energies

MDPI

Article

Energy Trading Strategy of Distributed Energy Resources Aggregator in Day-Ahead Market Considering Risk Preference Behaviors

Jun Dong [1], Xihao Dou [1], Dongran Liu [1], Aruhan Bao [1], Dongxue Wang [2,*] and Yunzhou Zhang [1]

[1] School of Economics and Management, North China Electric Power University, Beijing 102206, China
[2] School of Economics and Management, Wuhan University, Wuhan 430072, China
* Correspondence: 2021101050079@whu.edu.cn; Tel.: +86-156-2359-8277

Abstract: Distributed energy resources aggregators (DERAs) are permitted to participate in regional wholesale markets in many counties. At present, new market players such as aggregators participate in China's power market transactions. However, studies related to market trading strategy have mostly focused on centralized wind power and PV generation units. Few studies have been conducted on the decision-making strategies for DERAs in China's power market. This paper proposes an auxiliary decision-making model for distributed energy systems to participate in the day-ahead market with more reasonable trading strategies. Firstly, the Gaussian mixture model (GMM) is used to deal with the uncertainties of wind power and photovoltaic (PV) output in the distributed energy system. Secondly, the information gap decision theory (IGDT) is used to deal with the uncertainty of price fluctuations in the spot electricity market. Thirdly, according to the different risk preferences of the DERAs facing market price fluctuation, the robust decision model and opportunity decision-making model in the day-ahead market are constructed, respectively. Finally, to deal with the irrational behavior of the DERAs' perception of "gain" and "loss" with market risks in China's two-tier market environment, the prospect theory and the marine predator's algorithm (MPA) are employed to obtain a day-ahead trading decision scheme for DERA. The analyses show that RDES with robust preference can withstand greater price volatility in the day-ahead market; they will reduce the bidding expectations and increase the system operating cost to improve the achievability of the expected revenue. However, DERAs under the opportunity strategy is more inclined to sell electricity to the market and offset system operating costs with revenue. The proposed model can provide strategic reference for DERAs with different risk preferences to bid in day-ahead market and can improve the level of aggregators' participation in electricity trading.

Keywords: distributed energy resources aggregator; day-ahead transaction strategic; information gap decision theory; marine predators algorithm

Citation: Dong, J.; Dou, X.; Liu, D.; Bao, A.; Wang, D.; Zhang, Y. Energy Trading Strategy of Distributed Energy Resources Aggregator in Day-Ahead Market Considering Risk Preference Behaviors. *Energies* **2023**, *16*, 1629. https://doi.org/10.3390/en16041629

Academic Editors: Javier Contreras and Behnam Zakeri

Received: 7 November 2022
Revised: 3 January 2023
Accepted: 31 January 2023
Published: 6 February 2023

1. Introduction

At present, there is much research on the strategy of centralized wind power and PV generation units participating in the power wholesale market and retail market at home and abroad. On the contrary, due to the imperfect market-oriented mechanism of distributed trading in China, distributed resources are mainly connected to the grid with fixed on-grid pricing, so there is little research on the strategy of participating in power trading for DERAs in China. Most of the related research on distributed energy systems focuses on the design of trading mechanism of RDES with new subject participation. For example, P2P or P2G transaction mode design of shared energy storage or shared energy storage with multiple agents in DERS [1,2], demand response service mode analysis based on intelligent contract [3], P2P transaction research with electric vehicles [4], etc. The research on the trading strategy of distributed resources mainly focuses on the operation strategy of independent wind and PV generation units, microgrids [5,6] or virtual power plants [7,8], and so on, which is the basis for the decision-making of trading declarations. However, this kind of research ignores the risk preference of decision makers in the complex market environment and the subjective psychological factors facing risks. Therefore, it is necessary to study the power transaction assistant decision-making problem of DERAs in depth.

A large number of scholars carried out research on the bidding strategies of power generation enterprises focusing on traditional energy, such as thermal power, around 2002, and the bidding strategies that were mainly applied included cost analysis [9], electricity price forecast [10], optimal method [11], and game theory [12]. At the same time, based on block chain technology and experimental economics, some scholars studied the bidding strategy and bidding trading system of power producers through the methods of EWA algorithm [13], repast algorithm [14], agent [15,16], MAS [17], and so on. However, the output of wind power and PV has randomness and volatility, and the unreasonable bidding power in the day-ahead market will be assessed for deviation in the day-ahead balance market [18]. According to China's spot pilot program's current policy, new energy will be fully consumed in all provinces, and new energy organizations will employ the method of quoting without quotation, resulting in a significant link between new energy output and spot market pricing. The amount of fresh energy produced will have an impact on the spot market price. Simultaneously, the prediction of new energy output will influence the formation of trade decision plans of other market entities in the day-ahead and day-in markets, finally resulting in changes in the revenue of market participants in the spot market. At this stage, research on the uncertainty of wind power output and market price fluctuation is generally based on probability statistics analysis, generating a random fluctuation scenario analysis based on probability distribution function or describing based on historical scenarios [19,20]. However, this type of method needs to rely on a large number of data deduction to improve the accuracy of fitting, and the generation of typical scenarios for uncertain factors is limited; therefore, it is difficult to obtain the fluctuation range of uncertain factors [21]. However, the construction of the power spot market in China is in the early stage, especially the pilot construction of distributed trading is still in its infancy; therefore, the market transaction data is not sufficient. Therefore, how to obtain a scientific bidding strategy in the condition of limited market information is an urgent problem to be solved by market players in the current market development stage, and it is also a problem that must be faced by the pilot construction of distributed trading.

The IGDT [22] is a nonprobability statistical approach to deal with uncertainty, which does not need fuzzy membership function analysis or a probability distribution test for uncertain information, but only needs to analyze the gap of uncertain factors. Therefore, it can well describe the uncertainty of the power system and the power market. The IGDT is widely used in power systems. Soroudi [23] et al. modeled the uncertainty of the distributed generation output in the distribution network and obtained the optimal generation output combination through the IGDT model. Mavalizadeh [24] used the IGDT model to deal with the uncertainty of wind power and power price, and the uncertainty of distributed generation and node load, respectively, and at the same time constructed a robust recovery model. Moreover, some scholars have also conducted IGDT modeling for joint optimization of wind power output and virtual power plant scheduling, respectively [25–28]. In addition to its application in power system optimization, the IGDT has also made a beneficial attempt in power trading. Mazzi [29] assumed that the market members are the recipients of the market price and then declared the price based on the marginal operating cost of the unit; Y. Shen [30] and Li [31] et al. determined the declared power based on the operating arrangement of the unit on this basis. Zhao [32] et al. conducted a robust model based on IGDT for power allocation in the spot power market, which provides a risk-averse tool for power generation companies to make power allocation decisions with different expected returns. Considering the influence of the uncertainty of the market clearing price on the decision-making of power selling companies, Tang L [33] et al. established a decision-making model of power selling companies in bilateral contract and spot transaction mode based on IGDT, which provides a reference for power selling companies to participate in power transactions. However, most of the above research focuses on the single decision-making preference of the united whole, without considering the impact of individual risk preference differences within the system on the unified decision-making. With the development of RDES, the system will present the characteristics of multi-investors in the future. It is very difficult for RDES to determine the trading strategy based on the single risk preference of aggregators. Therefore, research on the influence of the risk preference of different trading agents on RDES's trading decision is of great significance to promote the sustainable development of the system

At present, new energy is given priority for full consumption in China's dual-track market environment, and new energy is only quoted in market transactions, not fully market-based transactions, resulting in more uncertainties and more complex market scenarios for market players to participate in market transactions. For new energy entities, how to make optimal decisions in the complex market environment has become an important issue in promoting the construction of new power systems. There is a lot of psychological evidence that people usually consider problems not in terms of total wealth but in terms of winning or losing. Different from the expected utility function theory in decision-making theory, prospect theory holds that it is difficult for decision makers to satisfy the hypothesis of a completely rational person in reality and their risk preference will change with the change of objective factors. Therefore, some scholars have applied prospect theory to deal with the subjective gain and loss preferences of Prosumers in distributed energy trading decisions [34]. Etesami, S.R. et al. used prospect theory to build a stochastic game model for the energy management of a smart grid [35]. The above research can effectively deal with the irrational decision-making behavior of decision makers in the uncertain environment.

According to research on both domestic and international electricity trading, the dual-track market mechanism, price volatility, distributed energy output uncertainty, and others are the main factors that affect the RDES's ability to develop a rational trading strategy and participate in the spot market. This research proposes a decision-making model for RDES to engage in day-ahead trading with an eye toward these crucial elements. First, in order to address the uncertainty of new energy output, the GMM is used to create typical scenarios of wind and solar output and load, and information gap theory is used to address the uncertainty of market-price fluctuation the day before. In order to explain the changes in income brought by various risk preferences, the robust decision-making model and opportunity decision-making model of day-ahead market transactions, respectively, are constructed, taking into account the DERA's attitude of avoiding and chasing market price risks. Thirdly, the decision-making of the day-ahead transactions for aggregators in distributed energy systems is constructed based on the characteristics of China's dual-track market, using prospect theory to deal with aggregators' irrational behavior under the perception of risk gain and loss, combined with the robust strategy and opportunity strategy scenarios proposed by the IDGT model. To decide the ultimate trading strategy, model the ocean hunting algorithm to acquire the most effective utility function in the two scenarios of the aggregator's recent statement of winning the bid and not winning the bid. Finally, this paper compiles the model by using Python, which is the mainstream programming tool at present, and verifies the rationality of the model proposed in this paper by using the spot pilot data of a province in China. The research framework of this paper is shown in Figure 1.

This paper builds a day-ahead trading decision model of a regional distributed energy system considering the risk preference behavior of the subject, which solves the problem, to some extent, wherein the current research does not consider the behavior preference of the distributed energy subject and the irrational behavior of a regional distributed energy system participating in electricity trading. The following are the key contributions:

(1) At present, most of the methods to deal with uncertain problems are based on probability and statistical analysis methods, which require a large amount of data. However, China's electricity market construction is in the primary stage and there are few market transaction data. Therefore, this paper uses the GMM and IGDT to effectively

deal with the uncertainty of new energy output and price fluctuations in the spot market. Meanwhile, to address the issue of the GMM easily convergent to the local optimal solution, this paper employs Spearman as the distance calculation formula based on the traditional algorithm, which effectively reduces the probability of the local optimal solution.

(2) The majority of recent papers only run robust models to develop decision schemes; this paper adds opportunity decision models on this basis, which can provide a basis for trading decisions for DERAs with different risk preferences given that DERAs with different risk preferences will exhibit risk-averse or risk-chasing behavioral characteristics in the face of market risks.

(3) Based on the characteristics of China's dual-track market, this paper employs prospect theory to examine the probability and utility value of aggregators' perceptions of "gain" and "loss" under various settlement methods, and then, solves them using the MPA optimizer to determine the optimal utility strategy. The difficulty of the algorithm's local optimal solution is decreased, and the model solving effect is enhanced, allowing the best utility strategy to be identified.

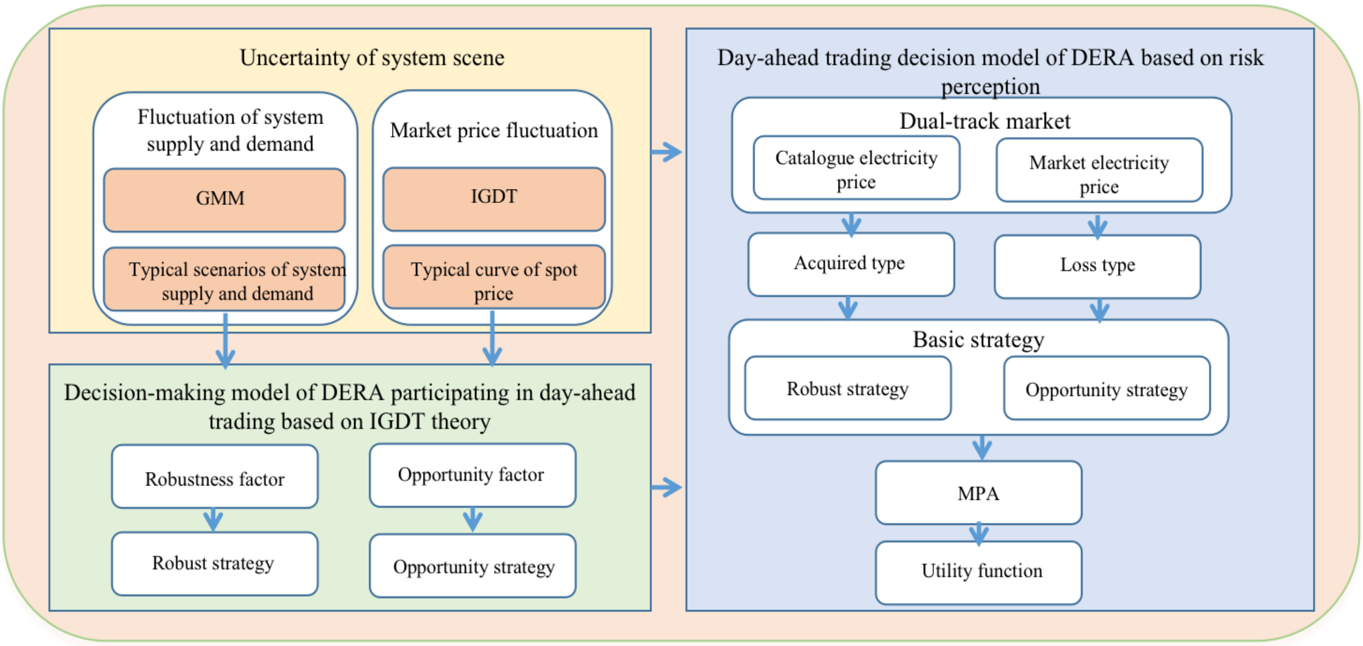

Figure 1. Research framework of single-stakeholder DERA transaction decision-making model in day-ahead market considering risk preference behaviors.

