INTRODUCTION

With the rapid development of communication equipment level, ubiquitous power Internet of Things and smart grid technology, demand response (DR) technology has gradually become a research hotspot in the power industry. In 2015, the national development and reform commission of China issued a notice on the comprehensive urban pilot project of power demand side management, aiming to attract users to voluntarily participate in DR. In 2019, the Energy Bureau of Shandong Province, China issued the “Notice on Carrying Out the Power Demand Response in 2019” and launched the first real-time power demand response from 14 to 16 on August 8 of the same year, responded to a load of 101,800 kW.

Abstract

The gradual improvement of the electricity market and the rapid development of demand response (DR) technology not only make the load aggregator (LA) integrate the demand side resources (DSR) to participate in the market becoming true, but also bring new problems and challenges to LA for formulating electricity purchasing optimization strategy. With the goal of minimizing the operating cost of LA participating in electricity market to purchase electricity and providing auxiliary services in response to the peak-shaving demand planning, a deterministic day-ahead electricity purchasing decision-making model is established. Considering the uncertainty of wind power output and real-time price and the different attitude of LA toward risk caused by uncertainty, we adopt stochastic scenario planning method to deal with the uncertainty of wind power output. And the information gap decision theory (IGDT) is introduced to transform the deterministic model into a day-ahead electricity purchasing decision-making model of LA under two different risk attitudes: risk-averse and risk-seeking. In order to verify the effectiveness of the proposed approach, a case study has been investigated and the day-ahead electricity purchased optimization strategy for LA under different risk attitudes has been obtained. Moreover, the results confirm that participating in DR and improving the reliability of LA response can effectively reduce the operating cost of LA and improve the system stability.

KEYWORDS
demand response, information gap decision theory, load aggregator, risk attitude, uncertainty
The current popularization of DSR such as distributed power generation (DG)\(^1\) and electric vehicles (EVs),\(^4\) as an important part of the smart grid, can be used to achieve load peak-shaving and valley filling, improve power quality, reduce system congestion, and improve system economic operation through central coordination of system operators level and other effects.\(^5,6\) However, due to the small capacity, large quantity, dispersed distribution, and strong randomness of DSR, it is not practical technically and economically to directly participate in DR. A specialized provider was proposed at home and abroad—Load Aggregator (LA),\(^7\) which is an independent organization that integrates DSR and makes a large and scattered medium-sized controllable loads in the system participating in DR and electricity market transactions. In the above-mentioned DR pilot cases, LA responded to a load of 50-200 kW, which shouldered half of the response load and played a role that cannot be ignored. Therefore, many domestic and foreign scholars conduct research on LA, the existing researches mostly focus on the operation mechanism and scheduling control strategy of LA, but there are research reports specifically on LA’s electricity purchasing strategy. This is detrimental to the establishment and long-term development of LA and the implementation of DR. However, LA will face different uncertainty factors\(^8\) when operating in the electricity market, which may bring cost impact to LA and users, as well as challenges to LA in formulating electricity purchasing strategy. Therefore, this paper studies the day-ahead electricity purchasing strategy of LA considering the uncertainty of distributed generation and market electricity price.

In the electricity market, LA acts as an agent for the users in a certain area to participate in the market to meet the electricity demand of the proxy users, which is not only a bridge between the end users and the electricity market, but a key role in DR.\(^9\) Under the premise of guaranteeing user reliability and economy, an optimal control strategy model of LA considering demand response was proposed in Ref. 10. A wind farm-LA coordinated operation mode (WLCOM) was proposed in Ref. 11, which enabled LAs to deal with wind farms directly at an agreement price. A spatio-temporal bi-layers scheduling model for EVs and LA considering response reliability was proposed in Ref. 12. Two dispatching models based on load aggregator and direct load control were put forward in Ref. 13, which incorporated the electric excitation and electricity price response. According to demand respond capacity for different loads, Ref. 14 established the cost-benefit model for users, LA, and power grid, respectively.

