A risk-averse day-ahead bidding strategy of transactive energy sharing microgrids with data-driven chance constraints

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Abstract: The rapid development of microgrids (MGs) with various prosumers promotes the accommodation of renewable distributed generation (RDG) and provides platforms for local energy sharing among prosumers. However, the operational uncertainties pose enormous challenges to the day-ahead bidding of MGs in the wholesale electricity market and there is an urgent need for a local market to facilitate the local energy sharing. Thus, this paper proposes a risk-averse day-ahead bidding strategy for MGs with full consideration of the multiple uncertainties originating from the wholesale electricity market, RDG and loads. Based on the transactive energy (TE) sharing concept, the local market is formulated as a Stackelberg game (SG) to effectively capture the strategic interaction among the MG and prosumers, where a distributed iterative algorithm with a bisection approach that only requires exchanging TE-related information is adopted to achieve the SG equilibrium without compromising privacy concerns. To handle the uncertainties of RDG and loads, the power balances are formulated as chance constraints and a data-driven quantile forecasting method is developed for achieving the computational tractability of chance constraints without any prior knowledge or probability distribution assumptions. Furthermore, a risk criterion of the conditional value-at-risk is incorporated in the day-ahead bidding model of MGs for risk aversion towards uncertainties of the wholesale electricity market. The effectiveness of the proposed solution is extensively demonstrated through numerical simulation.

Keywords: microgrid, day-ahead bidding, transactive energy sharing, Stackelberg game, chance constraints, conditional value-at-risk.

Nomenclature

Abbreviations:

MG	Microgrid
MGO	Microgrid operator
RDG	Renewable distributed generation
PV	Photovoltaics
WT	Wind turbines
DG	Distributed generator

PEMS	Prosumer energy management system
ESS	Electricity storage system
CDF	Cumulative distribution function
CVaR	Conditional value-at-risk

Indices/sets:

l	Index of hours.
t	Index of time slots.
i	Index of prosumers.
s	Index of real-time price scenarios.
Ω_H	Set of hours.
Ω_{TS}	Set of time slots.
Ω_{PS}	Set of prosumers.
Ω_S	Set of real-time price scenarios.

Parameters:

λ_l^{DA}	Day-ahead electricity price at l-th hour in the wholesale electricity market, in $/kWh.
λ_l^{RT}	Real-time electricity price at l-th hour in the wholesale electricity market, in $/kWh.
τ	Duration of each time slot, in hour.
λ^{p}	Penalty price for electricity deviation, in $/kWh.
r	Allowable ratio of electricity deviation from bidding, in p.u..
a,b,c	Cost coefficients of the dispatchable DG, in $/kWh^2, $/kWh and $, respectively.
$P_{\max}^{\mathrm{DG}}$	Maximum generating power of the dispatchable DG, in kW.
λ^{ramp}	Ramp rate of the dispatchable DG, in p.u..
ρ_m^{ESS}	Decay cost efficient of ESS for MG, in $/kWh.
$P_{\max,m}^{\mathrm{ESS}}$	Maximum charging/discharging power of ESS for MG, in kW.
$\eta_m^{\mathrm{ch}}, \eta_m^{\mathrm{dis}}$	Charging and discharging efficiency of ESS for MG, in p.u..
$E_{0,m}^{\mathrm{ESS}}$	Initially stored electricity of ESS for MG, in kWh.
$E_{\min,m}^{\mathrm{ESS}}, E_{\max,m}^{\mathrm{ESS}}$	Minimum and maximum stored electricity limits of ESS for MG, in kWh.

μ^{av}	Average electricity selling price by MGO to prosumers, in $/kWh.
$\mu_l^{\min}, \mu_l^{\max}$	Minimum and maximum electricity selling price limits at l-th hour by MGO to prosumers, in $/kWh.
ε	Electricity purchase price coefficient by MGO from prosumers, in p.u..
L	Total hours of the optimization horizon, in p.u..
$P_{t,m}^{\mathrm{Load}}$	Electricity load of MG at t-th time slot, in kW.
$P_{t,i}^{\mathrm{Load}}$	Electricity load of i-th prosumer at t-th time slot, in kW.
$P_{t,m}^{\mathrm{PV}}$	Generation of PV in MG at t-th time slot, in kW.
$P_{t,m}^{\mathrm{WT}}$	Generation of WT in MG at t-th time slot, in kW.
$P_{t,i}^{\mathrm{PV}}$	Generation of PV in i-th prosumer at t-th time slot, in kW.
$P_{t,i}^{\mathrm{WT}}$	Generation of WT in i-th prosumer at t-th time slot, in kW.
ρ_i^{ESS}	Decay cost efficient of ESS for i-th prosumer, in $/kWh.
$P_{\max,i}^{\mathrm{ESS}}$	Maximum charging/discharging power of ESS for i-th prosumer, in kW.
$E_{0,i}^{\mathrm{ESS}}$	Initially stored electricity of ESS for i-th prosumer, in kWh.
$E_{\min,i}^{\mathrm{ESS}}, E_{\max,i}^{\mathrm{ESS}}$	Minimum and maximum stored electricity limits of ESS for i-th prosumer, in kWh.
$\eta_i^{\mathrm{ch}}, \eta_i^{\mathrm{dis}}$	Charging and discharging efficiency of ESS for i-th prosumer, in p.u..
$P_{t,m}^{\mathrm{net}}$	Net electricity load of MG at t-th time slot, in kW.
η_m	Confidence level of power balance chance constraints for MG, in p.u..
$CDF_{t,m}^{-1}(\eta_m)$	Inverse function value of CDF at η_m for the uncertain variable $P_{t,m}^{\mathrm{net}}$, in kW.
π_s	Probability of s-th real-time price scenario occurrence, in p.u..
α	Confidence level of CVaR, in p.u..
β	Weighting parameter for risk aversion, in p.u..

Variables:

$\mu_{l,i}^{\mathrm{sell}}, \mu_{l,i}^{\mathrm{buy}}$	Electricity selling and purchase prices by MGO to and from i-th prosumer at l-th hour, in $/kWh.
$E_{l,i}^{\mathrm{sell}}, E_{l,i}^{\mathrm{buy}}$	Electricity purchased and sold by i-th prosumer from and to MGO at l-th hour, in kWh.
F_M	Objective function of MGO, in $.
$F_{s,m}$	F_M in the s-th real-time price scenario, in $.
F_i	Objective function of i-th prosumer, in $.

C^{DA}	Day-ahead bidding cost of MGO in the wholesale electricity market, in \$.
C^{RT}	Real-time electricity purchase cost of MGO in the wholesale electricity market, in \$.
C^{Pen}	Penalty cost of MGO in the wholesale electricity market, in \$.
C^{DG}	Operational cost of the dispatchable DG, in \$.
C_m^{ESS}	Decay cost of ESS for MGO, in \$.
C_m^{TE}	Transaction cost of MGO for purchasing electricity from prosumers, in \$.
R_m^{TE}	Transaction revenue of MGO for selling electricity to prosumers, in \$.
E_l^{DA}	Day-ahead bidding electricity of MGO in the wholesale electricity market at l-th hour, in kWh.
E_l^{RT}	Real-time consumed electricity of MGO in the wholesale electricity market at l-th hour, in kWh.
ΔE_l	Deviation between the real-time consumed and day-ahead bidding electricity of MGO in the wholesale electricity market at l-th hour, in kWh.
$\Delta E_l^{\mathrm{abs}}$	Auxiliary variable denotes the absolute value of ΔE_l, in kWh.
P_t^{grid}	Transmission power between MG and main grid at t-th time slot, in kW.
C_l^{pen}	Penalty cost of MGO in the wholesale electricity market at l-th hour, in \$.
P_t^{DG}	Generating power of the dispatchable DG at t-th time slot, in kW.
$P_{t,m}^{\mathrm{ch}}, P_{t,m}^{\mathrm{dis}}$	Charging and discharging power of ESS for MG at t-th time slot, in kW.
$E_{t,m}^{\mathrm{ESS}}$	Stored electricity of ESS for MG at t-th time slot, in kWh.
$P_{t,i}^{\mathrm{buy}}, P_{t,i}^{\mathrm{sell}}$	Electric power purchased and sold by i-th prosumer from and to MGO at t-th time slot, in kW.
C_i^{ESS}	Decay cost of ESS for i-th prosumer, in \$.
C_i^{TE}	Transaction cost of i-th prosumer for purchasing electricity from MGO, in \$.
R_i^{TE}	Transaction revenue of i-th prosumer for selling electricity to MGO, in \$.
$P_{t,i}^{\mathrm{ch}}, P_{t,i}^{\mathrm{dis}}$	Charging and discharging power of ESS for i-th prosumer at t-th time slot, in kW.
$E_{t,i}^{\mathrm{ESS}}$	Stored electricity of ESS for i-th prosumer at t-th time slot, in kWh.
$P_{t,m}^{\mathrm{supply}}$	Net electricity supply of MG at t-th time slot, in kW.
$CVaR_\alpha$	CVaR function at the confidence level α, in \$.
z	Value-at-risk, in \$.
$F_{s,m}$	Objective function of MGO in s-th real-time price scenario, in \$.
V_s	Auxiliary variable in s-th real-time price scenario, in \$.

1. Introduction

1.1 Background and motivation

With the increasing concerns regarding the global energy crisis and environmental degradation, the popularity and development of renewable distributed generation (RDG), e.g., photovoltaics (PV) and wind turbines (WT), have been significantly boosted in recent years due to their pollution-free and renewable characteristics [1]-[2]. Therefore, microgrids (MGs) have received tremendous interest as they are extensively recognized as a promising paradigm for facilitating the integration of RDG and improving electricity flexibility and efficiency [3]-[4]. In addition, an MG not only manages the resources under its jurisdiction but also acts as a retailer to provide electricity services to end-users. Regarding this matter, the MG can serve as an intermediate player to participate in the upstream wholesale electricity market on behalf of the end-users, since small-capacity users are unable to independently meet the market entry threshold [5]. In reality, the end-users are emerging as prosumers by equipping devices such as RDG and the electricity storage system (ESS) with the fast development of power technology [5]. The prosumers no longer passively consume the electricity supplied by the MG but instead interact with it [6]. As a result, the MG can provide a platform to coordinate energy sharing among it and the involved prosumers to enhance overall energy efficiency. However, the MG and prosumers are generally affiliated with different stakeholders, so they are privacy sensitive and marked by prominent competitive interests. The MG operator (MGO) aims to maximize the revenues from the electricity provision while the prosumers seek to minimize operating costs [7]. In summary, it is critical to investigate the day-ahead bidding problem of MGs with local energy sharing in the wholesale electricity market, particularly in the presence of multiple uncertainties arising from RDG, loads and the wholesale electricity market.

