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***Abstract*—Distributed prosumers face market risks such as price fluctuations, load demand changes, and renewable energy generation output uncertainties when participating in electricity energy and ancillary service markets. In this paper, a bid decision model for distributed prosumers in the daily electricity and ancillary market is established using the Information Gap Decision Theory (IGDT). First, the agency architecture for distributed prosumers participating in these markets is analyzed. Next, a multi-type distributed resource regulation model is constructed, forming the basis of a decision model for the participation of distributed prosumers in the joint energy and ancillary market. Then, the various uncertainties faced by prosumers in their decision-making process are quantitively modeled using the information entropy theory, and an IGDT-based robust optimization model for deriving bidding strategies is developed. Finally, the proposed model is validated in the modified IEEE 33-node distribution system, and the bidding strategies generated by the proposed model effectively addresses the multiple uncertainties faced by prosumers, safeguarding their profits.**

Keywords—IGDT, electricity energy market, ancillary services market, information entropy theory

I. INTRODUCTION

With the increasing share of uncertain resources such as wind power, solar photovoltaics, and demand response, relying solely on traditional supply-side and grid-side regulation measures is no longer sufficient to meet the flexibility requirements of the new power system[1]. Ancillary services in the electricity market serve as one of the means to enhance the flexibility of the power system by encouraging the participation of distributed prosumers, including commercial and industrial users and energy storage facilities. However, market risks such as price fluctuations and load demand variations have an impact on the profitability and enthusiasm of distributed prosumers. Therefore, under the premise of adhering to market rules and ensuring the safe and stable operation of the power system, selecting an appropriate bidding strategy under multiple uncertainties becomes a crucial issue for distributed prosumers participating in the ancillary service market [2-3].

In recent years, the academic community has conducted extensive research on the participation of emerging prosumers in ancillary service markets to facilitate coordination in the electricity market. An investment portfolio theory-based decision model for bidding on electric vehicle reserve capacity was proposed in [4]. A direct control-based temperature load bidding decision model considering comfort requirements for participation in day-ahead frequency regulation and reserve markets was developed in [5]. Considering the master-slave game relationship between aggregator and electric vehicles, Ref. [6] established a centralized electricity-reserve bidding optimization model that incorporates charging and discharging behavior preferences. However, the centralized optimization approach cannot protect the privacy of individual entities. The aforementioned models are deterministic and do not effectively consider the uncertainty factors faced by distributed prosumers in optimizing their bidding strategies.

Currently, the research foundation exists for strategies under uncertainty [7-8]. However, the uncertainty modeling methods have certain limitations: the interval method requires pre-determining the range of uncertain quantities, and obtaining the probability density function of random variables in fuzzy decision-making is challenging. Uncertainty optimization methods based on scenario generation effectively consider various typical scenarios [9-10]. However, the uncertainty decision methods based on scenario generation have some limitations. Too many scenarios can affect the accuracy of decision-making [11], and there is a lack of unified evaluation criteria for the diversity of scenarios and the variety of solutions.

IGDT is a probability-independent uncertainty decision method [12-14]. An IGDT-based comprehensive energy system expansion planning model that only considers load uncertainty was established in [15]. To handle multiple uncertainty factors, a two-level economic dispatch strategy based on IGDT for electric vehicle integration into a virtual power plant was proposed in [16] with linearly superposing the uncertain variables of load and time-of-use electricity prices as a single variable solution. A joint bidding strategy for wind-fire-energy storage participating in the electricity energy market based on IGDT was developed in [17], which equally weighted the uncertainties of solar, storage, and load. It should be noted that the aforementioned IGDT-based decision methods simplify the treatment of uncertainties. However, in the day-ahead electricity-reserve bidding decisions, prosumers face multiple uncertainties such as price fluctuations, load demand variations, and fluctuations in renewable energy generation. It is necessary to quantify the importance of each uncertainty factor. Based on this, this paper quantifies the weights of multiple uncertainty factors in the bidding decision model for prosumers using the theory of

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information entropy, and further constructs a robust optimization model based on IGDT.

In this context, this paper establishes a bidding decision model for prosumers in the day-ahead electricity-reserve market considering multiple uncertainty factors. First, a revenue model for prosumer electricity-reserve bidding is established. The weights of multiple uncertainty factors are quantified based on information entropy theory. A two-level optimization model based on IGDT is then formulated to determine strategies that can withstand the volatility of uncertainty factors, effectively safeguarding prosumer revenue.