2. Uncertainty Treatment of System Supply and Demand and Market Price Fluctuation

2.1. Uncertainty Treatment of System Supply and Demand Fluctuation

In this section, the historical data of wind power output, PV output, and load are clustered using the GMM. The expectation-maximization (EM) algorithm is used to calculate typical scenarios and scenario probabilities of supply demand for RDES. The strategy can be transformed from uncertainty scenarios to certainty scenarios. We can use this model to select the scenario with the highest probability from many uncertain new energy scenarios as a typical scenario to aid decision-making and provide a foundation for trading schemes with varying risk preferences in the following.

The GMM assumes that the input samples are distributed Gaussian with k unknown parameters. Samples with the same distribution are grouped into a single class. The GMM fits k mixed Gaussian distributions using the EM algorithm to obtain the mean μ_j and covariance $\varepsilon_j (1 \leq j \leq k)$ of each distribution. The specific steps are as follows [36]:

Step 1: initialize the parameters μ_j and ε_j of k multivariate Gaussian distributions, assuming that each mixture element has a diagonal matrix.
Step 2: iterate over all sample points and calculate the probability $\gamma_{i,j}$ of the jth Gaussian distribution of the sample points $x_i(i = 1, 2, \ldots, m)$, as shown in Formula (1).

$$\gamma_{i,j} = p(x_i|z_i = j) = \frac{1}{(2\pi)^{\frac{d}{2}} |\varepsilon_j|^{\frac{1}{2}}} \cdot \exp\left(-\frac{1}{2}(x_i - \mu_j)^T {\varepsilon_j}^{-1}(x_i - \mu_j)\right) \tag{1}$$

where $p(\cdot)$ is the probability function, z_i denotes the class to which x_i belongs, and d is the dimension of x_i.
Step 3: the updated values ${\mu_j}'$ and ${\varepsilon_j}'$ of the Gaussian distribution parameters μ_j and ε_j are obtained according to Formulas (2) and (3).

$${\mu_j}' = \frac{\sum_{i=1}^{m} \gamma_{i,j} x_i}{\sum_{i}^{m} \gamma_{i,j}} \tag{2}$$

$${\varepsilon_j}' = \frac{\sum_{i=1}^{m} \gamma_{i,j} (x_{i-}{\mu_j}')(x_{i-}{\mu_j}')^T}{\sum_{i}^{m} \gamma_{i,j}} \tag{3}$$

Step 4: repeat steps 2 and 3 until all Gaussian parameters converge.
Step 5: using the calculated Gaussian parameters, all samples are traversed, and the samples are classified into the class with the maximum probability $\gamma_{i,j}$.

Compared to the circular cluster of K-means, the GMM can present elliptical clusters due to the use of mean and standard deviation. At the same time, the GMM contains the concept of probability, which can realize that a data point belongs to multiple clusters, while the data points of K-means generally belong to only one cluster. However, the GMM also has some disadvantages, such as that it will easily converge to local optimal solutions, so the literature generally combines the GMM with other models for clustering.

2.2. Uncertainty Treatment of Market Price Fluctuation

China's electricity spot market is still in its early stages of development. The price mechanism of China's distributed energy trading market requires improvement, and the trading data are insufficient to accurately describe the impact of market price fluctuations on trading decisions. Therefore, considering that the IGDT model does not need to rely on large-scale data for probabilistic statistical analysis, this paper employs the IGDT model to deal with the uncertainty of market price fluctuations in the case of limited market information to provide a scientific foundation for RDES to participate in power trading-assisted decision-making.

Typically, the IGDT model consists of three parts, which are the system model, the uncertainty model [37], and the performance requirement [38] or implementation requirement.

The uncertainty of the spot wholesale market price is modeled using the IGDT's uncertainty processing model, as shown in Formula (4).

$$\begin{cases} \tau \in \mho(\alpha, \hat{\tau}) \\ \mho(\alpha, \hat{\tau}) = \left\{\tau : \frac{|\tau - \hat{\tau}|}{\hat{\tau}} \leq \alpha\right\} \quad \forall \alpha \geq 0 \end{cases} \tag{4}$$

where $\hat{\tau}$ is the forecast electricity spot market price, and α is the deviation between the predicted and the actual value of the price.

To reflect the decision effects under different risk preferences, IGDT is used to develop a robust optimization model and an opportunity optimization model. The robust optimization model seeks the greatest possible range of market price fluctuations while ensuring that the decision outcome is not less than expected, as expressed in Formula (5).

$$\hat{\alpha}(Q,\, c_R) = max\left\{\alpha : max_{\tau \in \mho(\alpha,\hat{\tau})} C(Q, \tau) \leq\, c_R,\, c_R = c_0(1 + \beta_R)\right\} \tag{5}$$

where Q is the purchasing power of the DERA, c_R is the robustness transaction cost threshold, c_0 is the transaction cost of the system under a deterministic scenario, and γ_R is the robustness factor: that is, the robust model cost deviation factor. When the market price fluctuates within the information gap interval, the larger the robustness factor γ_R is, the more robust the decision scheme is and the higher the transaction cost is.

Corresponding to the robust function, the IGDT chance model can be expressed as Formula (6).

$$\hat{\alpha}(Q,\ c_O) = min\left\{\alpha : min_{\tau\in\mho(\alpha,\hat{\tau})}C(Q,\tau) \le\ c_O,\ c_O = c_0(1-\beta_O)\right\} \tag{6}$$

where c_O is the opportunity transaction cost threshold of the regional system. γ_O is the opportunity factor, which can also be interpreted as the opportunity model cost deviation factor. When the market price is outside the information gap interval, the transaction cost of the DERA will be lower than the threshold γ_O of opportunity cost. The smaller the opportunity factor is, the greater the chance the decision maker may achieve the desired goal.

3. Day-Ahead Trading Decision Model of DERAs Based on IGDT and Prospect Theory

The operation of the spot pilot in China has revealed that the spot market has the characteristics of short clearing time, large price fluctuation, and rapid change of supply and demand in the market, which will directly affect the rationality of market subjects' decision-making and improve the risk of enterprise operation. As a result, market players must consider these risk variables while making preparations. At the same time, China is a dual-track market with illogical market transactions [39]. The risk preferences of market players must be addressed. Different trading strategies can adapt to the market's rapid changes depending on risk preferences. Currently, the majority of risk strategy research is conducted in a pure rational or pure market environment. In order to make more effective decision-making plans, this paper constructs robust and opportunity risk preferences, and on that basis, introduces prospect theory to account for decision makers' subjective feelings in a complex market environment. The decision-making behavior of distributed energy system operators is more in line with reality, according to their incomplete rationality.

3.1. The Optimal Model of Day-Ahead Trading Decisions of DERAs

3.1.1. Objective Function

The objective function of a DERA's day-ahead trading strategy is shown in Formula (7).

$$min\sum_{t=1}^{T}C_t = min\sum_{t=1}^{T}(\tau_{DA,t}\cdot P_{buy,t} + C_{G,t} + +C_{VM,t} - \tau_{DA,t}\cdot P_{sell,t}) \tag{7}$$

where C_t indicates the total operating cost of the DERA's participation in the day-ahead market, $\tau_{DA,t}$ is the day-ahead market price, and $P_{buy,t}$ and $P_{sell,t}$ represent the power purchased and sold in the day-ahead market, respectively. $C_{G,t}$ indicates the fuel gas cost, as shown in Formula (8). $C_{VM,t}$ indicates the operation and maintenance cost of each type of unit, as shown in Formula (9).

Where $\tau_{DA,pre,t}$ is the predicted value of the clearing price at time t in the day-ahead market, α is the fluctuation range of the price uncertainty parameter, satisfying $\alpha \ge 0$.

$$C_{G,t} = \rho\cdot(F_{g,t} + F_{b,t}) = \rho\cdot\left(\frac{P_{g,t}}{L_{hvng}\cdot\eta_g} + \frac{H_{b,t}}{L_{hvng}\cdot\eta_b}\right) \tag{8}$$

where ρ represents the unit fuel price. $F_{g,t}$ and $F_{b,t}$ represent the fuel consumption of the gas turbine and gas boiler in time t, respectively. $P_{g,t}$ is the power generation of the gas unit at time t. η_g is the power generation of the gas turbine. $H_{b,t}$ is the thermal power of the gas boiler at time t. η_b is the efficiency of the gas boiler. L_{hvng} is the low-level heat value of natural gas.

$$C_{VM,t} = P_{g,t} \cdot C_{g,vm,t} + H_{whb,t} \cdot C_{whb,vm,t} + H_{b,t} \cdot C_{b,vm,t} + H_{ac,t} \cdot C_{ac,vm,t} + P_{CH,t} \cdot C_{CH,vm,t} + (P_{chr,t} + P_{dis,t}) \cdot C_{bt,vm,t} \quad (9)$$

where $C_{g,vm,t}$ indicates the operation and maintenance cost of the gas turbine, and $H_{whb,t}$ is the thermal power of the waste heat boiler, which is calculated as shown in Formulas (10) and (11). $C_{whb,vm,t}$ and $C_{b,vm,t}$ are the operation and maintenance costs of preheating the boiler and gas boiler respectively. $H_{ac,t}$ is the suction chiller power, and $C_{ac,vm,t}$ is the suction chiller operation and maintenance cost. $P_{CH,t}$ is the electric chiller power, and $C_{CH,vm,t}$ is the electric chiller operation and maintenance cost. $P_{chr,t}$, $P_{dis,t}$, and $C_{bt,vm,t}$ are the charging power, discharging power, and cost of stored energy, respectively.

$$H_{whb,t} = H_{g,t} \cdot \eta_{whb} \quad (10)$$

$$H_{g,t} = \frac{P_{g,t} \cdot (1 - \eta_g - \eta_L)}{\eta_g} \quad (11)$$

3.1.2. Constraints

The power output and power balance constraints for each type of resource in the system are shown in Formulas (12) and (13).

(1) PV

$$0 \leq P_{PV,t} \leq P_{PV,max} \quad (12)$$

(2) Wind power

$$0 \leq P_{Wind,t} \leq P_{Wind,max} \quad (13)$$

where $P_{Wind,r,t}$ is the actual output of wind power.

(3) Micro gas turbines (MT)

(1) Equipment output constraint

$$u_{g,t} \mathrm{P}_g^{min} \leq P_{G,t} \leq u_{g,t} \mathrm{P}_g^{max} \quad (14)$$

where P_g^{max} and P_g^{min} are the maximum and minimum output of equipment g, respectively, and $u_{g,t}$ is a binary variable indicating the operating state of MT g. The operating state is taken as 1, otherwise, it is taken as 0.

(2) Equipment start-stop constraints

$$(u_{g,t}^{off} - u_{g,t}^{on}) \times |u_{g,t-1} - u_{g,t}| = u_{g,t-1} - u_{g,t} \quad (15)$$

$$u_{g,t}^{off} + u_{g,t}^{on} \leq 1 \quad (16)$$

where $u_{g,t}^{on}$ and $u_{g,t}^{off}$, respectively, represent the startup and shutdown state variables of MT g at time t. In the startup state, $u_{g,t}^{on}$ takes 1 and $u_{g,t}^{off}$ takes 0. In the shutdown state, $u_{g,t}^{on}$ takes 0 and $u_{g,t}^{off}$ takes 1.

(3) Climbing power constraint

$$-DR_g \leq P_{g,t} - P_{g,t-1} P_{g,t-1} \leq UR_g \quad (17)$$

where UR_g and DR_g are the up-climbing rate and down-climbing rate of equipment g, respectively.

(4) Rotate alternate constraint

$$R_{U,g,t} = min\left\{UR_g, \left(P_{g,t}^{max} - P_{g,t}\right)\right\} \tag{18}$$

$$R_{D,g,t} = min\left\{DR_g, \left(P_{g,t} - P_{g,t}^{min}\right)\right\} \tag{19}$$

(5) Gas fired boiler

$$H_{b,t} \leq H_{b,max} \tag{20}$$

where $H_{b,t}$ and $H_{b,max}$ are the thermal power and a maximum power of the gas boiler, respectively.