In this paper, the uncertainty of wind power output and real-time price is mainly considered. We adopt stochastic scenario planning method\(^15\) to deal with the former, while the latter generally adopts scenario-based method, aiming at the minimum cost or maximum benefit of aggregators and retailers, using robust optimization or conditional value-at-risk (CvaR) to establish a risk-averse optimization model. Ref. 16 adopted a scenario-based method to deal with the uncertainty of electricity price, and a risk-aversive energy dispatch model of smart grid retailer was proposed. The scenario-based method was used to simulate the electricity price and a bidding optimization model for a DER aggregator to participate in day-ahead market was established in Ref. 17. Ref. 18 used the scenario-based method to deal with the uncertainty of electricity price and a risk-averse optimal bidding strategy model for DSR aggregators in day-ahead electricity markets was established. To deal with the uncertainty of electricity price, a risk-constrained scenario-based stochastic programming framework was proposed in Ref. 19, where the MG aggregator’s risk aversion was modeled using CvaR. However, the accuracy of scenario-based method is related to the number of scenarios, the more the number of scenarios, the higher the accuracy, and too many scenarios will reduce the efficiency of the solution. In addition, the solution obtained is only optimal in the sense of probability. For a single event, especially when the actual market electricity price deviates greatly from the predicted value, the decision result may exceed the acceptance range of the decision maker. Robust optimization and C VaR only consider risk-averse aggregators and retailers, without fully considering the risk attitudes of aggregators and retailers. Information gap decision theory (IGDT)\(^20\) is an approach to quantify uncertainty even if probability distribution and fluctuation range are unknown, which can obtain risk-averse strategy and risk-seeking strategy by considering the risk attitude of the decision maker on the premise that the optimization result is not less than the expected target, providing the decision maker with more decision-making space. Based on IGDT, the bidding strategy model of microgrid operators considering the uncertainty of upstream power grid price was established in Ref. 21, the electricity purchased and sale decision-making model for electricity retailers considering the uncertainty of market clearing price under various retail contract modes was established in Ref. 22. The above literature demonstrates the effectiveness of using IGDT to deal with the market electricity price and provides strategic options for decision makers with different risk attitudes.

This paper aims at minimizing the operation cost of LA and studies electricity purchasing strategy of LA. While participating in the electricity market, LA also responds to the peak-shifting plan of the power grid dispatching center, providing DSR, and a LA day-ahead electricity purchasing optimization model is established. Considering the uncertainty of wind power output and real-time price, the former adopts stochastic scenario planning method, the latter adopts IGDT. Consequently, this paper obtains the day-ahead electricity purchasing strategy of LA with two different risk attitudes: risk-averse and risk-seeking. The main contributions of this work can be summarized as follows:
1. We adopt IGDT to deal with the uncertainty of real-time price, which has a practical advantage that finds the optimum strategy for any profit level, not for a given price scenario and without reliance on probability density functions or fuzzy membership of sets, etc.

2. LA responds to the peak-shifting plan of the power grid dispatching center and provides DSR for it. It can effectively link the peak of electricity consumption and promote the consumption of renewable energy.

3. The ability to integrate the DSR of LA was analyzed to study the impact on the operation cost of LA. The results show that the better the response reliability of LA, the better the development of LA. The results show that the better the response reliability of LA and the better the development of LA.

The remainder of the paper is organized as follows. The operating mechanism of LA is presented in Section 2. The electricity purchased decision-making deterministic model is established in the day-ahead market in Section 3. IGDT-based electricity purchase decision-making model in the day-ahead market is formulated in Section 4. Section 5 provides a case study to verify the effectiveness. And section 6 provides the conclusion.

2 OPERATING MECHANISM OF LA

As a bridge between other power system participants and the DSR, LA could not only integrate the DSR in a certain area to participate in the electricity market, act for users in the area to purchase electricity from the electricity market, meet the demand of user load, but participate in the peak-shaving plan, provide the DR, lighten the pressure of power grid operation, reduce the operating cost. The operating mechanism of LA is shown in Figure 1.

Common DSR are generally divided into three categories: simple adjustable load, energy storage device, and distributed generator. Simple adjustable load refers to the user load that is transferred, increased, and decreased in a short time depending on the load itself. Energy storage device refers to load transfer devices on the space-time level, such as lithium batteries and EVs. Distributed generator refers to small modular and environment compatible independent power source, such as photovoltaic, wind power, and internal combustion engines. In this paper, representative resources are selected from three types of DSR: the adjustable load, EVs, and wind power.

\[
\min F = \sum_{t=1}^{24} \sum_{w=1}^{N_w} \rho \left( \lambda^{DA}_t p^{DA}_t + \lambda^{RT}_t p^{RT}_t + \lambda^{DR}_t p^{DR}_t + U_t - \lambda^{DR}_t \left( p^{DR}_t + p^{DR}_W + p^{DR}_L \right) \right) \Delta t
\]