II. Day-Ahead Electricity-Reserve Market Bidding Decision Model

The flexible resources available to distributed prosumers on the distribution side include renewable energy generation devices, distributed fossil fuel generation devices, energy storage systems, and flexible loads. The prosumer agent integrates the dispersed resources of the prosumers and acts as a price receiver. Using predicted electricity and reserve market prices, the agent optimizes the bidding quantities of each prosumer. The optimization objective is to maximize the total revenue of all prosumers in time period *T*.

$$\max F_{\text{total}} = \sum_{i\in A} F_i = \sum_{i\in A}\sum_{t\in T}\left(F_{i,\text{ele}}^t + F_{i,\text{rev}}^t - C_{i,\text{opr}}^t\right) \quad (1)$$

Where A represents the set of prosumers, F_{total} represents the total revenue of all prosumers, F_i represents the total revenue of prosumers at node i, $F_{i,\text{ele}}^t$ represents the revenue of prosumers at node i in time period t from the day-ahead electricity market, $F_{i,\text{rev}}^t$ represents the revenue of prosumers from participating in the reserve ancillary services market, $C_{i,\text{opr}}^t$ represents the scheduling cost of their equipment.

(1) Electricity market revenue:

$$F_{i,\text{ele}}^t = \left(\varepsilon_{\text{s}}^t P_{i,\text{s}}^t - \varepsilon_{\text{b}}^t P_{i,\text{b}}^t\right)\Delta t \quad (2)$$

Where ε_{b}^t and ε_{s}^t represent the purchase and selling prices in the electricity market for time period t, respectively. $P_{i,\text{b}}^t$ and $P_{i,\text{s}}^t$ represent the purchased and sold power in the electricity market for prosumer at node i during time period t, respectively. Δt represents the duration of each optimization time period.

(2) Reserve ancillary services market revenue:

$$F_{i,\text{rev}}^t = \varepsilon_{\text{r}}^t (U_i^t + D_i^t) - \varepsilon_{\text{d}}^t \phi_{\text{d}}^t D_{i,\text{d}}^t + \varepsilon_{\text{u}}^t \phi_{\text{u}}^t U_{i,\text{u}}^t \quad (3)$$

Where ε_{r}^t represents the predicted clearing price in the day-ahead reserve capacity market. U_i^t and D_i^t represent the upward and downward reserve capacity at node i. ε_{u}^t and ε_{d}^t represent the predicted real-time prices for upward and downward reserve capacity activation, respectively. ϕ_{u}^t and ϕ_{d}^t represent the predicted real-time upward and downward reserve capacity activation rates.

(3) Prosumer equipment dispatch cost:

$$C_{i,\text{opr}}^t = \left[c_{i,\text{rg}} P_{i,\text{rg}}^t + c_{i,\text{dg}} P_{i,\text{dg}}^t + c_{i,\text{ess}}\left(P_{i,\text{dc}}^t + P_{i,\text{c}}^t\right)\right]\Delta t \quad (4)$$

Where $c_{i,\text{rg}}$, $c_{i,\text{dg}}$ and $c_{i,\text{ess}}$ represent the cost coefficients of renewable energy generation devices, distributed fossil fuel generation devices, and energy storage devices at node i, respectively. $P_{i,\text{rg}}^t$ and $P_{i,\text{dg}}^t$ represent the power generation of renewable energy generation devices and distributed fossil fuel generation devices at node i in time period t, respectively. $P_{i,\text{c}}^t$ and $P_{i,\text{dc}}^t$ represent the charging power and discharging power of energy storage devices, respectively.

The constraint conditions include:

(1) Power balance constraint:

$$P_{i,\text{s}}^t - P_{i,\text{b}}^t = P_{i,\text{rg}}^t + P_{i,\text{dg}}^t + P_{i,\text{dc}}^t - P_{i,\text{c}}^t - P_{i,\text{v}}^t - P_{i,\text{f}}^t = P_{i,\text{s,e}}^t \quad (5)$$

$$U_i^t = U_{i,\text{rg}}^t + U_{i,\text{dg}}^t + U_{i,\text{ess}}^t + U_{i,\text{v}}^t \quad (6)$$

$$D_i^t = D_{i,\text{rg}}^t + D_{i,\text{dg}}^t + D_{i,\text{ess}}^t + D_{i,\text{v}}^t \quad (7)$$