1.2 Related work

The energy sharing in MGs can effectively enhance energy utilization efficiency which has been demonstrated in several studies [8], and there have been some practical MG projects considering energy sharing [9]. Generally speaking, the operational framework for energy sharing depends on the features of participants. The power exchange within the clustered MGs was achieved in [10] by the formulated coordination optimization framework with a centralized control manner. A Nash bargaining-based model was formulated in [11] to fairly allocate the revenue from energy sharing among multi-energy MGs to incentivize their collaboration. A bi-level energy sharing model was proposed in [12], where the energy sharing among multiple lower-layer participants was collaborated by the upper-layer operator. However, the centralized dispatch will be impractical due to the different ownership of entities, which will result in privacy concerns. Some work adopted distributed optimization approaches, such as the alternating direction of multipliers (ADMM), to achieve energy sharing by only exchanging limited information [13]-[15]. In [13], an energy management strategy was developed to minimize the operating cost of the whole MG network, which was solved in a decentralized manner based on ADMM to settle the electricity sharing among MGs with privacy protection. However, the work did not involve the conflict of interests for different MGs. In contrast, the peer-to-peer energy trading framework was developed in [14] and [15] using ADMM, where Nash bargaining was employed to fairly allocate the benefits from energy sharing to participants to incentivize them to actively engage in sharing.

There is also a framework for achieving energy sharing that uses prices as key operational parameters to conduct transactive energy (TE), which integrates a series of economic and control mechanisms to achieve the equilibrium of interests among different participants [16]. The TE sharing is generally implemented by developing a local market in which participants determine their behaviors according to the market mechanisms. Thus, the operation of multiple entities can be effectively coordinated according to reasonable prices which act as indirect control signals. The existing studies of local TE markets mainly fall into two categories [6]. The first is internal energy trading based on an auction mechanism, where the participants are predetermined as buyers or sellers and their roles are fixed in the transaction. For example, in [17], the bidding information on the quantities of electricity purchased or sold by each partner was submitted to the MG market to implement trading within the MG thus achieving higher benefits. A dynamic alliance transaction framework for the multiple MGs system was developed in [18], where the trading enthusiasms of MGs were enhanced based on their contributions to the MG cluster when they act as sellers. However, such a mechanism is not suitable for TE among prosumers since they can both consume and supply electricity, in other words, act as buyers or sellers during different periods.

Another category of local TE markets is based on dynamic pricing, where an operator clears price signals to participants who adjust their energy utilization behaviors accordingly. As a result, the pricing schemes in the local markets become especially crucial, involving game theory, dual decomposition, etc. in the literature [19]. For instance, in [20], a linear energy pricing function was adopted to encourage energy sharing in an MG. The dual variables in the ADMM-based distributed optimization framework in [21] are regarded as the clearing energy price signals. In reality, the TE sharing process of the MG follow a clear sequential and hierarchical structure, where the MGO determines a pricing strategy and the prosumers then schedule their energy sharing plans which in turn affect the pricing strategy of the MGO. Besides, both MGO and prosumers pursue their individual optimal interest as different stakeholders. Therefore, it is suitable to characterize the complicated strategic interaction among them for balancing their interests based on the Stackelberg game (SG). The energy scheduling based on SG has attracted wide attention in studies [5], [7], [22]-[23]. A hierarchical stochastic scheduling approach of multi-community integrated energy systems via SG was developed in [7], where the system operator as the leader cleared energy prices to consumers which were the followers. The SG was adopted in [22] to coordinate the TE sharing of a community integrated energy system. The electricity trading between the utility company and multiple users was modeled as SG in [23], where a pricing function was employed to induce the users to join the game. However, the aforementioned work only considered the end-users as consumers while neglecting the features of the prosumers. A tri-layer SG approach was proposed in [5] for community grid energy management, where the uncertainties of RDG were considered in the energy scheduling of prosumers. Nevertheless, the sale of energy from the prosumers to the upper layer was not involved in this work. These previous studies have demonstrated the benefits of SG towards balancing the interests among multiple entities and in view of this, SG is leveraged in this paper to develop the local TE market of MG.

It is also very important to note that the operational uncertainties regarding stochastic RDG and fluctuating energy demands can pose enormous challenges to the reliable operation and energy scheduling of the MG. To deal with such uncertainties in decision-making, several approaches have been available, such as stochastic optimization [24], robust optimization [25] and chance-constrained programming. In terms of chance constraints, the core idea is to model uncertainties by ensuring that the constraints related to them are feasible with certain confidence levels. This enables the constraints to exhibit some elasticity so that decision-makers can easily strike a balance between cost and risk [26]. Therefore, the application of chance constraints in decision-making under uncertainties has been significantly promoted. In [27], the uncertainties arising from load and RDG were incorporated in the day-ahead scheduling of the power system using chance constraints. The RDG-related uncertainties were modeled by chance constraints in [28] and [29] to tackle the optimal power flow problem and tri-level energy scheduling of distribution networks, respectively. Although the aforementioned work proved the considerable effectiveness of chance constraints in coping with uncertainties, the implicit form of chance constraints presents a challenge in terms of direct solvability. In [27]-[29], the chance constraints were equivalently converted into deterministic constraints by assuming that the uncertain factors obey Gaussian distributions and are independent of each other. Similarly, a sample average approximation approach was adopted in [30] to solve chance constraints with the assumption of uncertainties obeying Gaussian distributions. A back-mapping approach was utilized in [31] to solve the optimization model based on chance constraints where the accurate probability distributions of uncertain factors were required. However, it is worth noting that the above methods can be challenging to implement in practice, since the probability distributions of uncertainties are often difficult to be accurately obtained, and the corresponding assumptions are also hard to hold. Hence, an effective method for solving optimization problems with chance constraints is urgent.

Generally, prosumers cannot directly participate in the wholesale electricity market independently due to limited capacity [5]. Thus, one of the tasks of MGs is to aggregate multiple prosumers to participate in the market on their behalf. The MGs need to make rational decisions based on the transaction rules of the wholesale market to reduce the cost of purchasing electricity from the market. The prevailing wholesale electricity markets include PJM, Guangdong and Iberian markets, etc. The energy management problem in these market contexts has gained widespread attention. For example, a day-ahead bidding strategy for multi-energy MGs was proposed in [32], and its effectiveness was validated by case studies in the PJM and Guangdong electricity markets. In [33], an optimal bidding strategy was developed to support the operation of an aggregator of prosumers in the Iberian electricity market. The optimal day-ahead bidding strategy for demand-side resource aggregators was developed under the PJM electricity market in [34]. To summarize, the trading structure of prevailing wholesale electricity markets generally includes a day-ahead market and a real-time market [35]. Therefore, the wholesale electricity market participation of MGs requires them to make bidding decisions in the day-ahead market, and subsequently schedule the actual electricity consumption in the real-time market based on the day-ahead bidding electricity. In this regard, making an optimal day-ahead bidding strategy is a key part for MGs to reduce operating costs. The real-time prices have a critical impact on the day-ahead bidding decisions of MGs and they tend to exhibit a high degree of uncertainty, which makes the day-ahead bidding a non-trivial task [34]. It can cause the risk of a significant increase in the electricity procurement cost for MGs in the wholesale market if the uncertainties associated with real-time prices are not to be handled properly. Several studies have been carried out to determine the day-ahead bidding strategy in consideration of electricity market uncertainties. For example, an optimal bidding strategy of MGs was developed in [36], where the uncertainties of electricity prices were modeled through multiple price scenarios. In [37], a day-ahead bidding strategy for electric vehicle aggregators was presented, where the uncertainties related to the real-time prices were accounted for by analyzing potential real-time price scenarios. Generally speaking, the MGO is risk averse towards uncertainties introduced by the wholesale electricity market and thus it is essential to incorporate a proper risk criterion into the day-ahead bidding strategy. In this regard, the conditional value-at-risk (CVaR) has received broad attention due to its advantages of numerical efficiency, calculation stability, etc. [38]. The CVaR was embedded in the optimal bidding strategy of demand-side resource aggregators in [34] to control the risk of participating in the uncertain market for ensuring the robustness of day-ahead bidding decisions. A conditional expectation optimization model with CVaR constraints was formulated in [39] to determine the bidding strategy of electric vehicle aggregators under market uncertainties. Nevertheless, the pricing schemes of MG or aggregators to end-users were not involved in these studies.

To summarize, there are still some technical challenges for further exploitation in the day-ahead bidding of TE sharing MGs, as follows: (1) The MGO and prosumers are generally affiliated with different stakeholders in practice. Therefore, it is urgent to formulate a local TE market to balance the interests of multiple parties while considering privacy protection; (2) in addition to participating in the internal energy transaction, the MGO is obliged to participate in the upstream wholesale electricity market. Hence, it is of significant importance for developing a day-ahead bidding model of TE sharing MGs to consider the wholesale market-related uncertainties while coordinating the bidding to the wholesale market and pricing to prosumers; (3) it is also crucial that the uncertainties associated with RDG and electricity loads must be properly handled to guarantee the reliable operation of the MG and prosumers.

1.3 Contributions and organization

This paper proposes a risk-averse day-ahead bidding strategy of TE sharing MGs with full consideration of multiple uncertainties arising from the wholesale electricity market, RDG and electricity loads. The proposed solution can effectively clear the electricity prices for the local TE market with a balance of multilateral interests to facilitate internal energy sharing while comprehensively dealing with multiple uncertainties based on their distinct properties. The effectiveness of the proposed solution is extensively validated through numerical simulation in the PJM electricity market. The major technical contributions made in this paper are summarized as follows:

- The local TE market is developed as an SG-based model to effectively capture the strategic interaction among the MGO and prosumers, and a distributed iterative algorithm with a bisection approach that only requires exchanging TE-related information is adopted to achieve game equilibrium without compromising privacy concerns.
- The power balances are formulated as chance constraints to simultaneously capture the supply-demand uncertainties introduced by RDG and electricity loads. To tackle the intractable chance constraints, a data-driven quantile forecasting method is developed to equivalently reformulate them as tractable deterministic constraints without any prior knowledge or probability distribution assumptions.
- A risk-averse day-ahead bidding strategy of MGs is developed by incorporating a risk criterion of CVaR to achieve financial risk aversion towards the uncertainties related to the wholesale electricity market.

The remainder of this paper is constructed as follows. Section 2 elaborates on the operational framework of the TE sharing MG and wholesale electricity market rules. The deterministic day-ahead bidding model for the TE sharing MG is first mathematically formulated in Section 3. Section 4 characterizes and models the uncertainties in the MG operation, based on which the deterministic model in Section 3 is extended to a risk-averse form, and an implementation flowchart of the proposed solution is given in this section. Numerical simulation is conducted in Section 5 and conclusions are summarized in Section 6.

2. Problem formulation

2.1 Operational framework of TE sharing MGs

Fig. 1 illustrates the operational framework of the TE sharing MG that is equipped with various electricity generation, storage and consumption units, such as dispatchable DG, RDG and ESS. Furthermore, the MG is also integrated with various end-users to provide them with electricity services. The end-users are considered prosumers as they consist of RDG, ESS and loads, and thus have the ability of electricity generation and consumption. In practice, the MG and individual prosumers are affiliated with different stakeholders and possess individual interests. Moreover, they are under the jurisdiction of MGO and the prosumer energy management system (PEMS), respectively. The electricity transactions between the MGO and prosumers are carried out in a local market, thus enabling energy sharing within the whole MG to improve overall energy efficiency. In addition, the MG is operated by the MGO in the wholesale electricity market to purchase electricity from the main grid. Therefore, the MGO is obliged to submit its electricity procurement decisions to the upstream wholesale market operator.