(1)

where the operating cost of LA includes 4 parts, namely day-ahead electricity purchasing cost, real-time electricity purchasing cost, penalty cost, and compensation income from auxiliary services. \( F \) is the operating cost of LA; \( \lambda^{DA}_t, \lambda^{RT}_t \), and \( \lambda^{DR}_t \) represent the day-ahead price, real-time price, and DR compensation price, respectively, in \( t \) th period, respectively; \( p^{DA}_t, p^{RT}_t, p^{DR}_t, p^{DR}_W, p^{DR}_L \) represent the purchasing electricity from day-ahead market and real-time market (when it is greater than 0, it means purchasing electricity; when it is less than 0, it means selling electricity), the discharge power of EVs participating
in DR, the wind power output participating in DR under scenario \( \omega \), and the responsive load of users participating in DR in \( t - th \) period, respectively. \( U_t \) represents the penalty cost occurred when real-time purchasing electricity exceeds purchasing electricity stipulated by the power grid dispatching center in \( t - th \) period; \( \rho_{\omega t} \) represents probability of scenario \( \omega \); and \( N_{\omega} \) represents number of scenarios.

### 3.2 Constraints

#### (1) Constrains of the adjustable load

With the development of demand respond technology, the adjustable user load can be divided into basic power load and power load participating in DR. It needs to be satisfied:

\[
P_{L,t} = P_{L,d} + P_{L,rt}, \quad \forall t
\]

(2)

where \( P_{L,t} \) represents the demand of user load in \( t - th \) period; \( P_{L,d} \) represents the basic power load of users in the agent area of LA in \( t - th \) period.

#### (2) Constrains of EVs charging and discharging power

In this paper, only private EVs in residential areas are considered. And it is assumed that the driving characteristics and related parameters of EVs have been mastered, and EVs are the same model. Among them, considering the V2G technology of EVs, the use of EVs discharging power can be mainly divided into two parts: One is the discharging power that participates in the DR; the other part meets the needs of users, which must meet:

\[
E_{t} = E_{t-1} + (P_{t}^{c} \eta_{c} - P_{t}^{d} / \eta_{d}), \quad \forall t
\]

where \( E_{t} \) represents stored energy of the EVs in \( t - th \) period; \( E_{t}^{min} \) and \( E_{t}^{max} \) represent the minimum and maximum limits of stored energy of the EVs in \( t - th \) period, respectively; \( \eta_{c} \) and \( \eta_{d} \) represent charging and discharging efficiencies of the EVs, respectively; \( \kappa_{t}^{c} \) and \( \kappa_{t}^{d} \) represent binary variable for charging and discharging modes of the EVs in \( t - th \) period, respectively; \( P_{t}^{c} \) represents the discharge power of EVs is to meet the needs of users in the LA agent area.

#### (3) Constrains of wind power output

Wind power output is mainly used in two parts: one is participating in the DR; the other is to meet the needs of users. It needs to be satisfied:

\[
p_{W,t,0}^{W} = \begin{cases} 0 & \text{for } v_{W,t,0} < v_{co} \\ v_{W,t,0}^{W} - v_{ci} & \text{for } v_{ci} < v_{W,t,0} < v_{r} \\ (v_{r} - v_{ci}) P_{r} + v_{W,t,0}^{W} - v_{r} & \text{for } v_{r} < v_{W,t,0} < v_{co} \\ v_{W,t,0}^{W} - v_{co} & \text{for } v_{W,t,0} > v_{co} \end{cases}, \quad \forall t, \omega (9)
\]

\[
0 \leq p_{W,t,0}^{W} \leq p_{W,0,\omega_{max}}, \quad \forall t, \omega (10)
\]

where \( p_{W,t,0}^{W} \) represents the actual output of wind power in \( t - th \) period under scenario \( \omega \). \( P_{r} \) represents rated output of wind power; \( v_{W,t,0}^{W} \) represents environment wind speed in \( t - th \) period under scenario \( \omega \); \( v_{r} \) and \( v_{co} \) represent rated and cut-in and cut-out wind speed respectively; \( P_{W,t,0}^{L} \) represents the wind power output to meet the needs of users in the LA agent area under scenario \( \omega \); and \( P_{W,0,\omega_{max}} \) represents the maximum wind power output under scenario \( \omega \).