(6) Electrochemical energy storage

$$W_i^{min} \leq W_{i,t} \leq W_i^{max} \tag{21}$$

$$0 \leq P_t^{i,chr} \leq \mathrm{P}_i^{i,max} * U_t^{i,chr} \tag{22}$$

$$0 \leq P_t^{i,dis} \leq \mathrm{P}_i^{i,max} * U_t^{i,dis} \tag{23}$$

$$U_t^{i,chr} + U_t^{i,dis} \leq 1 \tag{24}$$

where W_i^{min} and W_i^{max} are the minimum and maximum energy storage capacity of energy storage equipment i, respectively. $U_t^{i,chr}$ and $U_t^{i,dis}$ are the binary state variables indicating the charging and discharging of energy storage equipment i. In the charging state, $U_t^{i,chr}$ takes 1 and $U_t^{i,dis}$ takes 0, which is the opposite when discharging.

(7) Suction chiller

$$Q_{ac,t} = H_{ac} \cdot COP_{ac} \tag{25}$$

where $Q_{ac,t}$ is the cooling power of the suction chiller, H_{ac} is the input thermal power, and COP_{ac} is the efficiency of the electric refrigerator.

(8) Electric chiller

$$Q_{CH} = P_{CH} \cdot COP_{CH} \tag{26}$$

$$0 \leq P_{CH} \leq P_{CH,Max} \tag{27}$$

where Q_{CH} and P_{CH} are the electric chiller output and input power, respectively. COP_{CH} is the electric chiller performance coefficient. $P_{CH,Max}$ is the maximum input power of the electric chiller.

(9) Transaction constraints with the main network

$$0 \leq P_{buy,t} \leq U_{buy,t} P_{buy,max} \tag{28}$$

$$0 \leq P_{sell,t} \leq U_{sell,t} P_{sell,max} \tag{29}$$

$$U_{buy,t} + U_{sell,t} \leq 1 \tag{30}$$

where $P_{buy,t}$ and $P_{sell,t}$ are the purchasing power and selling of the DERA to the main network at time t. Considering the capacity limitation of the transmission network, $P_{buy,max}$ and $P_{sell,max}$ are the maximum values of the power interacting with the system with the external grid. $U_{buy,t}$ and $U_{sell,t}$ indicate the binary variables of the DERA power purchase and sale states, which ensures that the aggregator does not purchase and sells power at time t. When purchasing electricity, $U_{buy,t}$ takes 1 and $U_{sell,t}$ takes 0, and the opposite is true when selling electricity.

(10) Power balance constraints of system operation

$$P_{pv,t} + P_{wt,t} + P_{G,t} + \mathrm{P}_{dis,t} + P_{buy,t} - P_{sell,t} = P_{CH,t} + P_{chr,t} + P_{L,t} \tag{31}$$

$$H_{b,t} + H_{whb,t} = H_{ac,t} + H_{H,t}/\eta_{he} \tag{32}$$

$$H_{ac,t} \cdot COP_{ac} + COP_{CH} * P_{CH,t} = Q_{C,t} \tag{33}$$

$$0 \leq Q_{C,t} \leq Q_{max} \tag{34}$$

$$H_{H,t} \leq H_{max} \tag{35}$$

$$H_{b,t} \leq H_{b,max} \tag{36}$$

where $P_{L,t}, H_{H,t},\ and\ Q_{C,t}$ are the load of electricity, heat, and cold at time t, respectively. $P_{dis,t}$ and $P_{chr,t}$ are energy storage discharge power and charging power, respectively. $P_{CH,t}$ is the electric chiller input power. η_{he} is the heat exchange coefficient. COP_{CH} is the cooling efficiency of the electric chiller. Q_{max} is the maximum cold demand of the RDES.

3.2. Decision-Making Model of a DERA Participating in the Day-Ahead Trading Based on IGDT

The DERA is the power trading agent of the entities in the system and has the decision-making power over the system operation. Therefore, the DERA only needs to make decisions according to its risk preference in power trading, without considering the risk appetite of the subjects in the system. The robust model of the IGDT represents the maximum risk of hedging market price fluctuations without going above the expected cost level. The robustness factor β_R reflects the strength of the decision maker's hedge against the risk of price fluctuation. Therefore, the robust model of a DERA's trading decision in the day-ahead market based on the IGDT model is shown in Formula (37).

$$\begin{gathered} max_{P_{Q,t}} \alpha_\tau \\ \text{s.t.} \begin{cases} max_{\alpha_\tau}\left(\sum_{t=1}^{T} C_t\right) \leq (1+\beta_R)C_0 \\ \text{Formulas (12)–(36)} \\ \tau_{DA,t} = \tau_{DA,pre,t} + \alpha_\tau \cdot \tau_{DA,pre,t} \\ \tau_{DA,t} \geq max\left(\tau_{DA,min}, (1-\alpha_\tau)\tau_{DA,pre,t}\right) \\ \tau_{DA,t} \leq min\left(\tau_{DA,max}, (1+\alpha_\tau)\tau_{DA,pre,t}\right) \end{cases} \end{gathered} \tag{37}$$

Similarly, the opportunity model of the IGDT represents a trading strategy that seeks to minimize market price volatility at no higher than the expected cost level. The opportunity factor β_O reflects the degree of risk-seeking by the decision maker. Then, the day-ahead trading decision opportunity model is shown in Formula (38).

$$\begin{gathered} min_{P_{Q,t}} \alpha_\tau \\ s.t. \begin{cases} min_{\alpha_\tau}\left(\sum\limits_{t=1}^{T} C_t\right) \leq (1-\beta_O)C_0 \\ \text{Formulas (12)–(36)} \\ \tau_{DA,t} = \tau_{DA,pre,t} - \alpha_\tau \cdot \tau_{DA,pre,t} \\ \tau_{DA,t} \geq max\left(\tau_{DA,min}, (1-\alpha_\tau)\tau_{DA,pre,t}\right) \\ \tau_{DA,t} \leq min\left(\tau_{DA,max}, (1+\alpha_\tau)\tau_{DA,pre,t}\right) \end{cases} \end{gathered} \tag{38}$$

where α_τ is the range of market price fluctuations, β_R and β_O are the cost deviation coefficients of the robust model and opportunity model, respectively, which can be interpreted as risk tolerance. C_0 is the operating cost of the DERA participating in the day-ahead market under the deterministic scenario. T is the total number of periods. $\tau_{DA,min}$ and $\tau_{DA,max}$ are the highest and lowest clearing prices in the day-ahead market, respectively.

In the IGDT model, robust bidding agents are risk-averse in their decision-making. When the system needs to purchase power, it prefers to obtain a more robust decision by increasing the cost. Therefore, the IGDT robust bidding model can achieve the worst scenario of market price fluctuation using an optimization method under the given cost expectation, where all possible costs obtained by decision makers are not higher than their expected costs. On the contrary, opportunistic bidding subjects are risk speculative in their decision-making, and they are more willing to pursue the minimum possible cost under high risk and make more aggressive decisions. Therefore, the IGDT opportunistic-bidding model can realize the scenario of using optimization methods to find the minimum market price fluctuation under a given cost expectation. When the market price varies within the range of opportunity fluctuation, the minimum cost that the decision maker can achieve is its expected cost.

3.3. Day-Ahead Trading Decision Model of the DERA Based on Risk Perception

Prospect theory is one of the decision theories proposed by Daniel Kahneman and Tversky, professors of psychology at Princeton University, U.S. [40]. Prospect theory suggests that decision makers ultimately judge the merit of a decision solution based on the deviation between the strategy optimization outcome and the expectation, rather than the strategy optimization outcome itself. In an uncertain environment, on the one hand, decision makers are risk averse in the face of gains and risk adverse in the face of losses. On the other hand, they are more sensitive in the face of a small probability of occurrence than in the face of a large probability of occurrence. Therefore, based on the different reference points, decision makers have different perceptions of "gain" or "loss" when faced with the same benefit or cost due to different expectations.

In the dual-track market environment, it is assumed that a DERA trades electricity through the wholesale market-trading center. If it is successful in market trading, it will be settled at the market price, while if it is unsuccessful, it will be settled at the benchmark electricity price. According to the deviation between the market price and the benchmark price for settlement, the DERA considers the winning and nonwinning bids to determine the declared power and declared tariff of the main grid. In this paper, prospect theory is used to describe the perceived "gain" or "loss" of the DERA in terms of winning and losing bids.

(1) Power purchase decision model based on prospect theory

According to the IGDT model in Section 3.2, the range of market price fluctuations and trading strategies under the day-ahead robustness and opportunity scenarios at time t can be obtained. In this section, the cost paid by the benchmark feed-in tariff settlement method is used as the reference benchmark, and then, the expected cost of aggregators can be expressed as Formula (39).

$$C_{0,t} = \tau_{FIT,t} \cdot P_{buy,t} \tag{39}$$

where $C_{0,t}$ is the transaction cost of the DERA settled through the grid company at the benchmark tariff. τ_{FIT} is the fixed on-grid price. Therefore, the perceived deviation of the DERA's day-ahead transaction cost from the expected cost is shown in Formulas (40) and (41).

$$\Delta C_t = C_{0,t} - C(x_k)_t \tag{40}$$

$$C(x_k)_t = \begin{cases} \tau_{DA,t} \cdot P_{buy,m,t} & P_{buy,m,t} > 0 \\ C_{0,t} & P_{buy,m,t} = 0 \end{cases} \tag{41}$$

where $C(x_k)_t$ is the day-ahead transaction power purchase cost function of the DERA in decision scheme k, which considers two cases of winning bid and not winning bid; $P_{buy,m,t}$ denotes the winning electricity quantity in the market.

The value function reflects the DERA's subjective value perception of the cost deviation ΔC_t. When the cost of electricity purchase is lower than the expected cost, that is, when $\Delta C_t \geq 0$, the decision maker is "gaining" and tends to avoid risks; on the opposite end, it belongs to "losing", and the value function of cost deviation is shown in Formulas (42) and (43).

$$v(C(x_k))_R : \begin{cases} v(C(x_k))_R{}^+ = (\Delta C_t)^a & \Delta C_t \geq 0, P_{buy,m,t} > 0 \\ v(C(x_k))_R{}^- = -\gamma(-\Delta C_t)^b & \Delta C_t < 0, P_{buy,m,t} > 0 \end{cases} \tag{42}$$

$$v(C(x_k))_R : \begin{cases} v(C(x_k))_R{}^+ = (\Delta C_t)^a & \Delta C_t \geq 0,\ P_{buy,m,t} = 0 \\ v(C(x_k))_R{}^- = -\gamma(-\Delta C_t)^b & \Delta C_t < 0, P_{buy,m,t} = 0 \end{cases} \quad (43)$$

where $v(C(x_k))_R$ is the value function of the power purchase cost deviation of the aggregator under robust or opportunistic strategy; a and b are the risk preference coefficient and risk aversion coefficient, respectively.

According to the calculation results of the IGDT model, the market price fluctuation range α can be obtained. To simplify the solution process, it is assumed that the day-ahead market price obeys the normal distribution $N(E_{\tau,t}, \sigma_{\tau,t})$ in the fluctuation range, where $E_{\tau,t}$ and $\sigma_{\tau,t}$ represent the mean and variance of the market price at time t, respectively. Then, considering the different relationship between market price and benchmark electricity price, the probability of the occurrence of gain-perception and loss-perception events is determined.

(1) The market price is lower than the benchmark price

As the decision maker takes the benchmark electricity price as the reference value for settlement, when the market price is lower than the benchmark price, if the subject does not win the bid in the market, it is the same as expected and there is no risk perception. Acquisition perception exists if and only if the subject wins the bid. At this time, the probability of the acquisition perception of the DERA's power purchase is shown in Formula (44).

$$k^+ = F(\tau_{max}) - F(\tau') \quad (44)$$

where $F(\cdot)$ is the probability of the event under a normal distribution. τ_{max} is the maximum value of the predicted clearing electricity price, and τ' 'is the declared electricity price of scheme k.

Thus, the weight function of the perceived corresponding probability of power purchase is shown in Formula (45).

$$\omega(k)^+ = \frac{[k^+]^\theta}{\left[k^{+\theta} + (1-k^+)^\theta\right]^{1/\theta}} \quad (45)$$

where $\omega(k)^+$ is the probability weight function corresponding to the acquisition perception of DERAs in different decision scenarios; θ is the risk attitude coefficient corresponding to acquisition perception.

(2) Market price is higher than the benchmark electricity price

When the market price is higher than the benchmark price, if the subject does not win the bid in the market, it will be the same as the expected level and will not show risk perception. If the subject wins in the market, it will show the "loss" perception. In this case, the probability of the "loss" perception event of the DERA's power purchase is shown in Formula (46).

$$k^- = F(\tau_{max}) - F(\tau') \quad (46)$$

where $F(\cdot)$ is the probability of events under normal distribution; τ_{max} is the maximum value of predicted clearing electricity price; τ' is the declared electricity price of scheme k.