The appropriate settings of local market prices can stimulate prosumers to engage in collaborative energy sharing. In the TE sharing process, the MGO clears personalized electricity prices to each prosumer, and the prosumers then schedule their transaction commitments in response to prices which will in turn affect the price clearing scheme of the MGO. The MGO and prosumers pursue their competing interests by continually adjusting their strategies. Such a TE sharing process can be formulated as an SG model where the interaction process during the game is also schematically illustrated in **Fig. 1**, and the SG model has the following elements.

(1) Participants: MGO (leader) and prosumers (multiple followers).

(2) Strategy set: The strategy of the leader is the local market price clearing scheme denoted by $\left\{\mu_{l,i}^{\text{sell}}, \mu_{l,i}^{\text{buy}}\right\}$, while the strategies of followers are electricity transaction commitments based on cleared prices, represented as $\left\{E_{l,i}^{\text{sell}}, E_{l,i}^{\text{buy}}\right\}$. It is worth noting that the prices issued by the MGO are time-varying and may vary for each prosumer even for the same hour depending on their different transaction commitments.

(3) Utility functions: The utility functions for the MGO and prosumers are their individual objective functions which are detailed in the following sections.

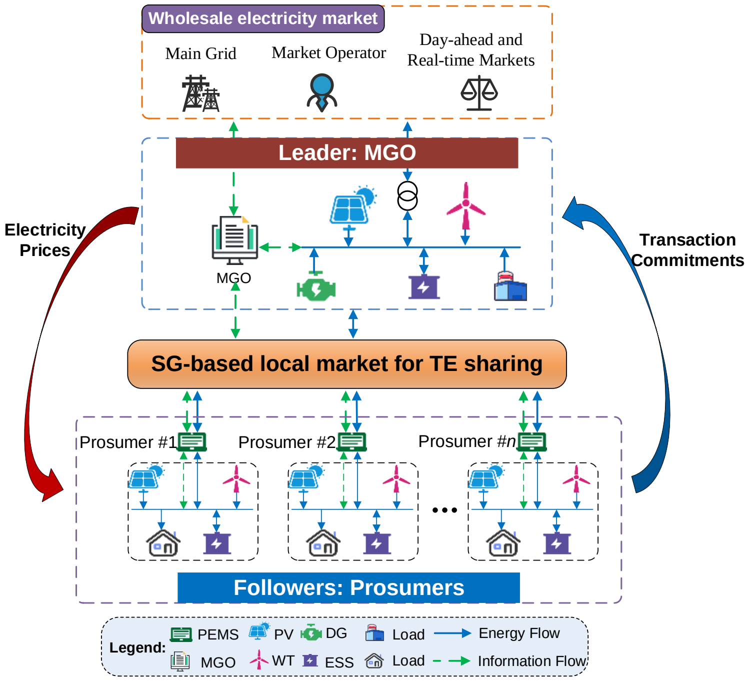


Fig. 1 Operational framework of a TE sharing MG.

2.2 Wholesale electricity market participation

The MGO needs to participate in the wholesale electricity market on behalf of the prosumers. In this paper, the proposed solution is implemented in a common pool trading-based wholesale electricity market consisting of a day-ahead energy market and a real-time balancing market where a two-settlement mechanism is used (e.g., the Guangdong and PJM electricity markets [40]-[41]). In the day-ahead market, the MGO needs to submit hourly non-priced bidding electricity that covers 24 hours of the following day to the market operator. After receiving bid information from all market participants, the market operator clears the day-ahead electricity prices. Then, the first settlement is performed based on the day-ahead prices along with the bidding electricity. The settlement in the real-time market is conducted according to the deviations between the real-time consumption and day-head bidding of electricity, as well as real-time electricity prices which are cleared by the market operator based on the real-time generation-load balance status and stored day-ahead bidding information. Besides, the MGO will be penalized for the electricity deviations if they exceed the tolerance thresholds (generally a certain percentage of the day-ahead bidding electricity, e.g., 20% in the PJM market). It is worth noting that although the prediction errors of day-ahead electricity prices can be neglected since they have a certain regularity, the real-time prices still exhibit high uncertainties associated with the fluctuating generation-load balance status [34], which pose significant challenges to the day-ahead bidding of MGO.

3. Deterministic day-ahead bidding model of SG-based TE sharing MGs

Assuming that the day-ahead and real-time electricity prices of the wholesale market, RDG and loads are accurately known, the deterministic day-ahead bidding model of an SG-based TE sharing MG is formulated in this section, including the leader model of the MGO and the follower model of prosumers. Then, the model is extended to a risk-averse form in Section 4 by characterizing and modeling the uncertainties in the MG operation.

3.1 Leader model of the MGO

The MGO aims to minimize the total operating costs while maximizing its revenues for providing electricity services to prosumers and all operational constraints must be satisfied. Therefore, the objective function of the leader model can be mathematically formulated as (1):

$$\min F_m = C^{\mathrm{DA}} + C^{\mathrm{RT}} + C^{\mathrm{Pen}} + C^{\mathrm{DG}} + C_m^{\mathrm{ESS}} + C_m^{\mathrm{TE}} - R_m^{\mathrm{TE}} \tag{1}$$

where the first three terms denote the day-ahead bidding cost, real-time electricity purchase cost and penalty cost in the wholesale electricity market, respectively. The fourth term represents the generation cost of dispatchable DG. The fifth term denotes the decay cost of ESS. The last two terms represent the cost and revenue of MGO for purchasing and selling electricity in the local market, respectively. Each term of the objective function (1) and the corresponding constraints are detailed below.

(1) Wholesale market participation: According to the transaction rules of the wholesale electricity market, the electricity costs to be paid by the MGO to the wholesale market operator include the day-ahead bidding cost C^{DA} and the real-time electricity purchase cost C^{RT}, which can be mathematically expressed as (2) and (3), respectively. Moreover, Eq. (4) indicates that the MGO generally participates in the wholesale market as a price-taker and thus the day-ahead bidding electricity cannot be less than 0. The electricity settlement of the wholesale market is on an hourly basis which is considered too rough for finely regulating the devices in the MG (viz., fine-grained energy dispatch of the MG). Therefore, a smaller time granularity of 15 minutes is adopted in this paper for the energy dispatch of the MG, which means the proposed strategy incorporates multiple time scales. In this regard, Eq. (5) quantifies the relationship between electricity and power for each hour. Note that there will be penalties to be imposed on the MGO for excessive electricity deviations in case the absolute values of the deviations are higher than the thresholds. Based on the transaction rules of the PJM market, the penalty at l-th hour is defined as (6) and thus the penalty cost is as shown in (7). By introducing auxiliary variables $\Delta E_l^{\mathrm{abs}}$, Eq. (6) can be linearized to constraints (8)~(9).

$$C^{\mathrm{DA}} = \sum_{l \in \Omega_H} \lambda_l^{\mathrm{DA}} E_l^{\mathrm{DA}} \tag{2}$$

$$C^{\mathrm{RT}}=\sum_{l\in\Omega_H}\lambda_l^{\mathrm{RT}}\left(E_l^{\mathrm{RT}}-E_l^{\mathrm{DA}}\right)=\sum_{l\in\Omega_H}\lambda_l^{\mathrm{RT}}\Delta E_l \tag{3}$$

$$E_l^{\mathrm{DA}}\geq 0 \tag{4}$$

$$E_l^{\mathrm{RT}}=\sum_{t\in[4l-3,4l]}P_t^{\mathrm{grid}}\tau,\forall l \tag{5}$$

$$C_l^{\mathrm{pen}}=\begin{cases}\lambda^{\mathrm{p}}\left(\left|\Delta E_l\right|-rE_l^{\mathrm{DA}}\right), \text{ if } \left|\Delta E_l\right|>rE_l^{\mathrm{DA}}\\ 0 \qquad , \quad \text{otherwise}\end{cases},\forall l \tag{6}$$

$$C^{\mathrm{Pen}}=\sum_{l\in\Omega_H}C_l^{\mathrm{Pen}} \tag{7}$$

$$C_l^{\mathrm{pen}}\geq 0,\ \ C_l^{\mathrm{pen}}\geq\lambda^{\mathrm{p}}\left(\Delta E_l^{\mathrm{abs}}-rE_l^{\mathrm{DA}}\right),\forall l \tag{8}$$

$$\Delta E_l^{\mathrm{abs}}\geq\Delta E_l,\Delta E_l^{\mathrm{abs}}\geq-\Delta E_l,\forall l \tag{9}$$

(2) Dispatchable DG: The operating cost and constraints of the dispatchable DG are given in (10)~(12). More specifically, Eq. (10) computes the DG generation cost and Eq. (11) limits the range of DG output power with consideration of the ramp constraint (12).

$$C^{\mathrm{DG}}=\sum_{t\in\Omega_{TS}}\left[\frac{a}{2}\left(P_t^{\mathrm{DG}}\right)^2+bP_t^{\mathrm{DG}}+c\right]\tau \tag{10}$$

$$0\leq P_t^{\mathrm{DG}}\leq P_{\max}^{\mathrm{DG}},\forall t \tag{11}$$

$$-\lambda^{\mathrm{ramp}}P_{\max}^{\mathrm{DG}}\leq P_t^{\mathrm{DG}}-P_{t-1}^{\mathrm{DG}}\leq\lambda^{\mathrm{ramp}}P_{\max}^{\mathrm{DG}},\forall t \tag{12}$$

(3) Electricity storage system: The decay cost of ESS can be expressed as a function of its charging and discharging power as shown in (13). Besides, Eq. (14)~(16) restrict the operating power and stored electricity of ESS to be within certain ranges to safeguard its health.

$$C_m^{\mathrm{ESS}}=\sum_{t\in\Omega_{TS}}\rho_m^{\mathrm{ESS}}\left(P_{t,m}^{\mathrm{ch}}+P_{t,m}^{\mathrm{dis}}\right)\tau \tag{13}$$

$$0\leq P_{t,m}^{\mathrm{ch}},P_{t,m}^{\mathrm{dis}}\leq P_{\max,m}^{\mathrm{ESS}},\forall t \tag{14}$$

$$E_{t,m}^{\mathrm{ESS}}=E_{t-1,m}^{\mathrm{ESS}}+\left(P_{t,m}^{\mathrm{ch}}\eta_m^{\mathrm{ch}}-P_{t,m}^{\mathrm{dis}}/\eta_m^{\mathrm{dis}}\right)\tau,\forall t \tag{15}$$

$$E_{\min,m}^{\mathrm{ESS}}\leq E_{t,m}^{\mathrm{ESS}}\leq E_{\max,m}^{\mathrm{ESS}},\forall t \tag{16}$$