#### (4) Constrains of power balance

\[
P_{t}^{DA} + P_{t}^{RT} + P_{W,t,0}^{L} + P_{t}^{d} = P_{L,0}^{d} + P_{t}^{c}, \quad \forall t, \omega (12)
\]

#### (5) Constrains of scheduling capacity

The power grid dispatching center issues a peak-shaving plan which specifies the peak-shaving capacity in \( t - th \) period. And DSR participates in peak-shaving through DR. That is:

\[
0 \leq P_{t}^{D} + P_{W,t,0}^{DR} + P_{L,0}^{D} \leq P_{t}^{DIS}, \quad \forall t, \omega (13)
\]

where \( P_{t}^{DIS} \) represents the peak-shaving power that the power grid dispatching center needs to schedule in \( t - th \) period.
(6) Constrain of penalty cost

The power grid dispatching center stipulates that the purchasing electricity by LA in the real-time market shall not exceed that in the day-ahead market, and penalty charges will be incurred when the threshold value is exceeded. It needs to be satisfied:

\[ U_t \geq \pi \left( \left| P_{RT,t} \right| - \theta \cdot P_{DA,t} \right) \Delta t, \quad \forall t \]  

(14)

where \( \pi \) represents the exceeded penalty price; \( \theta \) represents the percentage of the purchasing electricity in day-ahead market; \( \theta \cdot P_{DA,t} \) is a threshold for purchasing electricity in the day-ahead market. And if the real-time purchasing electricity exceeds the threshold, there will be penalty.

4 | IGDT-BASED ELECTRICITY PURCHASED DECISION-MAKING MODEL

4.1 | IGDT

Due to the uncertainty of the real-time price and the failure to obtain the probability distribution or parameters with its uncertain variables, the traditional forecasting method is difficult to forecast the market clearing price accurately. Using IGDT to model the deviation between the forecasting value of real-time price and the actual value of real-time price, a decision value considering the uncertainty of real-time price can be obtained.

When using IGDT to build a day-ahead market electricity purchased model with uncertainty, three factors need to be considered: system model, uncertainty set, and performance requirements.

(1) System model

The input and output parameters of the system model need to be determined firstly. For the day-ahead market electricity purchased model of LA, the input parameter of the system model is an uncertain variable, that is the real-time price \( \lambda_{RT,t} \), and the output parameter is the operating cost of LA \( F \).

(2) Uncertainty set

In the electricity purchasing strategy making process of LA participating in electricity market, there is a deviation between the forecasting value of real-time price and the actual value of real-time price. If the deviation between the two is not considered, the operating cost of LA will be affected. According to IGDT, the actual electricity price in the real-time market fluctuates slightly around the forecasting electricity price, which can be expressed as:

\[ \varphi(\mu, \lambda_{RT,t}) = \left\{ \lambda_{RT,t} : \frac{\lambda_{RT,t} - \lambda_{RT,t}}{\lambda_{RT,t}} \leq \mu \right\} \]  

(15)

where \( \mu \) represents the deviation between the actual value and the forecasting value of the real-time price, which is the fluctuation range of the actual market price. The greater the value of \( \mu \), the greater the acceptable risk; \( \lambda_{RT,t} \) represents the real-time price forecasted by LA.

(3) Performance requirements

Because changes in uncertain variables may affect the overall benefits of the system and consequent risks, different decision makers have different attitudes toward risks. According to decision makers’ risk preference level of, this paper divides LA into risk-averse LA and risk-seeking LA. The former inclined to be conservative and the latter inclined to be speculative. For risk-averse LA, on the premise of ensuring that the maximum operating cost of the decision does not exceed the expected value, the robust function is solved with the goal of maximizing the fluctuation range of uncertain variable, and the obtained decision value always meets the expected cost within the fluctuation range, which reflects the robustness of IGDT. For the risk-seeking LA, on the premise of ensuring that the minimum operating cost of the decision does not exceed the expected value, the opportunity function is solved with the goal of minimizing the fluctuation range of uncertain variable, and the obtained decision value always meets the expected cost within the fluctuation range, which reflects the opportunity of IGDT.

\[ \mu_{neg}(\lambda_{RT,t}, F) = \max \left\{ \mu : \lambda_{RT,t} \varphi(\mu, \lambda_{RT,t}) \leq F_{c1} \right\} \]  