$$U_i^t = \chi D_i^t \quad (8)$$

Where $P_{i,\text{v}}^t$ and $P_{i,\text{f}}^t$ represent the controllable and uncontrollable load values of the prosumer at node i in time period t, respectively. $U_{i,\text{rg}}^t$, $U_{i,\text{dg}}^t$, $U_{i,\text{ess}}^t$ and $U_{i,\text{v}}^t$ represent the upward capacity of their renewable energy generation devices, distributed fossil fuel generation devices, energy storage devices, and controllable load, respectively. $D_{i,\text{rg}}^t$, $D_{i,\text{dg}}^t$, $D_{i,\text{ess}}^t$ and $D_{i,\text{v}}^t$ represent the downward capacity of their renewable energy generation devices, distributed fossil fuel generation devices, energy storage devices, and controllable load, respectively. χ is the coefficient of the upward capacity to downward capacity ratio.

(2) Renewable energy generation device output constraint:

$$P_{i,\text{rg}}^t = P_{i,\text{rg-r}}^t - P_{i,\text{rg-c}}^t \quad (9)$$

$$0 \le P_{i,\text{rg-c}}^t \le P_{i,\text{rg-r}}^t \quad (10)$$

$$0 \le \frac{U_{i,\text{rg}}^t}{\Delta t} \le P_{i,\text{rg-c}}^t \quad (11)$$

$$0 \le \frac{D_{i,\text{rg}}^t}{\Delta t} \le P_{i,\text{rg-r}}^t - P_{i,\text{rg-c}}^t \quad (12)$$

Where $P_{i,\text{rg-r}}^t$ and $P_{i,\text{rg-c}}^t$ represent the predicted maximum output and the reduced output for reserve upward adjustment of the renewable energy generation device, respectively.

(3) Distributed fossil fuel generation device output constraint:

$$P_{i,\text{dg}}^{\min} \le P_{i,\text{dg}}^t \le P_{i,\text{dg}}^{\max} \quad (13)$$

$$-\gamma_{i,\text{dg}} \le P_{i,\text{dg}}^t - P_{i,\text{dg}}^{t-1} \le \gamma_{i,\text{dg}} \quad (14)$$

$$U_{i,\text{dg}}^t = \min\left\{\gamma_{i,\text{dg}}, P_{i,\text{dg}}^{\max} - P_{i,\text{dg}}^t\right\}\Delta t \quad (15)$$

$$D_{i,\text{dg}}^t = \min\left\{\gamma_{i,\text{dg}}, P_{i,\text{dg}}^t - P_{i,\text{dg}}^{\min}\right\}\Delta t \quad (16)$$

Where $P_{i,\text{dg}}^{\max}$ and $P_{i,\text{dg}}^{\min}$ represent the upper and lower limits of the output of the distributed fossil fuel generation device at node i, and $\gamma_{i,\text{dg}}$ represents the ramp rate limit of the generator, respectively.

(4) Energy storage device output constraint:

$$S_{i,\mathrm{ess}}^{t}=S_{i,\mathrm{ess}}^{t-1}+(\eta_{i,\mathrm{c}}P_{i,\mathrm{c}}^{t}-\frac{P_{i,\mathrm{dc}}^{t}}{\eta_{i,\mathrm{dc}}})\frac{\Delta t}{Q_{i,\mathrm{ess}}} \tag{17}$$

$$S_{i,\mathrm{ess}}^{\min}\le S_{i,\mathrm{ess}}^{t}\le S_{i,\mathrm{ess}}^{\max} \tag{18}$$

$$0\le P_{i,\mathrm{c}}^{t}\le y_{i,\mathrm{ess}}^{t}P_{i,\mathrm{c}}^{\max} \tag{19}$$

$$0\le P_{i,\mathrm{dc}}^{t}\le\left(1-y_{i,\mathrm{ess}}^{t}\right)P_{i,\mathrm{dc}}^{\max} \tag{20}$$

Where $S_{i,\mathrm{ess}}^{t}$ represents the state of charge of the energy storage device of the prosumer. $S_{i,\mathrm{ess}}^{\min}$ and $S_{i,\mathrm{ess}}^{\max}$ represent the lower and upper limits of its state of charge. $\eta_{i,\mathrm{dc}}$ and $\eta_{i,\mathrm{c}}$ represent the discharge efficiency and charge efficiency of the energy storage device, respectively. $Q_{i,\mathrm{ess}}$ is the rated capacity of the energy storage device. $P_{i,\mathrm{dc}}^{\max}$ and $P_{i,\mathrm{c}}^{\max}$ represent the maximum discharge power and maximum charge power, respectively. $y_{i,\mathrm{ess}}^{t}$ is the charging and discharging state variable, where 1 represents charging and 0 represents discharging.