(4) Transaction cost and revenue with prosumers in the local market: Given the electricity transaction commitments of prosumers (i.e., $E_{l,i}^{\mathrm{sell}}$ and $E_{l,i}^{\mathrm{buy}}$ which means the electricity sold and purchased by i-th prosumer to and from MGO at l-th hour) which are optimized by the follower model and thus treated as parameters here, the cost and revenue of the MGO in the local market can be expressed as (17) and (18), respectively. Similarly, the local market considers the hourly electricity settlement and energy dispatch with a smaller time granularity of 15 minutes, and thereby the relationship between electricity and power for each hour can be derived, as shown in (19)~(20). The personalized electricity prices $\mu_{l,i}^{\mathrm{sell}}$ and $\mu_{l,i}^{\mathrm{buy}}$ to each prosumer issued by the MGO are decision variables here and they must obey the pricing constraints shown in

(21)~(23). More concretely, Eq. (21) imposes constraints on the ranges of the electricity selling prices at each hour while Eq. (22) restricts the average selling price over the entire horizon as a constant to avoid the MGO from always setting the prices at the upper limits for the sake of maximizing revenues, thereby protecting the interests of prosumers to participate in energy sharing. Additionally, Eq. (23) ensures that the self-consumption of electricity for prosumers takes priority over sales to the MGO.

$$C^{\mathrm{TEm}} = \sum_{\substack{l\in\Omega_H,\\ i\in\Omega_{PS}}} \mu_{l,i}^{\mathrm{buy}} E_{l,i}^{\mathrm{sell}} \tag{17}$$

$$R^{\mathrm{TEm}} = \sum_{\substack{l\in\Omega_H,\\ i\in\Omega_{PS}}} \mu_{l,i}^{\mathrm{sell}} E_{l,i}^{\mathrm{buy}} \tag{18}$$

$$E_{l,i}^{\mathrm{sell}} = \sum_{t\in[4l-3,4l]} P_{t,i}^{\mathrm{sell}}\tau, \forall l,i \tag{19}$$

$$E_{l,i}^{\mathrm{buy}} = \sum_{t\in[4l-3,4l]} P_{t,i}^{\mathrm{buy}}\tau, \forall l,i \tag{20}$$

$$\mu_l^{\min} \le \mu_{l,i}^{\mathrm{sell}} \le \mu_l^{\max}, \forall l,i \tag{21}$$

$$\sum_{l\in\Omega_H} \mu_{l,i}^{\mathrm{sell}} = L\mu^{\mathrm{av}}, \forall i \tag{22}$$

$$\mu_{l,i}^{\mathrm{buy}} = \varepsilon\mu_{l,i}^{\mathrm{sell}}, \forall l,i \tag{23}$$

where $\varepsilon < 1$.

(5) Power balance: The power balance between supply and demand must be ensured during the operation of the MG, which can be expressed as (24). More specifically, the power sold to prosumers and consumed by electricity loads and ESS charging can be supplied by dispatchable DG, PV and WT generation, ESS discharging and power purchases from the main grid and prosumers.

$$P_t^{\mathrm{DG}} + P_t^{\mathrm{grid}} + P_{t,m}^{\mathrm{PV}} + P_{t,m}^{\mathrm{WT}} + P_{t,m}^{\mathrm{dis}} + \sum_{i\in\Omega_{PS}} P_{t,i}^{\mathrm{sell}} = \sum_{i\in\Omega_{PS}} P_{t,i}^{\mathrm{buy}} + P_{t,m}^{\mathrm{Load}} + P_{t,m}^{\mathrm{ch}}, \forall t \tag{24}$$

To summarize, the deterministic leader model of MGO is with (1) as the objective function subject to (2)~(5) and (7)~(24).

3.2 Follower model of prosumers

Based on the electricity prices of the local market issued by the MGO which are treated as parameters in the follower model, the prosumers aim to seek optimal electricity procurement strategy to minimize individual operating costs. The objective function of i-th prosumer is shown as (25).

$$\min F_i = C_i^{\mathrm{ESS}} + C_i^{\mathrm{TE}} - R_i^{\mathrm{TE}}, \forall i \tag{25}$$

The total costs are composed of the decay cost of the ESS and the cost and revenue for participating in the local market. The corresponding constraints for each term are given below.

(1) Electricity storage system: The ESS is also configured in some prosumers with a similar dynamic model and decay cost function as the ESS in the MG, as given in (26)~(29), and the meanings of each equation are not repeated here.

$$C_i^{\mathrm{ESS}} = \sum_{t\in\Omega_{TS}} \rho_i^{\mathrm{ESS}} \left(P_{t,i}^{\mathrm{ch}} + P_{t,i}^{\mathrm{dis}}\right)\tau, \forall i \tag{26}$$

$$0 \le P_{t,i}^{\mathrm{ch}}, P_{t,i}^{\mathrm{dis}} \le P_{\max,i}^{\mathrm{ESS}}, \forall t,i \tag{27}$$

$$E_{t,i}^{\mathrm{ESS}} = E_{t-1,i}^{\mathrm{ESS}} + \left(P_{t,i}^{\mathrm{ch}}\eta_i^{\mathrm{ch}} - P_{t,i}^{\mathrm{dis}} / \eta_i^{\mathrm{dis}}\right)\tau, \forall t,i \tag{28}$$

$$E_{\min,i}^{\mathrm{ESS}} \le E_{t,i}^{\mathrm{ESS}} \le E_{\max,i}^{\mathrm{ESS}}, \forall t,i \tag{29}$$

(2) Transaction costs and revenues with the MGO in the local market: The transaction costs and revenues of prosumers with the MGO are calculated as (30)~(31), respectively, based on the given local market prices. It can be seen that the costs and revenues from the perspective of prosumers are corresponding to the revenue and cost of the MGO, respectively.

$$C_i^{\mathrm{TE}} = \sum_{l\in\Omega_H} \mu_{l,i}^{\mathrm{sell}} E_{l,i}^{\mathrm{buy}}, \forall i \tag{30}$$

$$R_i^{\mathrm{TE}} = \sum_{l\in\Omega_H} \mu_{l,i}^{\mathrm{buy}} E_{l,i}^{\mathrm{sell}}, \forall i \tag{31}$$

(3) Power balance: Likewise, the power balances within the prosumers must be satisfied, as expressed in the following:

$$P_{t,i}^{\mathrm{dis}} + P_{t,i}^{\mathrm{PV}} + P_{t,i}^{\mathrm{WT}} + P_{t,i}^{\mathrm{buy}} = P_{t,i}^{\mathrm{sell}} + P_{t,i}^{\mathrm{Load}} + P_{t,i}^{\mathrm{ch}}, \forall t,i \tag{32}$$

Overall, the deterministic follower model of prosumers is with (25) as the objective function subject to (26)~(32).

4. Uncertainty characterizing and modeling

The day-ahead bidding of the MG is a non-trivial task due to the challenges posed by various uncertainties originating from the uncertain wholesale electricity market, stochastic RDG and fluctuating electricity loads. In this section, multiple uncertainties are comprehensively characterized and modeled based on their distinct properties to tackle these challenges.

4.1 Chance constraints of power balances

The original power balance constraints are subject to the uncertain factors introduced by both RDG and electricity loads, which need to be fully considered in the day-ahead bidding. The chance constraints can incorporate uncertain factors by restricting that the constraints are satisfied with certain confidence levels. It can achieve a moderate compromise of the original rigid constraints to easily strike a trade-off between cost and risk under uncertainties, which is thus regarded as an efficient approach for solving the decision-making problem with uncertainties. Hence, the chance-constrained technique is adopted in this paper to address such uncertainties in the day-ahead bidding model for guaranteeing the energy provision reliability of the MG and prosumers. Taking the power balance constraint (24) of the MG as an example, it can be expressed as (33) in the chance-constrained framework [42]. Herein, the net electricity load is considered directly by subtracting the power of RDG from the electricity load, which allows the supply and demand uncertainties to be captured simultaneously.

$$\Pr\left(P_{t,m}^{\text{supply}} \geq P_{t,m}^{\text{net}}\right) \geq \eta_m, \forall t \tag{33}$$

where $\Pr(\bullet)$ denotes the probability of event $(\bullet)$ occurrence; η_m represents the confidence level of the chance constraint. The net electricity supply and load are expressed as (34) and (35), respectively.

$$P_{t,m}^{\text{supply}} = P_t^{\text{DG}} + P_t^{\text{grid}} + \sum_{i \in \Omega_{PS}} P_{t,i}^{\text{sell}} - \sum_{i \in \Omega_{PS}} P_{t,i}^{\text{buy}} + P_{t,m}^{\text{dis}} - P_{t,m}^{\text{ch}}, \forall t \tag{34}$$

$$P_{t,m}^{\text{net}} = P_{t,m}^{\text{Load}} - P_{t,m}^{\text{PV}} - P_{t,m}^{\text{WT}}, \forall t \tag{35}$$

The chance constraint (33) can be equivalently converted into a tractable deterministic constraint for efficiently solving the optimization problem with the chance constraint of implicit form. According to the notion of cumulative distribution function (CDF), Eq. (36) can be derived.

$$P_{t,m}^{\text{supply}} \geq CDF_{t,m}^{-1}(\eta_m), \forall t \tag{36}$$

where $CDF_{t,m}^{-1}(\eta_m)$ represents the inverse function value of CDF at η_m for the uncertain variable $P_{t,m}^{\text{net}}$, which can also be interpreted as the quantile with nominal probability (i.e., confidence level) η_m for $P_{t,m}^{\text{net}}$ [43]. However, the accurate probability distribution of the uncertain variable $P_{t,m}^{\text{net}}$ can be hardly obtained in practice and thus the $CDF_{t,m}^{-1}(\bullet)$ in the analytic form is not available. In response to this challenge, a data-driven quantile forecasting method is developed based on the gradient boosted regression tree (GBRT) in this paper. The GBRT is an ensemble learning method based on the boosting framework that linearly combines multiple weak learners to achieve more efficient and accurate forecasting, and a more detailed description of GBRT can be found in [44] which is not repeated here. Besides, the Pinball loss function [44] is adopted in the training of the GBRT-based quantile forecasting model.

Following the developed data-driven quantile forecasting method based on GBRT, the quantile $CDF_{t,m}^{-1}(\eta_m)$ in (36) can be derived without any prior knowledge or probability distribution assumptions. Therefore, the chance constraint (33) can be equivalently converted into the tractable deterministic constraint (36). Similarly, the power balance constraints (32) in the follower model of prosumers can also be reformulated as chance constraints and the corresponding transformation can be made to consider the uncertain factors related to RDG and loads. The performance of the developed quantile forecasting method will be evaluated in Section 5.