(16)

\[ \mu_{opt}(\lambda_{RT,t}, F) = \min \left\{ \mu : \lambda_{RT,t} \varphi(\mu, \lambda_{RT,t}) \leq F_{c1} \right\} \]  

(17)

It can be seen from formulation (16) that the risk-averse LA tends to have a low risk and low returns with high stability. In the fluctuation range, the operating cost of LA is less than or equal to the expected cost \( F_{c1} \). Formulation (17) indicates that risk-seeking LA tends to be high risk with low stability and high returns. In the fluctuation range, the operating cost of LA is less than or equal to the expected cost \( F_{c2} \) and exists \( F_{c1} \leq F_{c2} \).
4.2 Risk-averse decision-making model

Considering the uncertainty of real-time price, the purpose of risk-averse strategy made by LA is to ensure that the operating cost in the fluctuation range is less than the expected cost and to avoid the risk caused by uncertainty. According to IGDT, the following risk-averse electricity purchasing decision-making model of LA in the day-ahead market is established:

\[
\max_{\mu_{neg}} \left\{ \lambda_i^{RT} \varphi_{\mu_{neg}, \lambda_i^{RT}} \right\} \text{subject to } (18)
\]

Here, we assume that the input parameters are predetermined values, and the optimal objective result of the deterministic decision-making model is \( F_0 \). So the expected cost \( F_{c1} \) of risk-averse LA can be expressed as \( F_0 \):

\[
F_{c1} = (1 + \delta) F_0
\]

where \( \delta \) represents the deviation factor of the risk-averse decision-making model, which is the deviation level between the expected cost and the optimal result of the deterministic model. In order to ensure the robustness of the decision-making strategy, the expected cost is greater than the decision value, so the value range of \( \delta \) is \([0, 1)\). The larger the value of \( \delta \), the greater the level of risk-averse decision value.

Then the actual real-time price is expressed as:

\[
\lambda_i^{RT} = (1 \pm \mu_{neg}) \lambda_i^{neg}
\]

For risk-averse LA, when the actual electricity price of the real-time market takes the maximum value, the operating cost of LA is the largest. Therefore:

\[
\lambda_i^{RT} = (1 + \mu_{neg}) \lambda_i^{neg}
\]

Introducing formulation (21) into formulation (18), the following formulation can be obtained by arranging:

\[
\max_{\mu_{neg}} \left\{ \lambda_i^{RT} \varphi_{\mu_{neg}, \lambda_i^{RT}} \right\} \text{subject to } (22)
\]

4.3 Risk-seeking decision-making model

Considering the uncertainty of real-time price, LA decision makers who tend to pursue risk seek greater benefits by high risk. That is, in a certain fluctuation range, the minimum operating cost is less than or equal to the expected cost. The following risk-seeking electricity purchasing decision-making model of LA in the day-ahead market is established:

\[
\min_{\mu_{opt}} \left\{ \lambda_i^{RT} \varphi_{\mu_{neg}, \lambda_i^{RT}} \right\} \text{subject to } (23)
\]

Here, the expected cost \( F_{c2} \) of the risk-seeking LA can be expressed as \( F_0 \):

\[
F_{c2} = (1 - \epsilon) F_0
\]

where \( \epsilon \) represents the deviation factor of the risk-seeking decision-making model, which is the deviation between the expected cost and the optimal result of the deterministic model. In order to ensure the opportunism of the decision-making strategy, the expected cost is greater than the decision value, so the value range of \( \epsilon \) is \([0, 1)\). The larger the value of \( \epsilon \), the greater the degree of risk-seeking decision value.

When the actual real-time price takes the minimum value, the operating cost of LA is the smallest. Therefore:

\[
\lambda_i^{RT} = (1 - \mu_{opt}) \lambda_i^{opt}
\]

Introducing formula (25) into formula (23), we get:

\[
\max_{\mu_{neg}} \left\{ \lambda_i^{RT} \varphi_{\mu_{neg}, \lambda_i^{RT}} \right\} \text{subject to } (26)
\]

4.4 Solving procedure

According to the above description, the solution steps are as follows:

1. The forecasting information including day-ahead electricity price, real-time price, user load, wind power output.
can be obtained by monte carlo method, stochastic scenario planning method and the historical data;

2. Regardless of the forecasting data inaccuracy, the optimal cost and electricity purchased strategy in the day-ahead market are obtained by solving the deterministic day-ahead electricity purchased decision-making model of LA;