The reserve capacity provided by the energy storage device should satisfy:

$$0\le\frac{U_{i,\mathrm{ess}}^{t}}{\Delta t}\le P_{i,\mathrm{dc}}^{\max}-P_{i,\mathrm{dc}}^{t} \tag{21}$$

$$0\le\frac{D_{i,\mathrm{ess}}^{t}}{\Delta t}\le P_{i,\mathrm{c}}^{\max}-P_{i,\mathrm{c}}^{t} \tag{22}$$

$$U_{i,\mathrm{ess}}^{t},D_{i,\mathrm{ess}}^{t}\le\frac{S_{i,\mathrm{ess}}^{\max}-S_{i,\mathrm{ess}}^{t+1}}{\eta_{i,\mathrm{c}}} \tag{23}$$

$$U_{i,\mathrm{ess}}^{t},D_{i,\mathrm{ess}}^{t}\le\left(S_{i,\mathrm{ess}}^{t+1}-S_{i,\mathrm{ess}}^{\min}\right)\eta_{i,\mathrm{dc}} \tag{24}$$

Equation (21) and (22) limit the reserve capacity provided by the energy storage device to the available capacity at the maximum charge and discharge power. Equation (23) and (24) ensure that the energy storage device only provides reserve capacity when its state of charge is within the lower and upper limits.

(5) Load constraint:

The shiftable load refers to the load that can be shifted according to the planned schedule and is subject to the constraint of the continuity of the electricity consumption process. Its characteristics can be described as follows:

$$P_{i,\mathrm{p\text{-}a}}^{t}=P_{i,\mathrm{p\text{-}r}}^{t}+P_{i,\mathrm{in}}^{t}-P_{i,\mathrm{out}}^{t} \tag{25}$$

$$P_{i,\mathrm{in}}^{t}=\sum_{k=1,k\ne t}^{T}x_{i,\mathrm{p}}^{k,t}P_{i,\mathrm{p\text{-}r}}^{1}+\sum_{w=1}^{W}\sum_{k=1,k\ne t-1}^{T}x_{i,\mathrm{p}}^{k,t-1}P_{i,\mathrm{p\text{-}r}}^{w+1} \tag{26}$$

$$P_{i,\mathrm{out}}^{t}=\sum_{k=1,k\ne t}^{T}x_{i,\mathrm{p}}^{t.k}P_{i,\mathrm{p\text{-}r}}^{1}+\sum_{w=1}^{W}\sum_{k=1,k\ne t-1}^{T}x_{i,\mathrm{p}}^{t-1,k}P_{i,\mathrm{p\text{-}r}}^{w+1} \tag{27}$$

Where $P_{i,\mathrm{p\text{-}a}}^{t}$ represents the adjusted shiftable load value at node *i* in time period *t*. $P_{i,\mathrm{p\text{-}r}}^{t}$ represents the predicted value of the shiftable load. $P_{i,\mathrm{in}}^{t}$ and $P_{i,\mathrm{out}}^{t}$ represent the shiftable load values shifted into and out. *W* represents the maximum duration of continuous operation for the shiftable load. $x_{i,\mathrm{p}}^{k,t}$ is a binary variable that takes a value of 0 or 1, where $x_{i,\mathrm{p}}^{k,t}=1$ and $x_{i,\mathrm{p}}^{k,t}=0$ indicate whether there is shiftable load shifted into or out of time period *t* from time period *k* at node *i*.

The interruptible load can provide upward reserve by reducing or interrupting the load. Its characteristics can be described as follows:

$$P_{i,\mathrm{x\text{-}a}}^{t}=P_{i,\mathrm{x\text{-}r}}^{t}-P_{i,\mathrm{x\text{-}c}}^{t} \tag{28}$$

$$0\le P_{i,\mathrm{x\text{-}c}}^{t}\le\beta_{i,\mathrm{x}}P_{i,\mathrm{x\text{-}r}}^{t} \tag{29}$$

Where $P_{i,\mathrm{x\text{-}a}}^{t}$ represents the adjusted interruptible load value at node *i* in time period *t*. $P_{i,\mathrm{x\text{-}r}}^{t}$ and $P_{i,\mathrm{x\text{-}c}}^{t}$ represent the predicted value and the reduction power value of the interruptible load. $\beta_{i,\mathrm{x}}$ represents the maximum reduction ratio allowed for the prosumer at node *i*.