4.2 Risk-averse modeling of wholesale electricity market uncertainties via CVaR

As stated previously, the real-time prices of the wholesale electricity market exhibit high uncertainties which pose significant challenges to the day-ahead bidding of the MG. For incorporating the uncertainties associated with real-time prices into the day-ahead bidding model, the uncertainties can be characterized by a representative set of real-time price scenarios. Given the representative set Ω_S of real-time price scenarios with the corresponding occurrence probabilities, the deterministic day-ahead bidding model (i.e., the leader model of the MGO) in Section 3.1 can be reformulated as (37) in the framework of stochastic optimization. Herein, only the model in compact form is presented due to the limited page space.

$$\min_{\mathbf{x},\mathbf{y}_s} \mathbf{c}^{\mathrm{T}}\mathbf{x} + \sum_{s\in\Omega_S} \pi_s L\left(\mathbf{x},\mathbf{y}_s,d_s\right)$$
$$s.t.\ \ \mathbf{x}\in\boldsymbol{\chi} \tag{37}$$
$$\mathbf{y}_s \in \boldsymbol{\gamma}\left(\mathbf{x},d_s\right)$$

It can be observed that the decision variables in (37) can be divided into two groups, i.e., $\mathbf{x}$ and $\mathbf{y}_s$. The first group $\mathbf{x}$ is called "here-and-now" decisions, which are independent of the real-time price scenarios, including the day-ahead bidding plan E_l^{DA} to the wholesale market operator, and electricity prices $\mu_{l,i}^{\mathrm{sell}}$ and $\mu_{l,i}^{\mathrm{buy}}$ for the local market. The second group $\mathbf{y}_s$ is called "wait-and-see" decisions and includes all remaining decision variables (e.g., the real-time consumed electricity), which depend on the realization of the real-time price scenarios and are impacted by the "here-and-now" decisions. Besides, $\boldsymbol{\chi}$ and $\boldsymbol{\gamma}\left(\mathbf{x},d_s\right)$ give the feasible regions of $\mathbf{x}$ and $\mathbf{y}_s$, respectively, where $\boldsymbol{\gamma}\left(\mathbf{x},d_s\right)$ indicates that $\mathbf{y}_s$ is optimized under $\mathbf{x}$ and the real-time price scenario d_s.

An optimal $\mathbf{x}^*$ can be obtained by solving the stochastic optimization model (37) to minimize the expected cost for all representative real-price scenarios. However, the $\mathbf{x}^*$ may be overly optimistic and thus can lead to a risk of unexpected cost increases in some unfavorable scenarios. Furthermore, the MGO is generally risk-averse toward the uncertainties of the wholesale electricity market. In this regard, it is essential for the MGO to incorporate a risk criterion in the day-ahead bidding model for achieving risk aversion, where the CVaR is adopted in this paper due to its advantages of numerical efficiency, calculation stability, etc. [38]. Based on the theory of CVaR, the CVaR at the confidence level of $\alpha\in\left(0,1\right)$ in the day-ahead bidding of MG represents the expected cost for the $\left(1-\alpha\right)$ fraction of worst-case scenarios and can be mathematically formulated as (38) [38].

$$CVaR_\alpha = \min\left\{ z + \frac{1}{1-\alpha}\sum_{s\in\Omega_S}\pi_s\left[F_{s,m}-z\right]^+ \right\} \tag{38}$$

where z is an auxiliary variable called value-at-risk; $F_{s,m}$ is called loss function that is the objective function F_m of the MGO model in the s-th real-time price scenario; $\left[\bullet\right]^+$ denotes the projector of $\max\left(\bullet,0\right)$. In addition, Eq. (38) can be linearized to (39)~(40) by adding auxiliary variables V_s.

$$CVaR_\alpha = \min z + \frac{1}{1-\alpha}\sum_{s\in\Omega_S}\pi_s V_s \tag{39}$$

$$V_s \ge 0, V_s \ge F_{s,m} - z, \forall s \tag{40}$$

For risk aversion using the CVaR, the objective function in the day-ahead bidding model (37) can be modified as follows:

$$\min_{\mathbf{x},\mathbf{y}_s,z} \mathbf{c}^{\mathrm{T}}\mathbf{x} + \sum_{s\in\Omega_S}\pi_s L\left(\mathbf{x},\mathbf{y}_s,d_s\right) + \beta CVaR_\alpha \tag{41}$$

where $\beta\ge 0$ is a weighting parameter set by the MGO based on its risk-averse preference. The case of

$\beta = 0$ represents risk neutrality, while $\beta > 0$ signifies risk aversion and a larger β indicates that the MGO is more concerned with risk.

4.3 Flowchart of the developed risk-averse day-ahead bidding strategy for TE sharing MGs

Fig. 2 illustrates the implementation processes of the proposed risk-averse day-ahead bidding strategy. Specifically, the models of the leader (i.e., MGO) and followers (i.e., prosumers) are first formulated respectively based on the collected input data. Then, the uncertainties of RDG and loads are characterized by chance constraints. Herein, the GBRT-based quantile forecasting method is developed based on historical data of net loads for the MG and prosumers, through which the chance constraints can be equivalently converted into tractable deterministic constraints. Furthermore, the leader model of MGO is reformulated as a risk-averse form through stochastic optimization with CVaR criterion to account for the uncertainties of the wholesale electricity market. Thus, the models of leader and follower considering multiple uncertainties are established. Finally, a distributed iterative algorithm is adopted to achieve the game equilibrium without compromising the privacy concerns of the MGO and prosumers. Moreover, a bisection approach is incorporated in the iteration to avoid the oscillation of electricity prices for the local market and thus assure game convergence. The core idea behind the bisection approach is to update the upper and lower bounds of pricing in each iteration, thus gradually narrowing the pricing interval while ensuring that the interval contains the equilibrium state. The implementation of the distributed iterative algorithm with the bisection approach is given in **Algorithm 1**. Here, the MGO and prosumers are only in charge of the model optimization within the jurisdiction and only TE-related information needs to be exchanged for privacy protection.

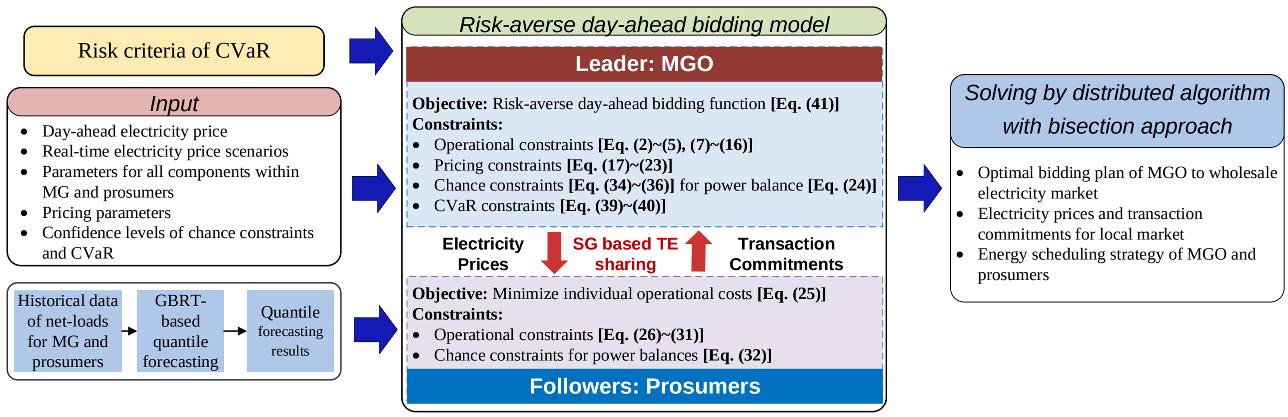


Fig. 2 Flowchart of the proposed risk-averse day-ahead bidding strategy for SG-based TE sharing MGs.

Algorithm 1: Distributed iterative algorithm with bisection approach.

Initialization: Initialize the iteration index $k=0$; Set the iterative convergence criterion ξ and maximum iterations K.
MGO initializes a feasible decision of $\mu_{t,i}^{\text{buy},*}$ and $\mu_{t,i}^{\text{sell},*}$ as k-th results of the leader model denoted by $\boldsymbol{\mu}^k$ and issues it to prosumers.

Repeat

1: Prosumers individually solve the follower models with known $\boldsymbol{\mu}^k$ to obtain the k-th optimal decision of $P_{t,i}^{\text{sellp},*}$ and $P_{t,i}^{\text{buyp},*}$ denoted by $\mathbf{P}^k$ and submit it to the MGO.

2: MGO solves the leader model with known $\mathbf{P}^k$ to obtain $k+1$-th optimal decision $\boldsymbol{\mu}^{k+1}$ and issues it to prosumers.

3: **If** $\left|\boldsymbol{\mu}^{k+1}-\boldsymbol{\mu}^k\right|/\boldsymbol{\mu}^k \le \xi$, **then**
  The SG reaches equilibrium and the decisions $\boldsymbol{\mu}^k$ and $\mathbf{P}^k$ are outputted and ***break***;
else
  $k=k+1$;
end

4: **If** $k \le 1$, **then**
  Return to **Step 1**;
end

5: **If** $\boldsymbol{\mu}^{k-2}=\boldsymbol{\mu}^k$, **then**
  $\boldsymbol{\mu}^k=(\boldsymbol{\mu}^{k-1}+\boldsymbol{\mu}^{k-2})/2$;
  Let $\boldsymbol{\mu}_{\min}^{k+1}=\min\left\{\boldsymbol{\mu}^{k-1},\boldsymbol{\mu}^k\right\}$ and $\boldsymbol{\mu}_{\max}^{k+1}=\max\left\{\boldsymbol{\mu}^{k-1},\boldsymbol{\mu}^k\right\}$.

6: Add the constraint $\boldsymbol{\mu}_{\min}^{k+1} \le \boldsymbol{\mu}^{k+1} \le \boldsymbol{\mu}_{\max}^{k+1}$, and repeat **Steps 1, 2 and 3;**
  If $\boldsymbol{\mu}^k=\boldsymbol{\mu}_{\max}^k$, **then**
    Let the lower bound $\boldsymbol{\mu}_{\min}^{k+1}=\boldsymbol{\mu}^k$;
  Elseif $\boldsymbol{\mu}^k=\boldsymbol{\mu}_{\min}^k$, **then**
    Let the upper bound $\boldsymbol{\mu}_{\max}^{k+1}=\boldsymbol{\mu}^k$;
  end
  Return to **Step 5**;
else
  Return to **Step 1**;
end

Until The iteration index k is larger than K.

5. Case studies

In this section, the effectiveness of the proposed solution is extensively validated through numerical simulation in the PJM electricity market. The GBRT-based quantile forecasting method is implemented using the scikit-learn package with Python API [45]. The optimization models of the MGO and prosumers are both implemented and solved using the Gurobi solver 9.5 with Python API [46]. All programs are executed on a PC equipped with 16GB RAM and i5-9400 processors. Furthermore, all data used for developing the quantile forecasting method and day-ahead bidding are available upon request. The simulation setup and numerical results are presented in the following subsections.

5.1 Simulation setup

In this paper, an MG with four prosumers is investigated and thus $\Omega_{PS}=\{1,2,3,4\}$. The configurations of the MG and prosumers are provided in **Table 1**. Generally, the prosumers are heterogeneous, i.e., they have different device configurations within them. For example, Prosumer #1 is configured with PV, WT and ESS while Prosumer #3 is configured with PV only. Moreover, the rated parameters of all devices within the MG and prosumers are provided in **Table 2**. The optimization horizon is one day with multiple time scales of 1 hour and 15 minutes (i.e., $\tau = 0.25$ hour), and thus $\Omega_H = \{1, 2, ..., 24\}$ (i.e., $L = 24$) and $\Omega_{TS} = \{1, 2, ..., 96\}$.

