when confronted with different types of AS; on the other hand, the grid-friendly nature of MGs can be fully utilized in the markets. The proposed model will provide new insights in the development of MGs.

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