Thus, the probability weighting function of the perceived corresponding power purchase is shown in Formula (47).

$$\omega(k)^- = \frac{[k^-]^\delta}{\left[k^{-\delta} + (1-k^-)^\delta\right]^{1/\delta}} \quad (47)$$

where $\omega(k)^-$ is the probability weight function of the DERA's perceived loss under different decision scenarios, and δ is the attitude risk factor of loss.

Based on the value function and probability weight function, the prospect theory model of the DERA's day-ahead power purchase decision is constructed, and the integrated utility prospect value of each decision option is solved separately. The optimal utility function of the day-ahead power purchase decision is shown in Formula (48).

$$maxU_k = v(x_k)^+ \cdot \omega(k)^+ + v(x_k)^- \cdot \omega(k)^- \tag{48}$$

where U_k is the integrated prospect value corresponding to the kth strategy.

(2) Power sale decision model based on prospect theory

The expected revenue of the aggregator is shown in Formula (49).

$$B_{0,t} = \tau_{FIT,t} \cdot P_{sell,t} \tag{49}$$

where $B_{0,t}$ is the trading revenue of the DERA when the grid company purchases electricity with the benchmark price. Therefore, the perceived deviation between the DERA's day-ahead trading income and the expected income is shown in Formulas (50) and (51).

$$\Delta B_t = B(x_k)_t - B_{0,t} \tag{50}$$

$$B(x_k)_t = \begin{cases} \tau_{DA,t} \cdot P_{sell,t} & P_{sell,t} > 0 \\ B_{0,t} & P_{sell,t} = 0 \end{cases} \tag{51}$$

where $B(x_k)_t$ is the day-ahead trading revenue function of the DERA in decision scheme k, and the winning and nonwinning cases are considered, respectively.

The value function reflects the DERA's subjective value perception of the revenue deviation ΔB_t. When the income from electricity sales is higher than the expected income, that is, when $\Delta B_t \geq 0$, the decision-making subject is "gaining" and has a tendency to avoid risks; on the opposite end, it is "losing", and the value function of revenue deviation is shown in Formulas (52) and (53).

$$v(B(x_k))_R : \begin{cases} v(B(x_k))_R{}^+ = \Delta B_t{}^a & \Delta B_t \geq 0, P_{buy,m,t} > 0 \\ v(B(x_k))_R{}^- = -\gamma(\Delta B_t)^b & \Delta B_t < 0, P_{buy,m,t} > 0 \end{cases} \tag{52}$$

$$v(B(x_k))_R : \begin{cases} v(B(x_k))_R{}^+ = \Delta B_t{}^a & \Delta B_t \geq 0, P_{buy,m,t} = 0 \\ v(B(x_k))_R{}^- = -\gamma(\Delta B_t)^b & \Delta B_t < 0, P_{buy,m,t} = 0 \end{cases} \tag{53}$$

where $v(B(x_k))_R$ is the deviation value function of the electricity sales income of aggregators under the robust or opportunistic strategy. a and b are the risk preference coefficient and risk aversion coefficient, respectively.

(1) Market price is higher than the benchmark electricity price

When a DERA plays the role of selling electricity at time t, if the market price is higher than the benchmark electricity price and the subject fails to win the bid in the market, it is the same as the expected income and there is no risk perception. The perception of acquisition exists if and only if the subject wins the bid. At this time t, the probability of obtaining a perception of DERA electricity sales is shown in Formula (54).

$$k^+ = F(\tau') - F(\tau_{min}) \tag{54}$$

where $F(\cdot)$ is the probability of the events under normal distribution; τ_{max} is the minimum value of predicted clearing electricity price; τ' is the declared electricity price of scheme k.

Thus, the probability weight function of the perceived corresponding probability of electricity sales is shown in Formula (55).

(2) The market price is lower than the benchmark price

When the market price is lower than the benchmark electricity price, if the subject fails to win the bid in the market, it will not show risk perception, and if the subject wins in the market, it will show the "losing" perception. The occurrence probability of the "losing" perception event of DERA is shown in Formula (55).

$$k^{-} = F(\tau') - F(\tau_{min}) \tag{55}$$

Therefore, the probability weighting function of electricity sales probability perceived as loss is the same as Formula (47).

Similarly, the optimal utility function of the day-ahead electricity selling decision is shown in Formula (48).

3.4. Solution to the Day-Ahead Transaction Decision-Making Model of a DERA Based on MPA

In this paper, the IGDT is used to build a robust model and an opportunistic model, both of which are two-layer optimization models. To obtain the trading strategy, the upper layer model is used to solve the uncertainty of market price fluctuation, and the lower layer model is solved to minimize the day-ahead transaction cost. Given the model's complex constraints, the MPA is used in this paper to solve the problem

The MPA is a novel meta-heuristic optimization algorithm proposed by Afshin Faramarzi et al. in 2020. The MPA optimization is performed in three stages: initialization stage, optimization stage, and FADs or eddy current effect stage [10]. The specific optimization process of the MPA is as follows [11]:

(1) Initialization phase. Set the algorithm parameters and initialize the prey position within the search range, as shown in Formulas (56)–(65):

$$X_0 = X_{min} + rand(X_{max} - X_{min}) \tag{56}$$

where X_{max} and X_{min} denote the range of prey search space, and $rand()$ is a random number within [0, 1].

(2) Optimization stage. The optimization phase is divided into the early iteration, middle iteration, and late iteration [41]. In the early iteration, the number of iterations is less than 1/3 of the maximum number of iterations, the predator is faster than the prey, a global search is performed, and the prey is updated by Brown's random wandering.

$$\begin{cases} stepsice_i = R_B \otimes (Elite_i - R_B \otimes prey_i) \\ prey_i = prey_i + P \cdot R_B \otimes stepsice_i \end{cases} \\ ter < \tfrac{1}{3}\max\_Iter \tag{57}$$

where $stepsice$ is the step size, R_B is a normally distributed Brownian wandering random vector, $Elite_i$ is the elite matrix constructed by the top predator, $prey_i$ is a prey matrix with the same dimension as the $Elite_i$, $\otimes$ is the item-by-item multiplication operation, P takes 0.5, and R is a uniform random vector on [0, 1]. N is the population size, and $Iter$ and max_$Iter$ denote the current and maximum number of iterations, respectively.

In the middle of the iteration, the current iteration is less than 2/3 of the maximum. The population is divided into two parts. The prey does levy motion and is responsible for the exploitation of the algorithm in the search space. The predator does Brownian motion, is responsible for the exploration of the algorithm in the search space, and gradually shifts from exploration to exploitation of the strategy [42].

At the end of the iteration, the current iteration is greater than 2/3 of the maximum iteration number, which mainly improves local exploitation, the predator wanders based on the levy, and it is slower than the prey.

$$\begin{cases} stepsice_i = R_L \otimes (R_L \otimes Elite_i - prey_i) \\ prey_i = Elite_i + P \cdot CF \otimes stepsice_i \\ Iter > \frac{2}{3}\max\_Iter \end{cases} \tag{58}$$

where R_L is a random vector of levy distribution and $CF = (1 - Iter/\max\_Iter)^{2Iter/\max\_Iter}$ is the adaptive parameter used to control predator movement compensation.

(3) Fish aggregation devices (FADs) or eddy current effect. This strategy typically alters the disorientation behavior of ocean predators, allowing the MPA to overcome the premature convergence problem and avoid falling into local extremes during the optimization search [43].

$$prey_i = \begin{cases} prey_i + CF[X_{min} + R_L \otimes (X_{max} - X_{min})] \otimes U, r \leq FADs \\ prey_i + [FADs(1-r) + r](prey_{r1} - prey_{r2}), r > FADs \end{cases} \tag{59}$$

where $FADs$ is the influence probability, which is set to 0.2, U is the binary vector, r is the random number within [0, 1], and $r1$ and $r2$ are the random indexes of the prey matrix, respectively. The solution process is shown in Figure A1.

For the solution of the prospect theory model, the expected cost obtained by IGDT solving and the range of market price fluctuations that satisfy the expected cost is first used as inputs to the model. Subsequently, the value functions corresponding to the robust decision and the opportunistic decision are discovered. Then, the probability weight functions under the two decision options are calculated, and the prospect value of each option is determined. Finally, the strategy with the highest prospect value is chosen as the DERA's best decision solution. Figure 2 depicts the solution process.

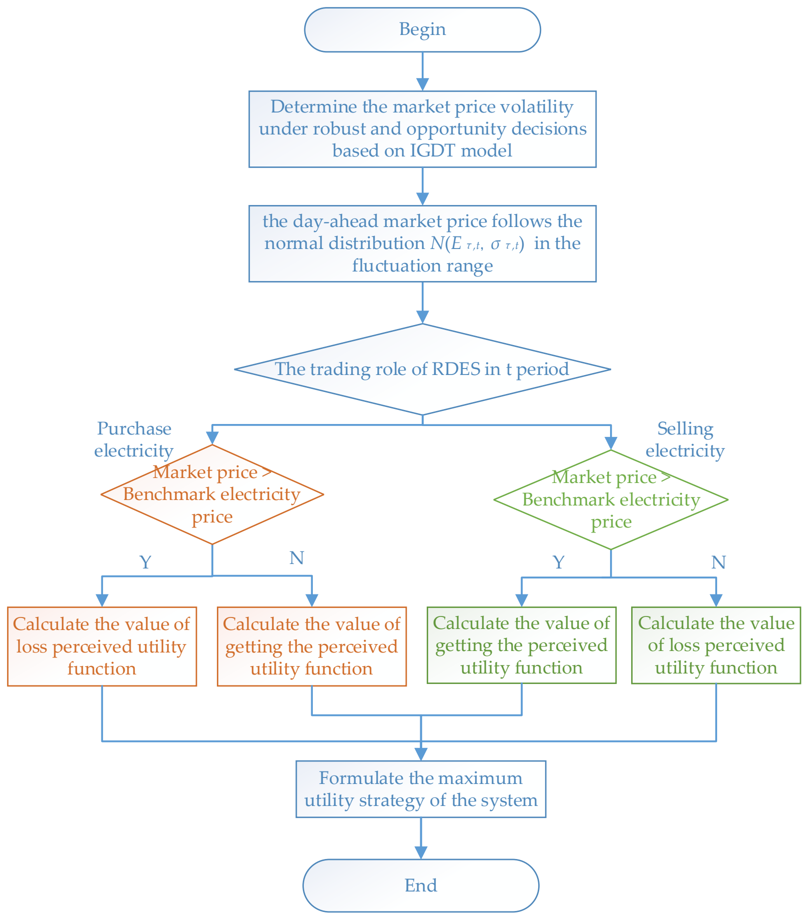

Figure 2. Optimal decision-making process with utility function for DERA.

4. Case Analysis

4.1. Basic Data and Scenario Settings

(1) Basic Data

In this section, the RDES containing MT, distributed wind power, PV, and industrial and commercial users is used as an example for simulation analysis. The maximum power load of RDES is 2.5 MW, the maximum cooling load is 1 MW, and the maximum heating load is 1MW. The specific technical and economic parameters of each type of subject are shown in Tables 1 and 2.

Table 1. Technical and economic parameters of the micro gas turbine.

Maximum Output Power (MW)	Minimum Output Power (MW)	Efficiency (%)	Energy Loss Rate (%)	Climbing Speed (MW/h)	Gas Price (CNY/m^3)
1	0.2	80	10	0.5	3.24

Table 2. Technical and economic parameters of wind and solar storage and electric chiller.

Equipment	Maximum Output Power (MW)	Minimum Output Power (MW)	Efficiency (%)	Climbing Speed (MW/h)	Operation and Maintenance Cost (CNY/MWh)
Wind power	1	0	-	0.6	110
PV	2	0	-	1.5	80
Energy storage	0.2	0.04	95	0.2	20
Electric chillers	1	0	95	-	30
Suction chiller	1	0	70	-	30
Gas fired boiler	1	0	73	-	20

In addition, the operation and maintenance cost of MT is 168.5 CNY/MWh, the low calorific value of natural gas is 9.7 MJ/m^3, and the conversion efficiency of the waste heat boiler is 75%.

Considering that the proposed model considers both uncertainty factors and the decision maker's preference behavior for risk, a 24-point decision scheme is selected to simulate the day-ahead trading model of the DERA to improve the solution efficiency.

First, this section selects the 92-day historical output curves of distributed wind power and PV in the summer of a province in China, and uses the GMM algorithm to screen the typical scenarios of wind power and PV unit outputs, as shown in Figures A3 and A4. The bold lines in Figures A3 and A4 are the scene clustering results obtained by the GMM method. Table 3 shows the probability of each scenario.

Therefore, the expected output scenarios of distributed wind power and PV are obtained as inputs to the IGDT model based on the occurrence probability of each type of scenario, as shown in Figure A2.