Table 1 Configurations of the MG and prosumers.

Item	MG	Prosumer #1	Prosumer #2	Prosumer #3	Prosumer #4
DG	✓	—	—	—	—
PV	✓	✓	✓	✓	—
WT	✓	✓	✓	—	✓
ESS	✓	✓	✓	—	—

Table 2 Rated parameters of all devices.

Item	Numerical value	Item	Numerical value	Item	Numerical value
$P_{\max}^{\mathrm{DG}}$	600	η_m^{dis}	0.95	$E_{0,1}^{\mathrm{ESS}}$	150
λ^{ramp}	0.5	ρ_m^{ESS}	0.001	$P_{\max,2}^{\mathrm{ESS}}$	100
a	0.00003	$E_{0,m}^{\mathrm{ESS}}$	300	$E_{\min,2}^{\mathrm{ESS}}$	80
b	0.02	$P_{\max,1}^{\mathrm{ESS}}$	125	$E_{\max,2}^{\mathrm{ESS}}$	320
c	0	$E_{\min,1}^{\mathrm{ESS}}$.	100	η_2^{ch}	0.95
$P_{\max,m}^{\mathrm{ESS}}$	250	$E_{\max,1}^{\mathrm{ESS}}$	400	η_2^{dis}	0.95
$E_{\min,m}^{\mathrm{ESS}}$	200	η_1^{ch}	0.96	ρ_2^{ESS}	0.0011
$E_{\max,m}^{\mathrm{ESS}}$	800	η_1^{dis}	0.96	$E_{0,2}^{\mathrm{ESS}}$	120
η_m^{ch}	0.95	ρ_1^{ESS}	0.0012		

The data on daily electricity prices in the wholesale electricity market are obtained from the PJM market [47]. The *K-means* based scenario reduction approach is adopted to extract 100 representative real-time price scenarios (i.e., $\Omega_S = \{1, 2, ..., 100\}$) and the corresponding occurrence probabilities from the historical real-time price scenarios in 2019-2020. The day-ahead prices are also essential in the day-ahead bidding of the MG, and they can be accurately predicted in contrast to real-time prices since they exhibit a certain regularity [34]. Therefore, it is assumed that the day-ahead prices are known and the day-ahead electricity prices for case studies are presented in **Fig. 3** [48]. Besides, the allowable ratio of electricity deviations from bidding for penalties, and the penalty price are 20% [49] and \$0.00298/kWh [39] in the PJM market, respectively. As suggested in [20], the lower and upper bounds of the pricing interval can be set referencing the prices in the wholesale market. Therefore, the pricing interval is set to $[0.8, 1.2]$ of the day-ahead prices and the average price μ^{av} is 0.9 of that for the day-ahead prices.

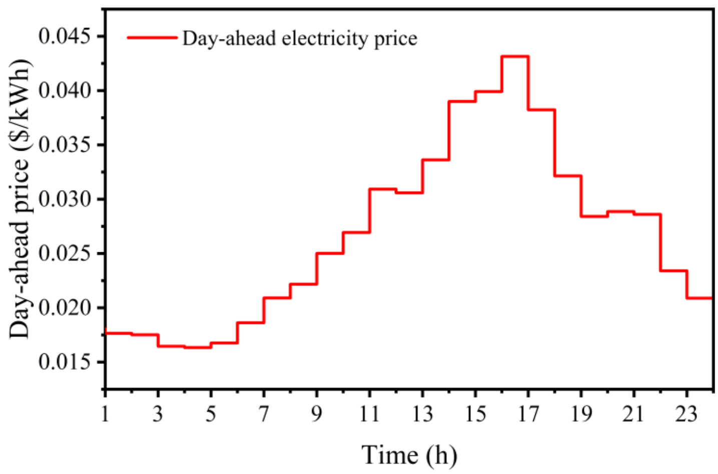
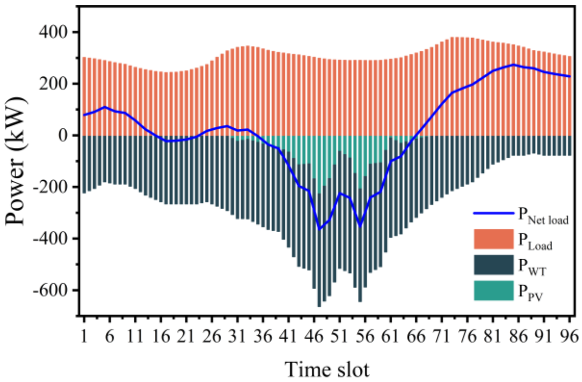
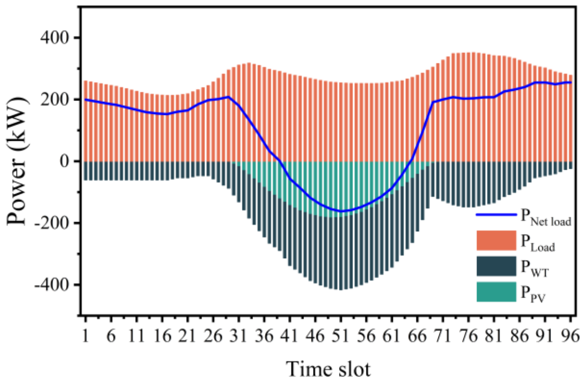


Fig. 3 Day-ahead electricity prices in the wholesale electricity market.

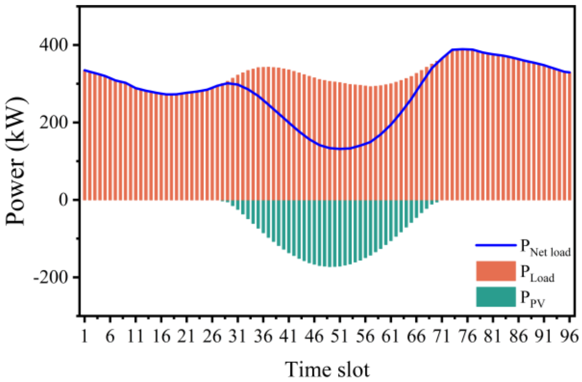
In this work, it is assumed that the point forecasts of RDG and electricity loads for the MG and prosumers are available and the point forecasts of RDG, electricity loads and net loads for each prosumer are depicted in **Fig. 4**. It can be observed that Prosumers #1 and #2 are configured with larger capacities of RDG and thus have surplus power at certain periods (e.g., time slots 40-60) to share to Prosumers #3 and #4 with power shortage. The confidence levels for chance constraints of power balances in the MG and prosumers are both set to 85%. The confidence level of CVaR is set to 0.95 and the risk weighting parameter is set to 0.1. The impacts of these parameters on the day-ahead bidding will be investigated in this paper.



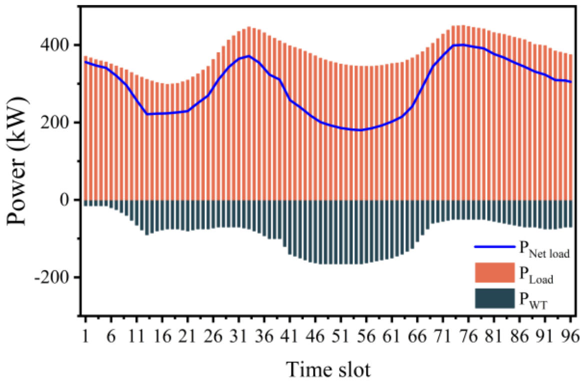
(a) Prosumer #1



(b) Prosumer #2



(c) Prosumer #3



(d) Prosumer #4

Fig. 4 Point forecasts of RDG, electricity loads and net loads for each prosumer.

5.2 Numerical results

5.2.1 Performance of the developed GBRT-based quantile forecasting method

Here, the performance of the developed GBRT-based quantile forecasting method is evaluated taking the net load of the MG as an example. In this work, 75% of the historical data is randomly selected as the training set and the remaining 25% is used as the test set. The input features of the GBRT model consist of 96 actual or point forecast values before each time slot. To verify the quantile forecasting performance of the developed method, the observed frequencies in the test set for which the actual power falls below the quantile forecasted results are calculated. **Table 3** shows that the observed frequencies and the corresponding confidence levels are very close with the average deviation between them being 0.0038. The results provide an intuitive metric to indicate that the developed method can accurately forecast quantiles of uncertain variables at various confidence levels thus providing information for the transformation of chance constraints into deterministic constraints [50].

Table 3 Observed frequencies of actual power below the quantiles at various confidence levels.

Confidence levels	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
Observed frequencies of net load	0.152473	0.251374	0.350275	0.458791	0.545788	0.649267	0.739927	0.85348	0.946886

5.2.2 Pricing and transaction results in the local market

The SG equilibrium can be derived by distributed solving the models of leader and followers established based on the quantile forecasting results. Taking Prosumer #1 as an example, **Fig. 5** presents the electricity selling prices of the local market for Prosumer #1 at hour #1 with and without bisection. It can be observed that the pricing strategy of the MGO starts to oscillate from the fourth iteration and finally converges to equilibrium at the sixth iteration with the effect of the bisection approach. Moreover, the expected costs of the MGO during the iteration process are provided in **Fig. 6**. As can be seen, the expected cost of the MGO also oscillates due to the oscillations in the pricing strategy without the bisection approach. When the bisection approach induces the pricing strategy to converge, the cost will also consequently converge. The observations demonstrate the effectiveness of the bisection approach in mitigating the oscillation during iteration to promote SG convergence.

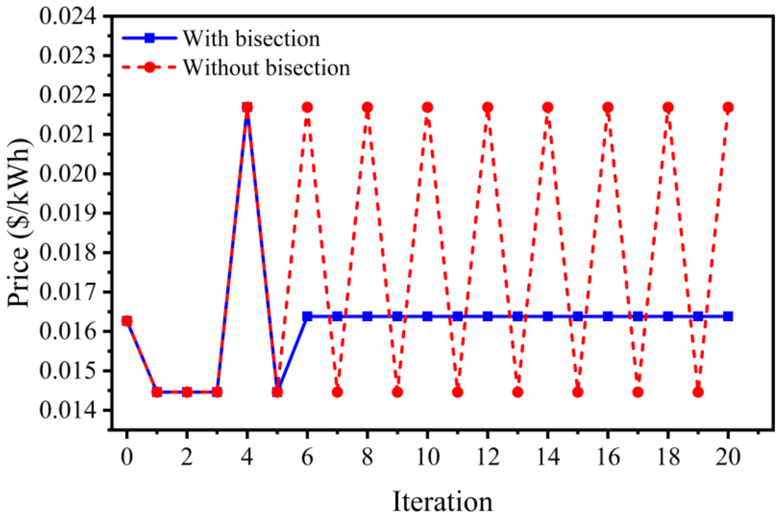


Fig. 5 Electricity selling prices of the local market for Prosumer #1 at hour #1 with and without bisection.