The total reserve capacity provided by shiftable load and interruptible load is given by:

$$U_{i,\mathrm{v}}^{t}=\left(P_{i,\mathrm{out}}^{t}+P_{i,\mathrm{x\text{-}c}}^{t}\right)\Delta t \tag{30}$$

$$D_{i,\mathrm{v}}^{t}=P_{i,\mathrm{in}}^{t}\Delta t \tag{31}$$

The uncontrollable load has no adjustable flexibility and does not provide reserve capacity. Its characteristics can be described as follows:

$$P_{i,\mathrm{f}}^{t}=P_{i,\mathrm{f\text{-}r}}^{t} \tag{32}$$

Where $P_{i,\mathrm{f\text{-}r}}^{t}$ represents the predicted value of the uncontrollable load at node *i* in time period *t*.

III. A ROBUST OPTIMIZATION MODEL CONSIDERING MULTIPLE UNCERTAINTIES

Due to the presence of uncertainty factors, risk-averse prosumers may require their agents to optimize bid quantities in a way that guarantees a minimum total revenue not less than a certain expected revenue F_{ex}. They aim to pursue a bidding strategy that maximizes resistance to the deviations caused by uncertain factors. Based on the IGDT risk decision-making theory [18-19], the following robust optimization model can be established:

$$\max_{\kappa_i}\ \xi\in\left[0,1\right] \tag{33}$$

$$s.t.\ \min\sum_{i\in A}F_i(X,\kappa_i) \tag{34}$$

$$(1-\xi_m)X_m\le X_m\le(1+\xi_m)X_m \tag{35}$$

$$\sum_{i\in A}F_i\left(X,\kappa_i\right)\ge F_{\mathrm{ex}}=\left(1-\sigma\right)\sum_{i\in A}F_{i,0} \tag{36}$$

$$\text{Equation (1)\textasciitilde(32)} \tag{37}$$

Where κ_i represents the set of bid quantities for prosumer *i* considering multiple uncertainties and risks. ξ represents the magnitude of the fluctuations of the uncertain parameter. X represents the actual values of uncertain parameters. Let $\xi_m\left(m=1,2\ldots5\right)$ denote the deviation coefficient for each of the five uncertain parameter indicators for the prosumer. X_m represents the normalized data after the normalization process. σ represents the acceptable range of revenue deviation, which is the deviation between the expected robust optimization objective and the optimal solution $\sum_{i\in A}F_{i,0}$ of the deterministic model when $\sigma\in(0,1)$.

A larger value σ of indicates a higher degree of risk aversion in the decision-making process.

Once the fluctuation coefficient ξ of the uncertain quantity is determined, it is apparent that the minimum total revenue for the prosumer occurs when each uncertain variable is equal to $1 \pm \xi_m$ times its nominal value. Therefore, Equation (35) can be transformed into:

$$P_{i,\text{rg-r}}^{t} = \left(1-\xi_1\right) P_{i,\text{rg-r}}^{t} \tag{38}$$

$$\varepsilon_{\text{b}}^{t} = \left(1+\xi_2\right) \varepsilon_{\text{b}}^{t},\ \varepsilon_{\text{s}}^{t} = \left(1-\xi_2\right) \varepsilon_{\text{s}}^{t} \tag{39}$$

$$\varepsilon_{\text{r}}^{t} = \left(1-\xi_3\right) \varepsilon_{\text{r}}^{t},\ \varepsilon_{\text{d}}^{t} = \left(1-\xi_3\right) \varepsilon_{\text{d}}^{t},\ \varepsilon_{\text{u}}^{t} = \left(1-\xi_3\right) \varepsilon_{\text{u}}^{t} \tag{40}$$

$$\phi_{\text{u}}^{t} = \left(1-\xi_4\right) \phi_{\text{u}}^{t}, \phi_{\text{d}}^{t} = \left(1-\xi_4\right) \phi_{\text{d}}^{t} \tag{41}$$

$$P_{i,\text{p-r}}^{t} = \left(1-\xi_5\right) P_{i,\text{p-r}}^{t}, P_{i,\text{x-r}}^{t} = \left(1-\xi_5\right) P_{i,\text{x-r}}^{t}, P_{i,\text{f-r}}^{t} = \left(1+\xi_5\right) P_{i,\text{f-r}}^{t} \tag{42}$$