3. Set the model deviation factor and solve the IGDT-based day-ahead electricity purchased decision-making model of LA. Then, the maximum uncertainty level of real-time price allowed by LA itself, and the corresponding expected operating cost and electricity purchased strategy in the day-ahead market can be obtained;

4. LA selects the corresponding day-ahead electricity purchased strategy according to its risk acceptance ability.

TABLE 1  Peak-shaving plan of power grid dispatching center

| Time/h | Demand/kW |
|--------|-----------|
| 11     | 3600      |
| 12     | 3400      |
| 13     | 3500      |
| 14     | 3700      |
| 15     | 4500      |

TABLE 2  Forecasted daily temperature, insulation, and wind speed for a sample day

| Time/h | Wind speed/(m/s) | Temperature/°C | Insulation/(W/m²) |
|--------|------------------|----------------|------------------|
| 1      | 10.5             | 24.7           | 0                |
| 2      | 13.5             | 24.5           | 0                |
| 3      | 14.9             | 24.3           | 0                |
| 4      | 15.6             | 24.4           | 0                |
| 5      | 19.5             | 24.5           | 93.5             |
| 6      | 20.6             | 26.5           | 219              |
| 7      | 14.4             | 27.5           | 467.5            |
| 8      | 14.1             | 28              | 637.5            |
| 9      | 11.3             | 28.5           | 780              |
| 10     | 9.7              | 28.8           | 916              |
| 11     | 7.0              | 29              | 1100             |
| 12     | 5.9              | 29.7           | 1033             |
| 13     | 8.9              | 29.8           | 850              |
| 14     | 9.5              | 30              | 680              |
| 15     | 10.4             | 29.8           | 595              |
| 16     | 8.8              | 29.5           | 255              |
| 17     | 7.1              | 29              | 212.5            |
| 18     | 8.3              | 27.7           | 153              |
| 19     | 9.9              | 26.5           | 63               |
| 20     | 7.5              | 24.8           | 0                |
| 21     | 8.8              | 25              | 0                |
| 22     | 9.8              | 24.8           | 0                |
| 23     | 9.2              | 24.6           | 0                |
| 24     | 8.4              | 24.8           | 0                |

5  CASE STUDY

5.1  Data source

In order to verify the effectiveness of the method and the accuracy of the model, the data of day-ahead price and real-time price are shown in Figure 2, and the user load data is shown in Figure 3. According to relevant forecasts, the power grid dispatching center releases the peak-shaving time and the demand of next day to LA. To facilitate calculation, the demand for the 4 periods in 1 hour is assumed equal, which is shown in Table 1. The forecasted daily temperature, irradiation, and wind speed for a sample day are presented in Table 2, and
the forecasting wind power output can be obtained as shown in Figure 4. Parameters of EVs are shown in Table 3. The compensation price of participating DR is $\delta_1^{DR} = 0.064$/kWh, penalty price $\pi = 0.05$/kW, $\theta = 20\%$.

5.2 Results analysis

The established day-ahead electricity purchasing decision-making model is a mixed integer programming problem. Without considering the uncertainty of real-time price and the accuracy of all forecasting data, the total operating cost of LA is 11 740.57$, and the remaining costs are shown in Table 4. Its LA day-ahead electricity purchasing strategy is shown in Figure 5.

![Wind power forecasting output curve](image)

**FIGURE 4** Wind power forecasting output curve

| Parameters       | Values | Units |
|------------------|--------|-------|
| $E_{max}$        | 60     | kW/h  |
| $E_{min}$        | 6      | kW/h  |
| $P_{max}$        | 18     | kW    |
| $P_{dmax}$       | 18     | kW    |
| $\eta_e$         | 90     | %     |
| $\eta_d$         | 90     | %     |

**TABLE 3** Parameters of a single EV

When considering the uncertainty of real-time price, the different expected operating cost is determined by changing deviation factors. The corresponding maximum fluctuation range of uncertain real-time price and day-ahead electricity purchased plan can be obtained by solving the IGDT-based electricity purchased decision-making model in the day-ahead market. The relationship between the deviation factor and the fluctuation range of real-time price is shown in Figure 6 and Table 5.