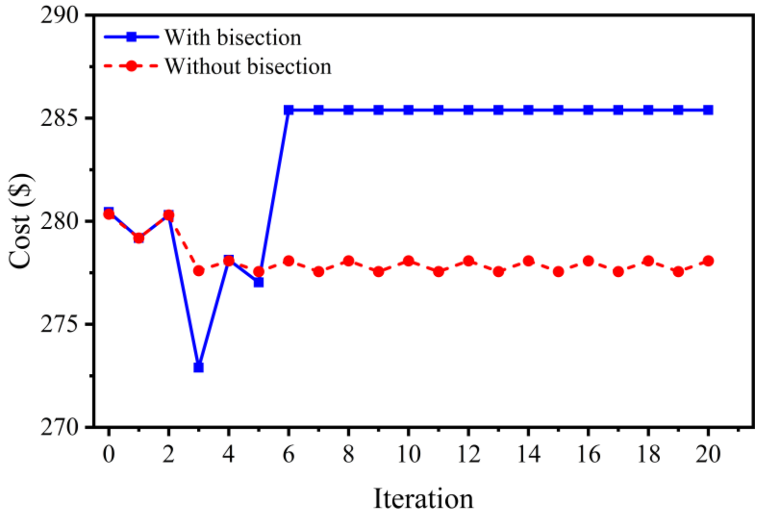
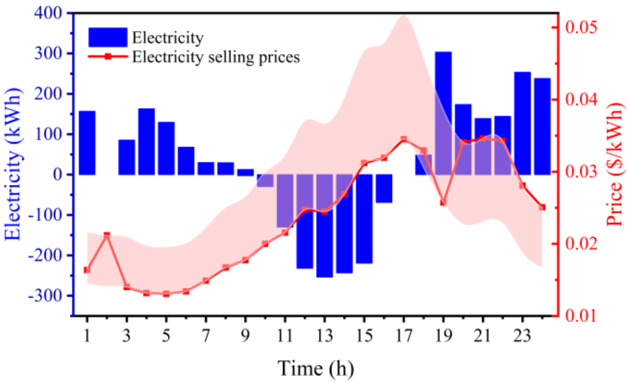


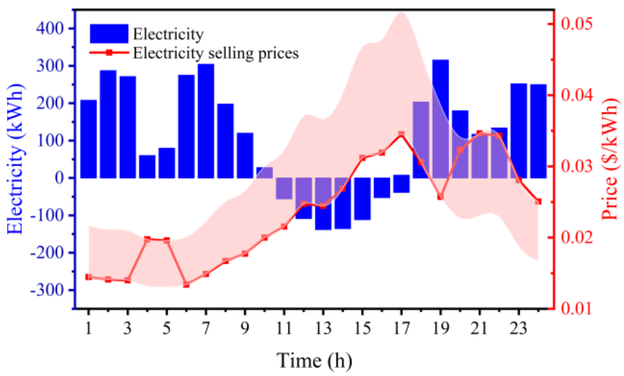
Fig. 6 Expected costs of the MGO with and without bisection.

After the SG between the MGO and the prosumers reaches equilibrium, the final transaction commitments of prosumers in the local market can be determined. **Fig. 7** illustrates the transaction commitments of all prosumers along with the corresponding electricity selling prices of the MGO throughout the day. Here, the positive or negative electricity indicates that the prosumer buys or sells electricity from or to the MGO. The shadowed portions of the figures indicate the pricing intervals of the MGO. **Fig. 7** clearly shows the strategic game processes between the MGO and prosumers. More specifically, the prosumers will increase their electricity purchases from the MGO when the prices are lower and conversely, they will decrease their electricity purchases with higher prices. For instance, Prosumers #1 and #2 purchase more electricity from MGO at hour #19. At hour #2, the price is relatively higher for Prosumer #1, so it purchases less electricity during the period. The phenomenon can also be observed from the energy dispatch results of Prosumer #1 as shown in **Fig. 8**, where the negative or positive power of the ESS indicates that it is in the charging or discharging state, respectively. As can be seen, during time slots #73~#76 (i.e., hour #19), Prosumer #1 purchases additional electricity from the MGO and stores it in the ESS for subsequent use during the periods with higher prices (e.g., time slots #80~#88). During time slots #5~#8 (i.e., hour #2), all electricity demands are satisfied by the ESS discharge and thus there is no need for Prosumer #1 to purchase electricity from the MGO. A similar phenomenon also occurs in the transaction commitments of Prosumer #2 at hours #4~#5. For Prosumers #3 and #4, they are not configured with ESS. Therefore, their electricity transaction commitments at each hour are entirely determined based on their net electricity loads. Nevertheless, the MGO will set electricity prices for each prosumer according to their demands at different hours of the day, as described in more detail below.

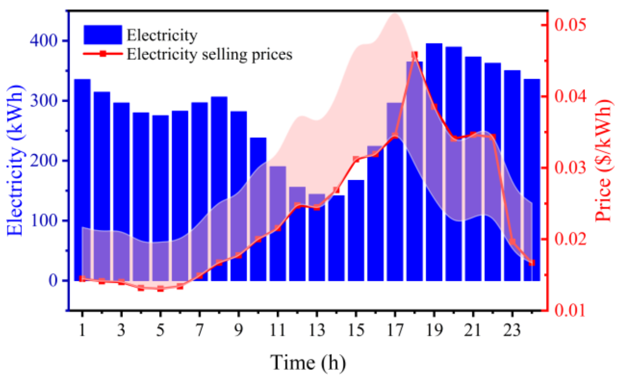
From the perspective of the MGO, it sets the prices at the lower bounds for Prosumer #1 during hours #10~#16 to reduce electricity purchase costs from Prosumer #1 since Prosumer #1 sells surplus electricity to the MGO during the periods. At hours #20~#24, Prosumer #1 buys relatively more electricity from the MGO and thus it sets higher prices for Prosumer #1 to more profitably pursue revenues. In addition, it should be noted that the average selling price over the entire horizon is restricted as a constant. Therefore, the prices cannot all be set at the lower or upper bounds of the pricing interval. In addition, the MGO has a similar price clearing behavior for Prosumer #2 as it does for Prosumer #1. As for Prosumers #3 and #4, they merely purchase electricity from the MGO. Therefore, the MGO personalized electricity prices to them according to their different electricity transaction commitments. For example, at hour #18, the electricity demands are higher for both Prosumers #3 and #4, so the MGO sets the price to the upper bound to seek profits.



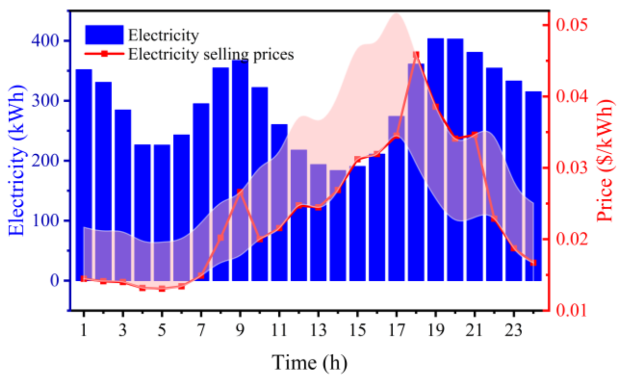
(a) Prosumer #1



(b) Prosumer #2



(c) Prosumer #3



(d) Prosumer #4

Fig. 7 Electricity transaction commitments and selling prices for each prosumer in the local market.

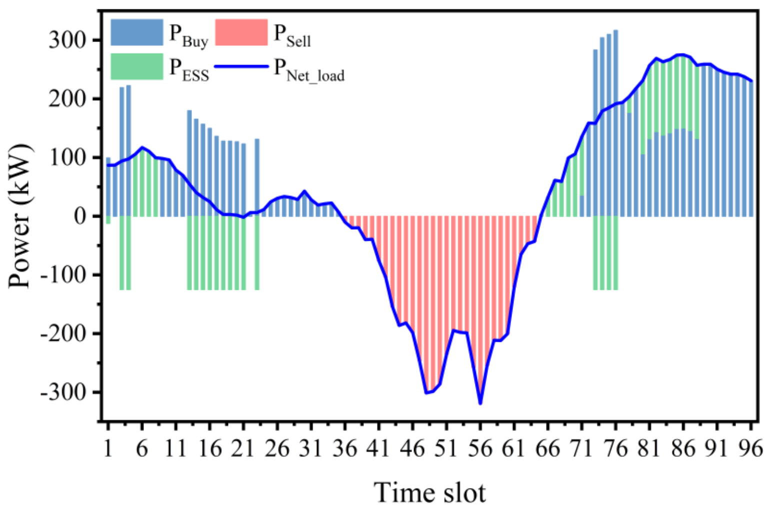


Fig. 8 Energy dispatch results of Prosumer #1.

The electricity transaction commitments of all prosumers with the MGO in the local market are summarily depicted in **Fig. 9**. As can be seen, Prosumers #1 and #2 share the surplus electricity to Prosumers #3 and #4 with electricity shortage during hours #10~#17 which indicates that the electricity complementarity among different prosumers can be achieved through transactions in the local market, thus reducing the electricity demand to the outside world for the entire MG.

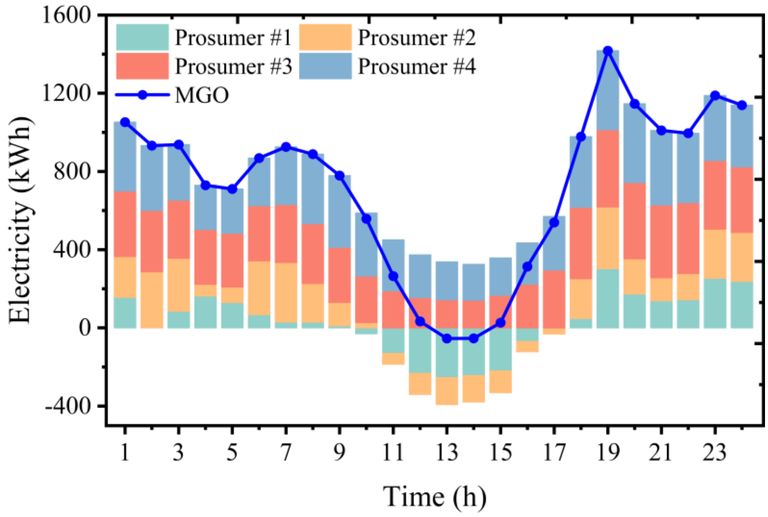


Fig. 9 Electricity transaction commitments of all prosumers with MGO in the local market.

5.2.3 Day-ahead bidding results of the MGO in the wholesale electricity market

Based on the transaction results in the local market, the MGO needs to make the day-ahead bidding decisions to the wholesale electricity market with consideration of the wholesale market uncertainties. **Fig. 10** presents the day-ahead bidding electricity of the MGO with the corresponding day-ahead prices. It can be observed that the proposed solution can effectively rationalize the day-ahead bidding decisions of the MGO with the guidance of day-ahead electricity prices. More specifically, the MGO bids for a larger amount of electricity during periods of lower day-ahead prices (e.g., hours #1~#5) and bids for less or even zero electricity during periods of higher day-ahead prices (e.g., hours #10~#18). This indicates that it is more profitable for the MGO to purchase electricity in the real-time market during periods of higher day-ahead prices. In addition to the higher day-ahead electricity prices during the periods of hours #10~#18, another reason that the MGO bids for less electricity during the periods is because the RDG configured in the MG and prosumers have a higher output power. As a result, the net loads of the entire MG are smaller and thus the electricity demands to the outside world are lower during the periods. This further demonstrates that the RDG and electricity complementarity among prosumers contributes to reducing the electricity procurement cost of the entire MG.