Table 3. Probabilities of ten sets of wind and PV power scenarios.

Wind Power Scenarios	Probability	PV Power Scenarios	Probability
1	0.0109	1	0.0543
2	0.0217	2	0.0326
3	0.0109	3	0.0217
4	0.1304	4	0.4239
5	0.4891	5	0.0761
6	0.0326	6	0.0761
7	0.0543	7	0.0870
8	0.1957	8	0.0543
9	0.0217	9	0.0978
10	0.0326	10	0.0761

Similarly, the GMM algorithm was used to obtain typical data of various RDES loads from the historical data of power, heat, and cooling loads of an industrial park in central China, as shown in Figure 3.

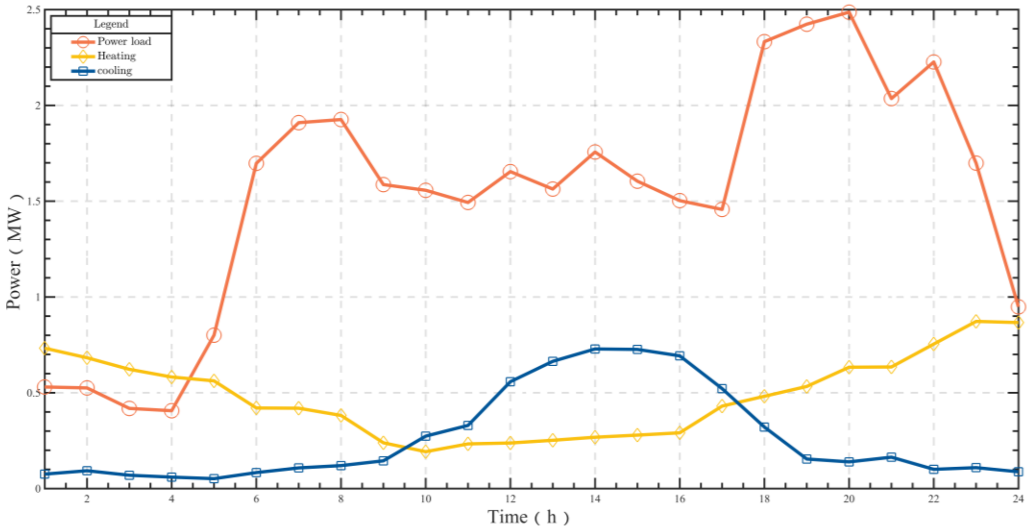

Figure 3. The daily cooling, heating, and power load of the RDES.

In this section, a spot pilot historical liquidation price in China is selected as the database, and the input data is processed based on the simulation results of the market price prediction model, and the day-ahead predicted market price can be obtained, as shown in Figure 4.

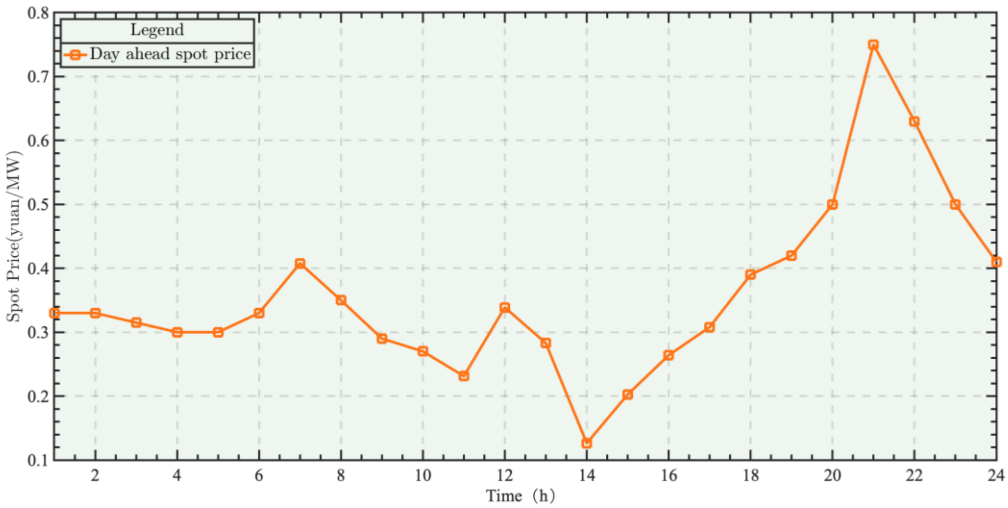

Figure 4. Forecasted day-ahead market price.

(2) Scene Settings

The subjective decision-making behavior of DERAs and different scenarios are considered to obtain the final power purchase strategy, and then, the effectiveness of the proposed model is analyzed. The scenarios include deterministic scenarios, uncertainty scenarios with supply and demand fluctuations, and RDES's power purchase strategies under multiple uncertainty scenarios with supply, demand, and market price fluctuations. The case study scenarios are shown in Table 4.

Table 4. Case study scenarios.

Number	Scenario Description
Scenario 1	It is assumed that the actual clearing price of the day-ahead market and the actual output of wind power and PV in RDES are both predicted values: that is, the decision scenario without considering the effect of uncertainty factors.
Scenario 2	Consider RDES's robust risk appetite and opportunistic risk appetite for market price fluctuations.
Scenario 3	Based on Scenario 2, consider the subjective behavioral impact of DERA's perceived "gain" and "loss" decisions in the dual-track market environment.

4.2. Analysis of Day-Ahead Trading Strategy of Aggregators Based on the IGDT

The usefulness of the model provided in this research is validated in this part using two common trading methods. First, the DERA's core day-ahead trading decision system is built on the deterministic scenario. Second, the IGDT model proposes the DERA day-ahead trading decision scheme for market information uncertainty.

(1) Analysis of day-ahead trading strategies for DERAs under a deterministic scenario

Assuming that DERAs can predict accurately the uncertainty of market price and new energy unit output in day-ahead trading, the trading scenario under a deterministic scenario can be obtained by solving the day-ahead trading optimization model of DERAs in Section 3.1, as shown in Figure 5.

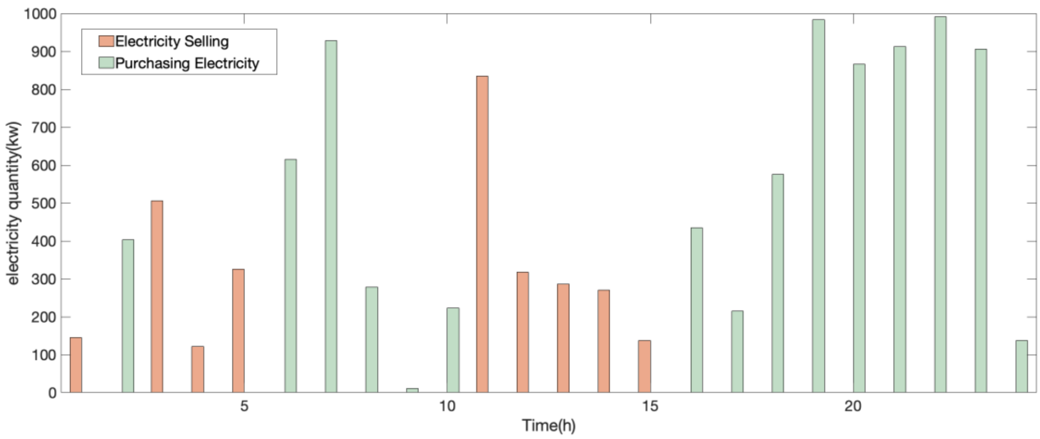

Figure 5. Bidding strategy of DERA without uncertainties.

In Figure 5, the horizontal axis indicates the period time, and the vertical axis indicates the purchase and sale power of the DERA. When the system supply is less than the demand, the DERA needs to purchase electricity from the wholesale market, as shown in the green bar graph. On the contrary, when the system supply exceeds the demand, the system surplus will be traded online, as shown in the brown bar graph. As can be seen from the figure, RDES sells power to the main grid at 1:00, 3:00–5:00, and 11:00–15:00, which occurs mainly due to the large generation of wind and PV units. In other hours, the DERA needs to purchase power from the main network. The maximum purchasing power is 0.99 MW, and the minimum operating cost is 9011.38 CNY. The operation of each electric price of equipment is shown in Figure 6.

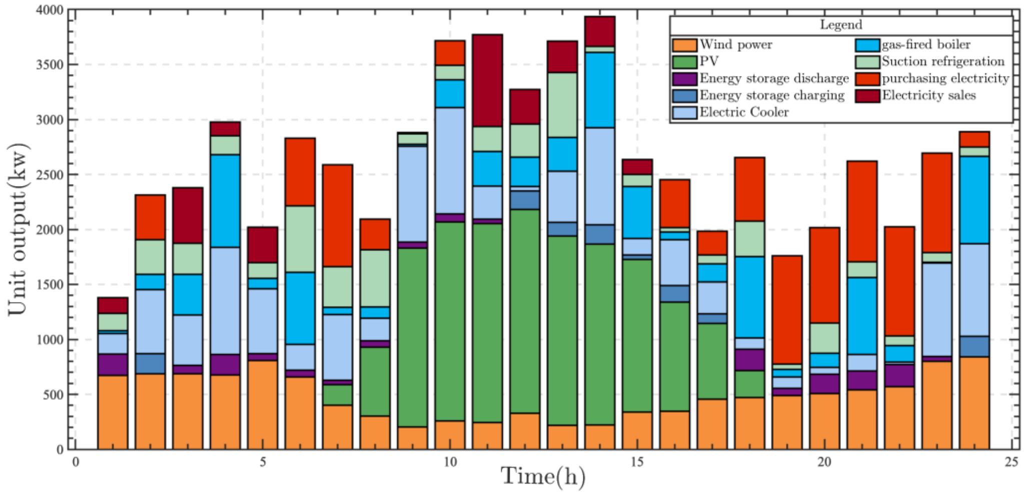

Figure 6. Volume of tradable electricity and operation of electrical units.

(2) Analysis of IGDT decision of the DERA considering risk preference of day-ahead market price fluctuation

In this section, the IGDT model is solved by using the MPA. The population size is 100, and the maximum number of iterations is 8000. The simulation model is implemented through Python 3.7. When the robust factor is taken as 0.6 and the expected cost is 9252.86 CNY, by solving the IGDT robust model, a robust strategy of DERAs participating in day-ahead trading can be obtained, as shown in Figure 7.

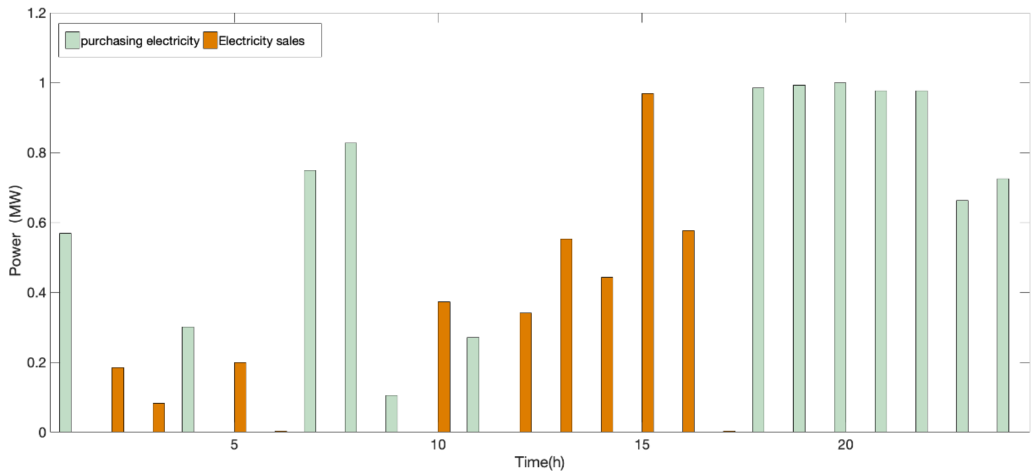

Figure 7. Robust strategy for DERAs in the day-ahead market.

Figure 7 shows that the strategy of decision makers with robust preference is different from the strategy in the determined scenario. At 2:00, 3:00, 5:00–6:00, 10:00, and 12:00–17:00, electricity is sold to the market and is purchased from the market at other times. In the robust scenario, the cost of power purchase for the system is 4961.21 CNY, and the revenue from power sales is 1020.41 CNY. Compared with the deterministic scenario, when choosing the power purchase and sale strategy, customers choose to sell power at the higher market price to ensure their basic returns. Meanwhile, from the power purchase and sale strategies of deterministic and robust scenarios, it can be obtained that the strategy of RDES is formulated based on the system generation capacity. At this time, the operation of each piece of equipment in the system is shown in Figure 8.