The IGDT robust decision-making model considering multiple uncertainties, represented by Equation (33)-(42), is a two-level optimization model. The upper-level objective is to maximize the deviation of uncertain quantities, corresponding to the worst-case scenario where the total revenue for prosumers is minimized. The solution steps for the IGDT-based robust optimization model are as follows:

Step 1: Set an initial value $k = 0$、$\xi_k = 0$. Disregard the uncertainty factors, i.e., $X = X$. Solve the deterministic model to obtain the bidding strategies $\kappa_{i,0}$ and the total revenue $\sum_{i \in A} F_{i,0}$ for each prosumer.

Step 2: For $\xi_{k+1} = \xi_k + \Delta\xi$、$k = k+1$, solve the optimization problem to obtain the optimal bidding strategies $\kappa_{i,k+1}$ for each prosumer with the fluctuation coefficient ξ_{k+1} of the uncertain quantity.

Step 3: Evaluate whether the total revenue $\sum_{i \in A} F_{i,k+1}$ of prosumers under the fluctuation coefficient ξ_{k+1} of the uncertain quantity meets the minimum required total revenue F_{ex}, according to Equation (37). If $\sum_{i \in A} F_{i,k+1} \le F_{\text{ex}}$, proceed to Step 4; otherwise, go back to Step 2.

Step 4: Obtain the maximum fluctuation range ξ_k of the uncertain quantity and the corresponding set $\kappa_{i,k}$ of bidding quantities for prosumers.

IV. Case Study and Results

A. Parameter Setting

The modified IEEE 33-node distribution system is used for case studies. The topological structure of the system is shown in Figure 1. It is assumed that there is a total of 12 distributed prosumers, located at nodes 2, 3, 4, 6, 9, 13, 17, 20, 21, 23, 28, and 32, referred to as prosumers *a-l*. Each prosumer is equipped with a battery energy storage system and a photovoltaic generation device. Load data and the maximum output of renewable energy generation devices are taken from references [20-21]. The optimization time interval is set as Δt=1h, and the number of optimization time intervals is *T=24*. The predicted values of electricity prices and reserve capacity prices for each time interval are obtained from reference [11].

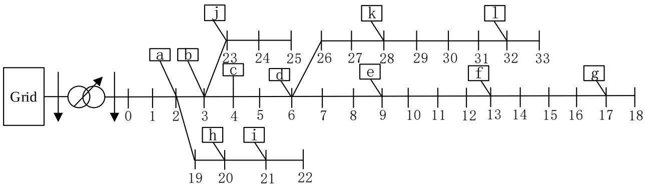
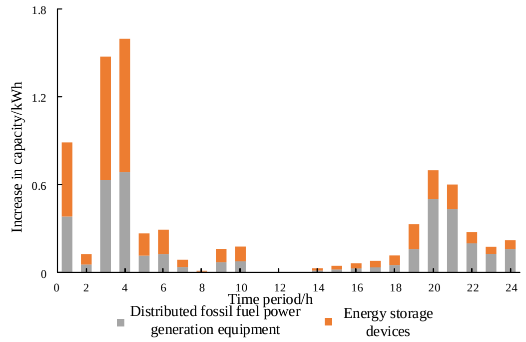
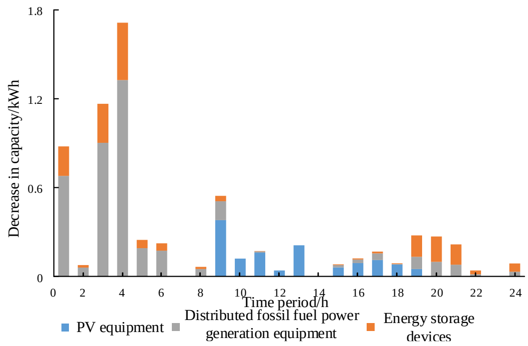