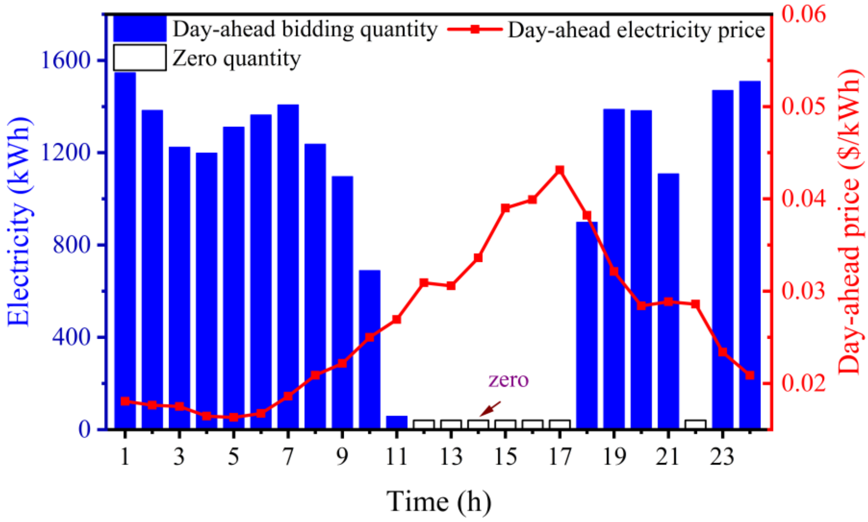


Fig. 10 Day-ahead bidding electricity of the MGO in the wholesale electricity market.

To verify the risk-averse performance of the proposed solution towards uncertainties of the real-time market, a risk-neutral strategy is performed as a benchmark, i.e., the weight β in (41) is set to zero. **Table 4** presents each term of MGO operating costs under different solutions for all real-time price scenarios in 2019-2020. As can be observed, the risk-neutral strategy has a lower day-ahead bidding cost than the proposed risk-averse strategy. However, the risk-neutral strategy may be too optimistic for the real-time market participation of the MGO. Because it focuses only on the expectation of operating costs while ignoring the risk of unexpected increases in operating costs under some unfavorable scenarios. Therefore, the risk-neutral strategy leads to a significant increase in MGO operating costs in the real-time market participation stage compared to the proposed risk-averse strategy, especially in the most unfavorable scenarios, as shown in **Table 4**. The risk-averse strategy achieves a 45.16% reduction in the maximum total cost of the MGO compared to the risk-neutral strategy where the average total costs are not significantly different. This demonstrates the effectiveness of the proposed solution in risk aversion toward unexpected costs caused by the uncertainties of the wholesale electricity market.

Table 4 Each term of MGO operating costs under different solutions.

Item	Day-ahead bidding cost ($)	Transaction revenue ($)	Average operating cost in real-time stage ($)	Maximum operating cost in real-time stage ($)	Average total cost ($)	Maximum total cost ($)
Risk-averse	449.17	411.79	243.53	418.28	280.90	455.66
Risk-neutral	384.69	407.47	304.84	853.64	282.06	830.85

5.2.4 Sensitivity analysis

In this part, a series of sensitivity analyses are conducted to investigate the impacts of different parameters on the day-ahead bidding of the MGO. Regarding this, the following three cases are implemented, and the corresponding results are detailed.

Case 1: With the fixed confidence levels for CVaR and chance constraints, the impact of various weights β for CVaR varying from 0.1 to 1.1 with an interval of 0.1 on the day-ahead bidding of the MGO is investigated. **Fig. 11** shows the variations of each cost with various weights β for all real-time price scenarios in 2019-2020. It can be observed that the maximum operating costs in the most unfavorable scenarios decrease as the weights increase, and the average costs have not experienced a dramatic change. This implies the ability of the day-ahead bidding decisions to cope with risks caused by the uncertainties of the wholesale electricity market is increased at a larger weight β. But this also can lead to a higher day-ahead bidding cost. It also can be seen that when the weight is greater than a certain value (i.e., 0.4), the changes in each cost will become slow. These observations inspire the MGO to set an appropriate weight β in practice according to its preference to strike a trade-off between the day-ahead bidding cost and risk aversion.

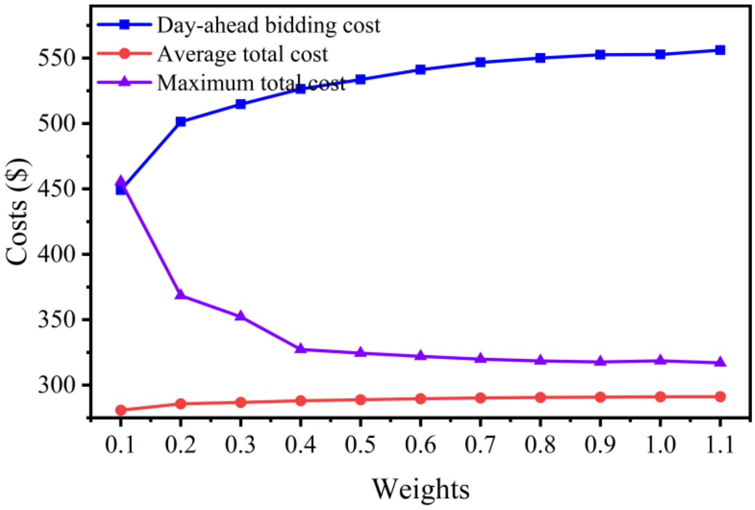


Fig. 11 Variations of each cost with various weights β.

Case 2: With the fixed weight for CVaR and fixed confidence levels for chance constraints, the impact of various confidence levels α for CVaR of [0.6, 0.7, 0.8, 0.9, 0.95, 0.99] on the day-ahead bidding of the MGO is investigated. **Fig. 12** illustrates the variations of each cost with various confidence levels α for all real-time price scenarios in 2019-2020. Since $CVaR_{\alpha}$ represents the expected cost in the $(1-\alpha)$ fraction of worst-case scenarios, the risk aversion degree of the MGO will raise as α increases. As a result, the maximum operating costs in the most unfavorable scenarios have a significant decrease at larger α, as shown in **Fig. 12**. However, raising the risk aversion degree can also lead to more conservative day-ahead bidding decisions by the MGO and thus higher day-ahead bidding costs.

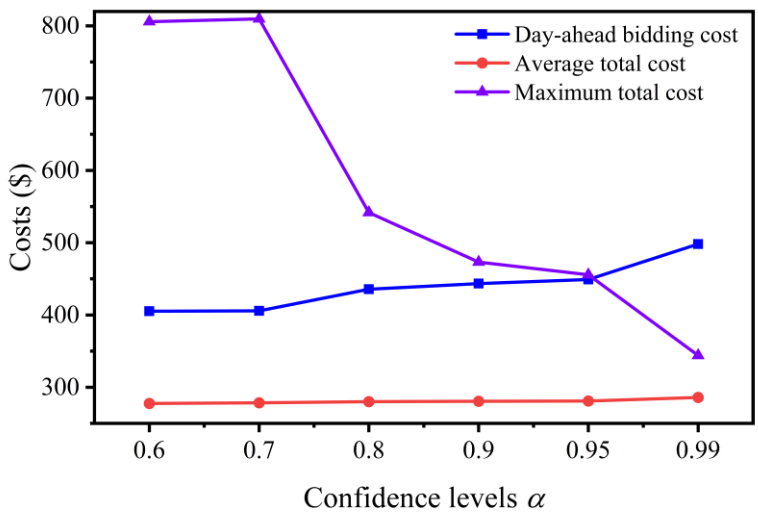


Fig. 12 Variations of each cost with various confidence levels α .

Case 3: With the fixed weight and confidence level for CVaR, the impact of various confidence levels for chance constraints of [0.65, 0.75, 0.85, 0.95] on the day-ahead bidding of the MGO and energy dispatch of prosumers is investigated. **Table 5** presents the day-ahead bidding costs of the MGO and the operating costs of prosumers at different confidence levels. It can be seen that as the confidence levels increase, the day-ahead bidding costs of the MGO and the operating costs of prosumers both increase. The reason is that both the MGO and prosumers are more conservative about their net loads at larger confidence levels, which leads to more conservative decisions and thus higher costs.

Table 5 Costs at different confidence levels of chance constraints.

Confidence levels	**0.65**	**0.75**	**0.85**	**0.95**
MGO day-ahead bidding ($)	436.03	439.64	449.17	460.48
Prosumer #1 ($)	18.00	19.28	21.27	37.55
Prosumer #2 ($)	52.77	53.88	55.71	63.03
Prosumer #3 ($)	162.95	163.43	164.86	172.58
Prosumer #4 ($)	170.31	171.81	172.28	175.02

6. Conclusions and future work

To realize the day-ahead bidding of MGs with various prosumers and local energy sharing under multiple uncertainties, this paper presents a risk-averse day-ahead bidding strategy of TE sharing MGs with data-driven chance constraints. In the proposed solution, an SG-based local market is established to support TE sharing among the MGO and prosumers, where a distributed iterative algorithm with a bisection approach is adopted to achieve game equilibrium without compromising their privacy concerns. The power balances are formulated as chance constraints to handle the uncertainties of RDG and loads, and a data-driven quantile forecasting method is developed to equivalently converted them into tractable deterministic constraints without any prior knowledge or probability distribution assumptions. Meanwhile, the CVaR is incorporated in the day-ahead bidding model of the MG to achieve financial risk aversion towards the uncertainties related to the wholesale electricity market.

The effectiveness of the proposed solution is extensively assessed through numerical simulation and the numerical results demonstrate that: 1) the developed GBRT-based quantile forecasting method can realize an outstanding quantile forecasting performance with the average deviation of 0.0038 between the observed frequencies and the corresponding confidence levels; 2) the SG-based local market can effectively capture the strategic interaction among the MGO and prosumers and the adopted distributed iterative algorithm with a bisection approach can mitigate the oscillation during iteration to promote SG convergence; 3) the proposed risk-averse day-ahead bidding model of the MG can effectively achieve risk aversion towards uncertainties of the real-time market, and it achieves a 45.16% reduction in the maximum total cost of the MGO, compared to the risk-neutral strategy.

The main focus of this paper is on the day-ahead bidding strategy of MGs with TE sharing under uncertainties. The intra-day operation of MGs is also an important research field, which will be further investigated in our future work. Moreover, considering the development of multi-energy MGs, further research efforts can be made to exploit the energy sharing of multiple energy forms (e.g., heat and electricity) based on local multi-energy integrated markets.

Acknowledgments

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