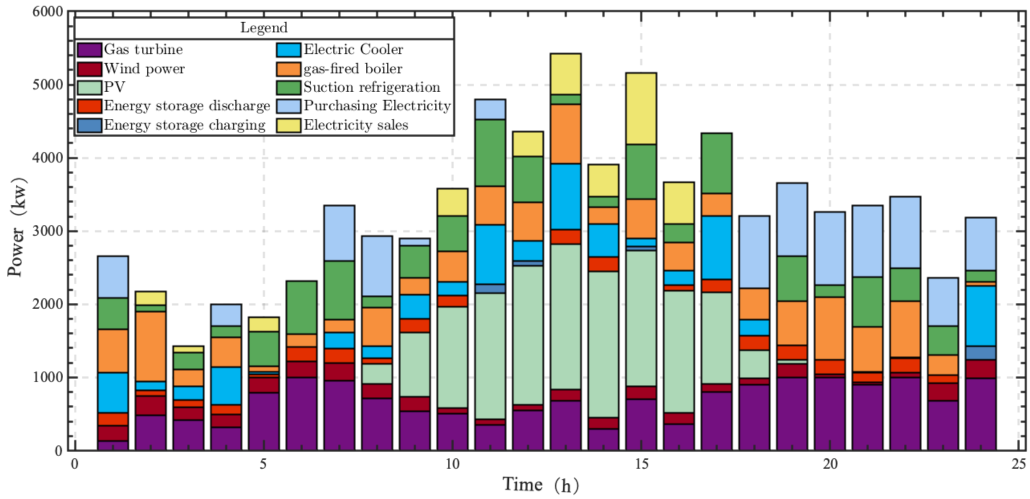

Figure 8. Volume of tradable electricity and operation of electrical units with the robust strategy.

Similarly, when the opportunity factor is taken as 0.2 and the expected cost is 5983.65 CNY, the cost of power purchase from the system to the main network is 6906.26 CNY, and the revenue from power sales is 736.634 CNY. At this time, the minimum deviation of the market price fluctuation is 0.62365. The day-ahead trading strategy for opportunistic DERAs is shown in Figure 9.

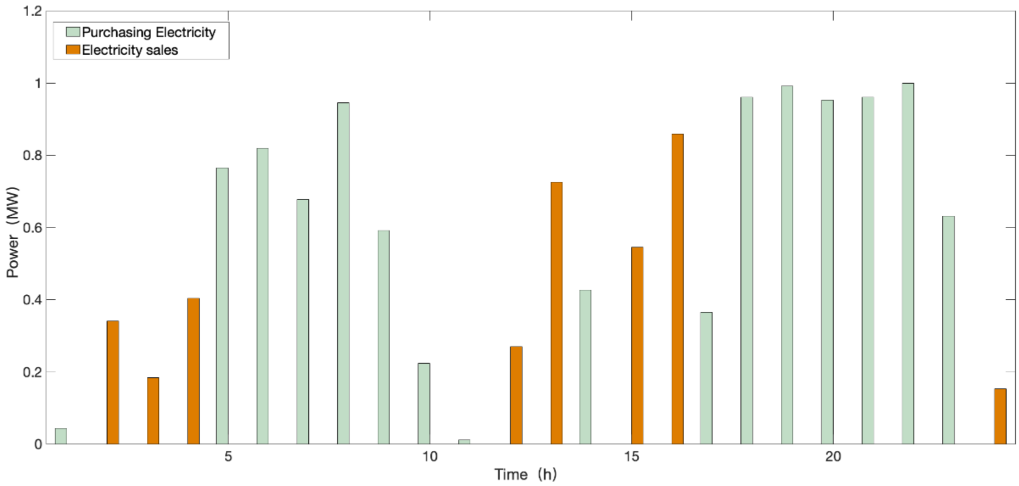

Figure 9. Opportunity strategy for DERA in the day-ahead market.

In the opportunity strategy scenario, the DERA receives revenue from selling electricity in the day-ahead market at 2:00–4:00, 12:00–13: 00, 15:00–16:00, and 24:00. At other times, the DERA needs to purchase electricity from the market due to system balance constraints. Compared to the robust strategy scenario, the DERA prefers to purchase electricity at a low price in the day-ahead market to reduce the cost and obtain potential benefits under the opportunity strategy. Under the robust strategy, the DERA chooses to increase the quantity of electricity sold and increase its revenue. The above data verifies that DERAs under the opportunity strategy prefer potential profit from price fluctuation risk. The system's output of each unit under the opportunity strategy is shown in Figure 10.

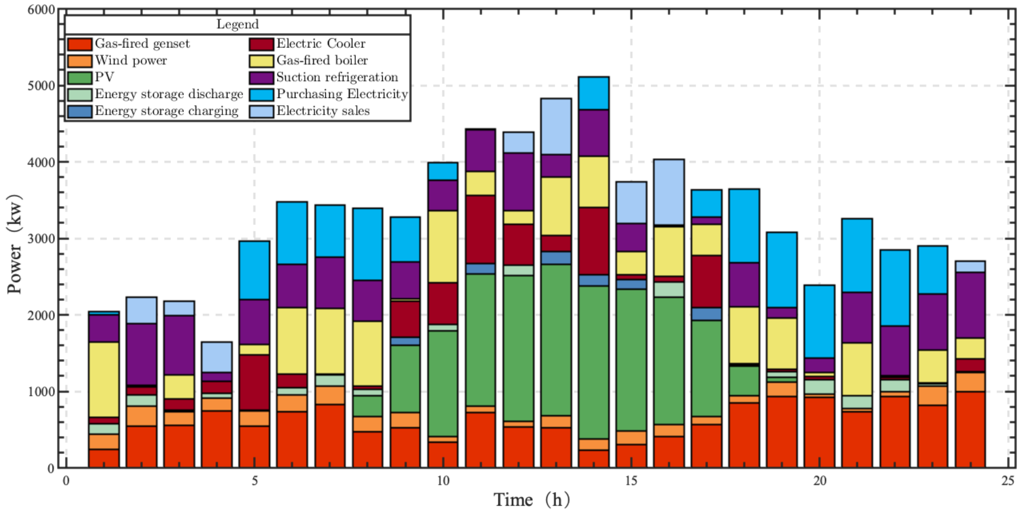

Figure 10. Volume of tradable electricity and electrical units operation with the opportunity strategy.

4.3. Analysis of Day-Ahead Trading Strategy of Aggregators under Different Factor Scenarios

To explore the influence of different robustness and opportunity factors on the DERA's day-ahead decision, the robust and opportunity strategies of DERAs under different desired goals are analyzed below by varying the values of the robustness and opportunity factors, as shown in Figures 11 and 12, respectively.

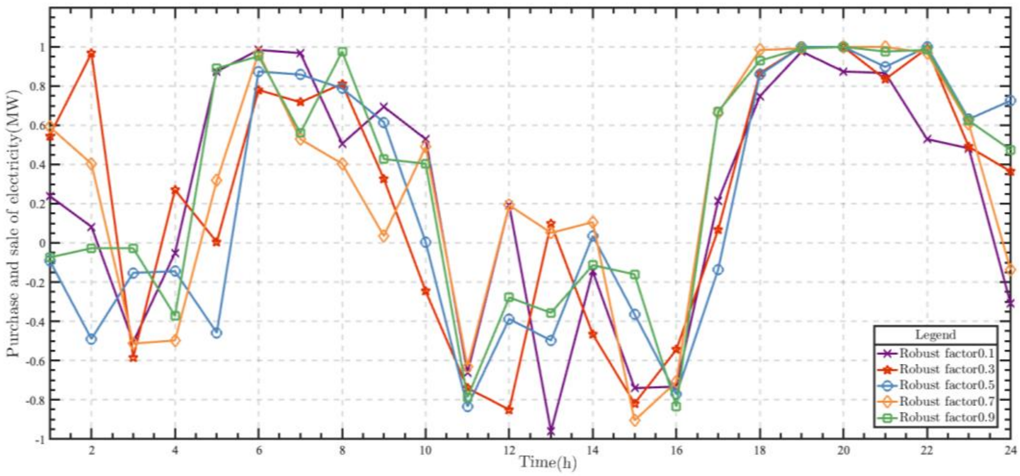

Figure 11. Robust decisions for DERA along with the robust factors.

The robust decision scenarios of DERAs corresponding to different robust factors are shown in Figure 11, where the horizontal coordinate indicates the time in the day-ahead market and the vertical coordinate indicates the power purchase and sale strategy adopted by the DERA.

The opportunity strategy reflects the risk-chasing characteristics of the DERA, and the opportunity factor affects the range of trading decisions made by the DERA. By varying the range of values of the opportunity factor, the range of trading strategies and opportunity deviations under different risk characteristics of DERAs can be obtained. To verify the strategy variation under different opportunity scenarios, the opportunity factors are taken as 0.1, 0.3, 0.5, 0.7, and 0.9, respectively. The trading strategies under different opportunity factors are shown in Figure 12.

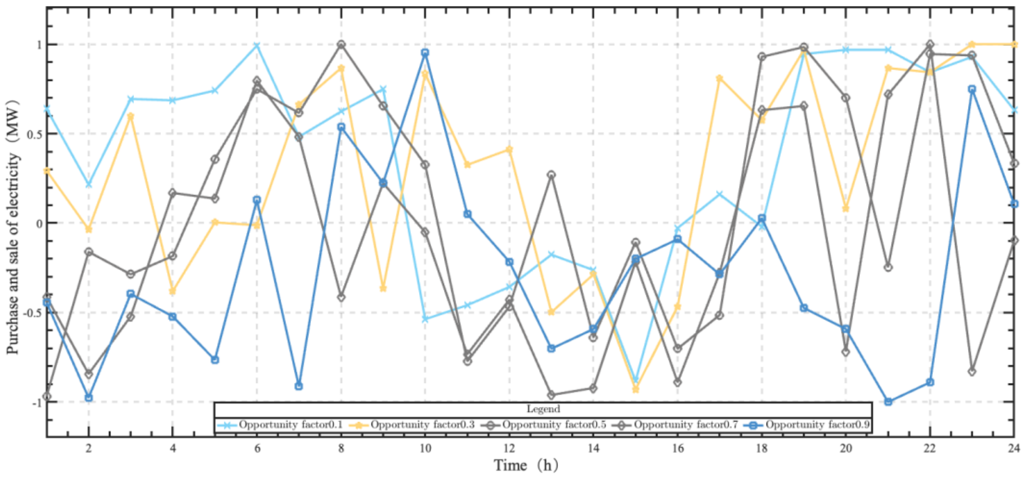

Figure 12. Opportunity decisions for DERA along with the opportunity factors.

The opportunity strategy emphasizes market participants' preference for opportunity gains from price fluctuations. As the opportunity factor is gradually increased, the DERA's risk preference for the day-ahead market gradually increases and the system's cost of operation is gradually reduced. At the same time, the DERA believes that the price volatility has also become greater. Compared to the robust strategy, the DERA under the opportunity strategy is more inclined to sell electricity to the market and offset system operating costs with revenue.

4.4. DERA Decision Analysis Based on Prospect Theory

At present, there are two main ways for RDES to interact with the power grid in China. The first one is that the DERA participates in the spot market, and the trading center will aggregate the liquidated power and settle the liquidated power according to the market price. The second one is that the grid will purchase the remaining unliquidated power of RDES according to the feed-in tariff of 0.55 CNY/kWh. According to a provincial day-ahead market data situation, the day-ahead market price fluctuation deviation obeys the normal distribution N($E_{\tau,t}, \sigma_{\tau,t}$), where $E_{\tau,t}$ and $\sigma_{\tau,t}$ represent the mean and variance of market price at time t, and the declared price step takes 0.005 CNY. According to the experimental determination of Kahneman and Tversky [40], the risk preference coefficient a is taken as 0.88. The risk aversion coefficient b is taken as 0.67, and θ and δ are taken as 0.61 and 0.67, respectively. The sensitivity coefficient γ of the DERA to loss and gain is taken as 1.25.

According to the IGDT scenario analysis, when the robustness factor is taken as 0.6, the expected cost is 9252.86 CNY and the minimum deviation of predicted market price fluctuation is 0.62365. Based on this scenario, the value of $\omega(k)$ and $v(x_k)$ under the perception of loss and gain of the DERA in the day-ahead market can be obtained, and then, the optimal utility offer strategy under the robust strategy can be obtained, as shown in Figure 13.

In Figure 13, a positive decision variable indicates that the DERA purchases electricity in the day-ahead market and a negative number indicates power sales. When purchasing electricity, if the market price is higher than the benchmark price, the DERA is more willing to increase the declared price, reduce the winning bid and increase the purchased electricity to reduce the system operating cost. When selling electricity, if the market price is higher than the benchmark price, the DERA is more willing to lower the declared price and increase the winning bid to reduce the electricity purchased by the power grid, thus increasing the system's revenue from electricity sales.