| The cost of day-ahead electricity purchase/$ | The cost of real-time electricity purchase/$ | The penalty cost/$ | The compensation cost/$ | the total operating cost/$ |
|---------------------------------------------|-------------------------------------------|-------------------|------------------------|--------------------------|
| 15 868.94                                   | −2782.69                                  | 0                 | −1345.71               | 11 740.57                |

**TABLE 4** The operating cost of LA without considering the uncertainty

5.2.1 The day-ahead electricity purchasing strategy of LA

When considering the uncertainty of real-time price, the difference expected operating cost is determined by changing deviation factors. And the corresponding maximum fluctuation range of uncertain real-time price and day-ahead electricity purchased plan can be obtained by solving the IGDT-based electricity purchased decision-making model in the day-ahead market. The relationship between the deviation factor and the fluctuation range of real-time price is shown in Figure 6 and Table 5.

It can be seen from Figure 6 that the deviation factor has a positive correlation with the fluctuation amplitude. In Table 5, for risk-averse LA, the deviation factor $\delta$ changes from 0 to 0.05, the fluctuation range of real-time price increases from 0 to 0.352 (the robustness coefficient $\mu_{neg}$ increases from 0 to 0.352), and the expected operating cost $F_{c1}$ also increases from 11 740.57$ to 12 327.57$. The results show that the higher the expected operating cost of LA, the better the robustness of the electricity purchased strategy, thus the lower the acceptable risk level, and the greater the allowable uncertainty fluctuation. For risk-seeking LA, the deviation factor $\delta$ changes from 0 to 0.05, the fluctuation range increases from 0 to 0.356 (the opportunity coefficient $\mu_{opt}$ increases from 0 to 0.356), and the expected operating cost $F_{c2}$ also decreases from 11 740.57$ to 11 153.57$. The results show that the lower the expected operating cost of LA, the better the opportunity of electricity purchased strategy, thus the higher the acceptable risk level, and the greater the fluctuation range of uncertainty.

When the expected operating cost of the risk-averse LA and the risk-seeking LA are $F_{c1} = 12 327.57$ and $F_{c2} = 11 153.57$ respectively, the robust coefficient is 0.352 and the opportunity coefficient is 0.356. That means, when the real-time price fluctuates within 0.352 and 0.356 of the forecast real-time price, the operating cost of the risk-averse LA is 12 327.57$ at most, and the operating cost of the risk-seeking LA is 11 153.57$ at least. At this time, the day-ahead electricity purchasing strategy of LA with different risk attitudes are shown in Figure 7 and Figure 8.

It can be seen from Figure 7 and Figure 8 that purchasing electricity by the risk-averse LA in the day-ahead market is greater than purchasing electricity by the risk-seeking LA
in the day-ahead market. This is because in order to avoid risks, risk-averse LA does not take the uncertainty of real-time price as the main influence, while risk-seeking LA pursues high risks in order to reduce cost, considering the uncertainty of real-time price. Taking into account the uncertainty of real-time price, risk-seeking LA will purchase electricity in the real-time market, while risk-averse LA will purchase electricity in the day-ahead market, but both of their electricity purchased strategy will meet their expected operating cost.

5.2.2 Results analysis under different scenarios

In order to verify the effectiveness of the IGDT-based day-ahead electricity purchased decision-making model of LA and the impact of participating in DR on the results, 4 scenarios are set as follows:

1. Scenario 1: Deterministic model, not participating in DR;
2. Scenario 2: IGDT model (taking risk-seeking model as an example, the deviation factor $\delta = 0.05$), not participating in DR;
3. Scenario 3: Deterministic model, participating in DR;
4. Scenario 4: IGDT model (taking risk-seeking model as an example, the deviation factor $\delta = 0.05$), participating in DR. The specific results are shown in Table 6.

From Table 6, it can be seen that the expected operating cost solved by the day-ahead electricity purchasing decision-making model of risk-seeking LA based on IGDT is less than the result solved by the deterministic model. Because in the deterministic model, LA is conservative in electricity purchasing strategy according to the level of day-ahead and

![FIGURE 5](image1.png)

**FIGURE 5** The day-ahead electricity purchasing strategy of LA without considering the uncertainty

![FIGURE 6](image2.png)