Fig. 1. Topology of IEEE 33-node power distribution system



(a) Increase in reserve capacity



(b) Decrease in reserve capacity

Fig. 2. Upward and downward band of each equipment owned by prosumer *b*

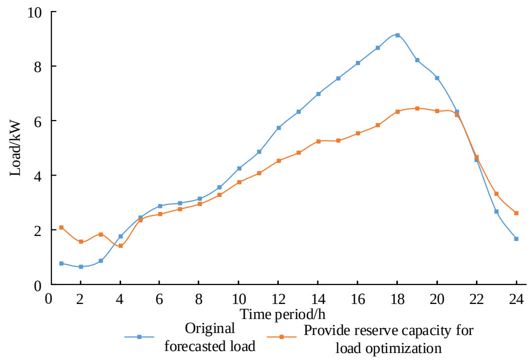


Fig. 3. Load curve of prosumer *b*

Figure 2 shows the reserve capacity provided by each device of prosumer *b*, and Figure 3 depicts the load curve of prosumer *b* before and after optimization. Due to the low load and device output in hour 1-4, both the energy storage system and distributed fossil energy generation devices can provide a large amount of upward and downward reserve capacity. During hour 9-19, which is the period of renewable energy generation, the photovoltaic generation device of prosumer *b* is dispatched at full capacity due to its low generation cost. Therefore, the photovoltaic generation device only provides a certain amount of downward reserve capacity. In the peak demand period from hour 19-22, the load is flattened through load shifting and load shedding, allowing the dispatchable distributed fossil energy generation devices and energy storage systems to provide a certain amount of downward reserve capacity. On average, the upward reserve capacity provided by the distributed fossil energy generation devices and energy storage systems is 28.3% higher than the downward reserve capacity.

B. *Simulation Results of Robust Optimization Model Considering Multiple Uncertainties*

The entropy weights of the uncertain variables, representing the relative importance of each uncertainty factor, are as follows: 0.211 for the maximum output of renewable energy, 0.123 for the electricity market price, 0.164 for the reserve market price, 0.307 for the reserve capacity utilization rate, and 0.195 for the load.

The profit deviation factor represents the deviation between the expected profit and the deterministic profit. Figure 4 shows the variation of the uncertainty coefficient ξ with the profit deviation factor σ. The red curve represents the sum of the uncertainty coefficients for the five uncertainty factors, i.e., $\sum_{i=1}^{5}\xi_m = \xi$. When $\sigma = 0$, the uncertainty coefficients for all five factors start from zero, indicating no profit deviation when all uncertainties are perfectly predicted. As σ increases, the ranges of fluctuation for the five uncertainty parameters also increase, indicating that prosumers adopt more robust bidding strategies to withstand a wider range of prediction errors at the cost of reducing expected profit.

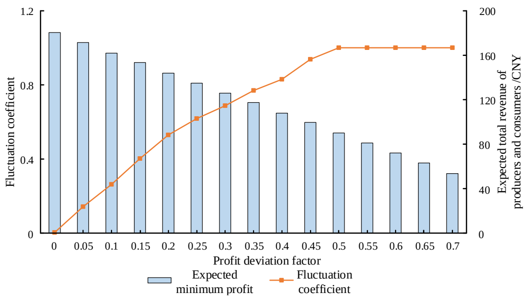
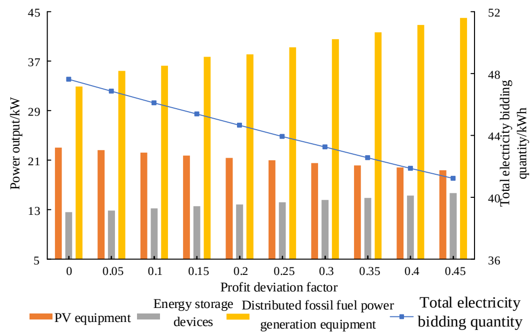


Fig. 4. Variation of uncertain quantity fluctuation coefficient and expected return with return deviation coefficient

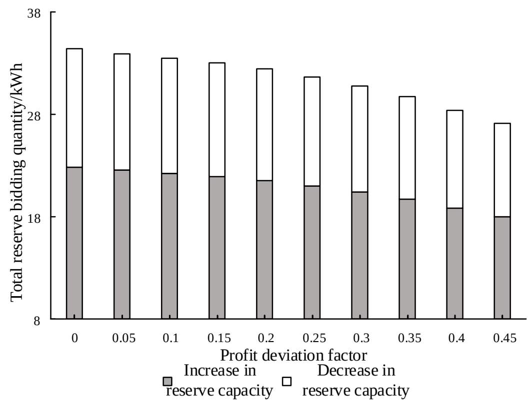
When $\sigma = 0.46$, the uncertainty coefficients ξ reach their maximum value of 1, and ξ remain unchanged as σ increases. This indicates that when $\sigma \geq 0.46$, the uncertainty constraints by Equation (38)-(42) are no longer effective boundary constraints, meaning that prosumers cannot further enhance the robustness of their bidding strategies by reducing their expected profit. Therefore, prosumers should set the expected total profit deviation to $\sigma \leq 0.46$.