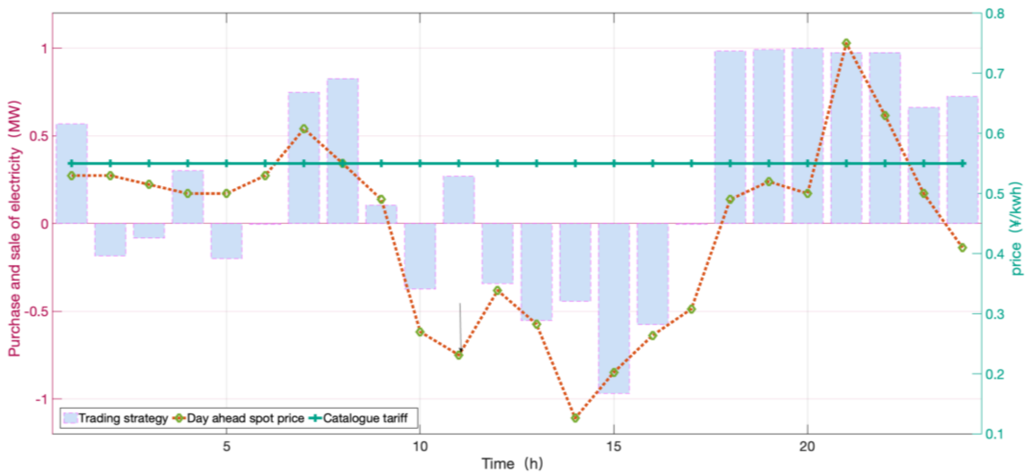

Figure 13. Robust bidding strategies of DERA considering psychological behavior.

When both the robustness factor and the opportunity factor are taken as 0.6, the optimal offer strategy for DERA participation in the day-ahead market under the opportunity strategy space can be obtained. The bidding strategy is shown in Figure 14.

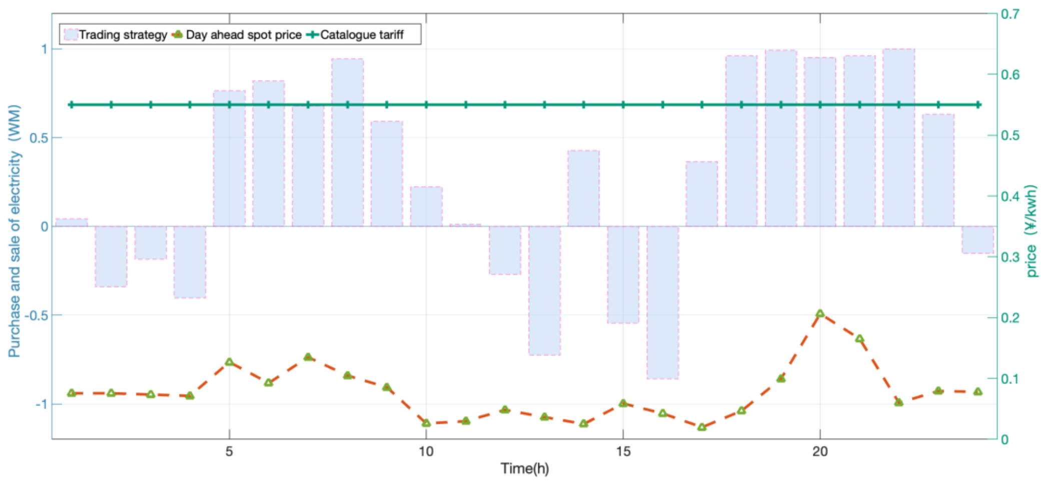

Figure 14. Opportunity bidding strategies of DERA considering psychological behavior.

4.5. Discussion

As evidenced by the preceding chapters' outcomes, when the supply and demand are in balance, the system will optimize the output of operating units according to the current price and demand of the external market. When the market price in the day-ahead decreases, the DERA will choose to sell or purchase electricity by judging the difference between its generation cost and the revenue from electricity sales. This phenomenon also proves that the day-ahead market price affects demand, reflecting the role of market mechanisms for optimal resource allocation.

The size of the robustness factor has an impact on the strategy of purchase and sale strategy, but the overall trend is similar. The change of robustness factor also affects the DERA's power purchase and sale strategy. By changing the value in the robustness factor, the upper and lower limits of the robustness deviation of the DERA's bidding strategy can be obtained. The robust optimization model can satisfy the optimal decision in the worst environment. Therefore, in the robust scenario, RDES can withstand greater price volatility in the day-ahead market, but the robust model is conservative, so the DERA will reduce the bidding expectations and increase the system operating cost to improve the achievability of the expected revenue.

For the opportunity strategy considering the DERA's psychological behavior, the DERA's forecasted market price will be lower than the benchmark tariff. Under the opportunity strategy, when the DERA participates in the day-ahead market as a power buyer, the DERA mainly adopts the strategy of declaring lower prices than the predicted market price to improve the winning rate and reduce the power purchase cost at the catalog tariff. On the contrary, when participating in the day-ahead market as a power producer, it will increase the declared price, reduce the winning rate, and prefer to settle at the grid catalog tariff, thus realizing higher revenue from electricity sales.

The trading-assisted decision model put forth in this paper can accomplish the following through the aforementioned case study: The GMM assists aggregators in better analyzing potential power-out scenarios and minimizing the effects of power-out uncertainty. The opportunity strategy and robust strategy produced by the IGDT model, in addition, further explain how the aggregator's strategy changes under various risk levels and the return curve produced by such changes, assisting market participants with various risk preferences in creating reasonable trading strategies. The aggregator can create a reasonable proportion strategy of guaranteed acceptable electricity and market telephone electricity against the backdrop of China's dual-track market by calculating the benefit function of various strategies based on the prospect theory to achieve the best overall benefit.

5. Conclusions

This paper presents a trading assistant decision-making model for distributed energy systems participating in the spot market based on an analysis of the key influencing factors of regional distributed energy systems. It emphasizes the influence of new energy output uncertainty, the market subject risk preference, and the dual-track market environment on the aggregator's trading behavior decision-making. These are the precise contents:

First, in order to lessen the impact of price volatility and new energy output uncertainty on trading choices, the Gaussian mixture model and IGDT model are applied.

Second, the robust strategy model and opportunity strategy model are constructed, respectively, taking into account the risk preferences of various aggregation quotients. The return curve under various strategies can serve as a tactical foundation for decision makers who are exposed to various types of risk.

Finally, the maximum utility strategy of day-ahead market transactions under the dual-track market environment is produced, providing a tactical foundation for distributed energy systems to engage in electricity transactions more effectively. This approach successfully addresses the subjective behavior elements of decision makers under the dual-track market environment.

The auxiliary decision model suggested in this paper can assist market participants in better adapting to spot trading in the context of a dual-track market, enhance distributed energy participants in developing more sensible trading decision-making schemes, and serve as a useful benchmark for developing spot market rules utilizing distributed energy trading. The market types for distributed energy participation will also diversify as distributed energy building picks up speed. In the future, it is necessary to deeply study the combination scheme of multiple market varieties for distributed energy transaction decision-making.

Author Contributions: Conceptualization, J.D. and X.D.; methodology, D.L.; software, X.D. and D.L.; validation, J.D., X.D. and D.L.; formal analysis, X.D.; investigation, D.L.; resources, Y.Z.; data curation, A.B.; writing—original draft preparation, X.D.; writing—review and editing, D.W.; visualization, X.D.; supervision, J.D.; project administration, J.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to thank the library of North China Electric Power University for its literature support.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

See Figures A1–A4.

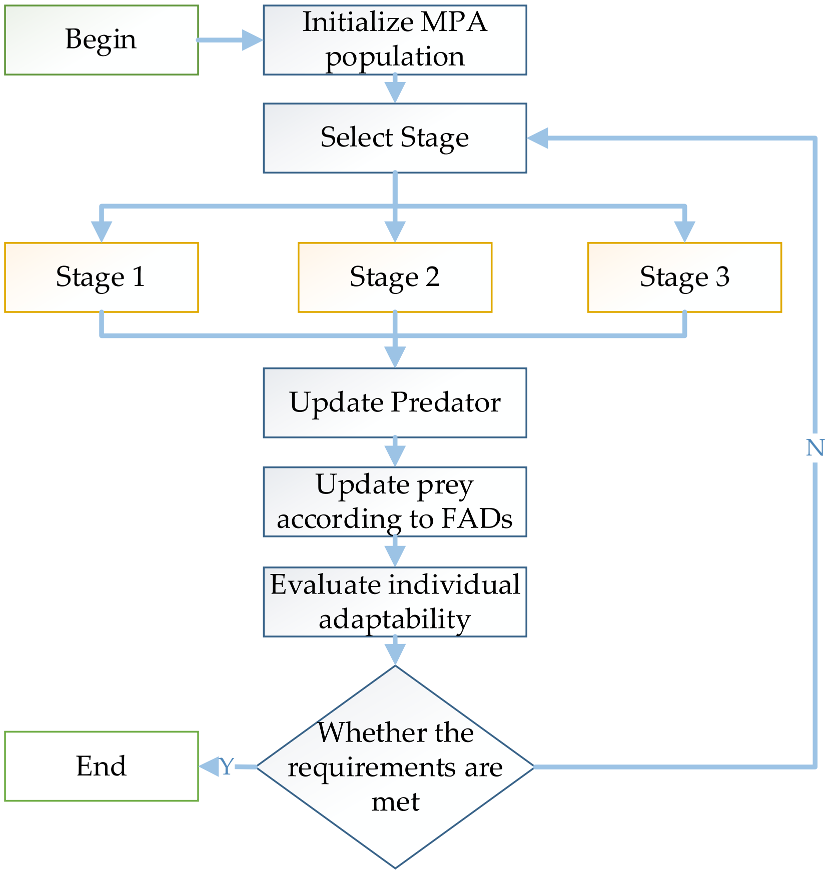

Figure A1. Solving process of MPA.

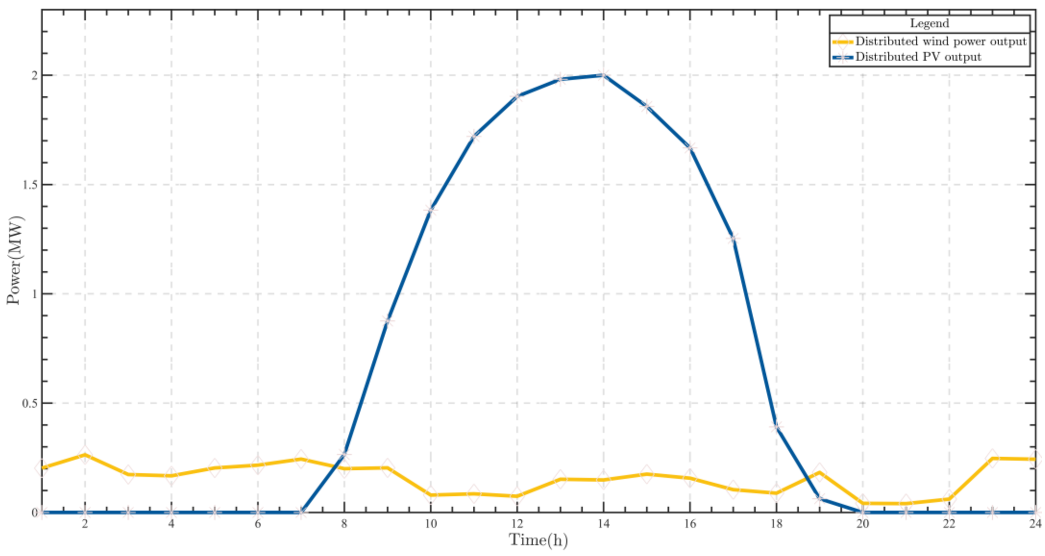

Figure A2. The output of distributed wind and photovoltaic power units.

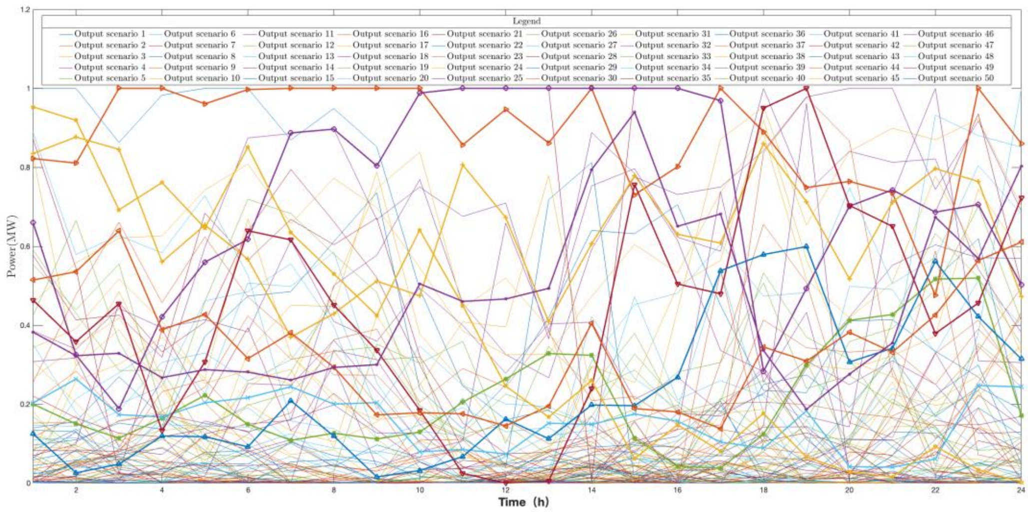

Figure A3. Clustering results of distributed wind power.