**FIGURE 6** Variation curve of fluctuation amplitude with deviation factor

| Deviation factor | Expected cost $F_c/\$ |
|------------------|------------------------|
| 0                | 11 740.57              |
| 0.005            | 11 799.27              |
| 0.010            | 11 857.97              |
| 0.015            | 11 916.67              |
| 0.020            | 11 975.37              |
| 0.025            | 12 034.07              |
| 0.030            | 12 092.77              |
| 0.035            | 12 151.47              |
| 0.040            | 12 210.17              |
| 0.045            | 12 268.87              |
| 0.050            | 12 327.57              |

| Deviation factor | Expected cost $F_c/\$ |
|------------------|------------------------|
| 0                | 11 740.57              |
| 0.005            | 11 799.27              |
| 0.010            | 11 857.97              |
| 0.015            | 11 916.67              |
| 0.020            | 11 975.37              |
| 0.025            | 12 034.07              |
| 0.030            | 12 092.77              |
| 0.035            | 12 151.47              |
| 0.040            | 12 210.17              |
| 0.045            | 12 268.87              |
| 0.050            | 12 327.57              |

**TABLE 5** Expected cost, robustness, and opportunity coefficient under different deviation factors.
real-time price and penalty mechanism, more electricity will be purchased in the day-ahead market. But when participating in DR, LA will buy more electricity in the day-ahead market in the case of low day-ahead price during the peak period. Although the risk is increased, due to the controllability of DSR, appropriate adjustments can be made when facing risks, and the operating cost of LA is still reduced. Compared with Scenario 3, Scenario 4 participates in DR with more peak regulation power and lower operating cost. This is because the IGDT-based day-ahead electricity purchased decision-making model of risk-seeking LA considers the uncertainty of real-time price, which can make better use of the advantages of low electricity price in the real-time market and also participate in DR to reduce risks. It also shows participating in DR has greater economic value in the case of the uncertainty of real-time price.

5.2.3 | Results analysis of reliability of LA

The level of LA’s ability to integrate DSR is related to the operational safety of the power system. To analyze the response reliability of LA, this paper describes the response reliability of LA from the perspective of capacity, and the confidence $\gamma$ meets the maximum capacity of the response task, which is called the LA confidence $\gamma$ response credible capacity. The results are shown in Figure 9.

It can be seen from Figure 9 that LA’s ability to integrate DSR will affect LA’s operating costs. The lower the integration capacity, the greater the operating costs. Therefore, when participating in market operation, LA needs to focus on its own DSR capability, which is not only related to the overall benefits of LA, but also related to the safety and economic level of the power system.

6 | CONCLUSION

This paper studies the electricity purchased decision-making optimization model of LA in the day-ahead market under DR. In order to deal with risks caused by the real-time price uncertainty, the electricity purchased strategy of LA with two

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**TABLE 6** Operating cost under different scenarios

| Scenario  | DR income/$ | Expected operating costs/$ |
|-----------|-------------|-----------------------------|
| Scenario 1 | 0           | 13,469.71                   |
| Scenario 2 | 0           | 14,527.43                   |
| Scenario 3 | 1,345.71    | 11,740.57                   |
| Scenario 4 | 1,274.85    | 12,327.57                   |

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**FIGURE 7** The day-ahead electricity purchasing strategy for the risk-seeking LA

**FIGURE 8** The day-ahead electricity purchasing strategy for the risk-averse LA

**FIGURE 9** The response reliability curve of LA
different risk attitudes is established based on IGDT. The effectiveness of the model is verified by case study, and the following conclusions can be drawn:

1. The uncertainty of real-time price is treated by IGDT approach, and different expectations are provided for different LA with different risk attitudes. Under the premise that the expectations are not exceeded, LA can accept the electricity price in a certain fluctuation range and select the corresponding day-ahead electricity purchased strategy, which provides new thinking for operational decision-making behavior and risk assessment issues.

2. IGDT approach divides LA into two types: risk-averse LA and risk-seeking LA. As the expected operating cost increases, the former will gradually increase the day-ahead electricity purchase, reduce real-time electricity purchase and increase the robustness of day-ahead electricity purchase strategy. The latter, with the reduction of expected operating cost, will gradually reduce the day-ahead electricity purchase, increase the real-time electricity purchase, and increase the day-ahead power purchase opportunity.

3. Considering that LA participates in the peak-shaving plan to provide auxiliary services, DR is introduced into the day-ahead electricity purchased decision-making model. The results show that it can effectively reduce its operating cost and improve the system stability.

4. The higher the reliability of LA response, the higher the overall effect level of LA, and the greater the role of LA in the market.

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