Let's analyze the profit situation of prosumers under the scenario $\sigma = 0.25$. From Figure 4, we can see that the minimum total profit for the 12 prosumers is 153.9 units, with a fluctuation coefficient of $\xi = 0.62$. This means that even with a 13.1% lower maximum output of renewable energy, 12.2% higher load than expected, 19.3% lower actual reserve utilization rate than predicted, 10.6% lower reserve market price than predicted, and 7.6% deviation in electricity market price compared to the prediction, the total profit of the prosumers can still be maintained at or above 153.9 units.

Figure 5 shows the equipment output and bidding quantity of prosumer *b* at different σ level. At $\sigma = 0.25$, the proportional contribution of the distributed fossil fuel-based generation and energy storage devices in prosumer *b*'s output increases by 14.6% and 7.2% respectively, while the output of the renewable energy generation device decreases by 5.6%. This indicates that as σ increases, the agent faces increased uncertainty and risk in optimizing bidding strategies, and therefore prefers to dispatch more stable devices (distributed fossil fuel-based generation and energy storage devices) to increase their output, while reducing the output of devices (renewable energy generation) with stochastic fluctuations. Compared to the deterministic model, due to the risk of price fluctuations in the electricity market and reserve market, the electricity market bidding quantity and reserve market bidding quantity of prosumer *b* decrease by 4.7% and 3.6% respectively. However, since prosumer *b* still has significant electricity demand, the decrease in bidding quantity is not significant.



(a) Device output and total electricity bidding quantity



(b) Total reserve bidding quantity

Fig. 5. Equipment output and total bid amount of prosumer *b* under different σ

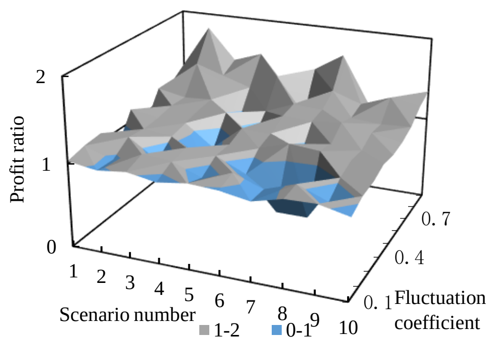


Fig. 6. Comparison of total revenue for different bidding strategy

C. Comparative Analysis

In each specific coefficient ξ of uncertainty, 10 typical scenarios were generated using the Monte Carlo random sampling method [9]. Figure 6 shows the comparison of total profits for all prosumers between deterministic bidding strategy and stochastic bidding strategy under each scenario. The profit ratio is defined as the ratio of total profit obtained from the stochastic strategy to the total profit obtained from the deterministic strategy. The results indicate that in 75.6% of the scenarios, the stochastic strategy outperforms the deterministic strategy in terms of total profit. Furthermore, as the uncertainty coefficient increases, the advantage of the stochastic bidding strategy becomes more pronounced. Specifically, when the coefficient reaches $\xi = 0.9$, the average total profit of the stochastic strategy is 37.4% higher than that of the deterministic strategy across all 10 scenarios.

V. Conclusion

This paper establishes a decision model for the joint energy and reserve market bidding of distributed prosumers based on information gap decision-making. Through case simulations, the following conclusions are drawn:

An agent-based approach for distributed prosumers is established, where the agent aggregates the dispersed bidding quantities of all prosumers and submits them to the day-ahead market. This approach effectively ensures the market participation of distributed prosumers.

By applying the information entropy theory, the various uncertainties faced by prosumers in the day-ahead bidding process can be quantified effectively. The bid strategy optimization model based on IGDT enhances the robustness of bid strategies, thereby effectively safeguarding the profits of prosumers.

In the future research, electricity transactions among prosumers, and the participation of distributed prosumers in medium to long-term power and carbon-green certificate trading will be studied and further integrated into the proposed models and methods.

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