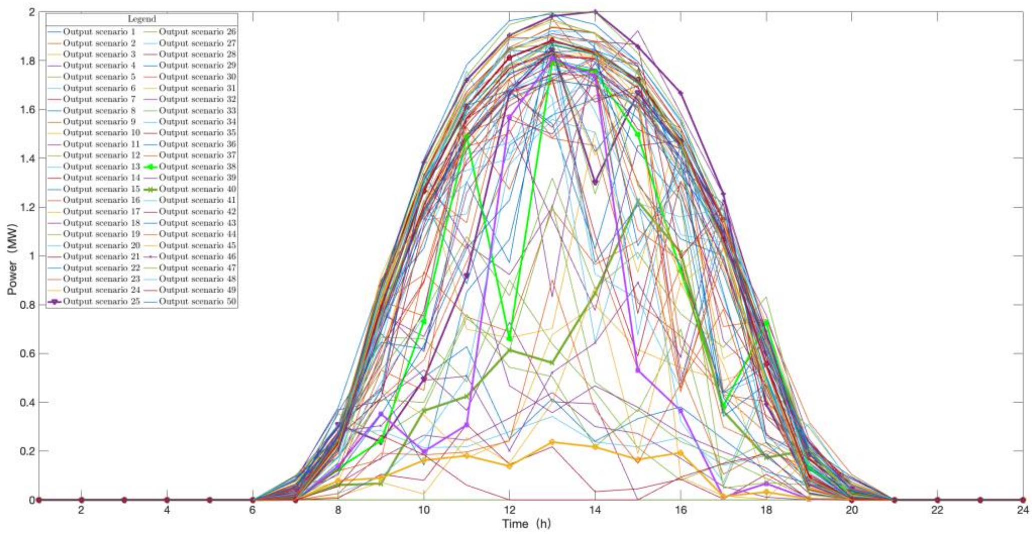

Figure A4. Clustering results of distributed solar power.

References

1. Zheng, B.; Wei, W.; Chen, Y.; Wu, Q.; Mei, S. A peer-to-peer energy trading market embedded with residential shared energy storage units. *Appl. Energy* **2022**, *308*, 118400. [CrossRef]
2. Rodrigues, D.L.; Ye, X.; Xia, X.; Zhu, B. Battery energy storage sizing optimisation for different ownership structures in a peer-to-peer energy sharing community. *Appl. Energy* **2020**, *262*, 114498. [CrossRef]
3. Di Silvestre, M.L.; Gallo, P.; Sanseverino, E.R.; Sciume, G.; Zizzo, G. Aggregation and remuneration in demand response with a blockchain-based framework. *IEEE Trans. Ind. Appl.* **2020**, *56*, 4248–4257. [CrossRef]
4. Kang, J.; Yu, R.; Huang, X.; Maharjan, S.; Zhang, Y.; Hossain, E. Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains. *IEEE Trans. Ind. Inform.* **2017**, *13*, 3154–3164. [CrossRef]
5. Nguyen, D.T.; Le, L.B. Optimal bidding strategy for microgrids considering renewable energy and building thermal dynamics. *IEEE Trans. Smart Grid* **2014**, *5*, 1608–1620. [CrossRef]
6. Mirzaei, M.A.; Hemmati, M.; Zare, K.; Abapour, M.; Mohammadi-Ivatloo, B.; Marzband, M.; Anvari-Moghaddam, A. A novel hybrid two-stage framework for flexible bidding strategy of reconfigurable micro-grid in day-ahead and real-time markets. *Int. J. Electr. Power* **2020**, *123*, 106293. [CrossRef]
7. Mashhour, E.; Moghaddas-Tafreshi, S.M. Bidding strategy of virtual power plant for participating in energy and spinning reserve markets—Part I: Problem formulation. *IEEE Trans. Power Syst.* **2010**, *26*, 949–956. [CrossRef]
8. Sadeghi, S.; Jahangir, H.; Vatandoust, B.; Golkar, M.A.; Ahmadian, A.; Elkamel, A. Optimal bidding strategy of a virtual power plant in day-ahead energy and frequency regulation markets: A deep learning-based approach. *Int. J. Electr. Power* **2021**, *127*, 106646. [CrossRef]

9. Xiao, Y.; Wang, X.; Wang, X.; Bie, C.H. Review and prospect of research on multi energy market coupling transaction. *Glob. Energy Internet* **2020**, *3*, 487–496. [CrossRef]
10. Conejo, A.J.; Nogales, F.J.; Arroyo, J.M. Price-taker bidding strategy under price uncertainty. *IEEE Trans. Power Syst.* **2002**, *17*, 1081–1088. [CrossRef]
11. Wen, F.; David, A.K. Optimal bidding strategies and modeling of imperfect information among competitive generators. *IEEE Trans. Power Syst.* **2001**, *16*, 15–21.
12. Kang, D.; Kim, B.H.; Hur, D. Supplier bidding strategy based on non-cooperative game theory concepts in single auction power pools. *Electr. Pow Syst. Res.* **2007**, *77*, 630–636. [CrossRef]
13. Jing, C.; Yang, Y. Application of the EWA Algorithm in Electricity Market Simulation. *Autom. Electr. Power Syst.* **2010**, *34*, 46–50.
14. Zhu, J.Y. Study on Bidding Strategy of Generation Company with Evolutionary Game Theory based on Repast Platform. Diploma Thesis, North China Electric Power University, Beijing, China, 2010.
15. Zhu, J.L. Agent-Based Bidding Strategy of Generators. Diploma Thesis, Beijing Jiaotong University, Beijing, China, 2010.
16. Ren, X.G. A Study of Generator Bidding Behavior Based-on Multi-Agent Simulation. Diploma Thesis, North China Electric Power University, Beijing, China, 2010.
17. Liang, Z.H. Simulation Research on Bidding Transaction System of Generation Market Based on MAS. Diploma Thesis, North China Electric Power University, Beijing, China, 2012.
18. Akbari, E.; Hooshmand, R.; Gholipour, M.; Parastegari, M. Stochastic programming-based optimal bidding of compressed air energy storage with wind and thermal generation units in energy and reserve markets. *Energy* **2019**, *171*, 535–546. [CrossRef]
19. Ansari, M.M.; Guo, C.; Shaikh, M.; Chopra, N.; Yang, B.; Pan, J.; Zhu, Y.; Huang, X. Considering the uncertainty of hydrothermal wind and solar-based DG. *Alex. Eng. J.* **2020**, *59*, 4211–4236. [CrossRef]
20. Yi, M.Y.; Tong, X.Y. Dynamic Economic Dispatch Considering Uncertainties of Wind Power and Load Forecast Error. *Power Syst. Technol.* **2019**, *43*, 4050–4057. [CrossRef]
21. Dong, J.; Dou, X.; Bao, A.; Zhang, Y.; Liu, D. Day-Ahead Spot Market Price Forecast Based on a Hybrid Extreme Learning Machine Technique: A Case Study in China. *Sustainability* **2022**, *14*, 7767. [CrossRef]
22. Ben-Haim, Y. *Info-Gap Decision Theory: Decisions under Severe Uncertainty*; Elsevier: Amsterdam, The Netherlands, 2006.
23. Soroudi, A.; Ehsan, M. IGDT based robust decision making tool for DNOs in load procurement under severe uncertainty. *IEEE Trans. Smart Grid* **2012**, *4*, 886–895. [CrossRef]
24. Mavalizadeh, H.; Ahmadi, A.; Gandoman, F.H.; Siano, P.; Shayanfar, H.A. Multi objective robust power system expansion planning considering generation units retirement. *IEEE Syst. J.* **2017**, *12*, 2664–2675. [CrossRef]
25. Sun, G.Q.; Zhou, Y.Z.; Wei, Z.N.; Geng, T.X.; Wang, Y.; Li, Y.C. Dispatch optimization model of virtual power plant based on hybrid stochastic programming and Information gap decision theory. *Electr. Power Autom. Equip.* **2017**, *37*, 112–118. [CrossRef]
26. Song, K.L.; Xie, Y.Y.; Chen, X.; Zhang, L.D.; Wang, C.G.; Yin, M.H. Robust Restoration Method for Power System Load Based on Information Gap Decision Theory. *Autom. Electr. Power Syst.* **2017**, *41*, 113–120+175.
27. Wang, C.Q.; Wei, H.; Wu, S.Y. Multi-power Combined Unit Commitment Based on Information Gap Decision Theory. *Proc. CSEE* **2018**, *38*, 3431–3440+3442. [CrossRef]
28. Pan, Z.X.; Liu, S.M.; Wang, Z.J.; Wang, S.; Ding, C.R. Dispatch Based on Information Gap Decision Theory for Power System with Wind Power. *Electr. Power Constr.* **2018**, *39*, 87–94.
29. Mazzi, N.; Kazempour, J.; Pinson, P. Price-taker offering strategy in electricity pay-as-bid markets. *IEEE Trans. Power Syst.* **2017**, *33*, 2175–2183. [CrossRef]
30. Shen, Y.; Wu, Z.Y.; Kang, Z.Q.; Xia, Q.; Dai, G.H. Strategic bidding with application of game theory. *Power Syst. Autom.* **2002**, *26*, 7–11.
31. Li, T.; Shahidehpour, M. Strategic bidding of transmission-constrained GENCOs with incomplete information. *IEEE Trans. Power Syst.* **2005**, *20*, 437–447. [CrossRef]
32. Zhao, C.; Zhang, S.H. Generation asset allocation strategies based on. *Control Decis.* **2017**, *32*, 751–754. [CrossRef]
33. Tang, L.; Liu, J.C.; Yang, Y.F.; Zhou, L. Study on Strategies of Electricity Procurement and Sale of Power Retailer with Multiple Retail Contract Modes Based on Information Gap Decision Theory. *Power Syst. Technol.* **2019**, *43*, 1978–1988.
34. El Rahi, G.; Etesami, S.R.; Saad, W.; Mandayam, N.B.; Poor, H.V. Managing price uncertainty in prosumer-centric energy trading: A prospect-theoretic Stackelberg game approach. *IEEE Trans. Smart Grid* **2017**, *10*, 702–713. [CrossRef]
35. Etesami, S.R.; Saad, W.; Mandayam, N.B.; Poor, H.V. Stochastic games for the smart grid energy management with prospect prosumers. *IEEE Trans. Automat. Contr.* **2018**, *63*, 2327–2342. [CrossRef]
36. Bai, Y.; Wang, Y.; Xia, Q.; Sun, X.; Yang, M.H.; Zhang, J. A Full-scenario SCED With Coordinative Optimization of Hydro-thermal-wind Power. *Proc. CSEE* **2013**, *33*, 2–9.
37. Ben-Haim, Y. Uncertainty, probability and information-gaps. *Reliab. Eng. Syst. Saf.* **2004**, *85*, 249–266. [CrossRef]
38. Zhao, Y.X. The Scheduling Strategies of Concentrating Solar Power Plants Considering Multi-Uncertainties and Multi-Resources Coordination. Diploma Thesis, Zhejiang University, Hangzhou, China, 2020.
39. Zhang, R.F.; Zhong, H.; Li, S.C.; Yao, S.K. Medium and Long Term Electric Power Decomposition Model of Wind-storage Combined System Based on Prospect Theory. *Smart Power* **2021**, *49*, 56–62.
40. Kahneman, D.; Tversky, A. Prospect theory: An analysis of decision under risk. In *Handbook of the Fundamentals of Financial Decision Making: Part I*; World Scientific: Singapore, 2013; pp. 99–127.

41. Yousri, D.; Abd Elaziz, M.; Oliva, D.; Abraham, A.; Alotaibi, M.A.; Hossain, M.A. Fractional-order comprehensive learning marine predators algorithm for global optimization and feature selection. *Knowl. Based Syst.* **2022**, *235*, 107603. [CrossRef]
42. Yousri, D.; Ousama, A.; Fathy, A.; Babu, T.S.; Allam, D. Managing the exchange of energy between microgrid elements based on multi-objective enhanced marine predators algorithm. *Alex. Eng. J.* **2022**, *61*, 8487–8505. [CrossRef]
43. Rashad, A.; Hassan, M.H.; Kamel, S.; Shahinzadeh, H. In Reconfiguration of Zafarana Stage-l Wind Farm Layout Based on Marine Predators Algorithm Considering Wake Effect. In Proceedings of the 2022 9th Iranian Conference on Renewable Energy & Distributed Generation (ICREDG), Mashhad, Iran, 23–24 February 2022; IEEE: Piscataway, NJ, USA; pp. 1–4.